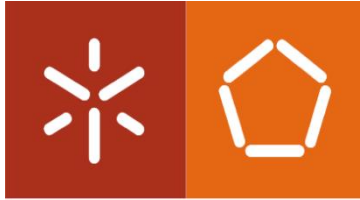




Universidade do Minho
Escola de Engenharia

Daniel Filipe Coelho Rocha

Automated Garment Recognition and Assessment System Using Computer Vision and Artificial Intelligence for Blind People



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**Automated Garment Recognition and
Assessment System Using Computer Vision
and Artificial Intelligence for Blind People**

Tese de Doutoramento
Programa Doutoral em Engenharia Eletrónica e de
Computadores

Trabalho efetuado sob a orientação do
Professor Doutor Vítor Hugo Mendes da Costa Carvalho
Professora Doutora Filomena Maria da Rocha Menezes de
Oliveira Soares

outubro de 2024

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ABSTRACT

Clothing management is one of the most significant challenges faced by blind and visually impaired people. By leveraging advanced technologies, such as computer vision and artificial intelligence (AI), this PhD work aimed at developing and validating a mechatronic device, the iSight prototype, able to assist in the identification of clothing types, colours, and conditions, primarily designed for blind and visually impaired users. Valuable insights were obtained from a nationwide survey, conducted in collaboration with the Association of the Blind and Amblyopes of Portugal (ACAPO), which revealed a high demand for technological solutions in garment management, with 95.7 % of respondents expressing willingness to adopt new technologies. The iSight prototype integrates a smart wardrobe equipped with an image acquisition system and controlled lighting, ensuring optimal image quality capture for accurate analysis. The device is controlled via a user-friendly mobile application, designed to be highly accessible and intuitive. The system's functionality was rigorously tested with 15 participants from ACAPO, encompassing both blind and low-vision people. The prototype's accuracy in identifying clothing categories and colours was highly acknowledged by users, with 60 % finding it very precise in identifying categories and 80 % in identifying colours. Additionally, 86.7% of participants rated the system's ability to detect stains and identify Near Field Communication (NFC) tags as highly effective. Finally, the obtained results demonstrated high levels of user satisfaction. Extensive statistical analyses confirmed significant positive correlations between the iSight functionalities and in users' confidence, self-esteem, well-being, and independence. These findings highlight the prototype's potential to significantly enhance the daily lives of visually impaired people. Key areas for further improvement were also identified by the users, namely the reduction of menu complexity and addition of detailed fabric information. In conclusion, this PhD work demonstrates the feasibility and effectiveness of integrating computer vision and AI technologies into a mechatronic device (smart wardrobe) to support blind and visually impaired people in garment identification and management. The iSight prototype offers a robust and user-friendly solution that significantly improves users' quality of life, offering room for future refinement and paving the way towards a truly disruptive product for smart and effective clothing management.

KEYWORDS: Artificial Intelligence (AI), Assistive Technology, Blind People, Clothing Identification and Modifications, Computer Vision, Mobile Application, Smart Wardrobe.

RESUMO

A gestão de vestuário é um dos maiores desafios enfrentados por pessoas cegas e com deficiência visual. Aproveitando tecnologias avançadas, como visão por computador e a inteligência artificial (IA), este trabalho de doutoramento teve como objetivo desenvolver e validar um dispositivo mecatrónico, o protótipo iSight, capaz de auxiliar na identificação de tipos de roupa, cores e modificações, criado principalmente para utilizadores cegos e com deficiência visual. Foram obtidos insights valiosos a partir de um inquérito nacional, realizado em colaboração com a Associação dos Cegos e Amblíopes de Portugal (ACAPO), que revelou uma elevada procura por soluções tecnológicas na gestão de vestuário, com 95,7% dos inquiridos a expressar vontade de adotar novas tecnologias. O protótipo iSight integra um guarda-roupa inteligente equipado com um sistema de aquisição de imagem e iluminação controlada, garantindo uma captação de imagem de qualidade para uma análise precisa. O dispositivo é controlado através de uma aplicação móvel de fácil utilização, desenhada para ser acessível e intuitiva. A funcionalidade do sistema foi rigorosamente testada com 15 participantes da ACAPO, abrangendo tanto pessoas cegas como pessoas com baixa visão. A precisão do protótipo na identificação de categorias de roupa e cores foi reconhecida pelos utilizadores, com 60% a considerá-lo muito preciso na identificação de categorias e 80% na identificação de cores. Adicionalmente, 86,7% dos participantes classificaram como eficaz a capacidade do sistema para detetar manchas e identificar etiquetas de Near Field Communication (NFC). Finalmente, os resultados obtidos demonstraram elevados níveis de satisfação dos utilizadores. Análises estatísticas confirmaram correlações positivas significativas entre as funcionalidades do iSight e a confiança, autoestima, bem-estar e independência dos utilizadores. Estes resultados destacam o potencial do protótipo para melhorar a vida diária das pessoas com deficiência visual. Áreas chave para melhoria futura foram identificadas pelos utilizadores, nomeadamente a redução da complexidade dos menus e a adição de informações detalhadas sobre os tecidos. Em conclusão, este trabalho demonstra a viabilidade e a eficácia da integração de tecnologias de visão computacional e IA num dispositivo mecatrónico (guarda-roupa inteligente) para apoiar pessoas cegas e com deficiência visual na identificação e gestão de vestuário. O protótipo iSight oferece uma solução robusta e de fácil utilização que melhora a qualidade de vida dos utilizadores, oferecendo margem para melhorias futuras e abrindo caminho para um produto disruptivo na gestão inteligente e eficaz de vestuário.

PALAVRAS-CHAVE: Aplicação Móvel, Guarda-Roupa Inteligente, Identificação e Modificação de Roupa, Inteligência Artificial (IA), Pessoas Cegas, Tecnologia Assistida, Visão Computacional.

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ABBREVIATIONS

AADVDB	<i>Associação De Apoio Aos Deficientes Visuais Do Distrito de Braga</i>
ACAPO	<i>Associação de Ambliopes e Cegos de Portugal</i>
AI	Artificial Intelligence
ANN	Artificial Neural Network
AP	Average Precision
API	Application Programming Interface
CAVI	Support Centre for Independent Living
CEICSH	Comissão de Ética para a Investigação em Ciências Sociais e Humanas
CMYK	Cyan Magenta Yellow Black
CNN	Convolutional Neural Network
CPU	Central Processing Unit
DC	Direct Current
EU	European Union
GPU	Graphics Processing Unit
GUI	Graphical User Interface
Hex	Hexadecimal
HSI	Hue Saturation Illumination
HSL	Hue Saturation Luminance
HSV	Hue Saturation Value
IDE	Integrated Development Environment
IIC	Inter-Integrated Circuit
IoT	Internet of Things
IOU	Intersection Over Union
IP	Ingress Protection
LED	Light Emitting Diode
MSCOCO	MicroSoft Common Objects in Context
MSVI	Moderate to Severe Vision Impairment
NFC	Near Field Communication
FDENet	Frequency Domain Enhancement Network
QR	Quick Response

RFID	R adio F ield I dentification
RGB	R ed G reen B lue
RNID	<i>Regulamento Nacional de Interoperabilidade Digital</i>
ROI	R egion O f I nterest
RPN	R egion P roposal N etwork
SDG	S ustainable D evelopment G oal
SIFT	S cale I nvariant F eature T ransform
SGD	S tochastic G radient D escent
SPI	S erial P eripheral I nterface
SSD	S ingle S hot M ultiBox D etector
STA	S tatistical F eature
SVM	S upport V ector M achine
UART	U niversal A synchronous R eceiver/ T ransmitter
UID	U nique I dentifier
URL	U niform R esource L ocator
VOC	V isual O bject C lasses
WHO	W orld H ealth O rganization

1 INTRODUCTION

Chapter Overview

The purpose of this chapter is to present the problem statement, the motivations, and the scope of the research. An overview of assistive technologies for clothing management for blind people is presented first. In the following section, the present work's objectives and ethical considerations are discussed. Finally, the results of the developed scientific activity are presented, as well as the structure of the dissertation.

1 Introduction

- 1.1 Problem Statement, Motivations, and Scope
 - 1.2 Objectives
 - 1.3 Contribution to Knowledge and Results of the developed scientific activity
 - 1.4 Results of the developed scientific activity
 - 1.5 Thesis Structure
-

1.1 Problem Statement, Motivations, and Scope

Blindness is a condition that affects thousands of people worldwide. An analysis of the Vision Atlas from the International Agency for the Prevention of Blindness reveals that worldwide, 43 million people are blind and 295 million have moderate-to-severe visual impairments (*Magnitude and Projections - The International Agency for the Prevention of Blindness*, n.d.). In addition, the World Health Organization (WHO) reports that at least 2.2 billion individuals worldwide suffer from a near or distance vision impairment, with nearly half of these cases being severe (*Blindness and Vision Impairment*, n.d.). In Portugal, according to the 2011 census (INE, 2012), there are approximately 900.000 people with vision difficulties, of whom approximately 28.000 are blind. Additionally, 23% of population state that have difficulties in seeing, even when using glasses or contact lenses. Such visual impairment, *e.g.* blindness, can significantly affect a person's psychological and cognitive functioning. Several studies have demonstrated that vision impairment is associated with a variety of negative health outcomes and a diminished quality of life (Chia *et al.*, 2006; Langelaan *et al.*, 2007).

Blind people can benefit from the use of assistive technology by reducing the negative effects of blindness and improving their quality of life. Sustainable Development Goal (SDG) 10 (Reduce Inequalities) is a fundamental objective in the development of inclusive technologies, which aims to reduce inequalities both within and between countries, promoting social, economic, and political inclusion for all people (*Goal 10 / Department of Economic and Social Affairs*, 2024). Hence, it is imperative to address the existing disparities and barriers that affect this community. To meet the unique needs of blind people and enhance their overall quality of life, inclusive technologies should be developed that cater to their specific needs and enhance their overall quality of life. The advancement of these technologies allows people with blindness to bridge the gap and participate fully in society on an equal basis, enhancing their mobility, navigation, and overall independence, thereby promoting inclusion.

Despite the proliferation of smart devices and the advancement of cutting-edge technology for blind people, most of the research has focused on navigation, mobility, and object recognition, ignoring aesthetic considerations (Bhowmick & Hazarika, 2017; Elmannai & Elleithy, 2017; Messaoudi *et al.*, 2022). Figure 1.1 illustrates this trend by providing an overview of research efforts across various domains in terms of number of publications between 2007-2023. Data was obtained from the SCOPUS database, using the following keywords search engine: 'Navigation AND Blind People', 'Mobility AND Blind People', 'Object Detection AND Blind People', 'Computer Vision AND Blind People', and 'Clothes AND Blind People'.

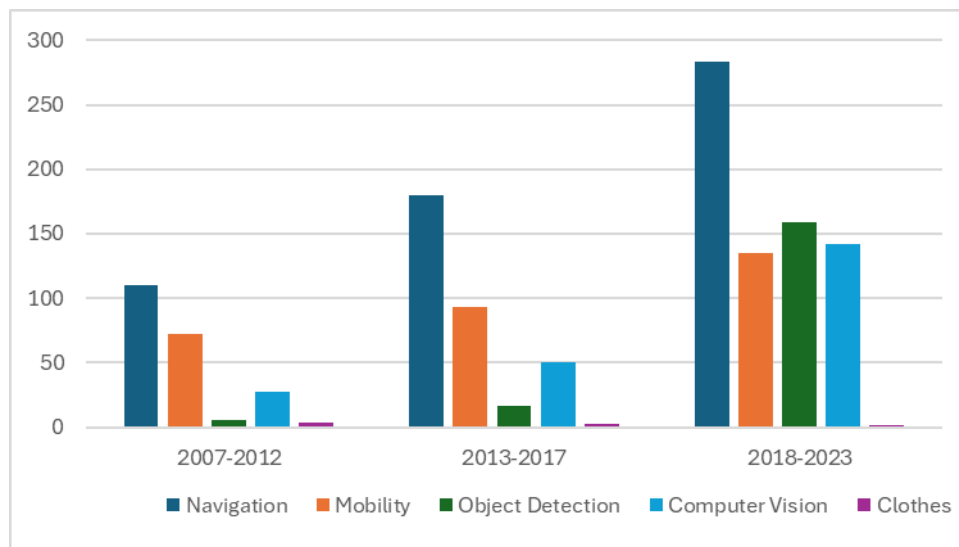


Figure 1.1: Bar chart illustrating the number of publications between 2007-2023 in various research areas concerning blind people. The search strategies employed include: 'Navigation AND Blind People', 'Mobility AND Blind People', 'Object Detection AND Blind People', 'Computer Vision AND Blind People', and 'Clothes AND Blind People'. Data was obtained from the SCOPUS database.

The analysis of the data presented in Figure 1.1 indicates that navigation and mobility-related technologies have received significant attention in recent years, with an increase in object detection and computer vision research from 2018 onwards. It is important to note, however, that the proportion of resources allocated to aesthetic considerations, as reflected in the "Clothes" category, remains relatively low throughout the period under study.

Clothing and style preferences for different occasions form an integral part of a person's identity (Johnson *et al.*, 2014). This has a significant impact on how they perceive themselves as well as how they are perceived by others (Adam & Galinsky, 2012; Johnson *et al.*, 2014). Blindness is often overlooked when it comes to aesthetics. Even though many believe that aesthetics is only concerned with visual appeal, it can hold significant relevance in daily life. Aesthetics can significantly affect a person's sense of identity, self-expression, well-being and self-esteem. Nevertheless, blind people may experience insecurity and stress when it comes to dressing-up due to the inability to recognize the condition of the garments. The inability to perceive visual cues or even colours can make dressing up a daily challenge. Additionally, blind people may be more likely to experience clothing staining and tearing due to their inherent difficulties in handling objects and performing daily tasks. For instance, detecting stains as soon as possible is essential to avoid them becoming permanent or difficult to remove. To address this gap, it is essential to develop technologies that cater to the aesthetic needs of blind people. By integrating innovative solutions

for clothing, we can enhance the self-confidence, comfort, style, and self-esteem of blind people. This will not only enhance their overall well-being but will also contribute to their social inclusion and equal participation in society.

In spite of the potential for technological solutions in the future, significant challenges remain to be overcome. Due to their visual impairment, these people face challenges in detecting minor irregularities or stains in clothing textures or fabrics, necessitating reliance on others for assistance. This is the premise behind the motivation of the present work - enable blind people to have an equal sense of confidence in what they wear, without permanently requiring human assistance. Sadly, this perception is still lacking in the lives of blind people, and clothing still presents a daily challenge for them. To address this absence of support, this work aimed at developing an innovative solution that combines state-of-the-art research and technology with conventional apparatus and furniture of common use. This resulted in the development of a wardrobe equipped with ideal lighting conditions and image capture capabilities that allows detecting stains and defects in clothing items, as well as identifying their colour and category using Artificial Intelligence (AI) algorithms. By combining this system with a mobile application, the user can manage and select clothing intelligently, which can propel his or her self-esteem, confidence, well-being, and self-confidence on a daily basis, filling a technological gap in the aesthetics and image of blind people. The validation of the developed work was conducted through a collaboration with the *Associação de Cegos e Ambliopes de Portugal* (ACAPO), the Portuguese Association for the Blind and Amblyopic, and the *Associação de Apoio aos Deficientes Visuais do Distrito de Braga* (AADVDB), the Association of Support for the Visually Impaired of Braga, which helped to identify key areas for improvement.

1.2 Objectives

This work aimed to design and create an innovative solution that merges cutting-edge research and technology with everyday devices. The result is a wardrobe designed with optimal lighting and image capture features that can detect stains and defects in clothing, as well as identify colours and categories using Artificial Intelligence algorithms. This endeavour should promote the autonomy of blind people in their daily activities, thereby enhancing their overall well-being.

To achieve this objective, specific goals were set, particularly:

- G1.** Conduct a nationwide survey distributed by ACAPO to assess user interest, needs, and receptivity to the study;
- G2.** Develop an algorithm for the acquisition, processing, and analysis of images using AI to identify

clothing types, colour and detect modifications;

G3. Develop user-friendly and accessible software integrated with the wardrobe management system to effectively manage and store all garment characteristics;

G4. Develop and assemble a mechatronic system (smart wardrobe) prototype to test the proposed methodology;

G5. Conduct testing and validation of the prototype with blind users to evaluate the system's effectiveness and usability.

In line with the aforementioned proposed objectives, the prototype aims to recognize and incorporate the following five fundamental aspects:

- Type of clothing;
- Colour of clothing;
- Modifications in the condition of clothing;
- Identification of clothing using Near Field Communication (NFC);
- Organization and management of their clothing.

Overall, this work intends to develop a support system to provide greater independence and consequent well-being in the management of clothes for blind people, contributing to fill a technological gap in relation to the aesthetics and image of a blind person. Afterwards, the following research questions arise:

RQ1: Is it possible to develop a method, using computer vision technology and artificial intelligence, to identify the type, colour and condition of garments?

RQ2: Is it possible to design a mechatronic device integrating computer vision and artificial intelligence technology to support blind people in the identification of type, colour and condition of garments?

1.3 Contribution to Knowledge and Results of the developed scientific activity

The present work has the potential to contribute significantly to the existing body of knowledge in assistive technologies for blind people by addressing a largely unexplored area within this field. The conducted literature review exposes a notable lack of scientific work dealing with aesthetics, specifically clothing management and condition for blind people as end users. Despite the availability of assistive systems, research has primarily focused on navigation and mobility, neglecting a crucial aspect of daily life: clothing management. It is important to note that clothing plays a significant role in our identity and well-being, contributing significantly to our sense of self-worth. Strangely, there are few dedicated systems for the management of clothing and condition verification that can be used on a daily basis and integrated into

conventional and general apparatus, e.g., stain and defect detection, particularly those specifically designed for the blind. While advances in computer vision and artificial intelligence offer promising solutions, current research focuses on applications in navigation and mobility, omitting the critical need for independent clothing management tools. In addition, the majority of existing defect detection research focuses on quality control in manufacturing processes, and there are no solutions designed for consumer use post-sales. As a result of this gap, the work presented in this thesis is both novel and necessary. With the development of a wardrobe that incorporates computer vision and artificial intelligence capabilities, it is expected that blind people will be empowered with autonomy and confidence in managing their wardrobe and clothing daily. Innovative approaches to detecting clothing stains, holes, and categorizing items by colour and type are particularly important. Despite being established in the field of computer vision, the methodologies used in the development of assistive devices for managing personal clothing are novel. By integrating these technologies with a user-friendly mobile application, this research enhances the practicality of clothing management for the blind and addresses a significant void in clothing modification detection solutions. In addition to providing a technological contribution, this development can also have a positive effect on a personal level, thus improving a person's self-esteem, confidence, and well-being.

The results of this PhD work contribute to the scientific field by advancing the application of algorithms for extracting clothing features, specifically aimed at addressing the challenges of clothing management for blind people. This research addresses the identification and classification of clothing categories, colours, and defects (such as stains and holes), tailored specifically for visually impaired users. This novel approach integrates multiple algorithms into a comprehensive system, providing a practical solution for independent clothing management. State-of-the-art algorithms for clothing classification, segmentation, and defect detection were fine-tuned to adapt them to the specific needs of blind users. Developing dedicated datasets for these tasks was essential, and the algorithms demonstrated high precision and recall, validating their effectiveness for consumer use. These technologies were integrated into a cohesive system that includes a smart wardrobe and a user-friendly mobile application, offering an innovative and practical solution for blind people.

This work serves as a starting point for future research, where different algorithm architectures and new datasets can be used and compared with this study. Identifying defects in complete clothing pieces is significantly more complex than in textile fabrics during production. The field can benefit from research that broadens the application range of existing tools and verifies their effectiveness with new datasets. Adding value to the field does not solely depend on disruptive research but also on enhancing the current

knowledge.

Moreover, this work fills a critical gap in helping blind people managing their clothes by demonstrating successful results with the proposed methodology, offering potential improvements for the lives of blind people. To the best knowledge of the author of this thesis, there are no studies that address combined identification and classification of clothing categories, colours, and defects for visually impaired people. Therefore, confirming the applicability of state-of-the-art technologies in this context is a valuable advancement. Additionally, expanding the range of application and validating the effectiveness of existing tools are pertinent contributions to the field.

Thus, the research undertaken in this thesis goes beyond developing a new product and provides a meaningful contribution to the field through the innovative application of established techniques to solve real-world problems faced by blind people. Although the conducted work primarily focused on blind users, interesting findings indicate the utility of expanding this technology to individuals with low vision, underscoring its capability to address a broader audience within the visually impaired community. This has profound implications for future research and development in assistive technologies that prioritize the needs and challenges of both blind and low-vision people.

1.4 Results of the developed scientific activity

The results of the research described in this thesis have been published in the subsequent international peer-reviewed journals and conferences:

Journal Articles:

- Rocha, D., Soares, F., Oliveira, E., & Carvalho, V. (2023). Blind People: Clothing Category Classification and Stain Detection Using Transfer Learning. *Applied Sciences*, 13(3). <https://doi.org/10.3390/app13031925>
- Rocha, D., Pinto, L., Machado, J., Soares, F., & Carvalho, V. (2023). Using Object Detection Technology to Identify Defects in Clothing for Blind People. *Sensors*, 23(9). <https://doi.org/10.3390/s23094381>

International Conferences Papers:

- Rocha, D., Carvalho, V., Soares, F., & Oliveira, E. (2019). Extracting Clothing Features for Blind People Using Image Processing and Machine Learning Techniques: First Insights BT - *VipIMAGE 2019* (J. M. R. S. Tavares & R. M. Natal Jorge, Eds.; pp. 411–418). Springer International Publishing.

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- Rocha, D., Carvalho, V., Soares, F., & Oliveira, E. (2020). Design of a Smart Mechatronic System to Combine Garments for Blind People: First Insights. In N. M. Garcia, I. M. Pires, & R. Goleva (Eds.), *IoT Technologies for HealthCare* (pp. 52–63). Springer International Publishing.
 - Rocha, D., Carvalho, V., Soares, F., & Oliveira, E. (2021). A Model Approach for an Automatic Clothing Combination System for Blind People. In E. I. Brooks, A. Brooks, C. Sylla, & A. K. Møller (Eds.), *Design, Learning, and Innovation* (pp. 74–85). Springer International Publishing.
 - Rocha, D., Carvalho, V., Soares, F., Oliveira, E., & Leão, C. P. (2022). Understand the Importance of Garments' Identification and Combination to Blind People. In T. Ahram & R. Taiar (Eds.), *Human Interaction, Emerging Technologies and Future Systems V* (pp. 74–81). Springer International Publishing.
 - Silva, L., Rocha, D., Soares, F. O., Esteves, J. S., & Carvalho, V. (2023). Automatic system to identify and manage garments for blind people. *Acta IMEKO*. <https://doi.org/10.21014/actaimeko.v12i3.1490>
 - Carvalho Mariana and Rocha, D. and C. V. (2024). An Automated Tool for Creating Clothing Catalog Databases: MyEyes–Fashion. In A. and E. E. Brooks Eva and Kalsgaard Møller (Ed.), *Design, Learning, and Innovation* (pp. 49–61). Springer Nature Switzerland.

1.5 Thesis Structure

This thesis is organized as follows:

- Chapter 2: This chapter provides a concise overview of the existing literature relevant to the research topic. It covers assistive technologies for blind people, identification and defects detection on clothes, neural networks for clothing identification, mobile interfaces, and applications focusing on blind people. The chapter concludes with a summary of key findings from the reviewed literature.
- Chapter 3: The theoretical concepts that support the technologies used throughout this thesis are discussed in this chapter. A brief introduction to blindness, computer vision, as well as machine learning, is presented in the first subchapter. Several key topics are addressed, including image classification, object detection, and instance segmentation, as well as their significance in the study. An overview of evaluation metrics pertinent to these techniques is also presented to support their implementation in practice.

- Chapter 4: The development process of the system is outlined in this chapter outlines, starting with a survey conducted to gather requirements and understand the significance of clothing for blind people (4.1). An overview of the system architecture (4.2) is provided afterwards, comprising the key components of the work, namely clothing category classification, identification of modifications on clothing. Each section briefly describes the functionality and purpose of these components within the system.
- Chapter 5: The development of the smart wardrobe prototype is described in this chapter, with a focus on its system design and component integration. It also covers the development of the mobile application, which allows blind and visually impaired users to control the wardrobe and manage clothing items independently.
- Chapter 6: This chapter introduces a case study endeavour focused on evaluating the effectiveness of a developed prototype tailored for use by blind people. Through a comprehensive analysis, the study examines the prototype's accessibility, interaction capabilities, and its potential contribution to enhancing their autonomy, confidence, and overall well-being.
- Chapter 7: Concluding insights derived from the research detailed in this thesis are presented here, along with an outlook on the future applications of assistive technologies for clothing specifically designed for blind people.

Chapter Summary

This section provides an overview of the developed work and the underlying motivations driving this study. It begins with a detailed problem statement, motivations, and the scope of the research (Section 1.1), followed by clearly defined objectives (Section 1.2). The contribution to knowledge and the results of the developed scientific activity are then summarized (Section 1.3 and Section 1.4). Finally, the structure of the thesis is outlined (Section 1.5), offering a brief description of the main contents of each chapter.

2 LITERATURE REVIEW

Chapter Overview

This chapter provides an overview of assistive technologies for blind people, with a particular focus on solutions for clothing management. First, various existing technologies for blind people are discussed, including smart wardrobe systems. Next, the chapter discusses methods for identifying clothing categories, followed by techniques for segmenting clothing. Lastly, the process of defect identification in clothing is explored, highlighting current advancements and challenges in the field.

2 Literature Review

- 2.1 Assistive Technologies for Blind People
 - 2.2 Clothing Category Identification
 - 2.3 Clothing Segmentation
 - 2.4 Defect Identification in Clothing
-

2.1 Assistive Technologies for Blind People

The rapid advancement of technology has significantly enhanced support systems for visually impaired people. This chapter reviews and analyses various existing solutions and projects that align with the technological framework intended for this research. The objective is to provide a comprehensive characterization of these technologies, while also identifying potential gaps and areas for further development and innovation. By critically evaluating these existing solutions, this chapter seeks to establish a foundation upon which new, improved methods can be developed to better support the visually impaired community.

2.1.1 Solutions for the Visually Impaired in Clothing Selection

Visually impaired individuals face significant challenges in selecting appropriate clothing, which is essential for personal dignity and confidence. Recent research has focused on developing technological solutions to assist visually impaired individuals with clothing-related tasks. Through technological advancements, a number of solutions have been developed to assist the visually impaired. Among these solutions are mobile applications, Internet of Things (IoT) systems, tactile labelling systems, and inclusive fashion design, all of which offer unique advantages and features.

To simplify the task of online shopping in the garment sector, a system was proposed by Yang Huiqiao and Peng (2015) that makes online shopping easier for the visually impaired. This idea took shape after several interviews with visually impaired students from the Special Education College of Peking University. These interactions highlighted challenges such as excessive advertising, unintuitive interfaces, and insufficient subdivisions of clothing categories. Based on this study, the authors proposed a web application to address the identified issues and help the visually impaired make informed decisions when purchasing clothing. Essential information about each item (name, type, photo, price, and sales volume) is displayed immediately below the respective photo, simplifying the search and reading process. Additionally, Stangl *et al.* (2018) developed the BrowseWithMe system, an AI-powered online shopping assistant designed to make online clothes shopping more accessible for visually impaired people. This system converts product web pages into a structured representation, allowing users to interactively ask for specific information about products. The study found that BrowseWithMe yields accurate image descriptions and makes the online shopping more accessible for visual impaired. Gatis Filho Sílvia José Vieira and de Assumpção Macedo (2018) introduced a system that uses NFC tags and Quick Response

(QR) codes on clothing to help visually impaired individuals match outfits. The system provides audio feedback on clothing combinations through an Android app, enabling users to select appropriate outfits independently. An audio assistive technology that helps blind individuals identify clothing patterns and colours is presented by N.Swathi and Jyothi (2020). Yang *et al.* (2014) developed a camera-based prototype system that recognizes clothing patterns and colours, providing verbal descriptions to visually impaired users. Participants provided positive feedback about the system, highlighting its ability to promote greater independence in their daily lives. Another example, proposed by (Allam Mahmoud and ElShaarawy, 2022) uses the Sequential Minimal Optimization method for clothing classification. Similarly, the system proposed by Yang *et al.* employs Statistical Feature (STA) and SIFT (Scale Invariant Feature Transform) algorithms for clothes pattern recognition. Stangl *et al.* (2018) introduced Vision4All, a deep learning fashion assistance solution that helps visually impaired users to identify clothing attributes such as colours, categories, textures, fabrics, styles, graphics, and text-based content on clothes. A prototype with an endoscopic camera attached to a fingertip, allowing for image capture and recognition of colours and patterns on clothing surfaces, was proposed by Medeiros *et al.* (2017). Rini J. and Thilagavathi (2015) proposed a system that recognizes four types of patterns (checkered, striped, irregular, and plain) and eleven colours using a camera for image capture and a Support Vector Machine (SVM) algorithm for classification. A method that converts visual information obtained from clothing into verbal exposition using Deep Neural Networks was presented by Tateno *et al.* (2020). This system captures photos of clothing combinations, which are then pre-processed to remove the person's face and extract key features. After processing the images, a mathematical model is applied to implement the system holistically, enabling it to automatically recognize and characterize the presented clothing items.

Inclusive fashion design aims to enhance the clothing selection experience for visually impaired individuals by incorporating tactile and functional elements. Dassoler *et al.* (2023) explored the development of inclusive fashion using sensory elements in clothing to allow visually impaired individuals to create tactile representations of shapes. This approach promotes individual expression and autonomy, cognitive and creative development, and a more enriching clothing experience.

Despite the aforementioned research, there are several commercial solutions available in the market, both as standalone devices and mobile applications. Regarding commercial devices, the Colorino is a colour identifier that detects approximately 150 different colours and announces them aloud. It features three volume levels and an option to use headphones. Additionally, the Colorino functions as a light detector, emitting distinct acoustic signals to differentiate between natural and artificial light sources (*Colorino – Color and Light Detector - Caretec*, 2024). A similar device, the ColorTest 2000, not only

identifies colours like the Colorino but also it reads dates and times and detects whether a household light is on or off (*ColorTest 2000 - Assistive Technology at Easter Seals Crossroads*, 2024).

An improved version of the Colorino, the Color Star Pro, offers a more compact and lightweight design for easier use. It features advanced speech output and enhanced measurement accuracy. Capable of detecting over 1,700 colour nuances, patterns, and contrasts, it uniquely translates these features into musical tones. The device is also highly effective in identifying light and its colours, making it an invaluable tool for individuals with visual impairments. Additionally, the Color Star Pro provides colour information in Red Green Blue (RGB) and Hue Saturation Luminance (HSL) formats, recognizes colour patterns, and can determine light temperature, further increasing its functionality (*Color Star Pro – Color and Light Detector - Caretec*, 2024). The ultimate version, the Color Star, is a sophisticated and portable colour identification device that can distinguish over 1,700 unique colour shades, conveyed through clear spoken voice output. It is also adept at measuring contrast, detecting Light Emitting Diode (LED) light colours, gauging ambient light intensity, and identifying patterns. This versatile device provides a comprehensive analysis of colour and light in various environments (*Color Star – Talking Color and Light Detector*, 2024). In terms of mobile applications, the V7 Aipoly is a mobile application that enables real-time identification of objects, texts, and colours, and communicates with the user through audio (*V7 Aipoly*, n.d.). Similarly, Colour Identifier is an iPhone application available on the App Store that detects the colour of any pixel in a photo or image, displaying colours in RGB, CMYK (Cyan, Magenta, Yellow, Black) and HEX (Hexadecimal) formats along with their names (*Color Identifier: Color Picker on the App Store*, 2024). Mobile applications can also play an essential role in human proximity, helping to combat social exclusion and directly addressing SDG 10. For example, Be My Eyes is a mobile application designed to assist visually impaired people through internet-based video calls. This application facilitates real-time assistance by connecting visually impaired users with volunteers who are available to help. If a visually impaired individual needs to verify the expiration date on a carton of milk, they can utilize the application to initiate a video call. A volunteer receives a notification and, if available, responds to provide the necessary assistance (*Be My Eyes - Trazendo Visão Aos Cegos e Pessoas Com Visão Reduzida*, 2024). This procedure can also be applied to tasks such as selecting clothing items or identifying their colours. It is noteworthy that the functionality of this application is entirely dependent on the availability of volunteers.

Muhsin *et al.* (2023) conducted a comprehensive review of substitutive assistive technologies for people with visual impairments, categorizing them based on the type of feedback (visual, haptic, or auditory). The study highlighted the limitations in user experience and the challenges of translating numerous

research prototypes into practical, widely adopted solutions. It emphasized the need for more effective assistive aids and the importance of distinguishing between the needs of individuals with partial vision, colour blindness, and those who are totally blind. Focusing on specific groups would allow for the development of more tailored and effective assistive technologies.

2.1.2 Smart Wardrobe Solutions

Some research has focused on developing smart wardrobe systems to assist blind individuals in managing their clothing. These systems typically employ technologies such as Radio Field Identification (RFID) (Goh *et al.*, 2011), NFC (Alabduljabbar, 2022), and IoT (Kathiravan, 2021) for garment identification and tracking.

Goh *et al.* (2011a) propose a smart wardrobe system using RFID technology to help users manage their clothing and make decisions based on preferences for colour, style, events, and emotions. Targeting busy entrepreneurs and colour-blind individuals, the system tracks garment movement within the wardrobe and stores clothing data from RFID tags. This technology aids users in making better wardrobe decisions and simplifies clothing management. Alabduljabbar (2022) introduced an IoT-based smart clothing system which employs NFC technology to help visually impaired people manage their closets independently, allowing to select and find appropriate clothing within their closets, through the use of smartphone to scan NFC tags. The system performed reasonably well and met the usability requirements for visually impaired people. A speech recognition software module for a smart closet, designed as assistive technology for visually impaired individuals was presented by Carolina Saucedo, Peña Ingrid and Alejandro Luna Gómez (2021). This system allows users to manage their clothing through voice commands, enabling tasks such as garment insertion, searching by description, and retrieval from the wardrobe. The module, developed for web-based environments, shows promise in enhancing the quality of life for visually impaired people.

The increasing demand for solutions within the concept of smart wardrobes has prompted the emergence of numerous solutions in the market. Each solution exhibits unique capabilities and can be subcategorized into physical and virtual implementations. Although these solutions are not specifically focused on blind individuals, they highlight the growing interest and potential in developing assistive technologies that can be adapted to meet the needs of visually impaired users. In 2019, the Fashion Application Programming Interface (API) mobile application (*Our Technology - Fashion Taste API*, 2024) was developed to manage wardrobes using QR code scanning. This solution allows users to create a virtual wardrobe for total

management, including adding or removing clothing items. The addition of items is based on scanning a QR code on the clothing label using the smartphone camera with the installed mobile application. Beyond wardrobe management, this smart wardrobe concept provides clothing usage advice, suggests new purchases based on user needs, and helps planning outfits. The technology is offered through a mobile application featuring an intuitive interface, dashboards, and statistical data showing the most worn items and suggested outfits. The Smart Closet solution (*Smart Closet: Your Personal Stylist*, 2024), introduced in 2018, also uses a mobile application for wardrobe management based on clothing purchases from various stores. This application allows users to fully manage their wardrobe items and obtain detailed statistics, such as the most worn pieces. However, this solution lacks “intelligence”, as it does not use machine learning or computer vision algorithms to autonomously identify clothing items or provide fashion advice. The Stylebook Closet App (*Stylebook Closet App: A Closet and Wardrobe Fashion App for the iPhone and iPad*, 2024) serves as a comprehensive tool for planning and organizing wardrobes. Users can upload images of their clothing items and create stylish outfits with minimal effort. The app includes a background removal feature to maintain a clean virtual wardrobe. Additional features such as a calendar, packing list, and inspiration board allow users to schedule and track their outfits, prepare packing lists for trips, and analyse their wardrobe usage. Analogous to Stylebook, Pureple combines simplicity with functionality. Its intuitive interface permits users to categorize their clothes, plan outfits, and pack for trips efficiently. A distinctive feature is its ability to allow users to open their closets to other users on the app for styling assistance (*Pureple - Outfit Organizer App*, 2024). Similarly, the Chicisimo app assists users in cataloguing their clothes and offers outfit inspiration from fashion enthusiasts worldwide. For instance, if a user seeks new ways to style a classic red dress, the app provides images of various styling options used by women globally (*Chicisimo - Build with Fashion Shoppers' Taste Data*, 2024). Cladwell offers users daily outfit suggestions and AI-powered styling advice based on the clothes already present in their wardrobe. This app facilitates the creation of a minimalist closet filled with capsule pieces. Unlike other wardrobe apps, users do not need to catalogue their wardrobe items manually. Instead, they select from pre-built capsule wardrobes, and the Cladwell wardrobe is populated with generic items from the chosen capsule. Users can then upload pictures of similar items from their actual wardrobe to replace the generic ones (*Cladwell / Simplify Your Life With A Capsule Wardrobe*, 2024). Acloset is a digital closet application that allows users to manage all their fashion items in one place, as well as buy and sell clothing items that are no longer needed. It enables the creation of outfit ideas, provides outfit recommendations and style analytics, and facilitates the buying and selling of pre-loved items at reasonable prices (Acloset - AI Fashion Assistant on the App Store, 2024).

2.2 Clothing Category Identification

In the last few years, deep learning techniques have arisen as a great method to solve problems in computer vision, such as image classification, object detection, face recognition and language processing, where convolutional neural networks (CNNs) play an imperative role (Voulodimos *et al.*, 2018a). This is particularly important for clothing category identification, as CNNs can extract important features from clothing images, enabling accurate identification and classification. The CNNs have exhibited excellent results and advances in image recognition since 2012 (D. Bhatt *et al.*, 2021; Patel *et al.*, 2022), when AlexNet (Krizhevsky *et al.*, 2012) was introduced on the ImageNet Large Scale Visual Recognition (ILSVRC) (Deng *et al.*, 2009; *ImageNet Large Scale Visual Recognition Competition (ILSVRC)*, 2024). The ImageNet competition consists of evaluating several algorithms for large-scale object detection and image classification, allowing researchers to compare detection across a variety of object classes. In recent years, several CNNs have been presented, such as: VGG (Simonyan & Zisserman, 2015), GoogLeNet (Szegedy *et al.*, 2014), SqueezeNet (Iandola *et al.*, 2016), Inception (Szegedy *et al.*, 2015), ResNet (K. He *et al.*, 2015), ShuffleNet (Ma *et al.*, 2018), MobileNet (Howard *et al.*, 2019; Sandler *et al.*, 2018), EfficientNet (Tan & Le, 2019), RegNet (Radosavovic *et al.*, 2020), among others, using these networks for different image classification problems.

In line with this premise, some researchers turned to the fashion world, making use of the more recent advances in computer vision to explore diverse areas such as fashion detection, fashion analysis and fashion recommendation, achieving promising results (W.-H. Cheng *et al.*, 2021). Given the core scope of this thesis, only fashion classification is covered throughout the work. A literature survey allowed identifying several studies that attempted to handle the classification of fashion images. Most of the authors evaluate their models based on top-k accuracy regarding clothing attributes recognition, normally with top-3 and top-5 scores, which means that the correct label is among the top k predicted labels.

The research of Chen *et al.* (2015) presented a network for describing people based in fine-grained clothing attributes with an accuracy of 48.32%. Similarly, Liu *et al.* (2016) introduced the FashionNet which learns clothing features by jointly predicting clothing attributes and landmarks. Predicted landmarks are used to pool or gate the learned features maps. The authors reported a top-3 classification accuracy of 93.01% and a top-5 of 97.01%. Another method to detect fashion items in a given image using deep convolutional neural networks, was performed by Hara *et al.* (2014), presenting a mean Average Precision (mAP) of 31.1%. Likewise, Corbière *et al.* (2017) proposed other method based on weakly supervised learning for classifying e-commerce products, presenting a top-3 category accuracy of 86.30% and a top-

5 92.80% accuracy. Later, Wang *et al.* (2018) proposed a fashion network to address fashion landmark detection and category classification with the introduction of intermediate attention layers for a better enhancement in clothing features, category classification and attribute estimation. In their work, accuracies of 90.99% and 95.75% were reported for top-3 and top-5, respectively. In another study by Li *et al.* (2019), the authors presented a two-stream convolutional neural network with one branch dedicated for landmark detection and the other one for category and attribute classification, allowing the model to learn the correlations among multiple tasks and consequently improvement in the results. Accuracies of 93.01% and 97.01% for top-3 and top-5 were reported, respectively. The fashion classification model proposed by Cho *et al.* (2019) allowed improving the performance taking into account the hierarchical dependences between class labels reaching accuracies of 91.24% and 95.68% in top-3 and top-5, respectively. A multitask deep learning architecture was then proposed by Lu *et al.* (2016) that groups similar tasks and promotes the creation of separated branches for unrelated tasks, with accuracy results of 83.24% and 90.39% for top-3 and top-5, respectively. Seo and Shin (2019) proposed a Hierarchical Convolutional Neural Network (H-CNN) for fashion apparel classification. The authors demonstrated that hierarchical image classification could minimize the model losses and improve its accuracy, with a result of 93.3%. The research of Fengzi *et al.* (2020) applied transfer learning using pertained models for automatically label uploaded photos on ecommerce industry. The authors reported an accuracy of 88.65%. Additionally, a condition CNN was proposed by Kolisnik, Hogan, and Zulkernine (2021), based on branching convolutional neural networks. The proposed branching can predict hierarchical labels of an image and the last label predict in the hierarchy is reported with an accuracy of 91.0%. A new algorithm for clothing category classification to address the complexity of diverse clothing styles was proposed by X. Liu *et al.* (2023). CloNet improves top-1 classification accuracy by 0.8% and reduces model size to one-third compared to state-of-the-art models. Furthermore, Shi *et al.* (2023) introduce Frequency Domain Enhancement Network (FDENet), a network for clothing category classification that captures advanced features like texture and contour information. FDENet uses spectrum enhancement and depthwise separable convolutions to improve feature extraction and reduce redundancy. It achieves a 1.3% improvement in top-1 accuracy on Deepfashion compared to current models.

Table 2.1 summarizes the data of the aforementioned works, including the used datasets.

Table 2.1: Literature overview on fashion image classification works (Rocha, Soares, *et al.*, 2023a).

Author	Dataset	Year	Accuracy
Hara <i>et al.</i> (2014)	Fashionista	2014	mAP: 31.1 %
Chen <i>et al.</i> (2015)	Street-data	2015	Top-1: 48.31 %
Liu <i>et al.</i> (2016)	DeepFashion	2016	Top-3: 82.58 %
Lu <i>et al.</i> (2016)	DeepFashion	2016	Top-3: 83.24 %
Corbière <i>et al.</i> (2017)	DeepFashion	2017	Top-3: 86.30 %
Wang <i>et al.</i> (2018)	DeepFashion-C	2018	Top-3: 90.99 %
Li <i>et al.</i> (2019)	DeepFashion-C	2019	Top-3: 93.01 %
Cho <i>et al.</i> (2019)	DeepFashion	2019	Top-3: 91.24 %
Seo and Shin. (2019)	Fashion-MINIST	2019	Top-1: 93.33 %
Fengzi <i>et al.</i> (2020)	Fashion Product Images	2020	Top-1: 88.65 % ¹
Kolisnik, Hogan, and Zulkernine(2021)	Fashion Product Images	2021	Top-1: 91.0 % ¹
X. Liu <i>et al.</i> (2023)	DeepFashion	2023	Top-1: 68.7 % ²
Shi <i>et al.</i> (2023)	DeepFashion	2023	Top-1: 71.22 % ²

¹Results only reported for fashion classification accuracy.

²Results only reported for DeepFashion dataset.

It becomes clear that there has been a great effort to build efficient methods for fashion category classification. However, as the works listed in Table 2.1 highlight, there is a lack of focus on developing systems to aid visual impaired people, and there is yet no solution capable of covering all the difficulties stated by a blind person, namely an automatic system for clothing type identification.

2.3 Clothing Segmentation

Image segmentation is the process of identifying and annotating various objects within images to classify them into distinct categories (K. K. Singh & Singh, 2012). This method has a wide range of applications, including driver assistance systems and disease detection. Within the realm of segmentation, there are two primary types: semantic segmentation and instance segmentation. Given that one of the main goals of this work is to identify clothing items to assist visually impaired people, it is crucial to perform pre-processing actions when capturing images of clothing. This ensures that the image presented to the user is as “clean” as possible. Therefore, it is necessary to segment the image and remove the background so that the colour detection algorithm can achieve the best results by analysing only the pixels relevant

to the clothing item. Below, a brief review of existing implementations in clothing image segmentation is presented.

Yingheng and Yueqi (2020) presented a method that aids fashion analysts and consumers in identifying types of clothing. Segmentation results are enhanced using a system that incorporates Multi-Attention Mask R-CNN, enabling the extraction of detailed information from clothing items. This implementation is particularly effective in delineating boundaries between clothing items, outperforming other Mask R-CNN implementations.

Another solution, described by Khurana *et al.* (2018) focuses on the problem of identifying and detecting clothing items in images. This method differentiates between various types of clothing that may have similar patterns or textures. The implementation consists of two modules: the first utilizes a Fully Convolutional Network for spatial boundary segmentation, and the second detects specific features to aid in recognizing boundaries. The results demonstrate an improvement over existing methods, reducing confusion in images with visually similar clothing items made of different materials.

DeepFashion2, a method designed to extract the maximum amount of data from photos of clothing items, was proposed by Ge *et al.* (2019). This method addresses the limitations of the DeepFashion system, aiming for accurate segmentation and identification of all clothing items in each photo. Moreover, it allowed generating a dataset comprising *ca.* 801,000 annotated images with identified types and styles. These images were segmented using masks and bounding boxes. The novel model, Match R-CNN, is based on Mask R-CNN (K. He, Gkioxari, Dollar, *et al.*, 2017). The results indicate a slight improvement in Average Precision compared to the Mask R-CNN and Match R-CNN models.

Complex backgrounds can make image segmentation a demanding task. DeepLabV3+, proposed by Wang *et al.* (2021), is a model that segments clothing items within complex backgrounds where the boundaries might be ambiguous. A new Neural Network architecture was redesigned to improve segmentation performance, showing better adaptability to the boundaries of each clothing item. After training the model and testing it on the dataset, the results showed that accuracy (97.26%), mean intersection over union (IoU) (93.23%), and average precision (AP) (90.56%) values were slightly higher than those obtained with the previous DeepLabv3+ model.

Tackling another issue, the method described by X. Zhang *et al.* (2020) recognizes sets of clothing items and identifies the year they belong to. Here, a CNN was used to segment the human body and classify the type of clothing within the segmented areas without background interference. A dataset of 9,339 images spanning eight years was used to validate the model, demonstrating good efficacy. Various segmentation models were tested, with SegNet achieving an IoU value of approximately 0.951, closely

matching the proposed method IoU value of 0.951. The proposed method also yielded the best classification results, with an accuracy of 0.805 compared to 0.785 using the ResNet101 model. Similarly, T. Yang *et al.* (2021) presented a method for segmenting images of clothing items captured in different positions allows for effectively detecting the silhouettes of shirts using instance segmentation with Mask R-CNN. Approximately 9,000 images were collected, segmented, and classified by various attributes. The experimental results showed that the model performed well in detecting short-sleeved shirts and collars, achieving AP values of 0.95 and 0.94, respectively.

Overall, the conducted literature review on clothing segmentation underlines the significance of advanced segmentation techniques in enhancing the accuracy and effectiveness of algorithms for identifying and analysing clothing items.

Table 2.2 summarizes the mentioned works on advanced image segmentation techniques for clothing identification.

Table 2.2: Summary of advanced image segmentation techniques for clothing identification

Method	Authors	Key Features	Applications	Performance
Fully Convolutional Network	Khurana <i>et al.</i> (2018)	Spatial boundary segmentation, feature detection	Identifying and detecting clothing items	Reduces confusion in images with similar patterns/textures
DeepFashion2	Ge <i>et al.</i> (2019)	Extracts maximum data, masks and bounding boxes	Accurate segmentation and identification of clothing items	Slight improvement in AP compared to Mask R-CNN and Match R-CNN
Multi-Attention Mask R-CNN	Yingheng and Yueqi (2020)	Enhances segmentation results, detailed information extraction	Fashion analysis, consumer identification	Outperforms other Mask R-CNN implementations in delineating boundaries
SegNet	X. Zhang <i>et al.</i> (2020)	Human body segmentation, clothing type classification	Recognizing sets of clothing items, year classification	IoU: 0.951, Classification Accuracy: 0.805
DeepLabV3+	Wang <i>et al.</i> (2021)	Segments within complex backgrounds, redesigned NN architecture	Adaptable segmentation performance	Accuracy: 97.26%, Mean IoU: 93.23%, AP: 90.56%
Instance Segmentation with Mask R-CNN	T. Yang <i>et al.</i> (2021)	Segments images of clothing in different positions	Detecting silhouettes of shirts	AP: 0.95 (short-sleeved shirts), AP: 0.94 (collars)

2.4 Defect Identification in Clothing

Defect detection in clothing remains a barely addressed topic on the literature. However, if the scope of the topic is expanded to the industry, some interesting works have been made, mainly regarding the fabric quality control in the textile industry. Such quality control approach still plays an important role in the industry and can be an appealing starting point for defect detection in clothing with other purposes in sight (Ngan *et al.*, 2011).

Based on the aforementioned approach, a literature survey allowed perceiving that machine vision based on image processing technology has replaced manual inspection and allows reducing costs and increasing the detection accuracy. An integral part of modern textile manufacturing is the automatic detection of fabric defects (C. Li *et al.*, 2021). More recently, due to their success in a variety of applications, deep learning methods have been applied to the detection of fabric defects (Kahraman & Durmuşoğlu, 2022b). A wide range of applications was developed using CNNs, such as image classification, object detection, and image segmentation (Lu, 2019). Defect detection using CNNs can be applied to several different objects (Ding *et al.*, 2020; Lv *et al.*, 2021; Roslan *et al.*, 2022). Comparatively to traditional image processing methods, CNNs can automatically extract useful features from data without requiring complex feature designs to be handcrafted (Tabernik *et al.*, 2020). Zhang *et al.* (H. Zhang *et al.*, 2018) presented a comparative study between different networks of YOLOv2, with proper optimization, in a collected yam-dyed fabric defect dataset, achieving an IoU of 0.667. Another method, unsupervised, based on multi-scale convolutional denoising autoencoder networks was presented by Mei *et al.* (2018). A particularity of this approach is the possibility of being trained with only a small number of defects without label ground truth or human intervention. A maximum accuracy of 85.2% was reported from four datasets. A deep fusion fabric defect detection algorithm, *i.e.* DenseNet121-SSD (Densely Connected Convolutional Networks 121- Single Shot MultiBox Detector), was proposed by X. He *et al.* (2020). By using a deep fusion method, the detection is more accurate, and the detection speed becomes more efficient, achieving a mAP of 78.6%.

Jing *et al.* (2022) proposed a deep learning segmentation model, *i.e.* Mobile-Unet, for fabric defect segmentation. Here, a benchmark is performed with conventional networks on two fabric image databases, the Yarn-dyed Fabric Images (YFI) and the Fabric Images (FI), allowing to reach IoU values of 0.92 and 0.70% for YFI and FI, respectively. A novel model of a defect detection system using artificial

defect data, based on stacked convolutional autoencoders, was then proposed by Han and Yu (2020). Their method was evaluated through a comparative study with U-Net with real defect data, and it was concluded that actual defects were detected using only non-defect and artificial data. Additionally, an optimized version of the Levenberg–Marquardt (LM) based artificial neural network (ANN) was developed for leather surfaces (Mohammed *et al.*, 2020). The later enables the classification and identification of defects in computer vision-based automated systems with an accuracy of 97.85%, compared with 60-70% obtained through manual inspection. Likewise, Xie and Wu (2020) proposed a robust fabric defect detection method, based on the improved RefineDet. Three databases were used to evaluate their study. Additionally, a segmentation network with a decision network was proposed by Huang *et al.* (2021), having as major advantage the reduced number of images needed to achieve accurate segmentation results. Furthermore, a deep learning model to classify fabric defects in seven categories based on CapsNet was proposed by Kahraman and Durmuşoğlu (2022a), achieving an accuracy of 98.71%. L. Cheng *et al.* (2023) proposed a Separation Convolution UNet (SCUNet) for textile defect detection, improving over costly and damaging manual inspections. SCUNet uses convolutional down sampling, depth-separable convolution, and IoU Loss, with only 4.27 million parameters. It processes fabric images to detect defects, using a dataset of 106 grayscale images with image cutting and data enhancement. Tested on the AITEX dataset, SCUNet achieved the following results: 98.01% accuracy, 96.86% recall, 98.07% specificity, and 34.32% mean Intersection over Union (mIoU).

Table 2.3 summarizes the main results of the aforementioned works, including the used datasets.

Table 2.3: Literature overview on textile fabric defect detection including the author, year, method, dataset, defect classes and metrics.

Author	Year	Method	Dataset	Defect Classes	Metrics
Zhang <i>et al.</i>	2018	DL object detection (YOLOV2)	Collected dataset: 276 manually labelled defect images	3	IoU: 0.667
Mei <i>et al.</i>	2018	Multiscale convolutional denoising autoencoder network model	Fabrics dataset: ca. 2000 samples of garments and fabrics	-	Accuracy: 83.8 %
			KTH-TIPS	-	Accuracy: 85.2 %
			Kylberg Texture: database of 28 texture classes	-	Accuracy: 80.3 %

Collected dataset: ms-Texture				-	Accuracy: 84.0 %
X. He <i>et al.</i>	2020	DenseNet-SSD	Collected dataset: 2072 images	6	mAP: 78.6 %
Yarn-dyed					
Fabric Images (YFI): 1340 images composed in a PRC textile factory.				4	IoU: 0.92; F1-Score: 0.95
Jing <i>et al.</i>	2020	DL segmentation (Mobile-Unet)	Fabric Images (FI): 106 images provided by the Industrial Automation Research Laboratory of the Department of Electrical and Electronic Engineering at Hong Kong University	6	IoU: 0.70; F1-Score: 0.82
Stacked convolutional autoencoders					
Han and Yu	2020		Synthetic and collected dataset	-	F1-Score: 0.763
A multilayer perceptron with a LM algorithm					
Mohammed <i>et al.</i>	2020		Collected dataset: 217 images	11	Accuracy: 97.85 %
TILDA dataset: 3200 images; only 4 classes were used from 8 in total, resulting in 1597 defect images.				4 of 8	mAP: 80.2 %; F1-Score: 82.1 %
Hong Kong patterned textures database: 82 defective images.				6	mAP: 87.0 %; F1-Score: 81.8 %
DAGM2007 Dataset: 2100 images				10	mAP: 96.9 %; F1-Score: 97.8 %
Dark red fabric (DRF)				4	IoU: 0.784
Patterned texture fabric (PTF)				6	IoU: 0.695
light blue fabric (LBF)				4	IoU: 0.616
Fiberglass fabric (FF)				5	IoU: 0.592
Kahraman and Durmuşoğlu	2022	Capsule Networks	TILDA dataset	7	Accuracy: 98.7 %
L. Cheng <i>et al.</i>	2023		AITEX dataset: 106 grayscale images	-	Accuracy: 98.01 %

The results presented in Table 2.3 demonstrate a lack of standardization in the evaluation metrics and datasets between studies, leading to difficulties in accurately comparing results. This can be attributed to

the diversity of tasks in defect detection, including defect classification, defect location, defect segmentation, and defect semantic segmentation, each requiring distinct metrics for evaluation.

C. Li *et al.* (2021) developed a survey based on fabric defect detection in textile manufacturing where learning-based algorithms (machine learning and deep learning) have been the most popular methods. Furthermore, the studies are focused on one-stage and two-stage detectors without a comparative study between them. One-stage detectors, such as You Look Once (YOLO) (Redmon *et al.*, 2015) and Single Shot Detector (SSD) (W. Liu *et al.*, 2015), are known for their speed, but also for their lower accuracy compared to two-stage detectors, such as Faster R-CNN (Ren *et al.*, 2015) and Mask R-CNN (K. He, Gkioxari, Dollár, *et al.*, 2017). On the other side, two-stage detectors offer improved accuracy but at the cost of slower performance.

Despite the similarities between clothing and textiles, a new approach is needed for detecting defects in clothing, especially to assist blind people. For that, different types of images must be analysed, and other than just textiles, resulting in the creation of new datasets. In the textile industry, fabrics usually emerge from the manufacturing process in a roll and undergoes stretching, augmenting the detection of defects. Furthermore, the magnification of images to fit the fabrics coming off the roll can greatly amplify any defects present, as depicted in Figure 2.1.

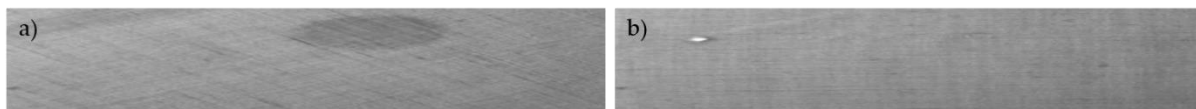


Figure 2.1: Examples of defects from TILDA Dataset: a) large oil stain in the upper right corner; b) medium-sized hole in the upper left corner (Rocha, Pinto, *et al.*, 2023).

It becomes clear that a comprehensive dataset that captures the entirety of a garment can provide crucial insights into identifying defects in the piece as a whole, thus leading to advancements in this field. Furthermore, textile fabrics' datasets may not capture important clothing features such as wrinkles, patterns, and buttonholes, which can present a significant challenge during its analysis, since defects can be hidden in the wrinkles of the clothes, or simply hidden by the way the garment was folded or stored, as illustrated in Figure 2.2.

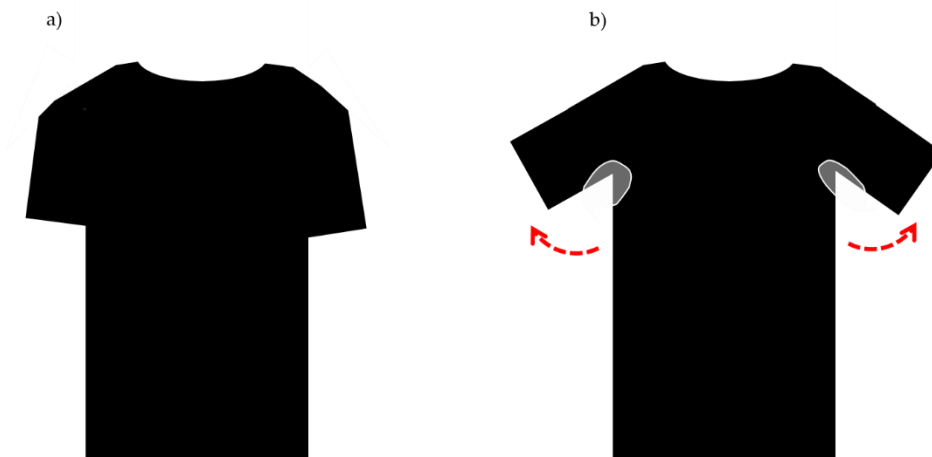


Figure 2.2: Visibility of the defects on clothing: a) imperceptible sweat stain; b) visible sweat stain (Rocha, Pinto, *et al.*, 2023).

This means that each clothing piece can be interpreted as different objects, since its shape and colour can vary significantly. Such particularity does not happen with rigid objects and whose colour does not change upon use. At present, and to the best knowledge of the author of this work, the literature still lacks a system that can automatically identify defects in clothing, an essential support tool for blind people to efficiently manage their wardrobe on a daily basis. Aiming at addressing this issue, this work presents a solution that utilizes a one-stage detector (YOLOv5) (Jocher *et al.*, 2022), fine-tuned specifically for this purpose, in line with other research studies that have also efficiently employed YOLOv5 in their research (Idrissi *et al.*, 2022; Nakaguchi & Ahamed, 2022). This solution will be described in detail in chapter 4. Object detection was chosen over semantic segmentation because the presence of the defect does not require identifying details such as colour, origin, type, diameter/area, or any other information that requires labelling every pixel in the image. Thus, blind individuals are informed about the presence of the imperfection without needing pixel-wise information, allowing the problem to be simplified to object detection. This approach offers a practical and efficient solution, enabling blind individuals to manage their appearance independently and with greater confidence. Moreover, the proposed solution demonstrates that computer vision can be employed to analyse and overcome this challenge, while opening the door to the possibility of becoming accessible to the blind community through a mobile application.

Chapter Summary

This literature review highlights the importance of technological innovation in promoting autonomy and enhancing the clothing selection experience for visually impaired individuals. These innovations, ranging

from smart clothing systems and online shopping assistants to inclusive fashion design and assistive technologies for clothing identification, address various challenges faced by visually impaired individuals in clothing selection. Future developments should focus on improving the usability, accessibility, and integration of these technologies into daily routines, ensuring that visually impaired individuals have the necessary tools to make informed clothing choices independently. Considering previous research, no single solution fully addresses all the issues proposed in this work, such as an automatic system for identifying clothing for the blind. Existing tools can help identify colours, patterns, and garments directly or indirectly, but they do not focus on a specific goal. The objective here is to develop a physical prototype capable of storing clothing items, identifying them, and assessing their condition promoting well-being, confidence, autonomy and well-being in the management of clothes for blind people.

3 THEORETICAL CONCEPTS

Chapter Overview

This chapter outlines the methodologies used in the present work. It begins with an overview of blindness and continues with a discussion on Artificial Intelligence, Machine Learning (ML), and Deep Learning (DL), emphasizing their roles in developing “intelligent” systems. The theoretical concepts of Neural Networks and Transfer Learning are presented, followed by the evaluation metrics used to assess model performance.

3 Theoretical concepts

- 3.1 Blindness
 - 3.2 Artificial Intelligence, Machine Learning and Deep Learning
 - 3.3 Neural Networks
 - 3.4 Transfer Learning
 - 3.5 Evaluation Metrics
-

3.1 Blindness

The human eye can be broadly compared to a photographic camera in terms of its functioning. Light reflected from objects passes through the cornea, pupil, and lens, eventually reaching the retina (*The Anatomy of the 'Camera' Eye* | UCL Institute of Ophthalmology - UCL – University College London, 2024). Here, specialized cells encode the visual information, which is then transmitted to the brain via the optic nerve, as illustrated in Figure 3.1.

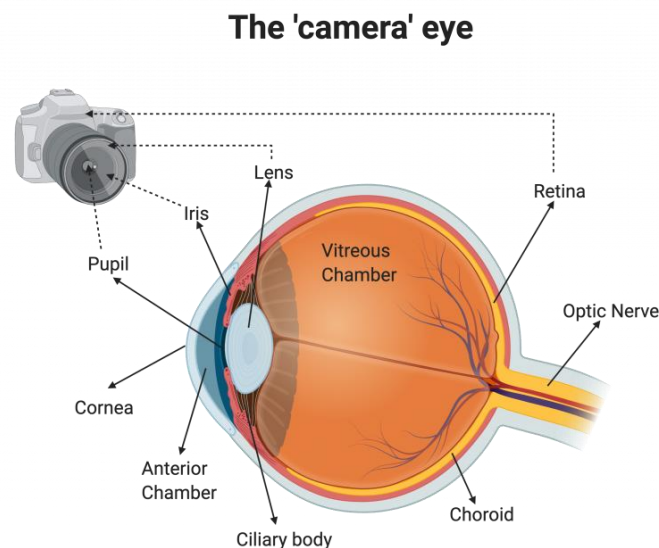


Figure 3.1: Constituents of the human eye, illustrating the pathway of light from the cornea to the retina and the optic nerve, and comparing its functioning to a photographic camera(*The Anatomy of the 'Camera' Eye* | UCL Institute of Ophthalmology - UCL – University College London, 2024) .

Among the five senses dominated by most humans, vision plays a particularly prominent role. A disability, by definition, refers to the partial or total loss of a part of the human body or its function, whether physical or psychological, which hinders an individual's ability to perform common daily activities (Enoch *et al.*, 2019; Khorrami-Nejad *et al.*, 2016). Visual impairment is one of the significant types of disabilities and can be categorized into two main forms. The first is low vision, which refers to visual impairments that cannot be fully corrected by standard means such as glasses or contact lenses. The second form is blindness, which denotes the total loss of vision (Medeiros *et al.*, 2017). Visual impairment, whether partial or total, significantly affects an individual's quality of life, limiting their ability to engage in daily activities independently. This limitation points out the importance of technological advancements aimed at supporting visually impaired people. Innovative solutions such as assistive devices and applications have been developed to enhance their autonomy and improve their quality of life. Technological aids range

from basic tools, like magnifying glasses and braille readers, to advanced digital applications that leverage artificial intelligence and machine learning. For instance, mobile applications that provide real-time audio descriptions of the user's surroundings or smart devices that assist in identifying objects and navigating spaces are becoming increasingly prevalent (Ghazal *et al.*, 2019; Najm *et al.*, 2022). These technologies not only offer practical support but also contribute to the social inclusion of visually impaired people by enabling them to perform tasks that would otherwise require assistance.

In summary, the eye functions similarly to a camera by capturing and transmitting visual information to the brain. Vision is a critical sense that greatly influences an individual's daily functioning. Visual impairments, whether in the form of low vision or blindness, present significant challenges that can be mitigated through the development and utilization of various assistive technologies.

3.2 Artificial Intelligence, Machine Learning and Deep Learning

Artificial intelligence is the development of computer systems that can perform tasks traditionally handled by human intelligence, *e.g.* speech recognition, understanding of natural language, and decision-making (Soori *et al.*, 2023). The fields of machine learning (ML) and deep learning (DL) are subfields of artificial intelligence, Figure 3.2, that use techniques of automatic learning to train computer models from data over time, resulting in improved performance.

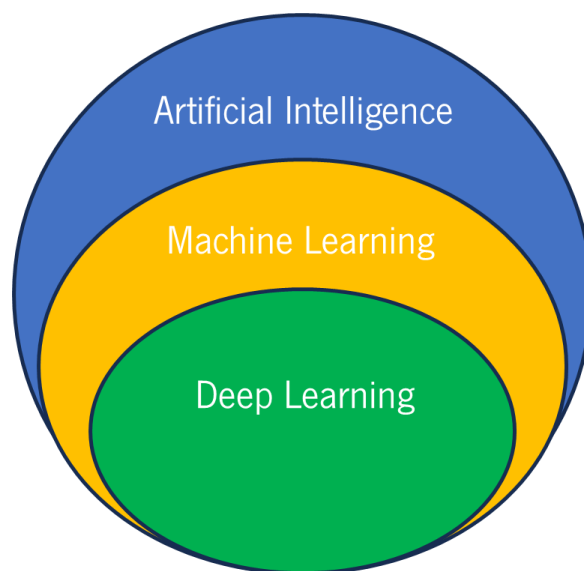


Figure 3.2: Interconnection between the fields/subfields of AI/ML/DL.

ML involves training computer models to learn from data and make predictions (Sarker, 2021b), whereas DL, a subset of ML, employs deep neural networks with multiple layers or stages through which data is processed for building a data-driven model to discover data structures automatically (Sarker, 2021a).

3.3 Neural Networks

Neural networks are a fundamental component of deep learning, modelled after the structure and function of the human brain. They typically consist of multiple layers, including an input layer, one or more hidden layers, and an output layer as depicted in Figure 3.3. The hidden layers are crucial for learning complex patterns and representations from the data (Kriegeskorte & Golan, 2019).

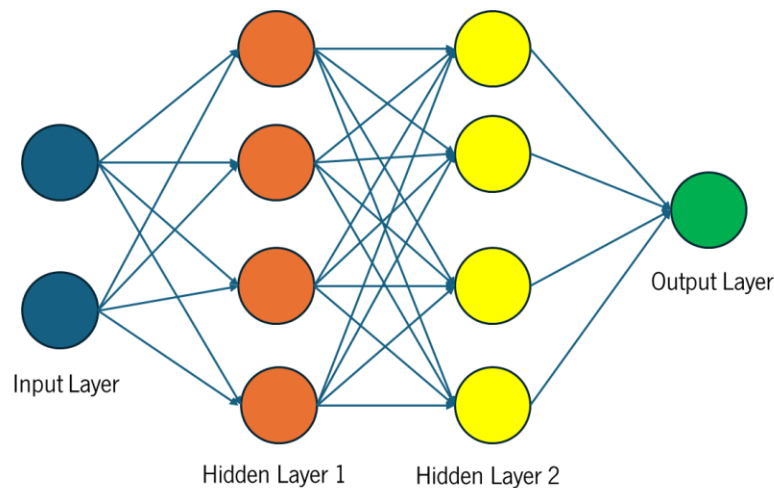


Figure 3.3: Deep neural network with two hidden layers.

During training, neural networks adjust their parameters (weights and biases) through a process called backpropagation. Backpropagation is essential for the network to gradually improve its ability to make accurate predictions or perform specific tasks (Lecun *et al.*, 2015). This learning process involves minimizing the difference between the network's predictions and the true targets, which is typically achieved through optimization algorithms. Optimization algorithms are vital in this process, with commonly used methods including stochastic gradient descent (SGD), Adam, and RMSprop (Kingma & Ba, 2014; Ruder, 2016). These algorithms iteratively adjust the learning rate and parameters to improve convergence and find the optimal set of weights and biases that minimize a predefined loss function. The loss function quantifies the discrepancy between predicted and actual values. The deep architecture of neural networks, characterized by multiple hidden layers, enables them to capture hierarchical features and intricate relationships within the data (Lecun *et al.*, 2015). For example, in image recognition tasks, lower layers may detect basic features such as edges and textures, while higher layers recognize more complex structures like shapes and objects. Neural networks have demonstrated remarkable versatility and effectiveness across a wide range of applications, from natural language processing and speech recognition to medical diagnosis and autonomous driving. This adaptability stems from their ability to

model non-linear relationships and represent high-dimensional data comprehensively.

3.3.1 Convolutional Neural Networks

Convolutional Neural Networks are a class of deep learning models specifically designed for image recognition and computer vision tasks (Krizhevsky *et al.*, 2012). They have demonstrated remarkable success in various applications, including image classification, object detection, and image segmentation (Minaee *et al.*, 2022; Rawat & Wang, 2017; Voulodimos *et al.*, 2018b; Z.-Q. Zhao *et al.*, 2019). CNNs are composed of multiple layers, each tasked with extracting different types of information from the input data. The architecture of CNNs comprises two primary modules: convolution and classification, as illustrated in Figure 3.4.

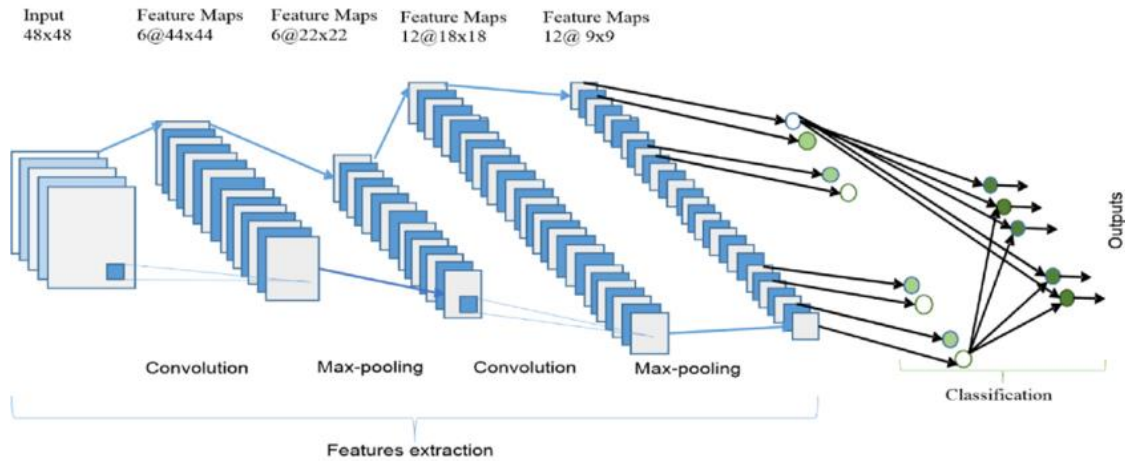


Figure 3.4: The architecture of a Convolutional Neural Network (CNN) comprises an input layer, several alternating convolutional and max-pooling layers, followed by a fully-connected layer and a classification layer (Alom *et al.*, 2019)

During the convolution stage, the network employs filters to extract specific elements from the images, abstracting and dividing the image into distinct parts. The processed data is then passed through a pooling layer, which reduces the dimensionality and computational load by downsampling the feature maps. In the final stage, the fully connected layer classifies the information obtained from the previous layers. By integrating these three stages—convolution, pooling, and classification—CNNs acquire the ability to identify and recognize regions of interest within each image.

One of the significant advantages of CNNs is their reduced need for pre-processing compared to other classification algorithms, as they can optimize filters through learning (X. Zhao *et al.*, 2024). Each neuron in a CNN calculates a value based on the inputs and a specific activation function. This value is adjusted using a weight vector, which is updated during the network's learning process. These weight vectors

represent the features that the network aims to prioritize.

3.3.2 Object Detection

Object detection, which involves identifying and localizing multiple objects within an image, is a fundamental task in computer vision. Several CNNs architectures have been developed to address this complex task (S. Agarwal *et al.*, 2019). These architectures can be broadly categorized into one-stage and two-stage detectors based on their architecture and processing steps. One-stage detectors, such as YOLO and Single-Shot MultiBox Detector (SSD), perform object detection in a single pass through the network. They divide the image into a grid and predict bounding boxes and class probabilities directly from the full image. This approach is typically faster and more suitable for real-time applications, though it may sacrifice some accuracy compared to two-stage detectors (Soviany & Ionescu, 2018; Y. Zhang *et al.*, 2021).

Since its initial release in 2015, YOLO has evolved significantly, reaching its eighth version, YOLOv9 (C.-Y. Wang *et al.*, 2024). Unlike region-based algorithms, YOLO directly predicts bounding box locations and class probabilities (Redmon *et al.*, 2016). The entire image is divided into a grid, with each grid cell predicting the bounding boxes and class probabilities for objects detected within it as depicted in Figure 3.5: In the YOLO architecture, the input image is segmented into an $S \times S$ grid, with each grid cell predicting B bounding boxes characterized by their position, size, and confidence score. The final label of a high-confidence bounding box is determined by the class probability map (Redmon *et al.*, 2016).

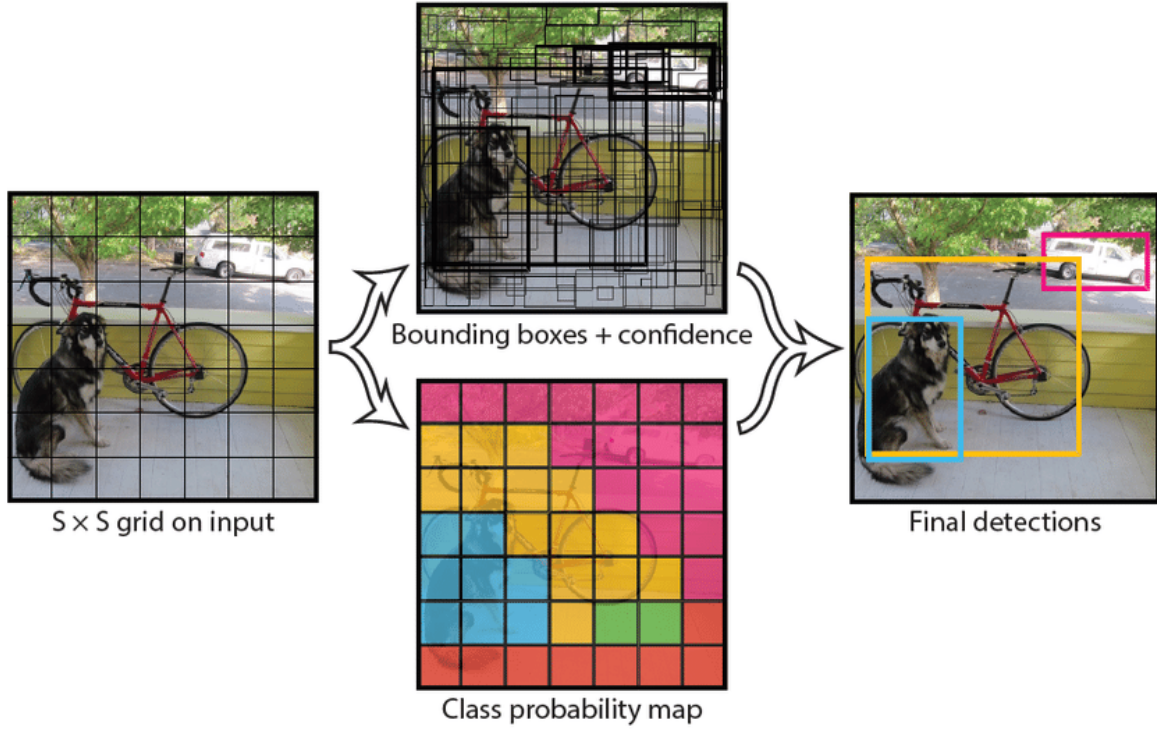


Figure 3.5: In the YOLO architecture, the input image is segmented into an $S \times S$ grid, with each grid cell predicting B bounding boxes characterized by their position, size, and confidence score. The final label of a high-confidence bounding box is determined by the class probability map (Redmon *et al.*, 2016).

This approach allows YOLO to perform object detection in a single pass through the network, enabling highly efficient and real-time object detection. Each iteration of YOLO has brought improvements in accuracy, speed, and architecture, with YOLOv9 benefiting from the latest advancements in deep learning and computer vision research (Terven *et al.*, 2023; C.-Y. Wang *et al.*, 2024).

SSD, introduced by Liu Wei and Anguelov (2016) presents a method for detecting objects in images using a single deep neural network. This approach discretizes the output space of bounding boxes into a set of priors with varying aspect ratios and scales for each feature map location. During prediction, the network generates confidence scores for each prior, indicating the presence of objects of interest, and adjusts the priors to better fit the object shapes. Additionally, the network combines predictions from multiple feature maps with different resolutions to naturally handle objects of various sizes. This one-stage detector is renowned for its balance between speed and accuracy. A comparison of SSD and YOLO architectures is depicted in Figure 3.6.

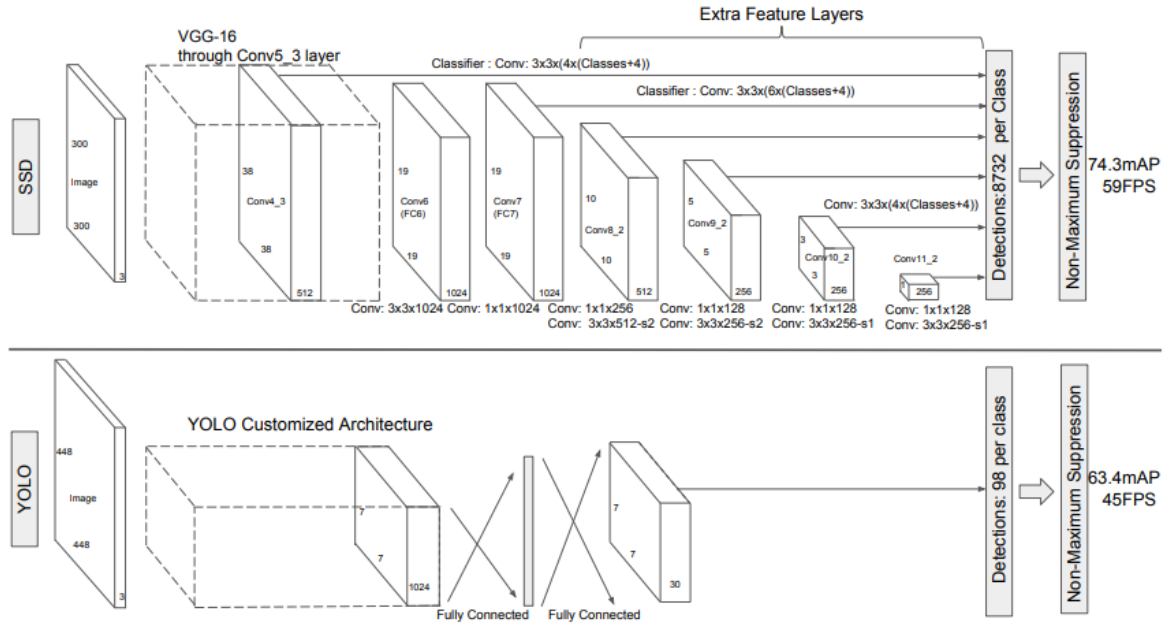


Figure 3.6: Comparison of two single-shot detection models: SSD and YOLO. The SSD model augments the base network with additional feature layers that predict adjustments to default boxes of varying scales and aspect ratios, along with corresponding confidence scores (Liu Wei and Anguelov, 2016).

Two-stage detectors, such as R-CNN, Fast R-CNN, and Faster R-CNN, operate in two steps. The first stage generates region proposals that are likely to contain objects. The second stage processes these proposals to refine the bounding boxes and classify the objects. This approach generally achieves higher accuracy but can be slower and more computationally intensive.

The R-CNN (Girshick *et al.*, 2014), Figure 3.7, was one of the first successful CNN-based methods for object detection. It introduced a multi-step pipeline consisting of Region Proposal, Feature Extraction, and Object Classification and Localization. While R-CNN made significant contributions to the field, its computational and memory inefficiencies limited its practical use in real-time and large-scale applications.

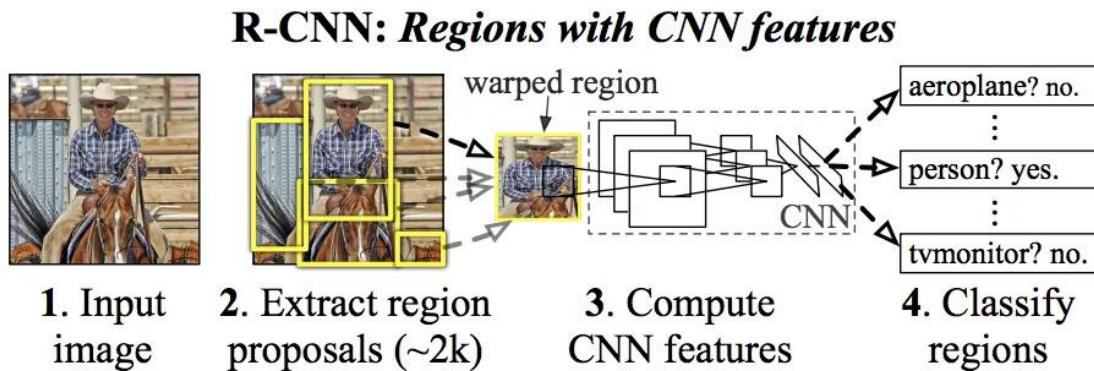


Figure 3.7: The multi-step pipeline of R-CNN, including region proposal, feature extraction, and object classification and localization (Girshick *et al.*, 2014).

To address the inefficiencies of R-CNN, Fast R-CNN was developed. This architecture optimizes the object detection pipeline, resulting in faster and more efficient processing (Girshick, 2015). Key improvements include feature sharing, a unified architecture, and end-to-end training. Faster R-CNN, Figure 3.8, further extends and improves upon the original R-CNN architecture, by introducing a novel Region Proposal Network (RPN) that shares convolutional features with the object detection network (Ren *et al.*, 2015).

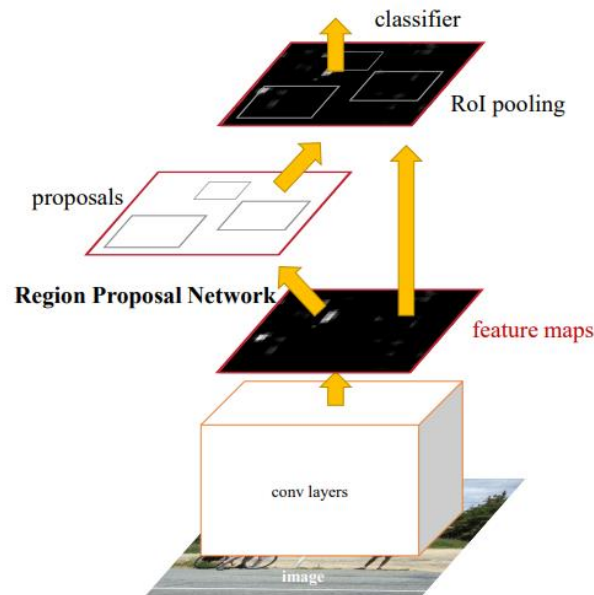


Figure 3.8: Faster R-CNN is a unified network for object detection, where the RPN module functions as the 'attention' mechanism within the network (Ren *et al.*, 2015).

This innovation addresses the computational and memory inefficiencies of R-CNN. Faster R-CNN also serves as the foundation for Mask R-CNN, which adds instance segmentation capabilities.

RetinaNet, proposed by Lin *et al.* (2018) introduces the Focal Loss, a loss function that addresses the class imbalance problem by focusing more on hard-to-classify samples. This architecture strikes a balance between the speed of one-stage detectors and the accuracy of two-stage detectors. Object detection continues to evolve with new methods and improvements, driven by ongoing advancements in deep learning and computer vision. The choice of the ideal architecture depends on the specific application requirements, such as accuracy, speed, and the capability to operate in real-time.

3.3.3 Image Segmentation

Image segmentation, a closely related but distinct task from object detection, involves partitioning an image into multiple segments or regions to locate objects and boundaries accurately. Unlike object detection, which provides bounding boxes around detected objects, image segmentation identifies the

exact pixels belonging to each object, providing a more detailed understanding of the scene. Instance segmentation, a subtype of image segmentation, not only detects objects but also segments each object's pixels to provide a pixel-level mask. This approach is particularly useful in applications where precise object boundaries are required (Sharma *et al.*, 2022) .

Several popular deep learning models are used for image segmentation. U-Net (Ronneberger *et al.*, 2015) employs a U-shaped architecture for the efficient segmentation of medical images, demonstrating high efficacy with small datasets and delivering precise segmentation results. Fully Convolutional Networks (FCNs) are capable of processing images of any size and generating spatial maps by substituting fully connected layers in conventional CNNs with convolutional layers, enabling pixel-by-pixel segmentation of entire images. SegNet (Badrinarayanan *et al.*, 2016) features an encoder-decoder network structure utilized in tasks such as scene understanding and object recognition. The encoder captures contextual information from the image, while the decoder leverages this context for precise localization and segmentation of objects. DeepLab (L.-C. Chen *et al.*, 2017) is distinguished by its use of atrous convolutions, which capture multi-scale context through multiple parallel filters.

Mask R-CNN, an extension of Faster R-CNN, is a prominent architecture for instance segmentation. Mask R-CNN enhances Faster R-CNN's object detection by predicting pixel masks for detected objects. It begins with a backbone that extracts feature maps from the input image, capturing hierarchical and contextual information. The RPN generates region proposals (bounding box candidates) for potential objects. These proposals are processed through the Region of Interest (ROI) Align layer to extract fixed-size feature maps, which are then passed through two branches: the region of interest classifier and the bounding box regressor (K. He, Gkioxari, Dollar, *et al.*, 2017). The classifier predicts the probabilities of object classes, and the regressor refines the bounding box coordinates. An additional branch, the mask prediction head, produces a binary mask for each object instance, representing pixel-level segmentation and distinguishing the object from the background as illustrated in Figure 3.9

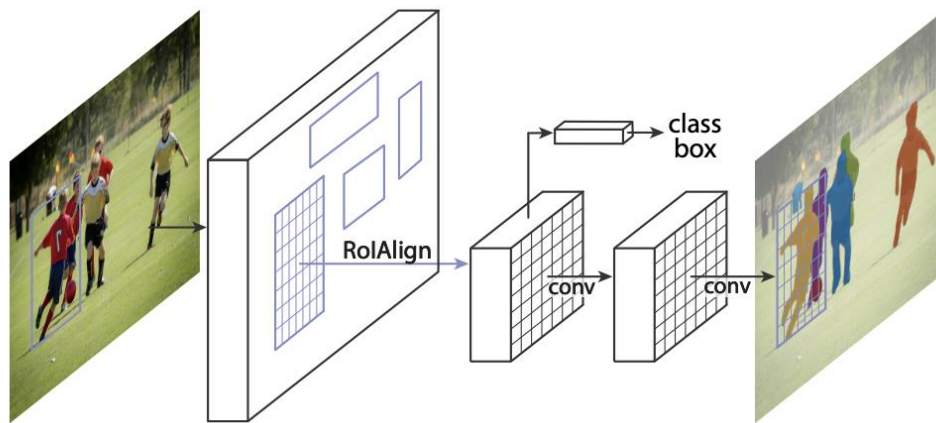


Figure 3.9: The Mask R-CNN architecture with pixel-level segmentation (K. He, Gkioxari, Dollar, *et al.*, 2017).

Starting from YOLOv5, YOLO has also incorporated image segmentation capabilities, allowing it to provide pixel-level masks for detected objects (Jocher, 2020). This integration of detection and segmentation in a single network underscores the trend towards more versatile and comprehensive computer vision models.

3.4 Transfer Learning

Transfer Learning is a machine learning technique that leverages a pre-trained model as a starting point for training a new model on a different task, thereby facilitating faster progress and optimization in the new task (Pan & Yang, 2010).

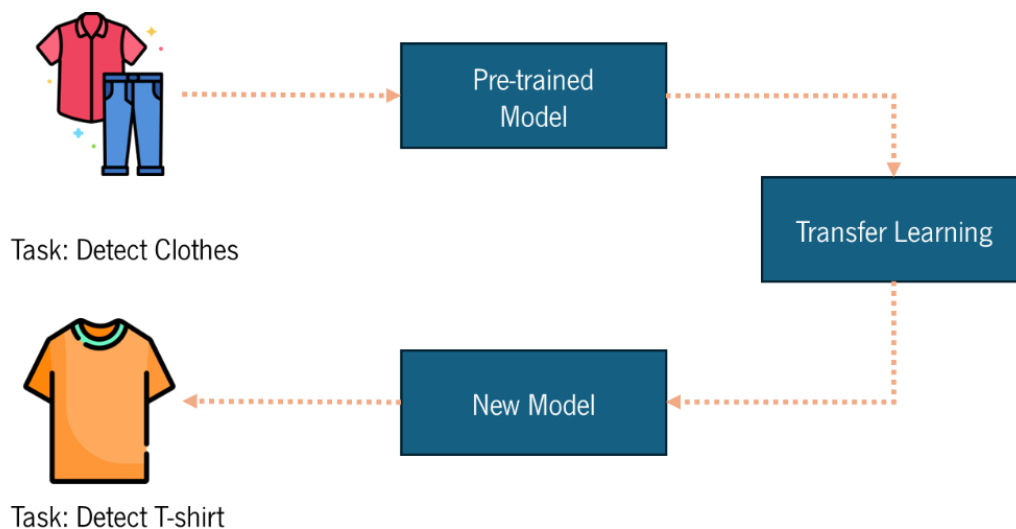


Figure 3.10: Workflow demonstrating the detection of clothes, where the model through transfer learning is used to detect specifically t-shirts.

In this approach, a pre-trained model, typically trained on a large dataset, is used to transfer the knowledge gained from that model to achieve superior results compared to training a model from scratch with a smaller dataset (Bichri *et al.*, 2023).

Transfer learning could be used in two different approaches, feature extraction and fine-tuning (Rosebrock, 2017). Regarding the first one, the head of the network, the fully connected layer (FC), is replaced, and it only retrains this part. Moreover, all the weights of the convolutional layers of the network are “frozen”. On the other hand, in the second approach, the head of the network is replaced, and a new head can be built, which is similar to feature extraction. However, it differs from the first one as the weights of the convolution neural network can be “unfrozen” and the entire network can be retrained. Overall, Transfer Learning is a powerful technique with numerous applications, particularly in computer vision tasks such as object detection and image classification. By leveraging pre-trained models and transferring knowledge across tasks, Transfer Learning enables efficient and effective model development even with limited labelled data (Nalini & Radhika, 2020; Ramdan *et al.*, 2020).

In the context pre-trained models like Mask R-CNN, Faster R-CNN, or RetinaNet, which are trained on large datasets such as COCO (Common Objects in Context), can be utilized for object detection tasks. For instance, segmentation, a pre-trained Mask R-CNN model trained on the COCO dataset can be fine-tuned on a dataset containing objects that require pixel-level segmentation (Jaikumar Punithaand Vandaele, 2021).

By employing Transfer Learning, models can be quickly adapted and optimized for new tasks, significantly enhancing the efficiency and effectiveness of machine learning applications in various domains.

3.5 Evaluation Metrics

Most of the authors evaluate their models based on top-k accuracy regarding clothing attributes recognition, normally in top-3 and top-5 scores (P. Li *et al.*, 2019).

It means that the correct label is among the top-k labels predicted. Nevertheless, the top-1 score is required in this work due to the practical application, meaning that the predicted class with the highest probability is the same as the target value.

As a result, it is necessary to use the following metrics:

- Accuracy (acc), relation of correctly predicted observations to the total observations:

$$\text{acc} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}} \quad (1)$$

- Precision (P), relation of correctly predicted positive observations to the total predicted positive observations:

$$P = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (2)$$

- Recall (R), relation of correctly predicted positive observations to the observations in the actual class:

$$R = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

- F1-Score, the weighted average of Precision and Recall:

$$\text{F1 - Score} = 2 * \frac{P * R}{P + R} \quad (4)$$

Where TP, FP and FN represent, respectively, the number of True Positives (TP), False Positives (FP) and False Negatives (FN).

The proposed methodology was evaluated using standard metrics for object detection competitions such as MicroSoft Common Objects in Context (MSCOCO) (Lin *et al.*, 2014) and Pascal Visual Object Classes (PASCAL VOC) (Everingham *et al.*, 2015) challenges, which include Average Precision (AP) and mean Average Precision (mAP). Since this methodology is intended for practical applications where only the presence of defects is important, regardless of their exact location, these metrics were computed using an IoU threshold of 0.50, as shown in Equation (5):

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \quad (5)$$

Equations (2) and (3) can be utilized to compute precision and recall using the preceding IoU.

Ultimately, a precision-recall curve (PR) is produced for the object class, and the area under the curve indicates the model's Average Precision (AP).

Chapter Summary

This chapter discusses the importance of vision and the technological solutions aimed at enhancing inclusion for visually impaired individuals. It explores concepts of AI, neural networks, and object detection, emphasizing the potential of these technologies to improve quality of life.

Vision is one of the most crucial senses for human interaction with the environment. However, conditions such as blindness and low vision present significant challenges for millions of people. To mitigate these challenges, assistive technologies, such as AI-based object detection systems, have been developed to support navigation and autonomy for visually impaired individuals. These tools have the potential to revolutionize the way these individuals interact with their surroundings, providing greater independence. The chapter also highlights the critical role of machine learning and deep learning in object detection and visual pattern recognition. Convolutional neural networks (CNNs), such as YOLO and Faster R-CNN, are discussed as effective models for identifying and localizing objects in real-time, with an emphasis on their accuracy and speed. These models not only detect objects but also segment them, as exemplified by Mask R-CNN, which offers detailed image segmentation by separating objects from the background with high precision.

Additionally, transfer learning is discussed as a technique that repurposes pre-trained models, enabling quick adaptation to new scenarios and reducing the time required to train custom systems. This method is particularly useful in situations where available data are limited, accelerating the development of new assistive applications.

The performance of object detection and segmentation models is evaluated using rigorous metrics, such as Average Precision (AP) and Intersection over Union (IoU), which quantify performance in object localization and identification. These metrics provide a clear view of system efficacy across various scenarios, suggesting that while the technology is advancing, there is still room for improvement in terms of accuracy and adaptability to more complex environments.

In conclusion, the innovations discussed in this chapter reveal the potential of AI to improve the quality of life for blind people, with particular emphasis on the use of CNNs and image segmentation technologies. Integrating these tools into current assistive devices may result in a more accessible and efficient experience, enabling greater independence for users and fostering a richer interaction with their environment.

4 SYSTEM DEVELOPMENT

Chapter Overview

This chapter describes the methodologies used in this study, focusing on the development of the system. It begins by describing the insights gathered through the National ACAPO Survey, which provided valuable input for the system design. Following this, the system requirements are discussed in detail, laying the foundation for its development. A comprehensive system overview is then provided, explaining the structure and functionality. Finally, the chapter concludes with an exploration of the deep learning approaches employed for category, colour, and modification classification.

4 System Development

- 4.1 Gathering Insights through Nacional ACAPO Survey
 - 4.2 System Requirements
 - 4.3 System Overview
 - 4.4 Deep Learning Approaches
-

The content of this chapter is part of the following publications:

- Rocha, D., Soares, F., Oliveira, E., & Carvalho, V. (2023). Blind People: Clothing Category Classification and Stain Detection Using Transfer Learning. *Applied Sciences*, 13(3). <https://doi.org/10.3390/app13031925>
- Rocha, D., Pinto, L., Machado, J., Soares, F., & Carvalho, V. (2023). Using Object Detection Technology to Identify Defects in Clothing for Blind People. *Sensors*, 23(9). <https://doi.org/10.3390/s23094381>
- Rocha, D., Carvalho, V., Soares, F., Oliveira, E., & Leão, C. P. (2022). Understand the Importance of Garments' Identification and Combination to Blind People. In T. Ahram & R. Taiar (Eds.), *Human Interaction, Emerging Technologies and Future Systems V* (pp. 74–81). Springer International Publishing.

4.1 Gathering Insights through Nacional ACAPO Survey

The objective of the survey was to gather insights from the blind community about their experiences and challenges in identifying and combining garments, as well as their use and satisfaction with existing supportive technologies. This information would help guide the development of new technological solutions aimed at assisting blind and visually impaired individuals with clothing management.

4.1.1 Sample

The sample of was essentially composed by blind associates of ACAPO, who were asked to fill a purpose-built survey, delivered by email.

4.1.2 Methodology

The design of the preliminary version of the survey was developed according to a need identified by ACAPO, regarding the identification and combination of garments for blind people. The development of the survey has fulfilled the following stage process: (1) design of the preliminary version, (2) pre-test of the preliminary version, (3) development of the final version incorporating the suggested improvements, and (4) delivery of the survey.

The pre-test of the preliminary version consisted of validating the questionnaire prepared by the research team to the representatives of ACAPO, including a member suffering from blindness. Afterwards, the development of the final version incorporated the suggested improvements detected during validation. These improvements consisted in reorganizing the method of response for determined questions in order to be more user-friendly. Finally, the survey was distributed to all the delegations of ACAPO in Portugal. Afterwards, these delegations have forwarded the survey to the associates by email.

4.1.3 Instrument: Perception of the importance in identifying and combining clothing for blind people

The final version of the survey, Appendix A1, consisted of a total of 25 questions divided into 5 main parts: (1) Personal identification, (2) Identification of the type of disability, (3) Clothing, (4) Technology and (5) Research and development.

The part of the *Personal Identification* included questions that aimed to gather information regarding the

characterization of the participant, such as age, gender, academic qualifications and current occupation. The second part of the questionnaire, *Identification of the type of disability*, enabled the analysis of conditions that caused blindness in the participants, as well as the age group in which these conditions occurred.

The third part, *Clothing*, includes 6 questions to identify the importance and concerns that blind people have regarding the actions they need to do to get dressed, to choose clothes and how they do shopping. In this subject, some questions were presented as statements. The answers were based on a 5-point *Likert* scale of agreement, importance or frequency.

The fourth part, *Technology*, includes 3 questions that aim to assess the knowledge, usability and satisfaction that blind community has in relation to the available supportive technologies. However, it is also possible to assess the proximity that this community has within this technology.

The fifth and last part, *Research and development*, includes 3 main questions and other 2 complementary. In this section, it is intended to assess the availability and the interest in developing a technology that supports the blind community identifying and combining clothes. Moreover, this section aims to assess if blind people want this technology to be available. The suggestions and opinions of the participants were taken into consideration in the final version.

4.1.4 Implementation

The data collected using google forms from July to September 2020 and the participation was voluntary and anonymous. The data was gathered in a table and analysed using the statistical software SPSS (Statistical Package for the Social Sciences) version 22. At this initial stage of analysis of the collected data, a descriptive statistic in which data was translated into percentage values was considered.

4.1.5 Participants Characterization

The sample of was essentially composed by blind associates of ACAPO, who were asked to fill a purpose-built survey, delivered by email. A total of 26 participants replied to the survey, of which 23 full responses fulfilled all the set conditions, and with only 3 being excluded due to not fulfilling the aforementioned conditions. In the present study, all the analyses were made considering the full responses.

To obtain the characterization of the participants in this survey, 4 variables were defined: age, gender, academic qualifications and profession.

It was observed that there was no equal distribution between age groups, with individuals between 45 and 54 years old presenting 52.2% of the answers, the youngest participant being 18 years old, and the oldest being 65 years old. Due to the wide range of participant's age, during the analysis of the survey, the variable age was grouped into two main groups, one for participants being 44 or less years old, and the second to participants being 45 years old or more. Regarding gender and education, most of the participants were female (73.9%), and had higher education (43.5%), with only 26.1% having, at least, nine years of basic education. In the analysis of the occupations, it was found that most of them were unemployed (30.4%), which highlights the difficulty of this population to get integrated in the labour market. F&B (food & beverage) and administrative services were the occupation areas with greater representativeness, accounting for 13% each. Other categories include all retired people and students, representing 17%.

4.1.6 Identification of the Type of Disability

The second part of the questionnaire contains two questions enabling each participant to identify the causes and types of conditions that caused the participants' loss of vision, as follows:

QII.1: Since what age are you visually impaired?

QII.2: What caused your disability?

On the basis of the received responses, the majority (69.6%) became blind during the first year of life. This shows that these participants do not have basic visual notions about the “world” around them. An identical result was obtained regarding the reason for the loss of vision, that is, 65.2% had lost their vision due to congenital disease, and only 8.7% as a result of an accident. The remaining 26.1% refers to acquired diseases or conditions. Congenital disease occurs during pregnancy, which explains the high number of participants with vision loss before reaching one year old. Hence, the conditions that originated blindness or vision loss were grouped in two main categories, congenital disease and acquired disease, with glaucoma and retinopathy being the main causes of vision loss, respectively.

4.1.7 Aesthetics and Clothing

The way we dress has a big impact on our daily lives and it is crucial to our well-being. This perception ranges from the importance that society gives to the way we dress to the importance of choosing clothing for the workplace, to help convey the right and appropriate image for the context in which we are inserted in. So, in the third part of the questionnaire, three statements were considered:

QIII.1: Vision is one of the senses that dominates the life of human beings. It allows them to know and perceive the world around them, while giving meaning to objects, concepts, ideas and tastes.

QIII.2: How to dress and the style we prefer for different occasions is part of someone's identity. Blind people do not have this sense, and dressing can be a difficult and stressful task. With the advancement of technology, it is important to minimize all the limitations of a blind person whilst organizing their own clothing.

QIII. 3: The lack of knowledge about the colours, the type of pattern or the condition of the garments makes this a daily challenge, in which the current resources are not the best.

And the following three questions:

QIII.4: Are you worried about matching garments?

QIII.5: How often do you need help buying clothing?

QIII.6: Where do you buy your clothes?

Due to the relatively small size of the sample, for all statements, the scale was recoded so that only two groups were possible: "agree" and "disagree", showing a positive or negative response for each statement. Fig.1 shows the distribution of results for the different statements.

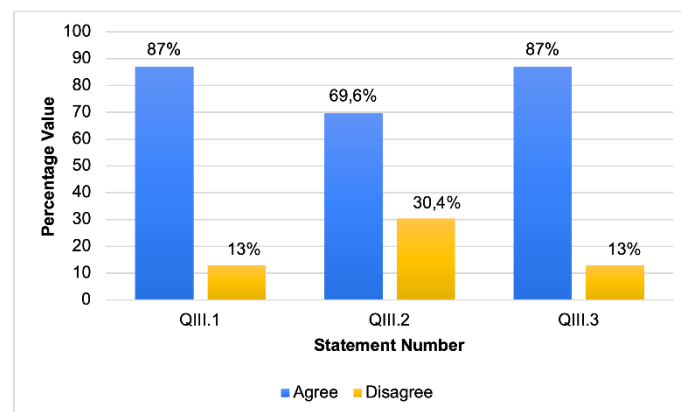


Figure 4.1: Positive and negative response distribution for each statement (Rocha *et al.*, 2022).

The majority of participants recognize that the sense of vision is crucial to the attribution of meanings and recognition of everything that surrounds us. The importance of aesthetics as a definition of our identity is also in agreement among the participants, as well as the daily difficulties experienced by participants due to the lack of resources. As expected, all participants have reinforced the importance of combine clothing for them, the majority of which (73.9%) saying that they frequently seek help to shop their clothes, mainly from family members, support centre professionals and CAVI (Support Centre for Independent Living).

When asked where they buy their clothes, all participants referred physical stores, with 39.1% also referring to do shopping online.

4.1.8 Technology

Technology has evolved considerably in this field; however, it is necessary to understand whether there is enough technology to minimize the obstacles faced by people with blind condition or vision loss, in their daily lives. So, in the fourth part of the questionnaire, after the identification of the device and system used, two questions were considered:

QIV.1: Are you aware of any technology for clothing identification?

QIV.2: How satisfied are you with the technology available on this topic?

Most of participants (65.2%) demonstrated to be aware of existing clothing identification technologies. Smartphone apps were pointed as main source of aid to detect colours. As an alternative, the same users opt for Colorino (*Colorino – Color and Light Detector - Caretec*, 2024). However, only 26.1% referred to be satisfied with the existing technology, which reinforces the importance of the topic addressed on this work contributes to the motivation behind it. Overall, *ca.* 89% of participants referred they used smartphones, 72% used a laptop, 33% used mobile phones and 11% tablet devices. Most smartphone users referred they had the IOS operating system.

4.1.9 Research and Development

Aesthetics has an impact on the image and appearance of our body, directly influencing our well-being, self-esteem and optimism in “day-to-day” life. The research and development conducted in this work sought to include these characteristics. Therefore, in the fifth part of the questionnaire, three main questions were considered:

QV.1: Would it be important to develop something that would make it possible to identify and combine clothing?

QV.2: How likely is it to use a technology that includes the act of identifying and combining clothing?

QV.3: Did you need help in completing this survey?

According to Figure 4.2, most participants (91.3%) agreed that a framework should be developed to help identifying and matching garments. In line with the previous answer, almost all participants (95.7%) were willing to use technology to help them identifying and combining clothes. When choosing the platform to

use the technology, the smartphone and the laptop were the preferred choices, accounting for 43.2% and 35.1%, respectively. Lastly, only 17.4% of participants stated that they sought some help to fill out the questionnaire.

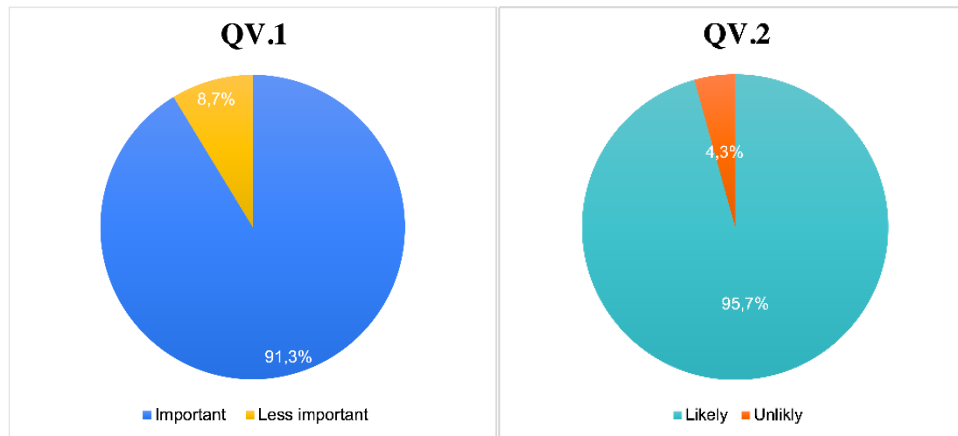


Figure 4.2: Results distribution for QV.1 and QV.2 (Rocha *et al.*, 2022).

4.1.10 Conclusions of the survey

Based on the collected and analysed information, it becomes important to develop tools that allow the identification and combination of garments. Moreover, *ca.* 95.5% of the respondents are available to use technology to help them in this task. Although the sample dimension used in the analysis could be considered small ($n=23$) to be representative for the blind population at national level, the authors believe that the collected results reinforce the central importance of aesthetics on clothing for blind people, who are becoming increasingly inserted in the labour market, following global and European guidelines of inclusion (*Reduzir as Desigualdades • ODS - BCSD Portugal*, n.d.).

Through the survey undertaken by the participants, it is possible to conclude that not knowing colours, patterns, and the overall condition of clothes is a major challenge that blind people face every day. This comes to emphasize the need to identify and combine clothing. Despite of all the difficulties, the existing offer of different technologies and support is very limited. So far, mobile phone applications and Colorino remain the leading sources of support used by blind people. Analysing the comments, participants have demonstrated their enthusiasm and willingness to collaborate in this research.

4.2 System Requirements

After analysing the results of the conducted survey and summarizing the key aspects of a system that could help blind people choose and characterize their clothes, especially with regard to their well-being, the system architecture and requirements were designed. The design phase involved identifying critical functionalities and components that would effectively address the needs highlighted by the survey respondents. The proposed system(Rocha *et al.*, 2021) aims to develop a comprehensive solution that includes the following key requirements:

- Clothing Classification: The system should accurately identify and categorize clothing items based on type (e.g., shirts, dresses).
- Colour Detection: It should precisely determine the colours of clothing items to assist users in making appropriate wardrobe choices.
- Defect Detection: The system must identify defects such as stains and holes to ensure that users are aware of the condition of their clothing.
- User-Friendly Mobile Interface: The mobile application should be highly accessible and intuitive, allowing blind and low-vision users to navigate and use the system with ease.
- Smart Wardrobe Integration: The system should include a smart wardrobe equipped with an image acquisition system and controlled lighting to capture high-quality images of clothing items.
- NFC Tagging: The system should support NFC tagging to facilitate the organization and retrieval of clothing information.
- Clothing Management: The application should enable users to manage their wardrobe, including adding new items, updating information, and verifying item details.

Once the system requirements were defined, it was possible to outline the methodology for its conception, as explained in the following section.

4.3 System Overview

The development of the iSight prototype was structured around three main components: (i) the collection of data and the application of deep learning algorithms for garment identification and modification detection, (ii) the design and implementation of the mechatronic device, specifically the automated wardrobe system, and (iii) the creation of a user-friendly mobile application. The workflow illustrating the main steps of this methodology is presented in Figure 4.3.

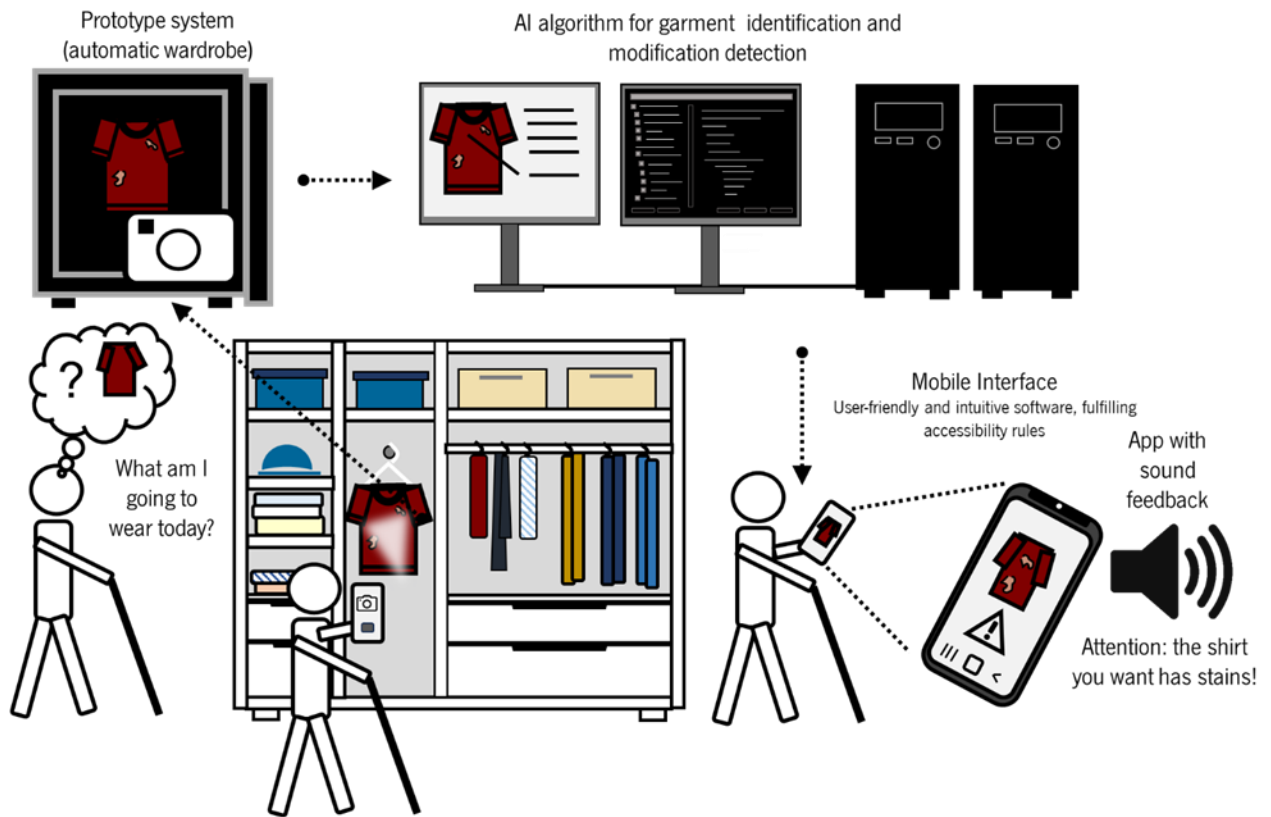


Figure 4.3: Schematic representation of the workflow comprised in the iSight prototype development.

The following subsections provide a detailed account of each component. Initially, the data collection process and the deployment of advanced deep learning algorithms are discussed, focusing on their role in accurately identifying garments and detecting modifications. Subsequently, the design, construction, and integration of the automated wardrobe system is elaborated (Chapter 5), highlighting its importance as the core mechatronic element of the iSight prototype. Finally, the development of the mobile application is explored, with an emphasis on its user-friendly interface and seamless integration with the automated wardrobe, ensuring accessibility and ease of use for visually impaired users.

4.4 Deep Learning Approaches

This subsection details three experiments using deep learning techniques. The first experiment addresses the classification of clothing categories using CNNs. The second experiment expands this approach by incorporating both segmentation and classification of clothing categories, in addition to extracting colour information. Lastly, the third experiment focuses on identifying modifications in clothing items.

4.4.1 First Experiment - Clothing Category Classification using CNN

In the first experiment, state-of-the-art deep learning techniques were leveraged through transfer learning to perform category classification using CNNs (Rocha *et al.*, 2019). The pipeline for applying deep learning to clothing category classification involves several key steps. The process begins with the selection, preparation, and pre-processing of a dataset. In parallel, several data augmentation techniques are employed to examine their effects on the results with and without its use. Finally, transfer learning is implemented, using state-of-the-art deep learning models to perform category classification using CNNs. Figure 4.4 illustrates this workflow.

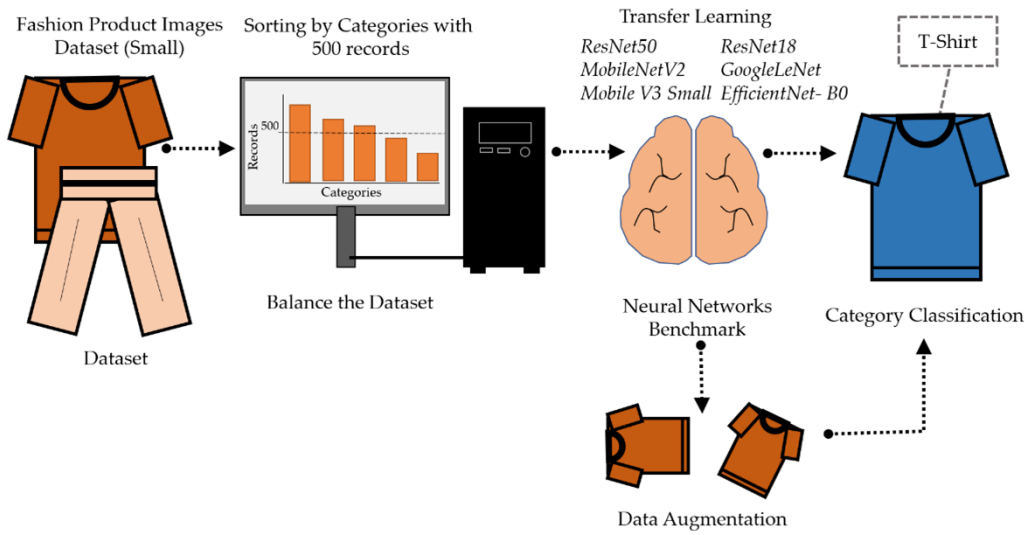


Figure 4.4: Workflow methodology for the classification of clothing categories (Rocha, Soares, *et al.*, 2023a).

4.4.1.1 Dataset preparation

To apply deep learning to clothing category classification, a dataset was needed before being fed into the neural networks. As a first step, it was necessary to identify a dataset that could meet this work's requirements. Considering that all images taken by the blind people are collected in a controlled environment and with one item of clothing at a time (Rocha *et al.*, 2020), and based on the authors' previous research (Rocha *et al.*, 2021), the authors were able to conclude that a reasonable quantity of data was required for training and obtaining more accurate results. For this reason, a research survey was conducted to identify available datasets - Table 4.1.

Table 4.1: Summary of available datasets for fashion category classification (Rocha, Soares, *et al.*, 2023a).

Dataset	Year	# of photos	Description
DeepFashion-C (Z. Liu, Luo, <i>et al.</i> , 2016)	2016	289,222	Annotated with clothing bounding box, pose variation type, landmark visibility, clothing type, category, and attributes.
Fashion Landmark Dataset (Z. Liu, Yan, <i>et al.</i> , 2016)	2016	123,016	Annotated with clothing type, pose variation type, landmark visibility, clothing bounding box, and human body joint.
FashionMinist (Xiao <i>et al.</i> , 2017)	2019	70,000	Grayscale image dataset associated with a label from 10 classes.
DeepFashion2 (Ge <i>et al.</i> , 2019)	2019	491,000	A versatile benchmark of four tasks including clothes detection, pose estimation, segmentation, and retrieval.
Fashion Product Images (Fashion Product Images Dataset Kaggle, n.d.)	2019	44,400	Annotated with gender, master category, subcategory, article type, base colour, season, year, usage and product description.

Based on the characteristics of each dataset, it was decided to use the Fashion Product Images Dataset, which is a smaller resolution version of the dataset. This dataset provides a variety of attributes that are relevant to the current and future needs of the project, such as category, colour, season, among others. However, despite the large number of annotated features included in the dataset, it still presents unbalanced data between article types, which were referred to as “categories” in this work. Figure 4.5 shows the clothing categories for which at least 500 images were considered in their distribution, *i.e.* each entry on the X axis represents a specific clothing category.

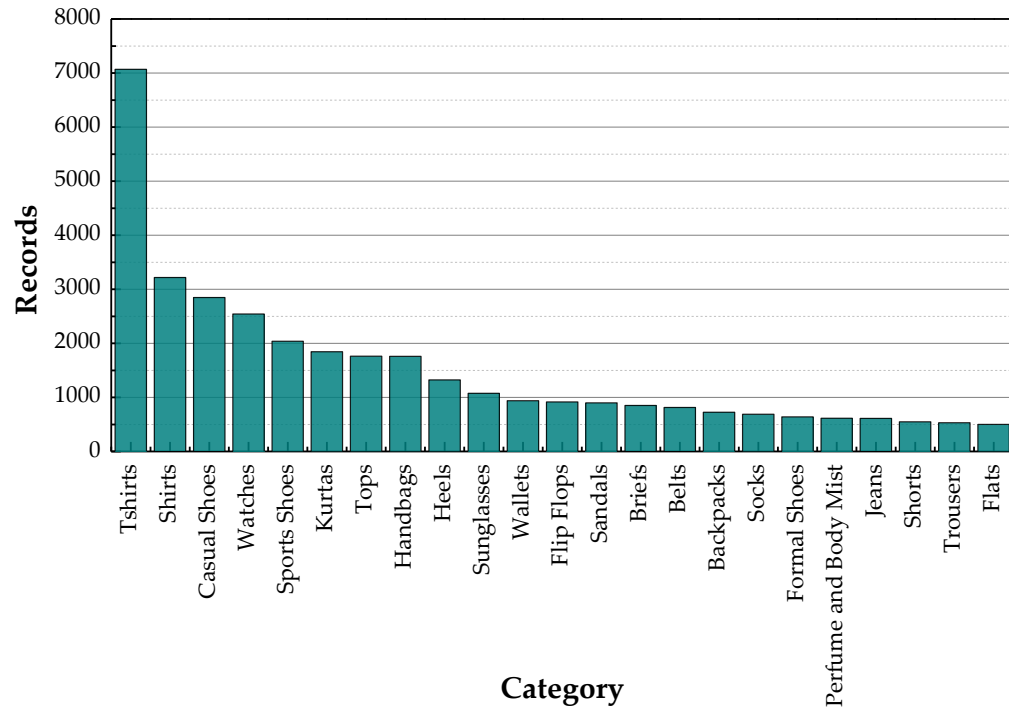


Figure 4.5: Distribution of the number of records for each article type/category (Fashion Product Images dataset) (Rocha, Soares, *et al.*, 2023a).

For a comprehensive and unbiased comparison between different categories, the dataset was carefully curated by selecting exactly 500 records from the initial complete range for each category as shown in Figure 4.5. This approach avoids imbalanced data, ensuring that each category in the dataset is adequately represented. A representative item from each category is illustrated in Figure 4.6, allowing for a better understanding of the dataset composition and diversity.

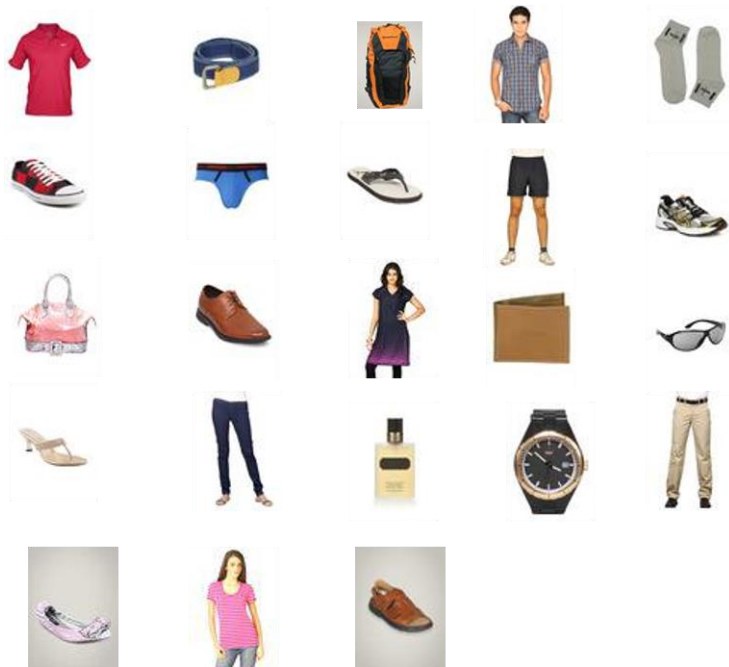


Figure 4.6: Sample images from the Fashion Product Images Dataset (Rocha, Soares, *et al.*, 2023a)

4.4.1.2 Classification of clothing category based on transfer learning.

The process of image classification involves assigning a label to each image based on its content and categorizing it accordingly. For accurate classification, relevant features must be extracted from the images.

There have been a variety of image classification problems that have been addressed using CNNs. The majority of these networks have a small amount of data and the process of training them entails high computational costs and a significant amount of time. As a consequence, transfer learning appears to be a viable solution, where a pre-trained network is retrained with another dataset, which enables training a network faster than training from scratch. Transfer learning could be used in two different ways: feature extraction and fine-tuning (Rosebrock, 2017). For the first one, the fully connect layer (FC), the head of the network, is replaced, and it simply retrains this layer. Moreover, all the weights of the convolutional layers of the network are “frozen”. The second approach, which is similar to feature extraction, involves the replacement of the network's head and the construction of a new head. As opposed to the first method, it allows the convolution neural network's weights to be “unfrozen” and the entire network to be retrained. In this work six implementations of CNNs were made, specifically those that, to the best knowledge of the authors, have never been used before in the Fashion Product Images dataset. The choice of the implementation was based on the different depths and parameters; notwithstanding, all implementations had the same resolution - Table 4.2. For this reason, this study uses the following networks: RestNet-18, ResNet-50, MobileNetV2, GoogleNet, MobileNet V3 (small), and EfficientNet - B0, allowing comparisons

of results obtained with these networks.

Table 4.2: Main characteristics of pre-trained models (Rocha, Soares, *et al.*, 2023a).

CNN	Parameters (Millions)	Image Size (pixels)
ResNet 50	25.6	224 x 224
ResNet18	11.7	
MobileNetV2	66	
GoogLeNet	7	
MobileNet V3 Small	67.66	
EfficientNet - B0	5.3	

4.4.1.3 Comparative analysis for different CNNs architectures.

Based upon the previously mentioned CNNs architectures, extracted features and fine-tuned methods, this section presents the results of three experiments conducted on the Fashion Product Images Dataset for the classification of clothing categories. While the two first experiments were based on fine-tuning, the third experiment relied on feature extraction. To compare the training and validation results among the networks, the hyperparameters – Table 4.3 – were left unchanged.

Table 4.3: Hyperparameters of model experiments (Rocha, Soares, *et al.*, 2023a).

Parameters	Value
Optimizer	SGD*
Momentum	0.9
Learning rate	0.001
Batch Size	16

*SGD - Stochastic gradient descent

As a loss function, cross-entropy loss (Equation 7) was employed to quantify the difference between predicted probabilities and actual class labels. When incorrect predictions are associated with high confidence, the cross-entropy loss penalizes them much more heavily, thereby encouraging more accurate predictions, being the result a probability value between 0 and 1.

$$L_{CE} = - \sum_{i=1}^n t_i \log(p_i), \quad \text{for } n \text{ classes,} \quad (7)$$

where t is the truth label and p is the Softmax probability for i^{th} class. Softmax is a function widely used

in deep learning, particularly in the context of computer vision, to handle N-dimensional vectors. It is employed to classify extracted vectors by determining the probability of each vector, ensuring that the sum of probabilities for all vectors in a dataset equals 1 (Bridle, 1989; Qi *et al.*, 2017).

A fine-tuning process involves training the entire network, which means that all layer weights are trainable (Rosebrock, 2017). To prevent the network from learning new batch normalization parameters, namely beta and gamma, the weights of batch normalization are set to non-trainable (Ioffe & Szegedy, 2015). If the fine-tuning examples differ significantly from those in the original training dataset, these batch statistics will differ greatly. Since the fine-tuning dataset is of a small size, relearning these parameters is not always desirable.

To implement the networks, Pytorch (Ansel *et al.*, 2024) was used as a library, and the networks were trained on a NVIDIA A100 running Ubuntu 20.04.2 LTS. The results of fine-tuning using pre-trained neural networks are shown in Table 4.4.

Table 4.4 - Test performance results (Rocha, Soares, *et al.*, 2023a).

Network	Train Accuracy	Validation Accuracy	Train Loss	Validation Loss	Epochs	Time (s)
ResNet-50	0.946	0.903	0.159	0.296	4	153.72
ResNet-18	0.939	0.904	0.183	0.279	4	111.66
MobileNet V2	0.917	0.898	0.233	0.290	4	139.04
GoogLeNet	0.940	0.907	0.189	0.279	7	266.20
MobileNet V3 (small)	0.917	0.883	0.234	0.327	7	241.66
Efficientnet-B0	0.927	0.900	0.210	0.295	12	539.59

As indicated in Table 4.4, GoogLeNet achieved the highest validation accuracy of 90.7%, while the other networks demonstrated similar accuracy values. The only exception was MobileNet V3, which was noted for its lower accuracy of 88.3%.

For this dataset, in the fine-tuning process, the depth of the same architecture (ResNet-18 and ResNet-50) was not relevant, resulting in approximately the same results, *i.e.* 90.4% and 90.3% validation accuracy values, respectively. Furthermore, increasing the depth results in a more time-consuming process, as the number of epochs required for approximately the same results is the same. Neither the depth of the networks nor the parameters show a correlation with accuracy.

Considering the synchronization time between the Central Processing Unit (CPU) and Graphics Processing unit (GPU), and implementing 400 iterations of GPU warm-up, the inference time for each network was evaluated. In Table 4.5, the average time and standard deviation are presented for 400 inferences of the same image, for each network.

Table 4.5: Inference time by network architecture (Rocha, Soares, *et al.*, 2023a).

Network	Time (ms)	Standard Deviation
ResNet 50	0.0126	0.251
ResNet18	0.0081	0.162
MobileNetV2	0.0117	0.235
GoogLeNet	0.0169	0.338
MobileNet V3 Small	0.0120	0.239
Efficientnet-B0	0.0197	0.394

The results presented in Table 4.5 indicate that ResNet-18 provides the fastest inference time. In addition, these results indicate that the inference time is not affected by the number of parameters nor by the architecture of the network. In addition, the standard deviation appears to be correlated with the inference time, as it increases along with the inference time.

As part of the second experiment, data augmentation techniques were utilized, including random horizontal flipping and random rotations. These data augmentation techniques were chosen to simulate variations that may occur during the capture of clothing images in addition to increasing the robustness of the dataset. Table 4.6 provides a summary of the results of this experiment.

Table 4.6: Test performance results with augmented data (Rocha, Soares, *et al.*, 2023a).

Network	Train Accuracy	Validation Accuracy	Train Loss	Validation Loss	Epochs	Time (s)
<i>w/Random Horizontal Flip</i>						
ResNet-50	0.958	0.906	0.112	0.307	6	262.63
ResNet-18	0.950	0.907	0.146	0.275	6	162.28
MobileNet V2	0.927	0.910	0.201	0.271	6	228.77
GoogLeNet	0.941	0.911	0.171	0.272	10	356.57
MobileNet V3 (small)	0.911	0.893	0.251	0.320	7	223.88
Efficientnet-B0	0.921	0.903	0.223	0.276	13	542.21
<i>w/Random Rotation (90)</i>						
ResNet-50	0.934	0.887	0.187	0.323	11	364.47
ResNet-18	0.914	0.887	0.238	0.339	10	272.93
MobileNet V2	0.911	0.887	0.245	0.334	12	464.70
GoogLeNet	0.908	0.894	0.269	0.306	14	509.61
MobileNet V3 (small)	0.896	0.880	0.281	0.379	15	481.10
Efficientnet-B0	0.896	0.880	0.295	0.321	18	804.20
<i>w/Random Horizontal Flip and w/Random Rotation (90)</i>						
ResNet-50	0.947	0.887	0.148	0.328	15	508.69
ResNet-18	0.904	0.885	0.260	0.331	11	306.74
MobileNet V2	0.908	0.884	0.255	0.334	13	539.59
GoogLeNet	0.903	0.883	0.259	0.325	17	608.41
MobileNet V3 (small)	0.899	0.880	0.271	0.369	17	533.98
Efficientnet-B0	0.908	0.891	0.254	0.304	25	1041.29

Based on the results of Table 4.6, it can be concluded that the random horizontal flips feature enhanced

the model's performance substantially. In the first experiment, GoogleLeNet was able to achieve the highest level of accuracy (91.1%), whereas MobileNet V3 (small) achieved the lowest level of accuracy (89.3%). Lastly, augmented data with random rotation resulted in poor performance. The precision, recall, and F1-score obtained for the GoogleLeNet network are presented in Table 4.7. In addition, Figure 4.7 depicts the confusion matrix for the model that achieved the best results based on the performance measurements (GoogleLeNet). The confusion matrix provides a visual representation of the classification model's performance.

Table 4.7: Classification report of the GoogLeNet network (Rocha, Soares, *et al.*, 2023a).

Network	Precision	Recall	F1-score	Support
Backpacks	0.99	0.96	0.98	110
Belts	1.00	1.00	1.00	102
Briefs	1.00	0.99	0.99	96
Casual Shoes	0.81	0.75	0.78	102
Flats	0.71	0.61	0.66	107
Flip Flops	0.88	0.94	0.91	124
Formal Shoes	0.98	0.94	0.96	104
Handbags	0.95	0.92	0.94	91
Heels	0.66	0.77	0.71	97
Jeans	0.99	0.90	0.95	115
Kurtas	0.93	0.95	0.94	101
Perfume and Body Mist	1.00	0.99	0.99	90
Sandals	0.86	0.83	0.84	105
Shirts	0.91	0.94	0.92	96
Shorts	0.98	0.99	0.98	96
Socks	0.97	0.99	0.98	90
Sports Shoes	0.81	0.86	0.83	90
Sunglasses	1.00	1.00	1.00	96
Tops	0.83	0.88	0.85	105
Trousers	0.88	0.98	0.92	88
T-shirts	0.93	0.83	0.88	90
Wallets	0.95	0.97	0.96	107
Watches	0.98	0.99	0.98	97
Accuracy			0.91	2299
Macro avg.	0.91	0.91	0.91	2299
Weighted avg.	0.91	0.91	0.91	2299

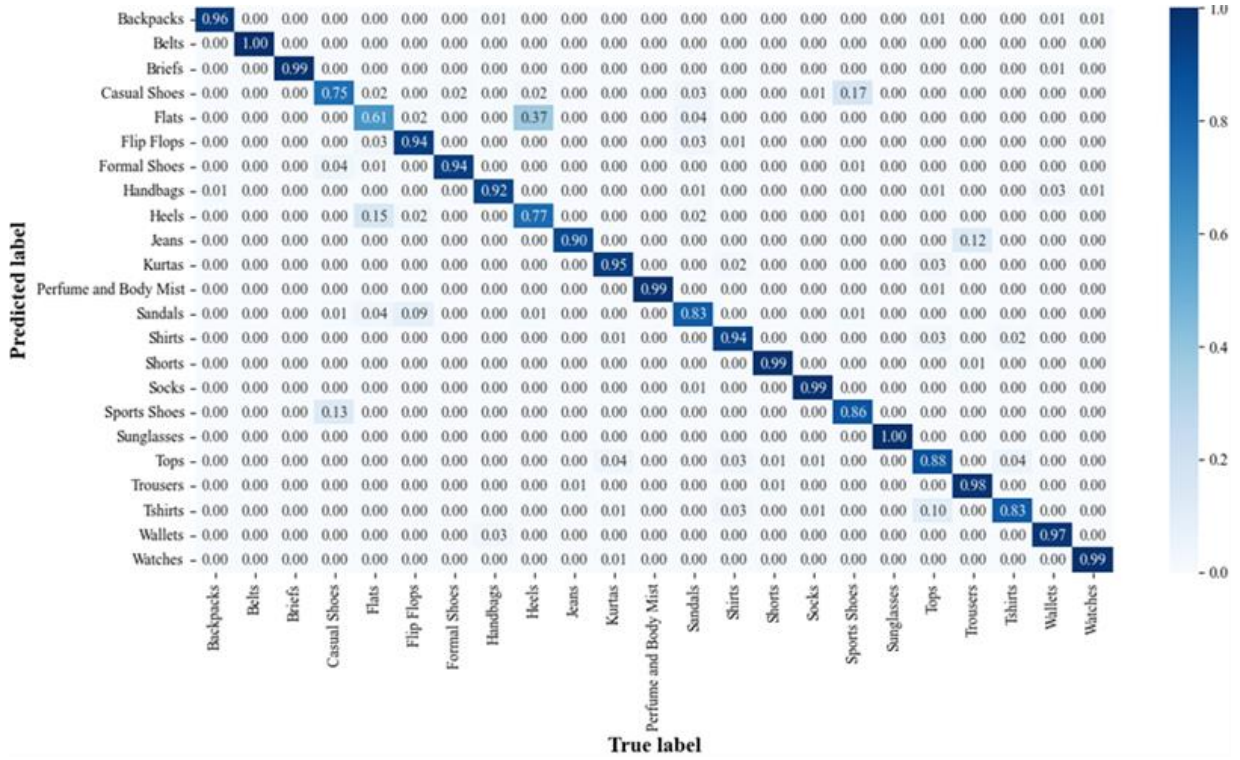


Figure 4.7: Confusion matrix from classification for the model that achieved the best results based on the performance measurements (GoogleLeNet) (Rocha, Soares, *et al.*, 2023a)

Independently from the good performance of the model, it is worth noting that there are some misclassifications between similar clothing articles, such as casual shoes and sport shoes, heels and flats, and t-shirts and tops (Figure 4.7).

In the third experiment, transfer learning was performed via feature extraction, where all layers, except the output layer, had its weights “frozen”. The obtained results show that the loss of the network is *ca.* 90 %, therefore not viable.

Overall, it can be concluded that the fine-tuned GoogleLeNet with augmented data, in conjunction with the proper hyperparameters, effectively outperforms the work proposed by Fengzi *et al.* (2020). By contrast, these results were obtained by fine-tuning all network layers and leveraging pre-trained weights in all architectures, rather than adding new head layers as in Fengzi *et al.* (2020). Furthermore, in this study, the various augmentations were evaluated in order to assess their contribution to performance, with rotation having the greatest impact on reduced performance, and horizontal flip having the greatest impact on increased performance. Contrary to this, Fengzi *et al.* (2020) combined all augmentations during training.

The accuracy of this study is similar to that obtained by Kolisnik, Hogan, and Zulkernine (2021), although the number of considered classes is not specified.

4.4.1.4 Conclusions of First Experiment

This study presents an analysis of clothing type identification and stain detection for blind individuals using deep learning models. Through comprehensive benchmarking, it was demonstrated that a deep learning model, particularly GoogleLeNet, can achieve up to 91% F1-Score in identifying clothing type categories, representing a significant improvement over previous literature. The study highlighted the effectiveness of transfer learning, where fine-tuning all network layers and leveraging pre-trained weights yielded superior results compared to traditional methods that add new head layers. Augmented data techniques, such as random horizontal flipping, were shown to further enhance model performance, while random rotations negatively impacted results. This underscores the importance of carefully selecting augmentation strategies to optimize model accuracy. It was also observed that the depth of the architecture (*e.g.*, ResNet-18 vs. ResNet-50) did not significantly affect validation accuracy, though it did influence the computational efficiency. ResNet-18, for instance, provided the fastest inference times without compromising accuracy. Despite the promising results, there are limitations to this study. One notable constraint is the reliance on images of clothing worn by models, which may introduce redundancy and lead to misclassifications between similar clothing articles, such as casual shoes and sport shoes, or t-shirts and tops. To build on these findings, further tests are necessary to determine the most effective types of data augmentation for the models used. Additionally, addressing the limitations related to image sources could enhance the model's robustness and generalizability.

In summary, the fine-tuned GoogleLeNet model, enhanced with appropriate data augmentation techniques, outperforms existing methods and offers a viable solution for clothing type identification for blind individuals. This study's results align with the accuracy levels reported Kolisnik, Hogan, and Zulkernine (2021), despite differences in class specifications, demonstrating the model's potential for practical applications.

4.4.2 **Second Experiment - Clothing Category Segmentation and Classification and Colour Extraction**

The second experiment extended the first by introducing clothing segmentation. While the first experiment focused on image classification, this one evaluates the problem as instance segmentation, refining predefined categories to accommodate different backgrounds and enabling the analysis of pixel colours as a result of segmentation. Hence, this process can be used to classify clothing categories and

characterize individual pixels based on their colours. The workflow is depicted in Figure 4.8.

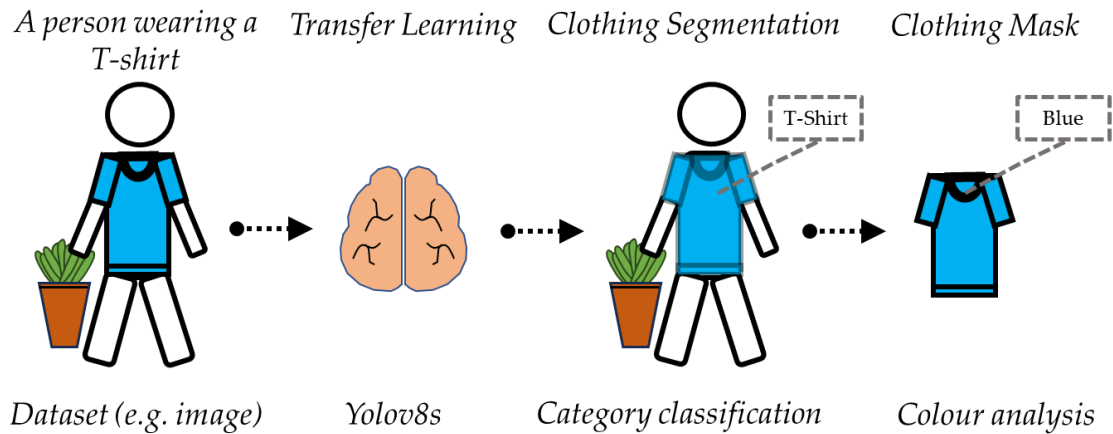


Figure 4.8 – Workflow for clothing segmentation and colour extraction.

4.4.2.1 Dataset collection

The developed dataset consists of 2,000 images that are equally distributed across eight categories of garments: dresses, jackets, pants, polos, shirts, shoes, shorts, and t-shirts. The present dataset is an enhancement and expansion of the previous one, incorporating a refined selection of the most significant categories.

In addition to refining the existing categories, new images were sourced from personal wardrobes and included diverse backgrounds in order to increase the dataset's robustness. As a result, each garment category is fully represented under a variety of conditions, improving its applicability in real-life scenarios. A sample of the images added to the dataset is depicted in Figure 4.9.



Figure 4.9 – Samples of images added to the dataset from personal wardrobes: a) jacket, b) jeans, c) dress, and d) shorts.

A split of 70/20/10 was used to divide the dataset into training, validation, and test sets, ensuring an equal distribution of data across all categories. As the objective of the study was not only to classify

garments, but also to segment them to extract pixel-level colour information, the study was approached as a problem of segmentation. For this purpose, the YOLOv8s model was employed, and the network was fine-tuned. While training, a variety of data augmentation techniques were applied, such as changes in hue, value, and saturation, horizontal flips, and scaling. As a result of these augmentation strategies, the model was enhanced in terms of robustness and generalizability.

Based on testing and experimentation throughout the training process, Table 4.8 presents the hyperparameters that yielded the best results.

Table 4.8: Hyperparameters (Image Size, Optimizer, Learning Rate, and Batch Size) of model experiments.

Parameters	Value
Image Size	640x640 pixels
Optimizer	SGD
Learning Rate	0.01
Batch Size	16

The results of this study, including performance metrics for each category, are presented in Table 4.9. Precision indicates a low percentage of false positives relatively to the total number of pixels correctly identified as part of an object mask. Recall refers to the percentage of pixels correctly identified as belonging to an object mask compared with the total number of pixels actually belonging to that mask - a low percentage indicates few false negatives. A mAP at IoU = 50 measures the average precision of the model's predictions when the intersection over union (IoU) is, at least, 50%. Table 4.9 summarizes the performance results.

Table 4.9 - Main performance results of model for clothing mask segmentation (Precision, Recall and AP at IoU = 0.50).

Category	Precision	Recall	AP at IoU = 0.50	AP
all	0.941	0.896	0.965	0.949
Dress	0.849	0.917	0.941	0.906
Jacket	1	0.911	0.99	0.955
Pants	0.989	0.875	0.97	0.96
Polo	0.953	0.837	0.96	0.952
Shirt	0.863	0.875	0.925	0.916
Shoes	0.996	1	0.995	0.995
Shorts	0.833	0.833	0.964	0.955
T-shirt	0.917	0.917	0.971	0.954

Table 4.9 presents the performance results for the YOLOv8s model in the task of segmenting clothing across various categories, as well as detailed metrics for each type of garment, focusing on segmentation masks. For the overall performance of the model across all categories ("all"), the model achieved a

precision of 0.941, a recall of 0.896, and an AP for an IoU of 0.5 of 0.965. These results indicate a high overall performance of the model when it comes to segmenting masks. In the dress category, the model had a precision of 0.849, a recall of 0.917, and a mAP of 0.941. Even though these results indicate good performance, the precision is slightly lower than in other categories. The jacket category demonstrated an excellent performance with a precision of 1.0 and a recall of 0.91, resulting in a mAP of 0.99, demonstrating an excellent ability of the model in identifying and segmenting jackets. In the pants category, a precision of 0.989, a recall of 0.875 and a mAP of 0.97 were obtained, indicating almost a perfect performance in the mask segmentation process. The polo category had a precision of 0.953, recall of 0.837, and mAP of 0.96. Despite the high precision, the lower recall indicates that the garment may not be fully detected. Shirts ("shirt") achieved a precision of 0.863, a recall of 0.875, and a mAP of 0.925, showing balanced performance, but with room for improvement. It is noteworthy that shoes had an almost perfect precision of 0.996, a recall of 1.0, and a mAP of 0.995, indicating excellent performance in this category. In the case of shorts, the precision was 0.992, the recall was 0.833, and the mAP was 0.964. The low recall indicates that some instances may not have been detected despite the high precision. Lastly, the t-shirts category demonstrated good overall performance with a reasonable balance between precision and recall, being 0.887 and 0.917 respectively, also achieving a mAP of 0.971. According to Figure 4.10, the confusion matrix for the YOLOv8s model provides detailed insight into its performance in the segmentation of clothing across various categories.

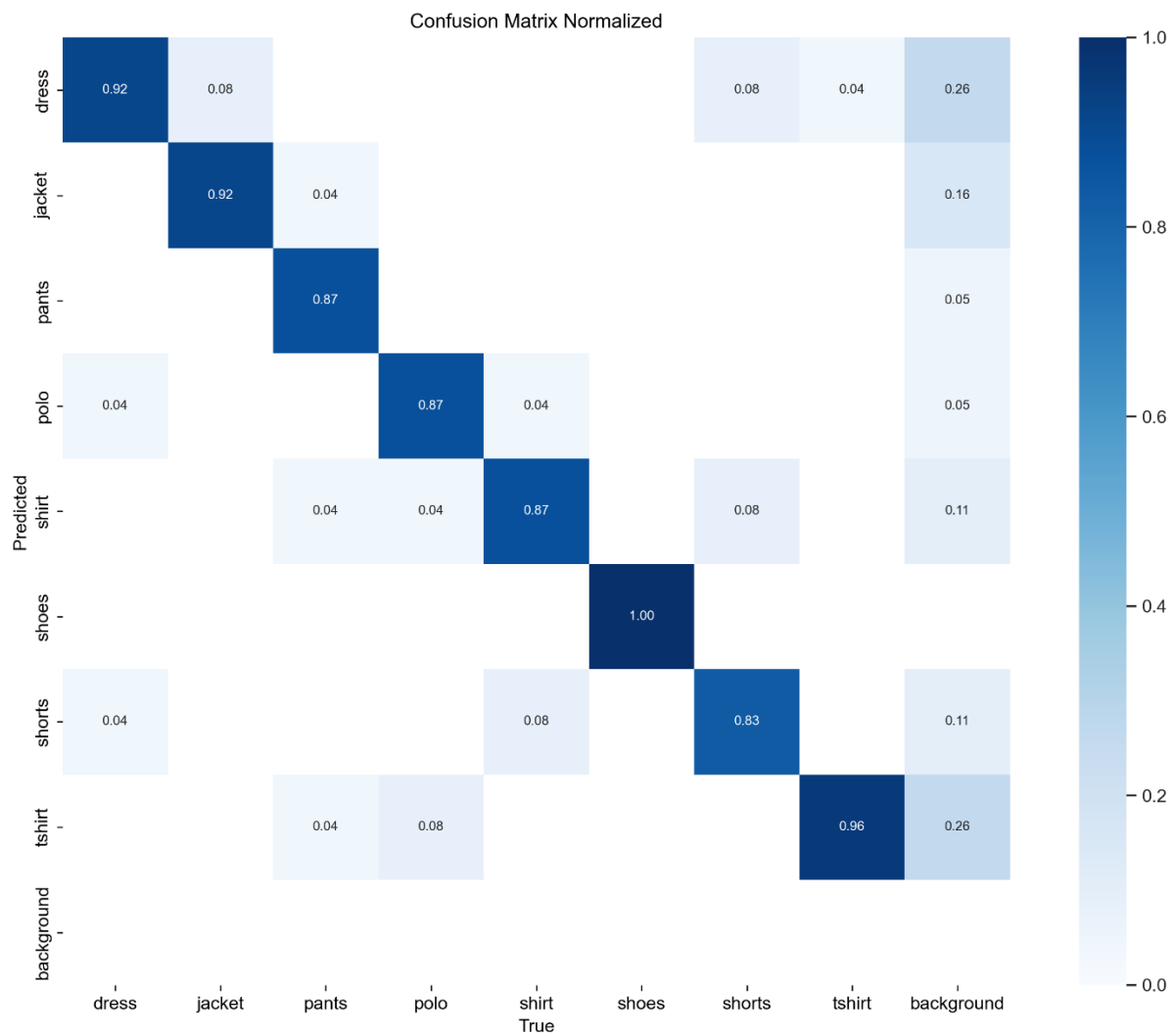


Figure 4.10 – Illustration of the relationship between predicted and true values in the confusion matrix of each clothing category.

This matrix – Figure 4.10 - provides an evaluation of where the model performs well and where it fails. The lower value for shorts may be attributed to misclassification with dresses and shirts, likely due to the similar poses of the models wearing these garments. Furthermore, t-shirts and polos are sometimes confused probably due to their similar shapes. Figure 4.11 illustrates some results from segmentation.



Figure 4.11: Example of inference images with category and respective segmentation mask: (a) Original image of pants; (b) Segmented image of pants; (c) Original image of a shirt; (d) Segmented image of the shirt.

After segmentation, the extracted mask was used to determine the colour of the clothing item. A pixel-level analysis of the resulting mask was conducted since the model generally performs well in classification. This involves extracting the segmentation mask of the clothing and converting it to the HSV colour space to determine the exact colour of the garment. Figure 4.12 illustrates the entire workflow.

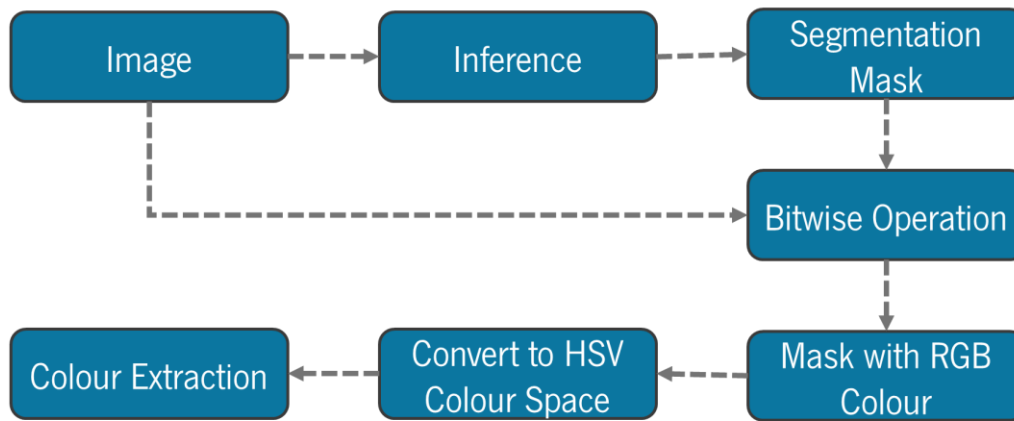


Figure 4.12: Workflow for colour extraction.

Using the black-and-white mask of the segmented region, a bitwise AND operation was performed on the original image. This process produces an image containing only the region of interest, namely segmented clothing, in the RGB colour space. This image is converted into a HSV colour space in order to extract the colour components. Due to the separation of the chrominance component (Hue) from the saturation and value components, the HSV colour space offers advantages when selecting a desired hue as compared to the RGB colour space. The hue of a particular colour is defined as an angular value between 0 and 360 degrees, with 0 degrees representing pure red, 120 degrees representing green, and 240 degrees representing blue. Since the context of the problem does not require distinguishing between light and dark shades or specific colours, the primary colours to be detected were defined. Therefore, specific colour intervals were used to define the Hue component analysis, including black, white, red, green, yellow, blue, orange, brown and pink. The colour extraction process, although not quantified by specific metrics such as accuracy or precision, contributes significantly to the overall functionality of the system by accurately identifying and distinguishing various clothing colours. By converting the segmented regions into the HSV colour space, it is possible to isolate the hue component, which simplifies the identification of the primary colours regardless of variations in lightness or saturation. Despite the absence of quantitative metrics, the qualitative assessment confirms that the defined hue intervals effectively cover the intended primary colours. This internal validation supports the system's capability to provide accessible and precise clothing identification.

4.4.2.2 Conclusions of Second Experiment

Following fine-tuning with data augmentation techniques, the YOLOv8s model was effective at segmenting various categories of clothing. Almost all categories showed high performance metrics for segmentation

masks, with jackets and shoes achieving near-perfect results. Even so, there is still room for improvement in categories such as dresses and shorts, where recall could be improved. Following the segmentation process, the mask of the segmented region was used to analyse the colours present in the clothing item. Due to the fact that it is not necessary to differentiate between detailed colour nuances in this context, nine essential colours were defined. Therefore, the HSV colour space was used, in which the Hue component was defined to encompass the defined colours.

4.4.3 Third Experiment - Identification of Modifications on Clothing

The third experiment aimed at identifying defects in clothing, *i.e.*, holes and stains, by using computer vision advances, namely deep learning algorithms. This experiment was divided into two stages, the first one aiming at the creation of a small dataset for stain detection using a neural network, and the second one at expanding the dataset and introducing other types of defects, as well as using a different neural network for defect detection and classification.

4.4.3.1 First Stage

During the initial phase of the first stage, images were captured in order to establish a dataset. Note that, at the time of the study, there was no publicly available database on clothing with stains. Then, a neural network was trained using transfer learning techniques to detect the presence of stains, as shown in Figure 4.13.

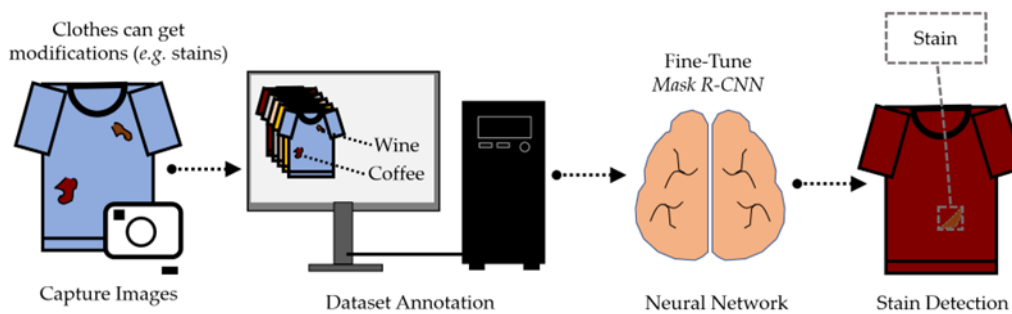


Figure 4.13: Workflow of the methodology used for detecting stains (Rocha *et al.*, 2023a).

As a result, a dataset with approximately 104 images was compiled. The garments in this dataset may display multiple stains that are distributed across various sections, resulting in a total of approximately 300 stains. These images were taken from personal wardrobes where coffee and wine stains were intentionally applied to clothing, as it is shown in Figure 4.14.



Figure 4.14: Stains distribution on clothing from the dataset, a) coffee stain; b) wine stain; c) multiple stains; d) backside stain (Rocha, Soares, *et al.*, 2023a).

Despite garments having two types of stains, the annotation process was carried out considering only one class, namely, "stain". Due to the annotations in the dataset and the limited amount of data, the transfer learning method was employed. By applying transfer learning, mask_rcnn_R_50_FPN_3x with ResNet50 was utilized as the backbone. A Mask R-CNN for stain detection was implemented using the Detectron2 library, (Wu *et al.*, 2019) the hyperparameters are presented in Table 4.10.

Table 4.10: Hyperparameters for fine-tuned Mask R-CNN (Rocha, Soares, *et al.*, 2023a).

Parameters	Value
Iterations	360
Learning rate	0.001
Batch size	1

As an extension of Faster R-CNN, Mask R-CNN incorporates instance segmentation as an enhancement. By adding pixel-level segmentation, this network has an advantage over Faster R-CNN, which labels every pixel that belongs to a detected object. The main results of the network performance and model losses from Mask R-CNN are presented in Table 4.11 and Table 4.12, respectively.

Table 4.11: A report on the evaluation of Common Objects in Context (COCO) (Rocha, Soares, *et al.*, 2023a).

Method	AP	AP at IoU = 0.50	AP at IoU = 0.75
Bounding Box	0.549	0.857	0.672
Segmentation	0.540	0.858	0.674

Table 4.12: A summary of the losses associated with the model (Rocha, Soares, *et al.*, 2023a).

Total Loss	Loss Classification	Loss Box Regression	Loss Mask
------------	---------------------	---------------------	-----------

0.480	0.053	0.154	0.240
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According to the COCO evaluator, the results presented in Table 4.11 are promising, particularly for the AP at IoU = 0.50 of 0.857, despite the small quantity of data. It is noteworthy that the highest verified loss was 0.240 (Table 4.12), indicating that the segmentation of the stain presented a more challenging task. The evaluation of the model allowed to conclude that the misclassifications were mainly related to the detection of brand logos in the clothing and the low contrast between the stain and the clothing colour, as shown in Figure 4.15.



Figure 4.15: Example of an item of clothing that has been misclassified (Rocha, Soares, *et al.*, 2023a).

This first stage presents an innovative method for detecting stains from a clothing image. The presented method, using a dataset of clothing with stains caused by wine and coffee, demonstrates the ability of a deep learning algorithm to accurately identify and locate stains on clothing. Despite the obtained results look promising, it is expected that they could be further improved when a larger dataset is used.

4.4.3.2 Second Stage

After evaluating the results of the initial stage, which included only a limited number of images depicting only one type of defect, *i.e.* stain, it became apparent that a broader approach could improve the results. As part of the study, it was decided to explore the inclusion of a new defect type, holes, along with a substantial expansion of the dataset. This expansion was intended to not only diversify the types of considered defects, but also enrich the dataset to provide a more comprehensive description of the problem. Moreover, it employed a different neural network architecture that addressed the problem through object detection rather than segmentation. In addition, techniques of data augmentation were

introduced and their influence on the results was evaluated. Figure 4.16 illustrates the workflow of this study, highlighting the sequential steps that were undertaken.

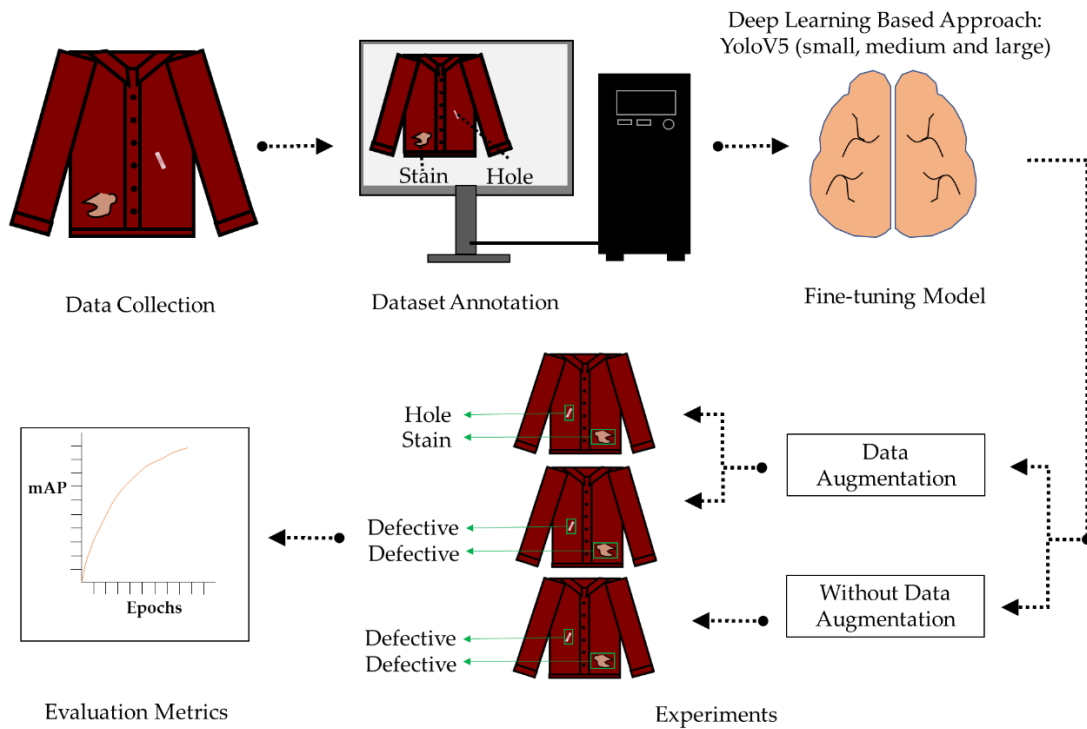


Figure 4.16: Overview of the proposed methodology for defect detection on clothing (Rocha, Pinto, *et al.*, 2023).

To the best knowledge of the authors, the previous research work on clothing stains detection (Rocha *et al.*, 2023) remains the only dataset that specifically focus on defects in clothing. As previously mentioned, it was necessary to expand the dataset from individuals' clothing collections, which was then deliberately altered through the creation of defects and manually labelled. A total of 340 images were produced by adding stain defects and incorporating hole defects to the dataset. The result is that each individual garment may exhibit several defects spread across various areas of the garment, such as on the backside, which results in a total of approximately 647 defects. An overview of the defect classes is shown in Table 4.13.

Table 4.13: A distribution of class defects, focusing on the two main class defects of interest in this study (Rocha, Pinto, *et al.*, 2023).

Class	Number of Defects
Stain	323
Hole	324

Despite the authors' intention of capturing the clothing items in a controlled setup, *i.e.*, all images taken

by blind people were captured in an automatic wardrobe (Rocha *et al.*, 2020) with one item of clothing at a time, including garment rotation, illumination, and multiple capture perspectives, various backgrounds and capturing perspectives were used to ensure that future images would meet those conditions. Representative images of the dataset are depicted in Figure 4.17.



Figure 4.17: Examples of sample images from the dataset, demonstrating different types of defects and distributions, with variations in backgrounds and illumination conditions: a) multiple stain defects; b) a combination of stain and hole defects; c) multiple hole defects; d) a single hole defect; e) hole defect on the backside; f) multiple stain defects (Rocha, Pinto, *et al.*, 2023).

The small scale of the defined dataset was found to be a challenge for future applications. To overcome this limitation and enable the model to generalize from various perspectives, data augmentation was employed to expand the dataset size. Through the augmentation process, a range of transformations, such as horizontal flipping, scaling, translation, and HSV changes, were applied to the images - Figure 4.18. The primary goal of these transformations was to replicate real-world contextual scenarios that often occur unnoticed by people with visual impairments, such as changes in lighting, colour, and orientation during inspection. This strategy resulted in the creation of novel and diverse images based on the original dataset.

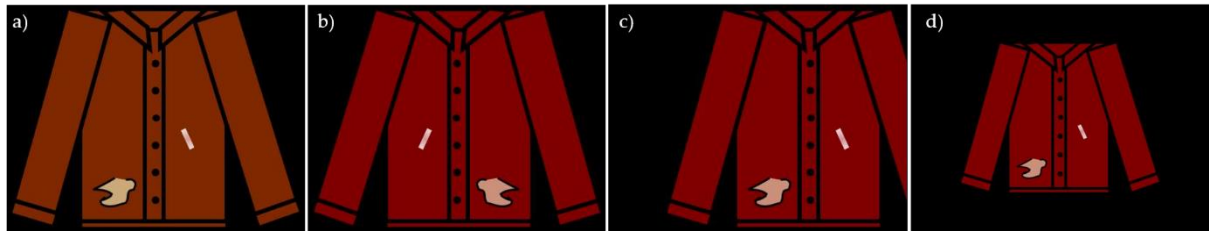


Figure 4.18: Data augmentation features in training: a) HSV; b) horizontal flipping; c) translation; d) scaling (Rocha, Pinto, *et al.*, 2023).

4.4.3.3 Deep Learning-based approach

Deep learning-based object detection technique was used to detect defects in clothing images. This method involves taking an image as input and creating a bounding box that indicates the defect's location. To accomplish this, a deep learning framework for object detection was utilized via transfer learning, specifically the fine-tuning, *i.e.* reusing a model that was initially developed for a specific situation and using it as a starting point for another model, aiming at addressing a different problem (Weiss *et al.*, 2016). In the field of deep learning, transfer learning is widely used due to the significant resources and time required for training neural networks (Pan & Yang, 2010). By leveraging pre-trained models, transfer learning optimizes performance when training the second model.

At the time of this study, the YOLOV5 – specifically the small, medium, and large models with different layer depths, real-time performance, and detection accuracy - was utilized to assess the difficulties involved in detecting defects using novel data, as it represented the most recent and advanced version available. The YOLOv5 object detection algorithm represents a continuous refinement and enhancement of the YOLO series (Bochkovskiy *et al.*, 2020; Redmon *et al.*, 2015; Redmon & Farhadi, 2018), where the accuracy of detection has shown noteworthy improvement and, in certain instances, outperforms two-stage detectors. Despite detection accuracy being less of a priority, YOLOs are widely adopted in various applications due to their faster inference speed (Diwan *et al.*, 2023).

To evaluate the challenges of proposing an automatic algorithm for detecting and categorizing clothing defects, three different experiments were conducted: (1) detection of defects on clothing, (2) detection of defects on clothing using data augmentation and (3) detection and classification of the defects using data augmentation.

4.4.3.4 Results and Discussion

In this section, a quantitative assessment of the proposed approach was conducted. Specifically, the experiments mentioned in section 4.3.3.3 were examined in detail across the following subsections.

To carry out the evaluation, the dataset was divided into three distinct groups: one for training, another for validation, and a third for testing. These groups were split in a ratio of 70%, 20%, and 10%, respectively. By doing so, it can be determined whether the network can effectively generalize to unseen data and be used for defect detection in clothing. All reported results are based on the best generalization achieved in the experiments. The experiments were set to run for 400 epochs, a range sufficient for convergence, and combined with the early stopping technique, which halts the training process if no improvement is observed for 10 epochs, effectively preventing overfitting. The tests were carried out on a server featuring an Intel(R) Xeon(R) Gold 6140 CPU 2.30Ghz processor (*Intel® Xeon® Gold 6140 Processor*, 2024), 128GB of RAM, and a NVIDIA Tesla V100-PCIE-16GB computing GPU (*NVIDIA TESLA V100 GPU ACCELERATOR*, 2024). Table 4.14 presents the uniform hyperparameters used throughout the training process in order to facilitate a comprehensive comparison of the different networks.

Table 4.14: Configuration of HyperParameters in Model Testing: Image Size, Optimizer, Learning Rate, and Batch Size (Rocha, Pinto, *et al.*, 2023).

Parameters	Value
Image Size	1024x1024 pixels
Optimizer	Stochastic Gradient Descent (SGD)
Learning Rate	0.01
Batch Size	16

4.4.3.5 Clothing defect detection

The first experiment consisted of performing the fine-tuning of the models using the gathered dataset, with the specific goal of detecting defects on clothing. Table 4.15 shows the resulting outcomes.

Table 4.15: Main results from the fine-tuning of the models without data augmentation for defect detection (Precision, Recall and AP at IoU = 0.50) (Rocha, Pinto, *et al.*, 2023).

Model	Precision	Recall	AP at IoU = 0.50
YOLOv5s6	0.85	0.41	0.62
YOLOv5m6	0.83	0.53	0.66
YOLOv5l6	0.86	0.60	0.73

According to Table 4.15, YOLOv5l6 has a superior AP at IoU = 0.50 (0.73) when compared to the other models. This outcome may be attributed to the number of undetected defects, as indicated by the recall (0.60) derived from Equation 3. In other words, the model's predictions contain false negatives, which adversely impact the AP. On the other hand, the high precision (0.86) indicates that the model has fewer

instances of false positives. However, YOLOV5s6, despite its high precision, has a lower recall value (0.41), which negatively affects the average precision. Although the medium model's generalization (YOLOv5m6) is superior to that of the small model (YOLOv5s6), its average precision is still influenced by the recall.

4.4.3.6 Clothing defect detection with data augmentation

The second stage of the development of the defects detection system aimed at enhancing the performance of the model through data augmentation. Table 4.16 presents the main outcomes of the second experiment based on the introduction of data augmentation.

Table 4.16: Main performance results of the models after introducing data augmentation for defect detection (Precision, Recall and AP at IoU = 0.50) (Rocha, Pinto, *et al.*, 2023).

Model	Precision	Recall	AP at IoU = 0.50
YOLOv5s6	0.78	0.54	0.69
YOLOv5m6	0.80	0.63	0.74
YOLOv5l6	0.94	0.58	0.76

The results of Table 4.16 reveal a noteworthy improvement in the models' generalization as a result of data augmentation. Specifically, the YOLOv5m6 model exhibited the most significant improvement, with an 8% increase in AP to 0.74 compared to the previous experiment. This improvement is a notable finding, indicating that data augmentation has a substantial positive impact on the generalization performance of the model. This can be primarily attributed to the reduced number of false negative predictions, as evidenced by the recall values. Figure 4.19 illustrates an example of a defect that went undetected by the YOLOv5m6 model but was subsequently identified with the aid of data augmentation.



Figure 4.19: Example of a defect undetected by the YOLOv5m6 model that was subsequently identified with the aid of data augmentation: a) original image; b) predicted image from model YOLOv5m6 without augmentation; c) Predicted image from model YOLOv5m6 with augmentation (Rocha, Pinto, *et al.*, 2023).

4.4.3.7 Clothing defect detection and classification with data augmentation

The third component of the development of the defects detection system included defect classification, enabling the evaluation of the type of defect. Table 4.17 presents the main performance results for each model, including the AP for each class, *i.e.*, holes and stains, as well as the mean average precision for both classes.

Table 4.17: Performance results of each model with data augmentation and defect classification (Precision, Recall and AP at IoU = 0.50) (Rocha, Pinto, *et al.*, 2023).

Model	Class	Precision	Recall	AP at IoU = 0.50
YOLOv5s6	all	0.849	0.538	0.688
	hole	0.836	0.448	0.610
	stain	0.863	0.628	0.765
YOLOv5m6	all	0.823	0.593	0.726
	hole	0.696	0.552	0.656
	stain	0.950	0.633	0.796
YOLOv5l6	all	0.915	0.543	0.747
	hole	0.889	0.552	0.741
	stain	0.941	0.533	0.753

The performance results from Table 4.17 indicate that stains are more accurately detected than holes, considering all metrics, which might be attributed to inherent difficulty in detecting holes in clothes, even to the human eye, many times because stains encompass a strong colour contrast, whereas holes are just a discontinuity in the fibre pattern, with the colour contrast coming only from shadowing. Although the YOLOv5l6 model has a higher AP value (0.747), the YOLOv5m6 model exhibits a higher recall value (0.633). On the other hand, the larger model has a higher precision value (0.915). The primary reason for the higher AP value of the YOLOv5l6 model is the significant difference in precision compared to the

YOLOv5m6 model. However, considering the context of this application, prioritizing recall over precision may be more beneficial. In other words, it is preferable for the model to have fewer false negatives than false positives. Figure 4.20 illustrates an example of a false positive, where the buttonholes are misinterpreted as a defect. This highlights the importance of having representative images that include such scenarios.



Figure 4.20: Example of a misinterpretation of a defect: a) original image; b) predicted image from model YOLOv5m6; c) predicted image from model YOLOv5l6 (Rocha, Pinto, *et al.*, 2023).

Based on the performance of the models across all experiments, the model YOLOv5l6 exhibits the best generalization to unseen data, *i.e.*, test dataset, when compared to other models. Figure 4.21 displays predicted images that encompass various scenarios, including variations in illumination, backgrounds, multiple defects, as well as challenging areas.



Figure 4.21: Examples of predicted images from the YOLOv5l6: a) single stain detection; b) multiple stain detection; c) multiple hole detection; d) hole detection near the seam (Rocha, Pinto, *et al.*, 2023).

The main constrain of using this model in a practical context is the computational cost. Such impact was evaluated through the calculation of the inference time for the test with the dataset. Table 4.18 exhibits the results of the inference time on the test dataset.

Table 4.18: Inference time on test dataset for the different YOLOv5 models tested (Rocha, Pinto, *et al.*, 2023).

Model	Inference Time (s)
YOLOV5s6	0.0092
YOLOV5m6	0.0112
YOLOV5l6	0.0157

These results suggest that, despite incurring computational costs, all models are believed acceptable due to the negligible required time. Thus, the findings indicate that implementing object detection technology with augmented data may be a successful strategy for identifying defects in clothing. This study stands out from previous research work (L. Cheng *et al.*, 2023), as it evaluates defect detection on clothing as a whole, instead of focusing on zoomed-out images of defects on stretched textiles and without background.

Upon comparing the new dataset created in this work with those from textile industry it becomes clear how challenging the task presented in this work is, mainly due to the presence of certain features such as buttonholes, which could potentially be interpreted as defects. Furthermore, this approach was proved to be effective in high demanding contexts, namely with wrinkled textiles, various backgrounds, different illumination, and diverse partners.

4.4.3.8 Conclusions of Third Experiment and future work

The detection and classification of clothing defects was successfully carried out with a deep learning approach. An enhanced dataset was constructed with new types of stains and with holes. Through the fine-tuning of three models from the YOLOv5 object detector, a total of three experiments was carried out. Data augmentation was demonstrated to be essential for a better generalization of the model, allowing to achieve higher precision results. Still, recall values demonstrate that the model can be improved to minimize false negatives. Maximum precision, recall, and average precision (AP) values of 0.915, 0.543, and 0.747, respectively, were achieved with the YOLOv5l6 model for defect detection and classification. The detection of holes was found to be more challenging than the detection of stains, which emphasizes the importance of integrating the findings of this study in an automatic wardrobe that could take multiple cameras capture from different clothing perspectives.

The dataset built in this work demonstrates that object detection technology can be used to accurately detect and classify defects on clothing autonomously. Moreover, it represents the first step for the creation of a mobile application that can effectively detect multiple defects on clothing, based on the integration of these findings in an automated closet system as a future step.

5 SMART WARDROBE PROTOTYPE

Chapter Overview

This chapter presents a detailed description of the smart wardrobe prototype and its key components, followed by an overview of the mobile application developed to control the system. The aim of this chapter is to outline the design and essential elements necessary for the development of a mechatronic prototype – a smart wardrobe system capable of identifying clothing characteristics such as type, colour, and alterations within a controlled environment.

5 Smart Wardrobe Prototype

5.1 Prototype System Design

5.2 Main Components of the Developed Prototype

5.3 Mobile Application Interface

5.1 Prototype System Design

The primary objective is to simulate a prototype closely resembling real-world scenarios, from which the entire hardware infrastructure can be seamlessly transferred to individual wardrobes. Therefore, it is essential to carefully select adaptable components to ensure the prototype's effectiveness. Hence, the prototype must meet a number of specifications that are essential to the integration and functionality of the product, namely:

- Identify the type, colour, and modifications of the garment;
- Implement a NFC reader to extract each garment's unique identifier;
- Maintain a controlled lighting environment to ensure accurate assessment;
- Automate the rotation of garments to evaluate both sides;
- Include a camera for acquiring images;
- Establish TCP/IP communication to control all hardware components remotely.

To prove the concept (Rocha *et al.*, 2020) and devise a readily deployable solution, a compact IKEA wardrobe measuring 80 cm by 50 cm by 30 cm (height x width x depth) was initially selected for the evaluation of appropriately sized garments (Silva *et al.*, 2023). The system, however, faced some limitations. The constrained dimensions of the wardrobe restricted its use to garments of diminutive proportions, primarily tailored for children. Further, the imaging process was hampered by partial capture, which necessitates the rotation of the camera and the subsequent application of a stitching algorithm to incorporate different segments of the image. Also, as the effectiveness of the NFC reader depends on the orientation of the garment, a variation in the accuracy of the read occurred. Lastly, the wardrobe's irremovable support infrastructure complicated the process of garment replacement, making a quick garment change a difficult task. As a result, these challenges led to the design of a new prototype architecture, as shown in Figure 5.1.



Figure 5.1: iSight Smart Wardrobe Prototype.

The dimensions of the smart wardrobe prototype depicted in Figure 5.1, 123 cm by 120 cm by 63 cm (height x width x depth), enabled its effectiveness to demonstrate the proposed solution and its transportation for testing purposes. In the next subsection a detailed description of its components is provided.

5.2 Main Components of the Developed Prototype

Before detailing the individual components of the smart wardrobe prototype, an overview is provided in Figure 5.2, which illustrates the schematic layout of the prototype and highlights the interconnections between key hardware components, including the Raspberry PI, DC motor, camera, lighting system, and NFC reader.

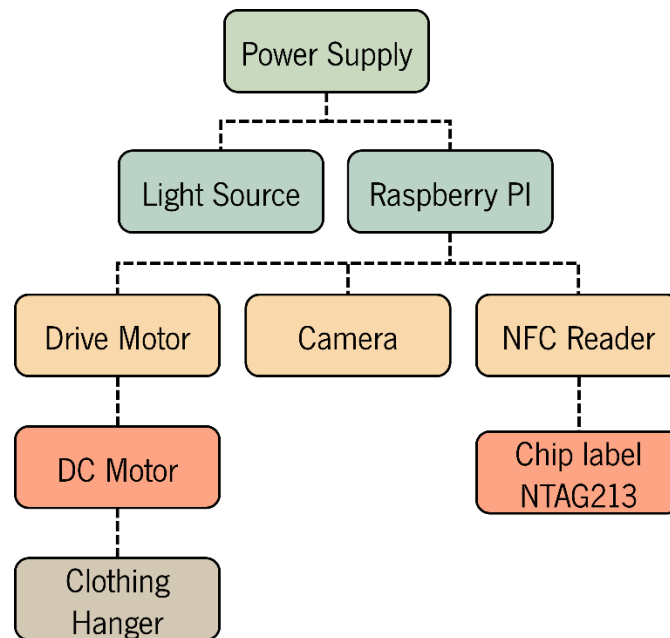


Figure 5.2 - Schematic layout of the smart wardrobe prototype.

This schematic, Figure 5.2, provides a representation of the Smart Wardrobe Prototype, highlighting the key components and their roles within the system. These components are outlined and described in detail below:

- **Raspberry PI:** Acts as the central unit, managing the operation and coordination of all other hardware elements.
- **Camera:** Captures images of the garments to facilitate visual analysis and identification.
- **Lights:** Provide controlled illumination, ensuring clear and consistent image capture.
- **DC Motor:** Rotates the garments, allowing the camera to assess them from multiple angles.
- **NFC Reader:** Uniquely identifies each garment using Near Field Communication (NFC) technology.

The system is ultimately accessed and controlled through a TCP/IP communication interface, enabling remote operation and integration with external devices.

In the following subsections, a detailed analysis of each component is provided.

5.2.1 DC Motor

Nema 17 stepper motor, model 42BYGH48-23D (*Motor de Passo Nema 17 p/ Impressora 3D - 42BYGH48-23D*, 2024) - Figure 5.3 - is a type of electric motor widely used in applications requiring precise positioning, such as rotating a shaft at a specific angle. Due to its exceptional cost-effectiveness,

this motor has a high torque and a limited step angle of 1.8 degrees, which guarantees accurate and reliable performance.



Figure 5.3 Nema 17 stepper motor.

Table 5.1 provides the specifications of the DC motor used in the prototype.

Table 5.1: Nema 17 motor specifications (*Motor de Passo Nema 17 p/ Impressora 3D - 42BYGH48-23D*, 2024).

Specifications	Description
Torque	55 N.cm
Step	1.8 degrees
Number of Steps	200
Phase Current	1.7A
Number of Phases	2
Number of Wires	4
Shaft Diameter	5mm
Motor Length	48mm

5.2.2 Drive Motor

The driver motor A4988(*Driver Para Motor - A4988*, 2024) - Figure 5.4- is a widely used stepper motor driver renowned for its efficiency in controlling bipolar stepper motors. It provides an effective means of controlling the current and polarity of the motor coils, enabling precise motion control.



Figure 5.4: Picture of the driver motor A4988 used in the developed prototype.

Equipped with current limitation and adjustable settings, along with overheating protection and five different microstep resolutions (up to 1/16-step), this motor is designed to meet the demands of various motion control applications. Table 5.2 describes the main specifications of the A4988 driver motor.

Table 5.2. Description of the A4988 specifications (*Driver Para Motor - A4988*, 2024).

Specifications	Description
Control Method	Step and direction control
Logic Voltage	3-5.5V
Motor Output Voltage	8-35V
Microstep Resolutions	Full-step, Half-step, 1/4-step, 1/8-step, 1/16-step
Current Control	Adjustable, allowing setting of maximum output current using a potentiometer, enabling utilization of voltages above nominal motor voltage for higher step rates
Voltage Regulator	Built-in
Protection Features	Current overload and short-circuit protection

The specifications presented above make the A4988 stepper motor driver used in a wide range of motion control systems, offering versatility, reliability, and precise control over stepper motor operations.

5.2.3 Raspberry PI

The Raspberry Pi 4 Model B (*Raspberry Pi 4 Model B*, 2024) - Figure 5.5 - is a single-board minicomputer. This central processing unit is equipped with a 1.5GHz quad-core Arm® Cortex®-A72 CPU and 8GB of RAM. Because of its high-performance CPU and ample memory, the Raspberry Pi 4 Model B is ideally suited for processing-intensive applications. The advanced graphics capability and high-resolution video

output capabilities allow for robust multimedia processing. Moreover, both USB 3.0 and USB 2.0 ports, true Gigabit Ethernet, and dual HDMI outputs provide versatile connectivity and fast data transfers.



Figure 5.5: Picture of a Raspberry Pi 4 Model B used in the developed prototype.

5.2.4 Camera

The Official Raspberry Pi Camera Module V3 (*Raspberry Pi Camera Module 3*, 2024) - Figure 5.6 - equipped with a 12MP sensor, is designed to offer high-resolution imaging capabilities suitable for a variety of applications. This module utilizes the Sony IMX708 sensor (*Raspberry Pi Camera Module 3*, 2024), which boasts advanced features and specifications tailored for enhanced performance.



Figure 5.6: V3 Oficial Raspberry Pi, 12MP, 120°, camera module, used in the developed prototype.

The camera module's high resolution of 12MP ensures detailed image capture, while the sensor's compact size (7.4mm diagonal) and pixel dimensions ($1.4\mu\text{m} \times 1.4\mu\text{m}$) contribute to high sensitivity and image quality. Table 5.3 details the camera specifications.

Table 5.3: Module camera raspberry pi 4 specifications (*Raspberry Pi Camera Module 3*, 2024).

Specifications	Description
Sensor	Sony IMX708
Resolution	12MP
Sensor size	7.4mm sensor diagonal
Pixel size	1.4 μ m $\times$ 1.4 μ m
Horizontal/vertical	4608 $\times$ 2592 pixels
Infrared (IR) cut filter	Integrated
Autofocus system	Phase Detection Autofocus
Dimensions	25mm $\times$ 24mm $\times$ 11.5mm

The wide variant of the lens - Table 5.4 - provides an effective focal length of 2.75mm and an aperture of f/2.2, delivering a broad diagonal field of view of 120 degrees at a 16:9 aspect ratio. This wide field of view is suitable for capturing expansive scenes and ensures flexibility in framing subjects. The focus ranges from 5cm to infinity, which allows for versatility in shooting distances, making it a robust choice for both close-up and wide-angle photography.

Table 5.4: Specification of lens (*Raspberry Pi Camera Module 3*, 2024) .

Specifications	Description
Effective Focal Length	2.75mm
Aperture	f/2.2
Diagonal Field of View	120 degrees (at 16:9 aspect ratio)
Horizontal Field of View	102 degrees
Vertical Field of View	67 degrees
Focus Range	5cm to infinity
Horizontal/vertical	4608 $\times$ 2592 pixels
IR cut filter	Integrated
Autofocus system	Phase Detection Autofocus
Dimensions	25mm $\times$ 24mm $\times$ 11.5mm

Thus, the Official Raspberry Pi Camera Module V3 combines high-resolution imaging with advanced autofocus and a wide field of view.

5.2.5 NFC Reader

Based on the PN532 chip, the ITEAD PN532 NFC module (*PN532*, 2024) – Figure 5.7 - is designed for 13.56MHz near-field communication. Featuring an onboard antenna, this module eliminates the need for an external antenna coil. It can support multiple communication interfaces, including SPI (Serial Peripheral Interface), IIC (Inter-Integrated Circuit), and UART (Universal Asynchronous Receiver/Transmitter), ensuring a wide range of integration options. It is also noteworthy that the manufacturer provides NFC libraries for Raspberry Pi, which simplifies NFC-enabled product development.



Figure 5.7. ITEAD PN532 NFC reader used in the developed prototype.

The specifications of the NFC reader are listed below in Table 5.5.

Table 5.5: Specifications of ITEAD PN532 NFC module (*PN532*, 2024).

Specifications	Description
Integrated Circuit (IC)	NXP PN532
Operating Voltage	3.3V
Power Supply Voltage	3.3~5.5V
Max Supply Current	150mA
Working Current (Standby Mode)	100mA
Working Current (Write Mode)	120mA
Working Current (Read Mode)	120mA
Interface	SPI, UART, IIC

5.2.6 Light Source

This lighting source - Figure 5.8 - used in the developed prototype consists of a 300-LED SMD 5050 strip

(5050 LED, 2024) emitting a cool white light. The device is powered by a 12V power supply, making it suitable for use with low-voltage systems. In addition to its flexibility and ease of installation, the strip is designed with an adhesive backing that allows it to be attached to a variety of surfaces. The device has an Ingress Protection (IP) 20 rating (*Ingress Protection (IP) Ratings, 2024*), which makes it suitable for indoor use. With a length of 5 meters and a density of 60 LEDs per meter, the strip provides ample illumination.



Figure 5.8. LED strip 5M SMD 5050, 300LEDS 60LEDS/M 12V IP20 used in the developed prototype (*Fita LED 5m SMD 5050 300leds 60leds/m 12v IP20 - Branco Frio, 2024*).

It is noteworthy that this LED strip can be cut and electrically reconnected at intervals of every three LEDs, thus allowing for tailored lengths and configurations to meet specific requirements. A 120-degree luminous angle ensures a broad and uniform distribution of light, which is particularly useful for applications that require enhanced visibility and clarity, since it provides consistent and optimal lighting conditions throughout the illuminated area.

5.2.7 Power Supply

Designed to sustain uninterrupted operation, the industrial power supply used in this work – Figure 5.9 – is capable of delivering a stable output voltage of 12Vdc in conjunction with a current of up to 5 Amps. The input voltage range is 100-240 Vac, and the output power is 60W (*Fonte Alimentação Industrial 12V 60W 5A, 2024*).



Figure 5.9. Picture of the 12V 60W 5A power supply incorporated in the developed prototype.

This power supply provides safeguards against adverse conditions, including overload, short circuit, overvoltage, and overheating, ensuring the integrity of the connected device and the entire system. It measures 160mm x 98mm x 42 mm and it is suitable for industrial applications requiring a reliable power supply.

5.2.8 **Chip label NTAG213**

The NTAG213 label (*NTAG213*, 2024) - Figure 5.10- is minimally invasive and can be used for a variety of purposes. The label holds an IP67 certification and is water-resistant when applied to dry surfaces. It can be submerged in water for up to thirty minutes at a depth of one meter.



Figure 5.10. Chip label NFCTAG213 applied to the developed prototype.

As outlined in Table 5.6, this label includes key technical specifications.

Table 5.6. NFCTAG213 label specifications (*NTAG213*, 2024).

Specifications	Description
Chip	NTAG213
Frequency	13.56 MHz
Memory	144 bytes
Data Transfer Rate:	106 kbits/s

A suitable amount of memory is provided by the NXP NTAG®213, which is suitable for storing additional information.

5.2.9 Clothing hanger

The hanger - Figure 5.11- is designed to ensure that all clothing items are positioned appropriately for image capture. Its conception aims to optimize visibility and accessibility during testing. The hanger easily fits into a support structure that ensures it is secured in the correct position.



Figure 5.11. Purpose-built branded clothing hanger developed for the iSight prototype.

5.2.10 Prototype Operation

The primary objective of the mechatronic system is the automated management of clothing for blind people. The developed system is composed of three main phases: the physical prototype (wardrobe), the

mobile interface, and the inference models, as demonstrated in Figure 5.12.

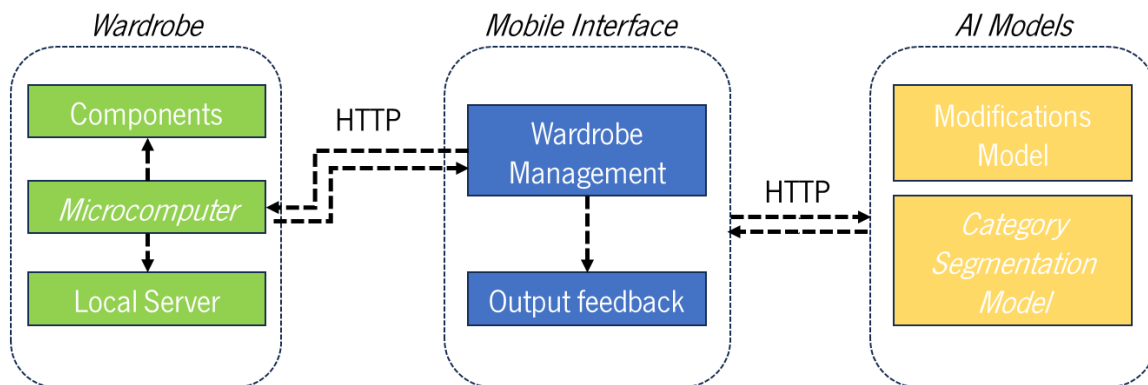


Figure 5.12. Schematics of the three main phases and communication included in the iSight prototype.

The operation of the wardrobe is controlled by a Raspberry Pi, which functions as a local server. In order to provide a user interface between the physical prototype and the user, it was necessary to create a server on the Raspberry Pi that could handle user requests efficiently. This server hosted on the development board using the Flask framework (*Welcome to Flask – Flask Documentation (3.0.x)*, 2024). The transmission of data is facilitated through network communication, specifically through the HyperText Transfer Protocol (HTTP). HTTP is an application-layer protocol used for the transmission of hypermedia documents between clients and servers (*An Overview of HTTP - HTTP / MDN*, 2024). An HTTP protocol specifies the format and transmission of messages by utilizing a URL (Uniform Resource Locator) to identify the URL of the web resource and a port number to identify the listening endpoint of the server. This server can process three types of requests: image capture, NFC tag reading, and motor control to adjust the position of the hanger. Figure 5.13 describes the flowchart of wardrobe server.

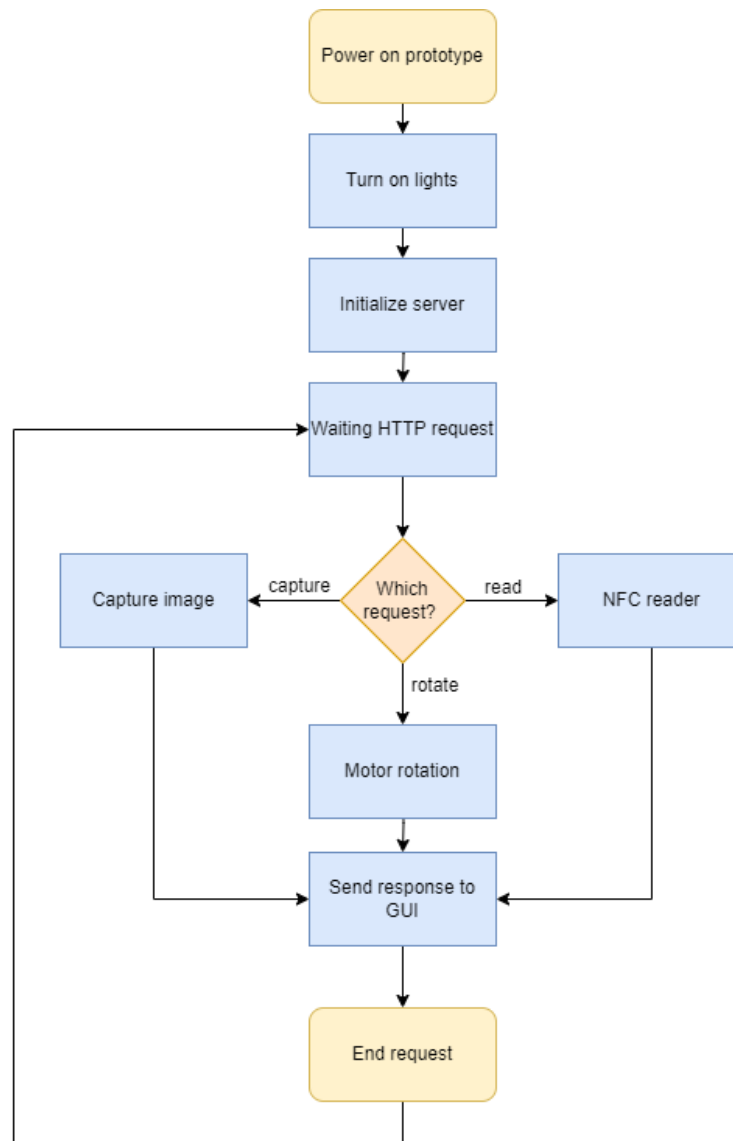


Figure 5.13: Flowchart of wardrobe server.

Figure 5.14 illustrates the initial state of the wardrobe when it is powered on. The wardrobe's interior is entirely covered with chroma key fabric to provide a uniform colour for image acquisition, enhancing image consistency. The LED strips located on the left panel are powered by a 12V power supply, as shown in Figure 5.14a. Positioned centrally is the official Raspberry Pi Camera Module V3, as depicted in Figure 5.14b.

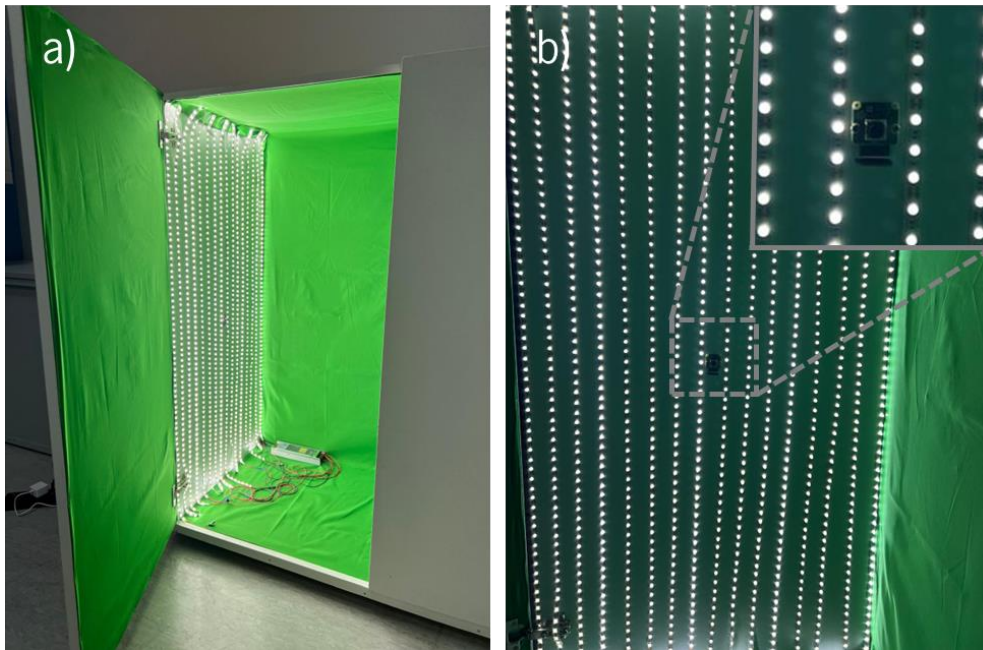


Figure 5.14: General view of the wardrobe interior: a) LED strips applied on the left panel; b) camera placed in the middle of LED strips.

The light source is essential for ensuring the quality of images captured by the camera, providing sufficient illumination for the clear identification of clothing items regardless of environmental conditions. In this technique, both the sensor (camera) and the light source are positioned on the same side of the object being captured. This method is typically employed to obtain detailed information about the texture and other surface characteristics of the object. This type of illumination can be categorized into two subtypes: one that primarily leverages specular reflections and another that predominantly utilizes reflected rays constituting diffuse reflection. In scenarios where light reflected by a flat surface is captured by the optical system, non-flat characteristics such as holes can reflect the light outside the lens's maximum acceptance angle, thereby revealing dark features, as schematized in Figure 5.15.

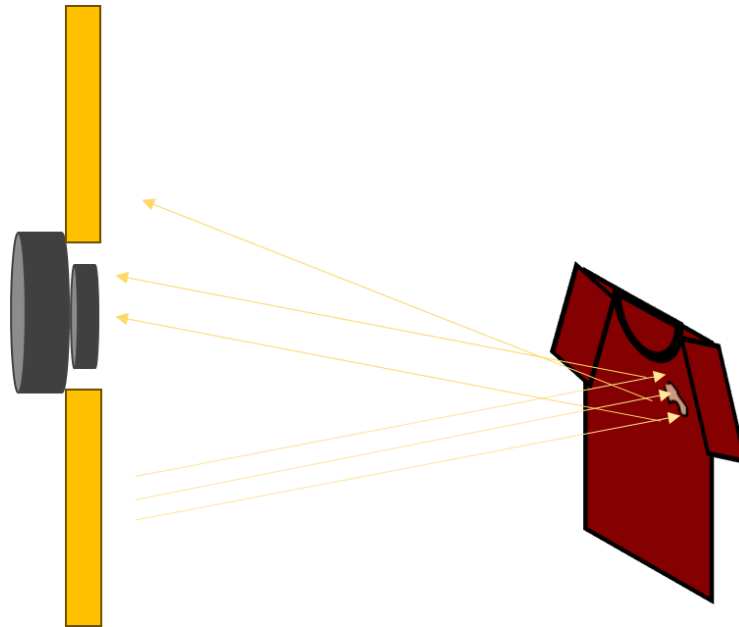


Figure 5.15: Reflective illumination in hole defect. This image shows how light reflected from a flat surface is affected by non-flat features like holes, which can redirect light outside the lens's acceptance angle, creating dark areas that reveal surface defects.

At the same time, the server, *i.e.* the Raspberry Pi mounted on the external left panel (*Raspberry Pi 4 Model B*, 2024), is initialized and begins awaiting HTTP requests from the graphical user interface (GUI), *i.e.* mobile interface.

If the request is to capture an image, the camera is initialized to execute the capture. As explained before, this specific camera was selected based on its 120° lens wide diagonal field of view, which allows for a minimal distance to effectively capture the entirety of the garment. This wide-angle lens ensures comprehensive coverage facilitating detailed imaging of the clothing item, ensuring no part of the garment is omitted in the capture process.

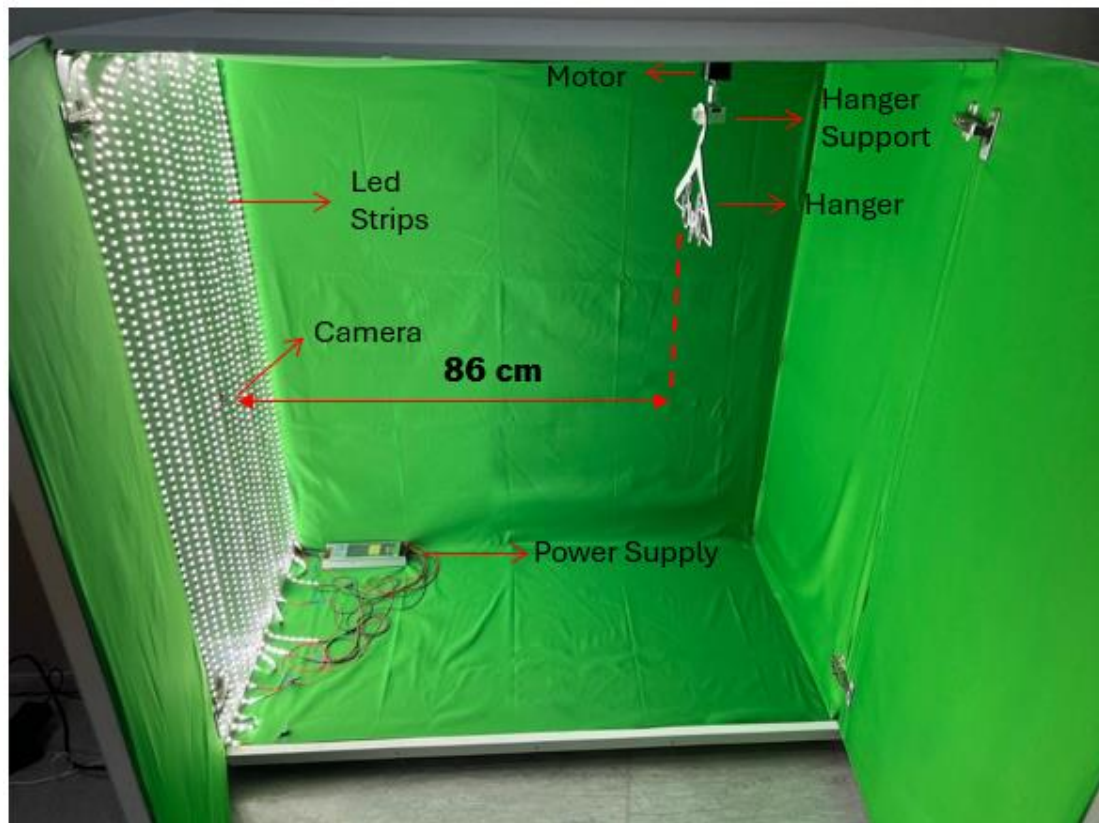


Figure 5.16: Interior of the wardrobe showing the distance from the camera to the hanger and internal components.

Upon receiving the rotation request, the motor situated on the top right side (Figure 5.16 and Figure 5.17), which supports the hanger (Figure 5.16 and Figure 5.17), is activated to rotate 180 degrees. This feature enables the system to capture garments from both sides, enhancing operational efficiency and flexibility. The ability to rotate the hanger motor by 180 degrees is crucial for processes that require access to both sides of the garment, such as inspection of modifications.



Figure 5.17: Motor supporting the hanger.

Another potential request that can be handled by the system involves reading the NFC tag attached to each garment. The placement of these tags on garments has been designed to be minimally invasive. Thus, the tag can be found either on the original clothing label, as illustrated in Figure 5.18.



Figure 5.18: NFC tag attached to the clothing label.

To facilitate this, an NFC reader has been integrated into the wardrobe system (Figure 5.19). This reader is tasked with retrieving the unique identifier (UID) code from the NFC tags, as per the user's request. Specifically, an NFC reader is strategically positioned on the exterior left side of the wardrobe to ensure seamless reading of the NFC tags affixed to the garments, as demonstrated in Figure 5.19.



Figure 5.19: NFC Reader.

The integration and connectivity of all system components with the Raspberry Pi controller are comprehensively illustrated in the schematic diagram provided in Figure 5.20.

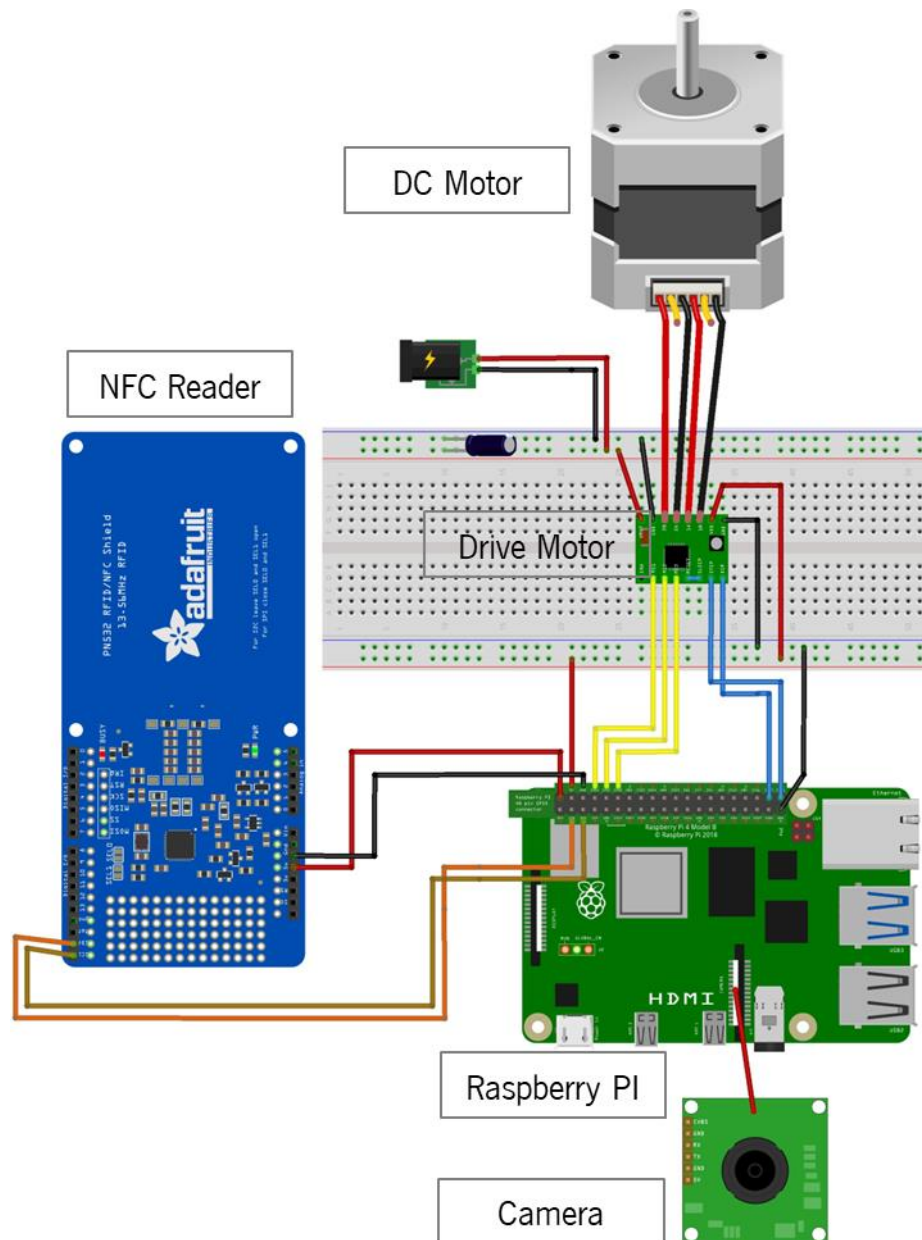


Figure 5.20: Schematic diagram illustrating the integration and connectivity of system components with the Raspberry PI controller

This diagram (Figure 4.41) offers a detailed overview of the setup, highlighting the interfacing of the NFC reader, camera module, and motor rotation with the Raspberry PI, thereby elucidating the system's operational framework. The data captured from image processing and NFC tag reading is transmitted from the Raspberry PI to the GUI. Additionally, the mobile interface processes the output from the wardrobe server and, when necessary, communicates with AI models for inference.

5.3 Mobile Application Interface

The purpose of this section is to explore the development of a mobile interface, emphasizing compliance with accessibility standards.

5.3.1 Accessibility

In the European Union (EU), the standard that encompasses accessibility requirements for the web and mobile applications is the EN301549 standard (*Introdução à Norma Europeia EN 301 549 - Acessibilidade.Gov.Pt*, 2024). This standard is essentially a copy of the WCAG 2.1 'AA' compliance. In Portugal, these requirements are included in the *Regulamento Nacional de Interoperabilidade Digital* (RNID) as decreed by D.L. No. 83/2018(*DL n.o 83/2018 - Acessibilidade Dos Sítios Web e Das Aplicações Móveis - Acessibilidade.Gov.Pt*, 2024). According to this decree, "Accessibility" refers to the principles and techniques to be observed in the design, construction, maintenance, and updating of websites and mobile applications to make their content more accessible to users, especially people with disabilities. In compliance with Article 5, this accessibility entails several requirements regarding information and navigation which this study must also adhere to in order to be accessible to the blind. Therefore, in the context of information, the following aspects are considered:

1. Presentation of information and interface components in a manner perceivable by users.
2. Ensuring the functionality of the user interface, making sure that the components and navigation are actionable.
3. Information and the operation of the user interface must be easily understood.
4. Interpretation by assistive technologies to be reliably interpreted by a wide range of user agents.

Adhering to these principles ensures that the iSight mobile application aligns with both EU and Portuguese accessibility standards, thereby facilitating an inclusive user experience for visually impaired individuals.

5.3.2 Mobile Interface Features

Given the intended user base of Portuguese-speaking people with visual impairments, the application has been meticulously designed in Portuguese and developed using a cross-platform language. This strategic choice facilitates comprehensive testing and deployment across both iOS and Android devices, ensuring broad accessibility and functionality. To address the initial project requirements, a detailed block diagram

representing the entire layout of the application was developed and it is depicted in Figure 5.21.

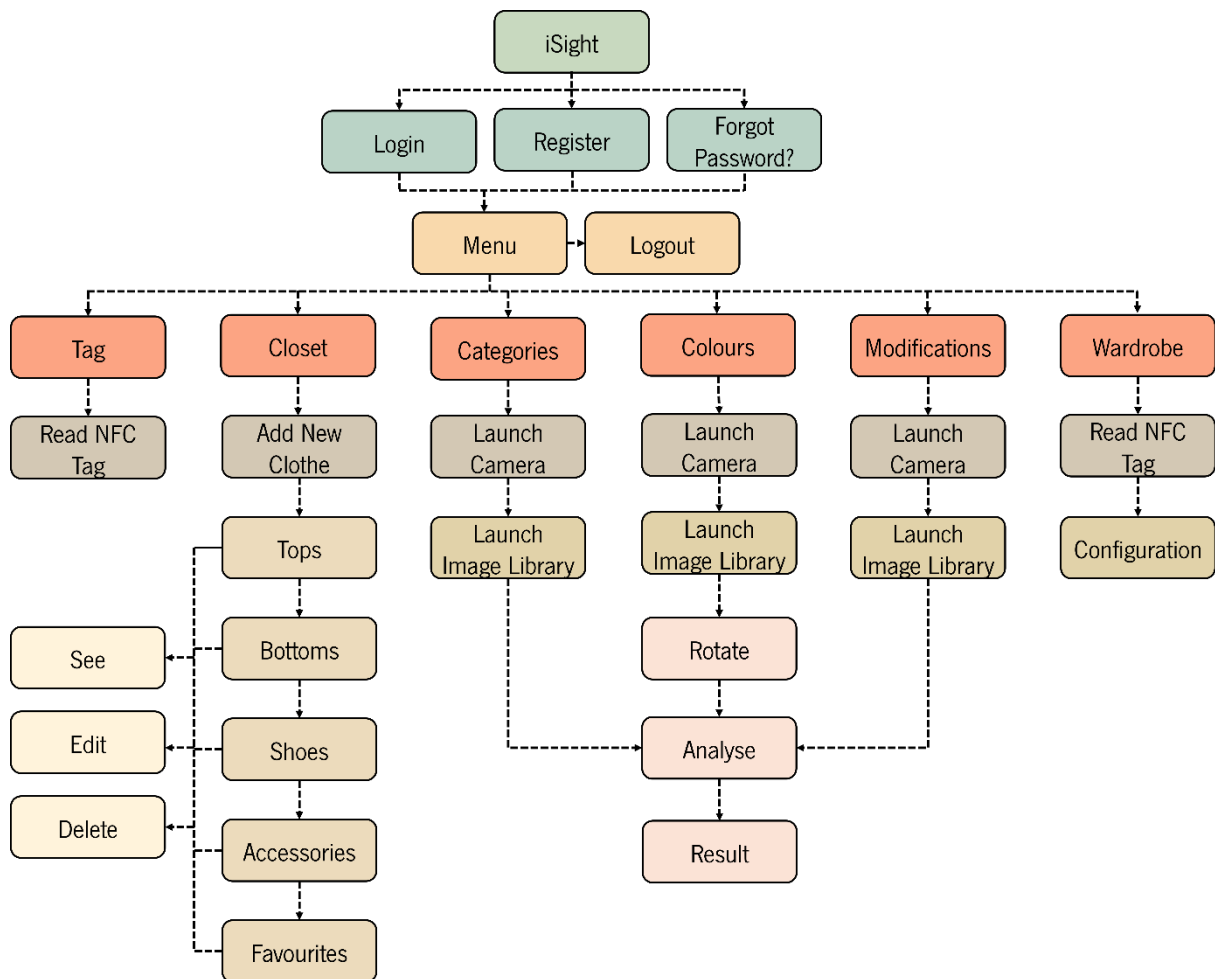


Figure 5.21: iSight mobile interface block diagram.

The application is exclusively accessible to people with disabilities, leveraging screen readers or Braille displays as graphical interfaces between the blind user and the computer. These interfaces interpret the information displayed on the screen, enabling seamless interaction and navigation. Although developed using a cross-platform language, the application was primarily designed and tested for iOS devices to ensure robust performance and accessibility. Upon examining Figure 5.21, it becomes apparent that following the login process, six primary elements emerge: Tag, Clothes, Categories, Colours, Modifications, and Wardrobe.

To navigate the application, users must enable VoiceOver, a gesture-based screen reader that allows iPhone use without visual input. This feature provides auditory descriptions of on-screen content, ranging from battery levels to caller identification and the current application in use. When the user touches or swipes the screen, VoiceOver announces the name of the element under the finger, including icons and

text, and enables interaction with buttons and navigation to other screens using specific VoiceOver gestures. The iSight main menu is presented below in Figure 5.22.

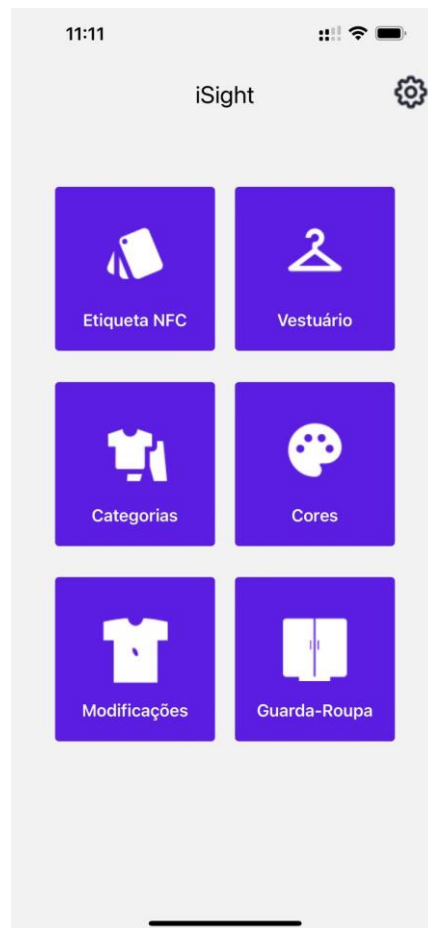


Figure 5.22: iSight main menu.

The first menu (Figure 4.43), NFC Tag, is used to read tags associated with clothing items. Upon selection, the user is informed of the need to ensure the tag is correctly placed on the clothing item, as illustrated in Figure 5.23. Once confirmed, the user can press the button to read the tag.

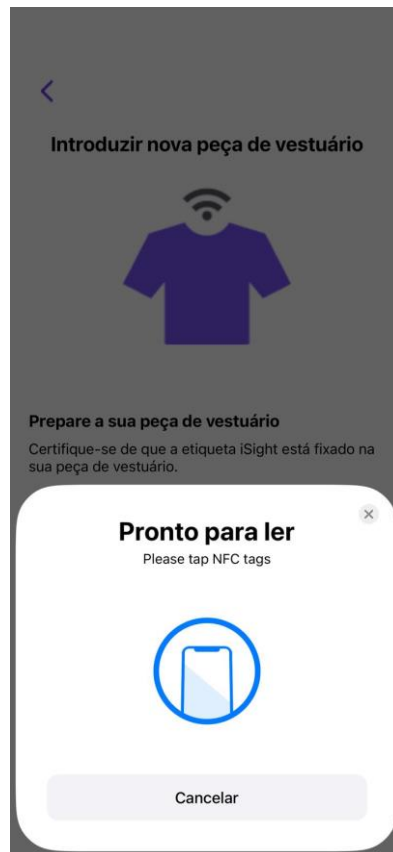


Figure 5.23: Read NFC Tag

The NFC Tag menu utilizes the mobile device's NFC reader, requiring the user to simply bring the tag close to the device. After reading, the user is notified with a haptic alert showing the clothing item associated with the tag. The user can then obtain the clothing item's characteristics, edit, or delete it. If the tag is not previously associated with a clothing item, the reader informs the user, allowing them to add a new clothing item.

In the second menu, Closet, users can browse their previously saved clothing items within the application. This section is divided into five categories: Tops, Bottoms, Footwear, Accessories, and Favourites (Figure 5.24).

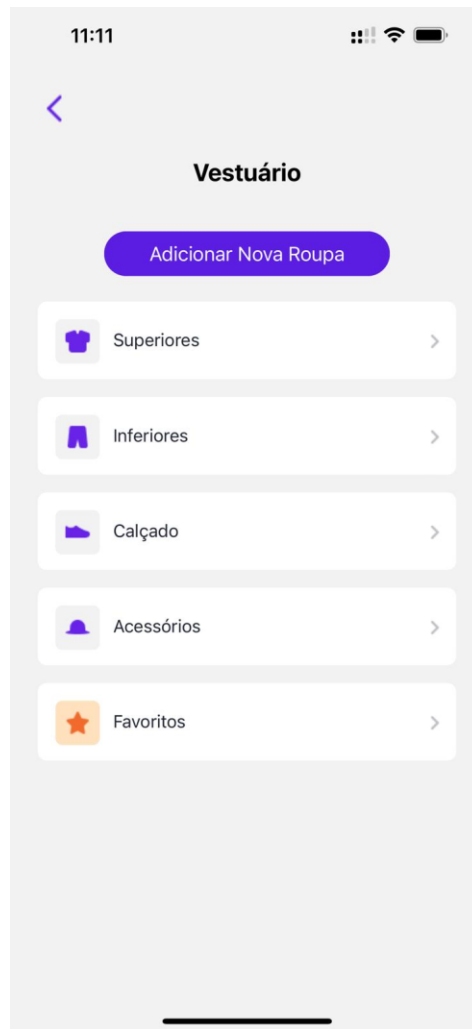


Figure 5.24: Closet Menu.

The categorization offered in the Closet Menu (Figure 4.45) aims to facilitate better management for the user in searching for and selecting clothing items. The user can select the desired categories, and upon selection, all clothes belonging to these categories will appear listed, as illustrated in Figure 5.25.

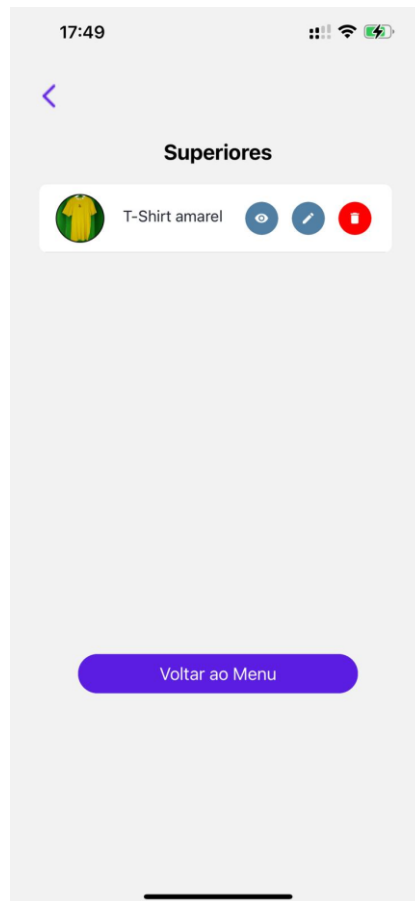


Figure 5.25: Clothing list for upper clothes category.

Furthermore, the user can select the desired clothing item, with options to edit, delete, or obtain the characteristics of the garment. If the user wishes to obtain all the information corresponding to the clothing item, it will be displayed as demonstrated in Figure 5.26.

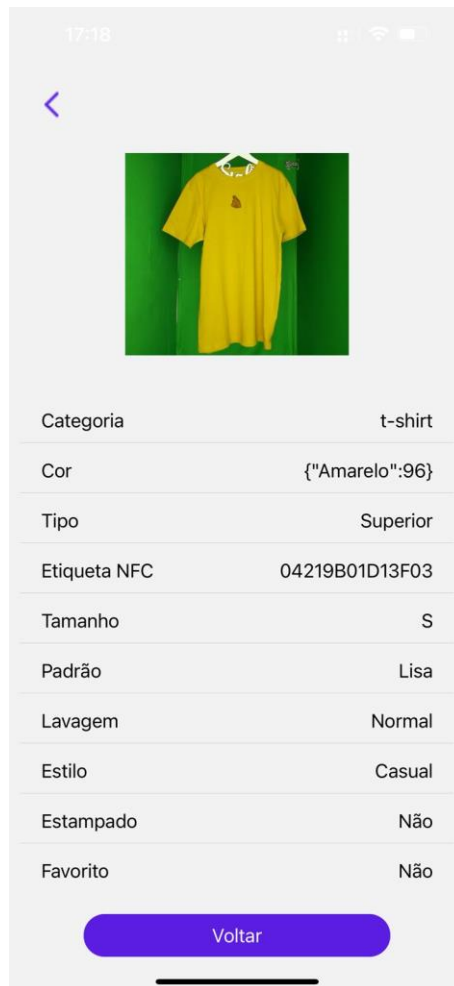


Figure 5.26: Detailed information corresponding to a selected clothing item.

Additionally, in Closet Menu, the user can add a new clothing item by selecting the "Add New Clothing" button. Upon selection, the application sends a request to the wardrobe server to capture an image. Once the image is returned, it is sent to the AI model server to determine the category and colours of the clothing item. Consequently, the user receives a notification confirming successful navigation to the form completion menu, with the category and colour fields automatically filled, along with the respective photo of the clothing item. Subsequently, the user can add various available fields, which are optional, as illustrated in Figure 4.48. However, it is necessary to add a description of the clothing item to facilitate easy association for future use.

a) 15:13

<

Abrir Câmera e Capturar Imagem

Carregar Imagem da Biblioteca

Descrição

Categoria

tshirt

Cor

{\"Amarelo\":96}

Tipo

b) 15:13

<

Calçado

Etiqueta NFC

Tamanho

Padrão

Lavagem

Estilo

Estampado

Favorito

Não ☒ Sim

Figure 5.27. Overview of the “Add new clothing item” menu: a) Description, Category, Colour and Type fields; b) NFC Tag, Size, Pattern, Washing, Style and Printed fields.

The approach materialized in the “Add new clothing item” submenu allows the user to autonomously input essential characteristics when adding a new clothing item, with the remaining fields being optional. After filling out the form, the user can save the item, making it available and accessible in the corresponding section of the Clothing menu, *e.g.*, Tops.

In the following menus, Categories and Colours, the navigation panel allows the user to automatically determine the category and colours of the clothing item, as indicated by the menu names. The user can take a photo of the clothing item from the wardrobe or import one from their photo library – Figure 5.28.

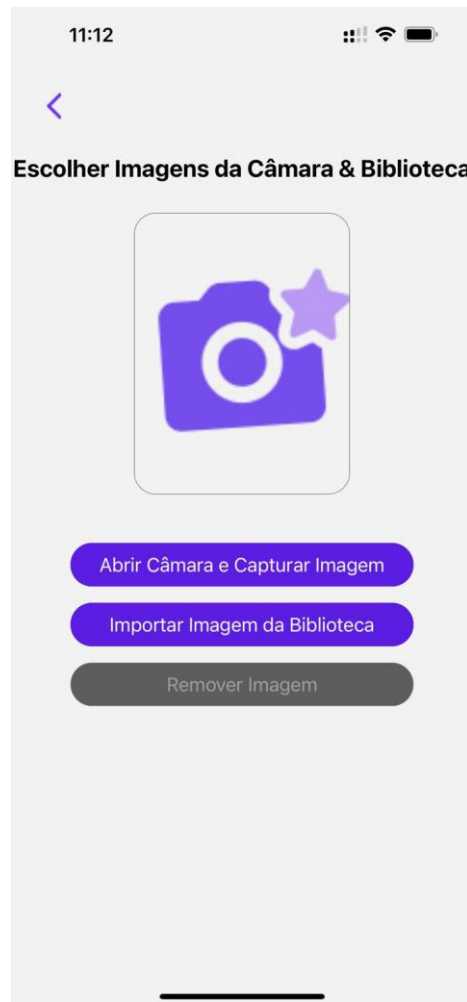


Figure 5.28: Submenu of the Categories and Colours Menu.

If the user chooses to take a photo, an HTTP request is initiated to the wardrobe server for image capture, which then returns the image. Immediately, a new HTTP request with the image is sent to the AI model server for inference. The result is returned according to the request; for instance, if it is a colour request, the colour and corresponding percentage are provided, allowing the distinction of predominant colours, as illustrated in Figure 5.29.

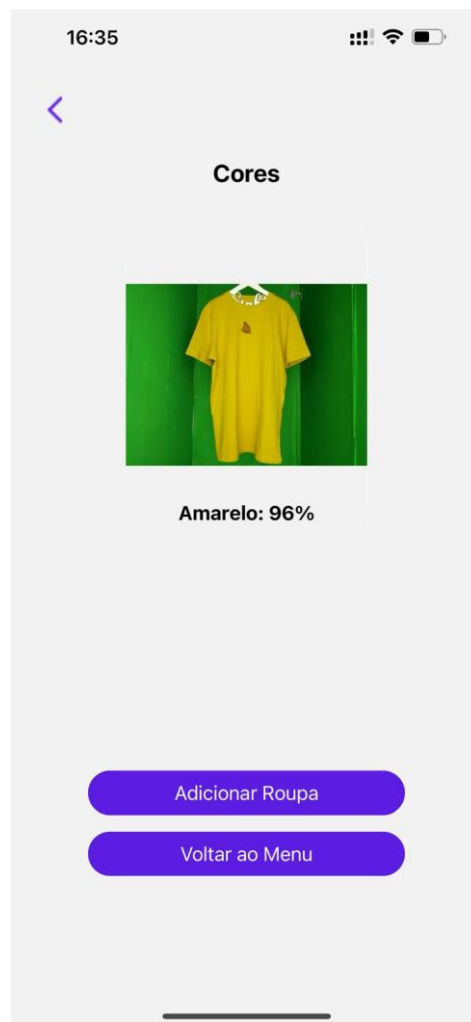


Figure 5.29. Example of a returned result from colour analysis.

Despite involving two HTTP requests - one for image capture and another for inference - the pipeline is swift, and the user is notified of the successful operation through a haptic alert on their device. For category requests, the pipeline remains the same, differing only in the inference response. After receiving the result, the user can always add the clothing item, being redirected to the form navigation panel as previously described.

The Modifications menu is similar to the Category and Colour menus, but the later allows the analysis of clothing items from both sides using a button to rotate the item - Figure 5.30.



Figure 5.30. Submenu included in the Modifications menu.

The pipeline for this process differs in the model utilized, employing a specific model designed for modifications inference. This model is tailored to detect and analyse defects such as stains or holes in the clothing item. Upon completion of the inference process, the results are presented to the user, providing detailed information about the number of detected stains or holes on the garment, as illustrated in Figure 5.31. This detailed feedback enables the user to make informed decisions regarding the condition and maintenance of their clothing items, ensuring they can address any issues promptly. This functionality is particularly useful for maintaining the quality and appearance of their wardrobe, further enhancing the overall user experience.



Figure 5.31. Example of a returned result from the Modifications Analysis.

The final menu pertains to the wardrobe settings - Figure 5.32. In this menu, users can configure IP addresses and ports for communication with the wardrobe server and the AI model server through the Settings submenu. The NFC Tag submenu allows for reading NFC tags, similar to the first menu, but utilizing the NFC reader present in the wardrobe.

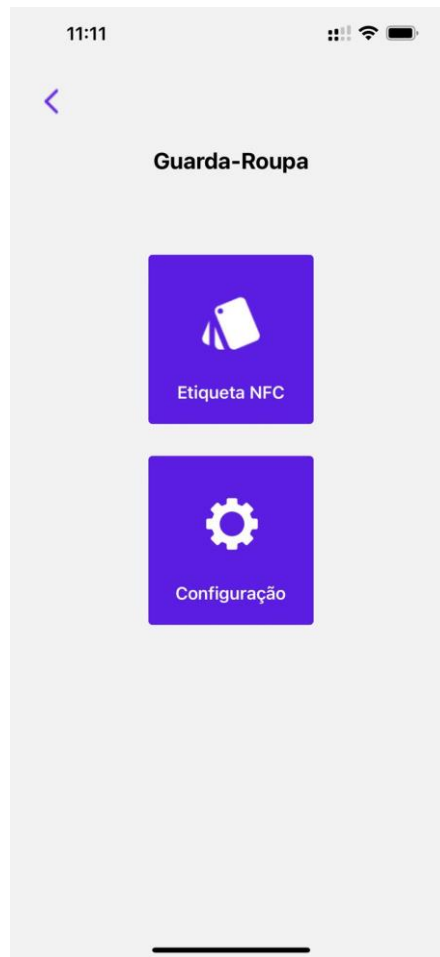


Figure 5.32. Wardrobe menu details.

Although this feature may seem redundant, it is useful when the mobile device's NFC reader is unavailable.

In summary, designing an application that specifically addresses the needs of blind people and incorporating advanced technologies such as NFC, AI models, this study represents a significant advancement in accessibility and usability for blind users. The integration of these technologies ensures that users can independently manage their wardrobe, make informed choices, and efficiently organize their clothing items. This comprehensive approach not only enhances the user experience but also empowers blind people by providing them with the necessary tools for greater autonomy and self-reliance in their daily lives.

Chapter Summary

This chapter offers a comprehensive overview of the development and components of the smart wardrobe prototype, detailing its design, core elements, and the associated mobile application interface aimed at

improving wardrobe management for visually impaired individuals.

The prototype system was engineered to identify clothing characteristics such as type, colour, and modifications through a mechatronic setup, which is remotely controlled via a mobile application. The initial prototype encountered limitations related to spatial constraints and image capture difficulties. Consequently, the design was revised to a larger model. The revised prototype features a chroma key fabric lining to facilitate uniform image capture and incorporates a DC motor (Nema 17) for rotating garments to enable viewing of both sides. Key components of the developed prototype include the Nema 17 stepper motor, an A4988 motor driver, a Raspberry Pi 4 Model B, a high-resolution 12MP camera, an NFC reader utilizing the PN532 chip, a controlled LED strip for lighting, and a 12V power supply. NFC NTAG213 tags were employed to label clothing items, allowing for the reading of unique identifiers. The system operates through a Raspberry Pi, which serves as a local server handling requests from a mobile interface. These requests encompass capturing images, reading NFC tags, and controlling the motor for garment rotation. A wide-angle camera aids in capturing comprehensive images, while the motor rotates the hanger 180 degrees to provide a full view of both sides of the clothing. The NFC reader is strategically positioned to ensure efficient tag reading.

An accessible and user-friendly mobile application was developed to enable blind users to independently organize and identify clothing items. Ensuring accessibility was a primary objective; therefore, the application adheres to standards such as EN301549 in the EU and WCAG 2.1 AA requirements. In Portugal, these standards are reinforced by the *Regulamento Nacional de Interoperabilidade Digital* (RNID) under DL No. 83/2018, ensuring that the application is perceivable, operable, understandable, and compatible with assistive technologies such as screen readers and Braille displays. The mobile interface was designed with a focus on a Portuguese-speaking user base with visual impairments, employing a cross-platform development approach for compatibility with both iOS and Android devices. Features include VoiceOver for iOS, facilitating interaction through auditory cues and gestures. The application supports NFC tag reading, closet management, and clothing categorization via AI analysis based on colour and type. Users interact with the system through the mobile application, which communicates with the Raspberry Pi via HTTP requests. This includes image capture, NFC tag reading, and motor control. The application processes the data and, when necessary, interfaces with AI models to provide detailed feedback on clothing items, including identification and recommendations based on user preferences. In summary, the iSight prototype is designed to offer an accessible and practical solution for wardrobe management, with the potential to significantly enhance independence and improve the daily lives of visually impaired users.

6 EVALUATION OF PROTOTYPE

Chapter Overview

The following chapter describes the results of a survey conducted to validate the iSight prototype. Members of ACAPO (*Associação dos Cegos e Amblíopes de Portugal*) participated in a structured testing protocol followed by a detailed questionnaire. The goal was to gather feedback on the usability, accessibility, and overall importance of the iSight prototype for the visually impaired community.

6 Evaluation of Prototype

- 6.1 Ethical Considerations
 - 6.2 Testing Protocol
 - 6.3 Questionnaire Methodology
 - 6.4 Results and Analysis
 - 6.5 Statistical analysis and relevant findings
-

Chapter 6 presents the evaluation and validation of the iSight prototype, designed to assist blind individuals in managing their clothing. The chapter starts with ethical considerations, ensuring participants' safety and well-being through ethical approvals and informed consent. The testing protocol involved a structured process where participants were introduced to the prototype, engaged in hands-on testing, and guided through scenarios to evaluate specific functionalities like colour and category evaluation, detection of modifications, adding new clothing items, and database verification. After the testing, participants provided immediate feedback and completed a comprehensive questionnaire. The questionnaire methodology involved developing a detailed set of questions, initially tested with ACAPO board members, to gather in-depth feedback on the prototype. The results and analysis section presents the findings from the questionnaire, covering demographics, types of visual impairment, technology use, accessibility of the mobile application, usability of the prototype, and the perceived importance of the iSight system. Statistical analysis was conducted to explore relationships such as the correlation between ease of navigation and user satisfaction, the impact of technology familiarity on ease of navigation and overall experience, and the effectiveness of the prototype in identifying clothing features. The analysis also examined user suggestions for improvements and compared feedback between blind users and those with low vision.

The chapter concludes with a summary of the statistical tests, hypotheses, results, and significance levels, highlighting key findings and areas for further development. This comprehensive evaluation demonstrates the iSight prototype's potential to enhance the independence and quality of life for visually impaired users.

Figure 6.1 summarizes the main steps and iterations in Chapter 5:

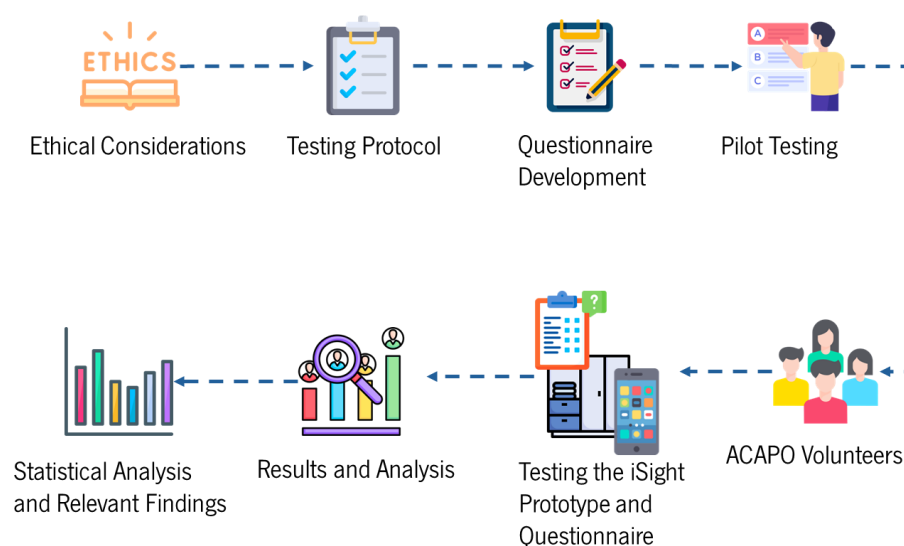


Figure 6.1: Workflow of the iSight prototype testing and validation process.

This workflow illustrates the structured process followed in evaluating and validating the iSight prototype, from ethical considerations and testing protocols to detailed statistical analyses and user feedback, providing a clear overview of the chapter's content and methodology.

6.1 Ethical Considerations

To ensure the safety and well-being of the participants, ethical considerations were paramount. A consent form is included in Appendices 2 and 3, which documents that the testing protocol and the questionnaire were submitted to the Ethics Committee for Research in Social and Human Sciences (Comissão de Ética para a Investigação em Ciências Sociais e Humanas - CEICSH) of the University of Minho and received approval under code CEICSH 185/2023. The corresponding ethical approval document is provided in Appendix 4. Prior to participating in the study, each participant signed an informed consent form acknowledging their understanding of the study's purpose, procedures, potential risks, and their right to withdraw at any time without any consequence. As a result of this consent, participants were made aware of their involvement and the nature of the study, adhering to ethical standards and protecting their privacy and rights.

6.2 Testing Protocol

To ensure a comprehensive evaluation of the iSight prototype, a structured testing protocol was followed. Participants were given detailed instructions on how to use the prototype, which included the following steps:

1. Introduction to the Prototype: each participant was provided with an overview of the iSight prototype, including its purpose and its features.
2. Hands-on Testing: participants were given a set period to interact with the prototype independently, allowing them to explore its functionalities and interface.
3. Guided Scenario: To evaluate the iSight prototype, participants were guided through a series of tasks designed to test its functionality in the following real-world scenarios:
 - a. Categorization and Colour Evaluation - Participants were asked to request an assistant to provide a piece of clothing for colour evaluation. They were instructed to place the clothing item in the wardrobe, ensuring it was parallel to the sides. Participants then

navigated to the "Colours" menu and captured an image of the clothing item, verifying the colour evaluation results with the assistant. Optionally, participants could repeat the process in the "Category" menu to determine the category of the clothing item and verify these results with the assistant as well.

- b. Evaluation of Modifications on a Clothing Item: participants requested an assistant to provide a clothing item with modifications, such as stains or holes. They placed the item in the wardrobe, ensuring it was parallel to the sides. Participants accessed the "Modifications" menu and captured an image of the clothing item, subsequently confirming the modification results with the assistant.
- c. Adding a Clothing Item: participants requested an assistant to provide a piece of clothing. They placed the clothing item in the wardrobe, ensuring it was parallel to the sides. Participants opened the "Clothing" section and selected "Add New Clothing Item." After capturing the image, they verified the automatic filling of characteristics such as category and colour, completing any additional information as desired. Participants also had the option to add the NFC tag automatically using the provided button.
- d. Verification in the Database: participants requested an assistant to provide a previously added clothing item. From the main menu of the application, they accessed the "NFC Tag" function, brought the tag of the clothing item close to the NFC reader, and confirmed that the item was registered in the database. Alternatively, they could use the wardrobe's NFC reader, located in the upper left corner, accessed via the "Wardrobe" menu followed by "NFC Tag".

- 4. Feedback Session: after completing the tasks, participants discussed their experiences with a facilitator, providing immediate feedback on any issues or suggestions for improvement.

Upon completing the testing protocol, participants were asked to complete a comprehensive questionnaire to document their experiences and evaluations. Figure 6.2 shows participants engaging with the iSight prototype during the hands-on testing phase.



Figure 6.2: ACAPO members interacting with the iSight prototype during the testing phase, showcasing hands-on engagement: a) Participant using the mechatronic device; b) Participant using the iSight mobile application.

6.3 Questionnaire Methodology

To evaluate the effectiveness and usability of the iSight prototype, a comprehensive questionnaire was developed. The detailed questionnaire is provided in Appendix A5. Before distribution to the participants, a pilot test was conducted with two members of the ACAPO board. This pilot testing allowed for improvements and corrections in the semantic formulation of the questionnaire, ensuring clarity and effectiveness in capturing the necessary data.

The questionnaire was designed to gather detailed feedback on various aspects of the iSight prototype. A total of 15 participants voluntarily took part in the study. The responses were analysed using SPSS 22, and a *Likert* scale was employed to measure levels of agreement, importance, or frequency across various questions. In the *Likert* scale used, a lower score indicated a negative opinion, while a higher score indicated a positive opinion. The questionnaire comprised 36 questions divided into six main sections, described as follows:

- I. Personal Identification: this section gathered demographic information about the participants, including age, gender, academic qualifications, and current occupation.

-
- II. Identification of Disability Type: this section aimed to identify the condition that caused blindness in the participants and the age group at which this condition occurred. It included three questions to determine the type of disability.
 - III. Technology: comprising nine questions, this section assessed the participants' knowledge, usability, and satisfaction with the available supportive technologies. It also evaluated the proximity of the blind community to these technologies. Responses were based on a 5-point *Likert* scale evaluating comfort, agreement, satisfaction, importance, and frequency. These questions were designed to align with the study's objective of understanding current technological gaps and the potential for integrating new solutions like the iSight prototype. By evaluating participants' familiarity and comfort with existing technologies, the study aimed to gauge the readiness of the target demographics to adopt new assistive tools.
 - IV. Accessibility of the iSight Mobile Application: this section included four main questions and a complementary one, and it aimed at assessing the accessibility and usability of the iSight mobile interface. Participants rated their experiences on a 5-point *Likert* scale assessing difficulty, agreement, satisfaction, and clarity. The questions in this section were directly aligned with the objective of ensuring the mobile application was user-friendly and met accessibility standards, which is crucial for its adoption and efficacy among visually impaired users.
 - V. Usability of the iSight Prototype: with three questions, this section evaluated the ease of use and utility of the prototype. It also sought to understand how the blind community would prefer this technology to be available. Responses were gauged on a 5-point *Likert* scale examining difficulty, precision, effectiveness, agreement, satisfaction, and clarity. This section's questions were crafted to align with the study's goal of creating a practical and easy-to-use system. By assessing usability, the study aimed to identify potential barriers and areas for improvement, ensuring that the prototype meets the real-world needs of its users.
 - VI. Assessment of the Importance of iSight: the final section consisted of six questions aimed at evaluating the importance and potential usefulness of the prototype. Participants provided ratings for each aspect of the prototype distinctly. Suggestions and opinions from participants were incorporated into the final version. Open-ended responses from sections IV and V were combined in this section due to redundancy, as participants sometimes answered questions belonging to other sections. This section was particularly important for aligning the study's objectives with user needs, as it provided direct feedback on how well the prototype addresses the daily challenges

faced by visually impaired people. Understanding the perceived importance and usefulness of the iSight prototype was crucial for validating its potential impact.

Although the prototype was initially designed for blind people, the study included both blind participants and those with low vision, who have some residual visual capability. This approach aimed to ensure broader applicability and to allow for comparison between fully blind people and those with low vision. Therefore, the term "visual impairment" is used in the analysis of the questionnaire to encompass both blind and low-vision participants.

6.4 Results and Analysis

This section presents a detailed examination of the questionnaire results, which cover various aspects of the iSight prototype evaluation. The analysis is organized into key areas corresponding to the six main parts of the questionnaire previously identified. This comprehensive analysis aims to understand the importance and contribution of iSight in enhancing users' daily lives, particularly focusing on their confidence, self-esteem, well-being, and independence.

I. Personal Identification

The study involved a sample size of 15 participants who voluntarily agreed to participate, as previously identified. The majority of the participants were female, accounting for 60%, while males accounted for 40%. The age distribution of the participants reveals that a significant majority belongs to the older age groups, with 66.7% of participants (specifically 10) being aged 55 or more, 20 % (specifically 3) falling within the 35-44 year-old range, and 13.3 % (specifically 2) falling within the 45-54 year-old range. This data indicates that the feedback and evaluation of the iSight prototype come predominantly from older users, with a smaller representation from the middle-aged group.

The educational qualifications of the participants exhibit significant variation. The data indicates that 33.3% of the participants have completed 4 years of schooling, which corresponds to the 1st cycle of basic education. Following, 20% of the participants have completed 6 years of schooling, aligning with the 2nd cycle of basic education, 13.3% completed 9 years of schooling, representing the 3rd cycle of basic education and 20% completed 12 years of schooling, corresponding to secondary education. Finally, 6.7% of the participants have completed 11 years of schooling, and another 6.7% hold a bachelor's degree. This diverse range of educational backgrounds is crucial for analysing the feedback on the iSight prototype, as it reflects a wide array of literacy and cognitive skills among the participants. The professional

background of the participants is diverse, with a significant number being retirees, as illustrated in Figure 6.3. Specifically, the data reveals that 60% of the participants are retired, of which 55.6% are women. The data also includes 13.3% of participants working as call centre operators. Additionally, the sample features 13.3% domestic workers, including those not currently working, and another 6.7% employed as laundry workers. Finally, 6.7% of the participants are employed as a technical director and psychologist.

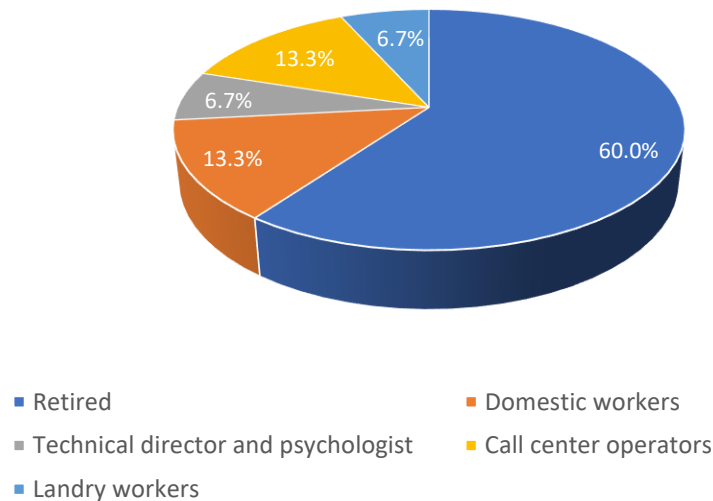


Figure 6.3: Distribution of professional background of participants.

This distribution highlights that the majority of participants are retirees, suggesting that the iSight prototype may need to address the unique needs and perspectives of older demographics. The inclusion of call centre operators and a technical director/psychologist provides insights from people actively engaged in professional activities, offering a broader perspective on the prototype's usability across different lifestyles and daily routines. This distribution also aligns with the age demographics, confirming that the 10 participants in the oldest age group predominantly have lower educational qualifications, further emphasizing the need to tailor the iSight prototype to accommodate their specific requirements and preferences.

To contextualize the study sample and provide a global perspective on visual impairment, the findings from the study can be related to global statistics. According to Lancet Global Healthy (Burton *et al.*, 2021) in 2020, approximately 43.28 million people are blind, with a prevalence that significantly increases with age. The majority of those affected are older adults, with 77.7% of blind individuals being aged 50 or older. This aligns with the study's finding that 66.7% of participants are aged 55 or more, highlighting a similar age distribution in the sample.

Globally, in 2020, it was estimated that 18.1 million people of working age (15-64 years) were blind, and 142.6 million had moderate to severe vision impairment (MSVI). The overall reduction in employment for people with blindness or MSVI is estimated to be 30.2%. This significant employment gap underscores the challenges faced by visually impaired individuals in securing and maintaining employment.

The study sample reflects this global scenario, with a high percentage of participants not currently engaged in employment. The relative reduction in employment for people with vision impairment contributes to these losses (Burton *et al.*, 2021).

Moreover, the global prevalence of blindness shows a higher prevalence among women, who account for 55% of those affected. In this study, women also make up a majority of the participants (60%), reinforcing the gender imbalance observed globally. This demographic similarity underscores the relevance of the study's findings to the broader context of visual impairment.

By addressing the needs of visually impaired individuals through assistive technologies such as the iSight prototype, the aim is to mitigate these employment challenges. Enhancing their ability to independently manage daily tasks, such as clothing selection and maintenance, can improve their quality of life and potentially increase their participation in the workforce. This approach could contribute to reducing the global productivity losses associated with vision impairment.

In addition, an analysis of the educational and professional backgrounds of the study participants reveals an interesting trend. In this study, 3 out of the 4 participants who attained a 12th-grade education or higher hold better employment positions and have been visually impaired since birth. The only exception is an individual who became visually impaired between the ages of 18 and 24 and also attained a 12th-grade education. This observation aligns with existing literature, which indicates that individuals with childhood-onset visual impairment tend to achieve higher education levels and subsequently better employment prospects (Pavey *et al.*, 2008). Additionally, it has been noted that students who are blind or visually impaired are increasingly pursuing postsecondary education, with 16% of freshmen with disabilities identifying as partially sighted or blind (Schneider, 2001). Higher educational attainment is linked to better employment outcomes for individuals with visual impairments (McDonnall & Tatch, 2021). This consistency between the study's findings and the literature underscores the representativeness of the sample and the relevance of the study's findings in a broader context.

II. Identification of Disability Type

Participants were asked about the age at which they became visually impaired. The responses show a

wide range of ages, indicating different experiences with visual impairment, as illustrated in Figure 6.4.

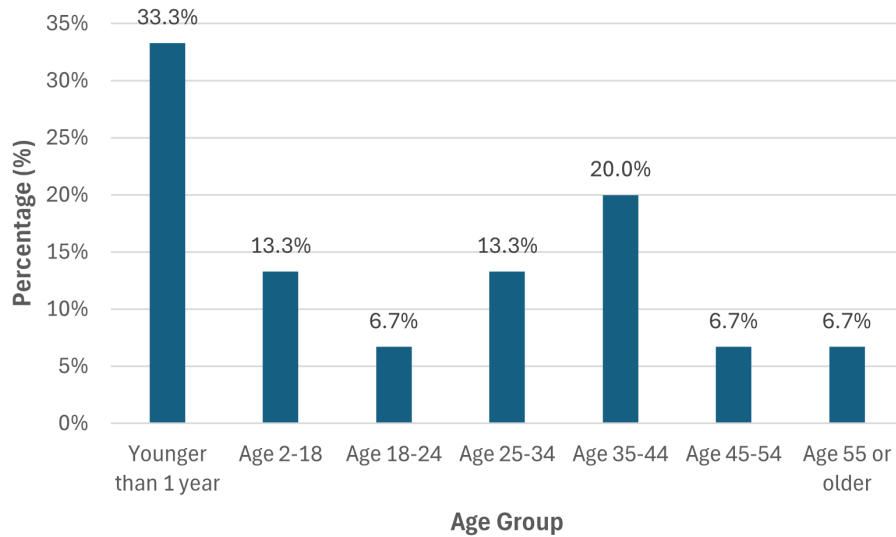


Figure 6.4: Age distribution of the time that visual impairment occurred among participants.

These data reveals that a significant number of participants (33.3%) have been visually impaired since birth or shortly thereafter (younger than 1 year). Following, 20% experienced visual impairment between 35 and 44 years old, while 13.3% became visually impaired between 25 and 34 years old, and another 13.3% between the 2 and 18 years old. Smaller groups reported the onset of visual impairment during the age range of 18-24, 45-54, and 55 or more years old, accounting for 6.7% each.

Additionally, the survey included a question to identify the cause of visual impairment among the participants. The results indicate a mix of congenital and acquired conditions. Specifically, 60% of the participants reported that their blindness was caused by an acquired disease, while the remaining 40% indicated that their condition was congenital. This data provides insight into the diversity of the causes of visual impairment within the participant group.

Regarding the specific types of conditions causing visual impairment, the data shows a variety of conditions. *Retinitis pigmentosa* was the most common, affecting 46.7% of the participants. Other conditions included diabetic retinopathy (13.3%), and glaucoma, ischemic optic neuropathy, Stargardt disease, retinal detachment, dry eye syndrome, and myopia, each accounting for 6.7%, as depicted in Figure 6.5.

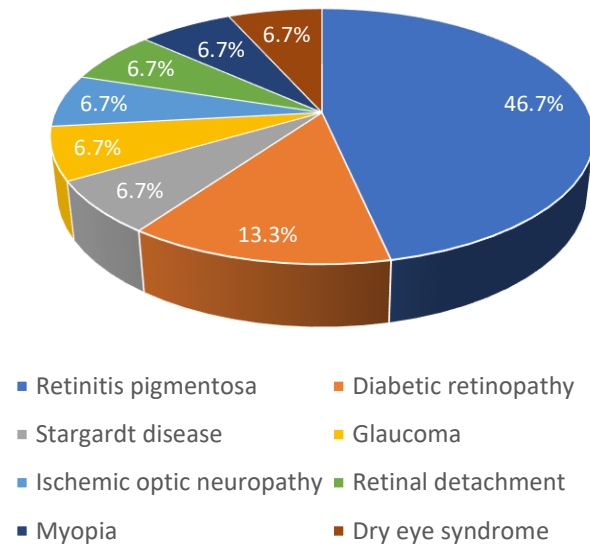


Figure 6.5: Distribution of conditions.

Understanding the age at which participants became visually impaired, along with the cause and specific type of their blindness, is crucial for tailoring the iSight prototype to their specific needs. Those who have been visually impaired from a very young age may have different requirements and adaptations compared to those who lost their vision later in life. This insight helps in designing a more effective and user-friendly assistive device.

These data are consistent with the leading causes identified globally (Burton *et al.*, 2021). This comparison substantiates the sample's representation of the broader population of visually impaired individuals. Figure 6.6 provides a visual representation of these causes.

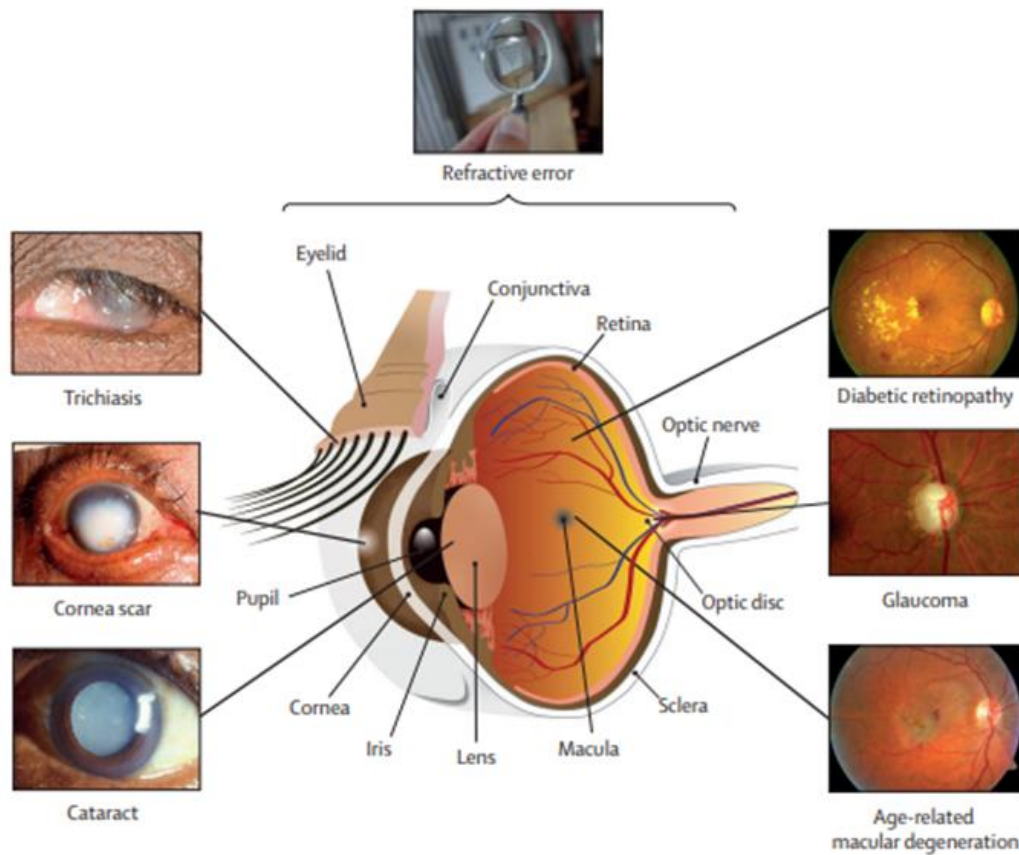


Figure 6.6: Visual representation of common causes of visual impairment (Burton *et al.*, 2021)

III. Technology

The responses in this third section highlighted the current state of technology adoption among the blind community. It provides insights on their familiarity with supportive technologies, their satisfaction levels, and the frequency of use.

QIII.1: Do you currently use any application dedicated to clothing?

The responses indicate that the majority of participants, 67 %, do not currently use any applications dedicated to managing clothing, while 33 % do use such applications. This suggests that there is a significant opportunity for the iSight prototype to fill a gap in technology usage among visually impaired people in the context of clothing management. For those who indicated usage of clothing-related applications, further details were sought on the specific applications used. One participant reported using colour detectors on an Android mobile device, and four participants reported using the Colorino device. This additional information highlights that among those using clothing-related technology, the Colorino device is the most commonly used. Colorino is a well-known colour identifier for visually impaired people,

which helps users distinguish colours in their clothing. The use of colour detection applications and devices emphasizes the importance of colour identification in clothing management for the visually impaired community. Interestingly, among the users of these technologies, only one user had a low literacy level. This suggests that the adoption of such devices is not significantly hindered by literacy barriers, indicating their user-friendly nature and accessibility. Additionally, the majority of these people are still engaged in professional activities and have not yet retired. This detail highlights the continued need for practical and efficient solutions to support visually impaired people in their active professional lives, ensuring they can manage their clothing choices effectively and maintain their professional appearance.

QIII.2: To what extent do you feel comfortable using technological devices such as smartphones and computers?

The responses varied, with the majority indicating a moderate level of comfort. Specifically, 40 % of the participants reported feeling very comfortable, 53.3 % felt somewhat comfortable, and 6.7 % felt somewhat uncomfortable. These data suggest that most participants feel, at least, somewhat comfortable using technological devices, with a substantial portion feeling very comfortable. This overall comfort with technology is highly motivating for the adoption of the iSight prototype, as it indicates that most users are likely to be receptive to using a new technological solution for clothing management. Understanding these comfort levels helps in designing user interfaces and features that cater to the varying degrees of technological proficiency among the participants.

QIII.3: How often do you use technological devices in your daily life?

The frequency of technological device usage was overwhelmingly in favour of daily use. Fourteen participants indicated daily use (*ca.* 93.3 %), while only one participant representing *ca.* 6.7 % reported occasional use. These data indicate that most participants use technological devices daily. This high frequency of daily use further supports the potential acceptance and integration of the iSight prototype into their daily routines. The prevalence of daily technology use among participants highlights their familiarity and comfort with digital tools, making them well-suited for adopting new technological solutions like the iSight prototype.

QIII.4.: How would you rate your ability to use software and applications specifically designed for blind people, such as screen readers?

The responses showed that while a significant number of participants (46.7 %) rate their skills as average, there is also a considerable proportion with very high (26.6 %) and high (13.3 %) proficiency levels. Only 13.3 % rated their skills as low. This range of abilities underscores the importance of designing the iSight prototype to be accessible and user-friendly for users with varying levels of technical proficiency. By ensuring that the prototype is intuitive and easy to navigate, it can cater to the needs of both highly skilled users and those with less experience using specialized software for the visually impaired.

QIII.5: To what extent do you believe that technologies improve your quality of life and independence?

Ten participants, representing ca. 66.7 %, felt that technologies improve their quality of life and independence very significantly, while five participants, 33.3 %, believed that technologies improve their lives significantly, with only one participant, 6.7 %, feeling that the improvement is moderate. This high level of perceived benefit from technology underscores the critical role that technological solutions like the iSight prototype can play in enhancing the daily lives and autonomy of visually impaired people. Designing the iSight prototype to meet these expectations can further reinforce its positive impact and ensure its widespread adoption and use.

QIII.6: How often do you seek to learn and explore new technologies adapted to your needs?

The interest in learning and exploring new technologies adapted to visually impaired people's needs was high. The gathered data reveal that a significant majority of participants, 73.3 %, are always looking to learn and explore new technologies, while 20 % do so regularly, and only one participant, representing 6.7 %, rarely seeks new technologies. This high level of engagement with adaptive technologies suggests that the iSight prototype has a receptive audience eager to integrate new solutions into the daily lives of the participants. This enthusiasm for exploring new technologies highlights the potential for positive reception and sustained use of the iSight prototype among the visually impaired community.

QIII.7: How do you evaluate the support and accessibility of technologies for blind people?

The support and accessibility of technologies for visually impaired people received mostly positive feedback. Specifically, 53.3 % rated the support as satisfactory, while 40 % rated it as very satisfactory, and only 6.7 % had no opinion. This feedback underscores the importance of continuing to develop and refine assistive technologies to meet the needs and expectations of visually impaired users. Ensuring that the iSight prototype offers robust support and high accessibility will be crucial for its success and adoption

among this group of users.

QIII.8: To what extent do you feel that technologies facilitate greater social and professional inclusion in your life?

The role of technologies in facilitating greater social and professional inclusion was overwhelmingly positive. The obtained data reveal that 93.3 % of the participants believe that technologies contribute very significantly to their social and professional inclusion, while the remaining 6.7 % consider the impact to be just significant. This highlights the critical role that technology plays in enabling visually impaired people to participate more actively in social and professional settings. The strong endorsement of technology's role in inclusion supports the continued development and implementation of innovative solutions like the iSight prototype to further enhance these opportunities for visually impaired users.

QIII.9: Do you consider technologies to be a useful tool for your education or training?

The usefulness of technologies as tools for education or training was highly endorsed. The collected data indicate that all participants find technologies to be beneficial for their education or training, with 46.7 % rating them as extremely useful and 53.3 % as very useful. This strong endorsement highlights the importance of integrating educational and training functionalities into the iSight prototype. By ensuring that the prototype supports educational and training needs, it can provide substantial benefits to visually impaired people, enhancing their learning experiences and professional development opportunities.

IV. Accessibility of the iSight Mobile Application

Feedback on the accessibility and usability of the iSight mobile application was gathered through detailed questions in the fourth section. Participants provided valuable suggestions and opinions, which were crucial for refining the application's user interface and ensuring it met the high standards of accessibility required by the visually impaired community.

QIV.1: How do you evaluate the ease of navigation in the mobile application?

The responses were generally positive, indicating a favourable user experience. A total of 66.7 % of participants rated the navigation as easy, while 33.3 % rated it as very easy. This feedback suggests that the mobile application's interface is user-friendly and accessible for visually impaired users. The high ratings for ease of navigation indicate that the design and layout of the application effectively met the needs of the target user group. Ensuring ease of navigation is crucial for the successful adoption and

continued use of the application, as it directly impacts the overall user experience. The positive evaluation of navigation within the mobile application highlights the importance of maintaining simplicity and intuitiveness in the user interface design. This will help users efficiently perform tasks and access features without unnecessary complexity or frustration. The feedback also provides valuable insights for further refinement and improvement, ensuring that the application remains accessible and user-friendly for all users.

QIV.2: Does the mobile application provide image descriptions or textual alternatives for visual elements adequately?

The responses indicated a strong overall satisfaction with the application's provision of image descriptions and textual alternatives. Specifically, 53.3 % of participants rated the descriptions as excellent, 26.7 % as good, and 20 % as adequate. No participants rated the descriptions as poor or very poor. The positive feedback on the application's image descriptions and textual alternatives emphasizes the effectiveness of these features in enhancing accessibility. Providing clear and comprehensive descriptions allows visually impaired users to fully engage with visual content, making the application more inclusive and usable. The high ratings for image descriptions and textual alternatives suggest that the application meets or exceeds the expectations of most users in this regard. This aspect of the application's accessibility is crucial, as it ensures that all users, regardless of visual ability, can access and understand the content presented within the app. The feedback also highlights the importance of continuing to prioritize and refine these features to maintain high standards of accessibility and user satisfaction.

QIV.3: How do you evaluate the clarity and organization of the textual content in the mobile application?

The data indicate that the majority of participants found the textual content to be either very clear or clear. Specifically, 53.3 % of participants rated the content as very clear, while 46.6 % rated it as clear. There were no responses indicating that the content was unclear. The high ratings for clarity and organization of textual content suggest that the application effectively communicates information in a way that it is easily understandable for visually impaired users. This clarity is essential for ensuring that users can navigate the application and access the information they need without confusion or difficulty. The positive feedback regarding the textual content highlights the importance of maintaining high standards for clarity and organization. Clear and well-organized content helps users efficiently finding and comprehending the information they need, enhancing their overall experience with the application. This feedback is valuable

for ongoing improvements, ensuring that the application continues to meet the needs of its users effectively.

QIV.4: How do you evaluate the overall user experience of the mobile application?

The responses show a high level of overall satisfaction with the mobile application. Specifically, 66.7% of participants rated their experience as very satisfactory, while 33.3% rated it as satisfactory. No participants rated their experience as unsatisfactory or very unsatisfactory. The high ratings for overall user experience suggest that the mobile application successfully meets the needs and expectations of visually impaired users. The positive evaluations indicate that the application provides a satisfactory and user-friendly experience, which is crucial for ensuring continued use and acceptance. The feedback on the overall user experience emphasizes the importance of maintaining a high level of user satisfaction through continuous improvements and updates. By addressing any potential issues and incorporating user feedback, the application can further enhance its usability and effectiveness, ensuring it remains a valuable tool for visually impaired people.

V. Usability of the iSight Prototype

The usability of the iSight prototype was assessed through questions focused on the ease of use and utility of the device. Participants' feedback indicated how intuitive they found the prototype and its effectiveness in meeting their needs. The fifth section also explores the preferred methods of technology delivery and availability for the blind community.

QV.1: Evaluate in the ease of use of the iSight prototype, which includes both the mobile application and the smart wardrobe.

The responses were overwhelmingly positive, indicating a high level of user-friendliness and accessibility. A total of 53.3% of participants found the iSight prototype to be very easy to use, while 46.7% found it just easy to use. No participants reported difficulties or rated the ease of use as less than easy. This feedback suggests that the iSight prototype successfully meets the usability requirements of its target user group, ensuring that the combination of the mobile application and smart wardrobe is intuitive and straightforward for visually impaired users. The high ratings for ease of use indicate that the design and functionality of both the mobile application and the smart wardrobe are well-integrated and accessible. This is crucial for encouraging the adoption and consistent use of the iSight prototype, as users are more likely to engage with technology that they find easy to navigate and operate.

QV.2: Evaluate the accuracy of the iSight prototype in identifying the category and colours of clothing items.

For the accuracy in identifying the category of clothing items, 60 % of participants rated it as "very precise," while 40 % rated it just as "precise." For the accuracy in identifying the colours of clothing items, 80% of participants rated it as "very precise," while 20 % rated it as "precise."

Most participants found the iSight prototype to be highly accurate in identifying both the category and colours of clothing items. However, a small number of participants (20 %) reported a divergence in their responses, rating the accuracy as "precise" for category identification and "very precise" for colour identification. The remaining participants provided consistent ratings for both category and colour accuracy. This suggests that while the iSight prototype generally performs well in both areas, there is a perceived higher accuracy in colour identification compared to category identification among some users.

QV.3: Evaluated the iSight prototype's ability to detect stains and identify NFC tags.

The responses for detecting stains were overwhelmingly positive, with the majority, 86.7 %, rating it as "highly effective." Similarly, the identification of NFC tags also received high ratings, with most participants, 86.7 %, finding it "highly effective." There was a strong correlation between the participants' ratings for these two functionalities, indicating that users generally found both features to be highly effective. Specifically, participants who rated the iSight prototype as "very precise" for both category and colour identification consistently rated its ability to detect stains and identify NFC tags as "highly effective." Participants who rated category identification as "precise" but colour identification as "very precise" also showed high ratings for detecting stains and NFC tags, though with some minor variations. Those who rated both category and colour identification as "precise" tended to rate stain and NFC tag detection as "effective," though some rated these capabilities higher. This consistency across responses suggests that the iSight prototype performs reliably across different functionalities, providing users with an effective tool for managing their clothing. The strong performance in colour identification and NFC tag detection is particularly noteworthy, as it highlights the prototype's ability to handle complex tasks with high precision. In summary, the usability and accuracy of the iSight prototype are highly rated by participants, indicating that the prototype meets the needs and expectations of visually impaired users. The positive feedback on ease of use and accuracy underscores the effectiveness of the design and functionality of the iSight prototype. Continuing to refine these aspects based on user feedback will be important for further enhancing the user experience and ensuring the successful adoption of the technology. The strong

correlation between responses across different functionalities reinforces the prototype's overall reliability and effectiveness in assisting visually impaired people in managing their wardrobe. The additional comments and suggestions provide valuable insights for future improvements, ensuring the system remains user-centric and responsive to the needs of its users.

VI. Assessment of the Importance of iSight

This assessment aims to evaluate the perceived importance of the iSight prototype among users, specifically examining its effectiveness in facilitating the clothing selection process, identifying specific characteristics and modifications in garments, and enhancing wardrobe organization. By analysing user feedback and satisfaction, the study seeks to elucidate the prototype's impact and pinpoint areas for potential enhancement.

QVI.1: Evaluate the importance of the iSight prototype through two statements concerning its functionality. S1: "iSight facilitates the process of selecting clothes, while allowing identification of characteristics and modifications to the original state." S2: "iSight organizes my clothes effectively."

The responses were compellingly positive. For the statement S1, 66.7 % of participants strongly agreed, and 33.3 % just agreed. Similarly, for the statement S2, 66.7 % of participants strongly agreed, while 33.3 % just agreed. These results indicate a high level of agreement among participants regarding the importance and effectiveness of the iSight prototype in both facilitating the selection of clothes and organizing them effectively. The majority of participants strongly agree that the prototype significantly aids in these aspects, suggesting that the system meets critical needs for visually impaired users in managing their wardrobe. The consistent positive responses across both statements reflect the perceived value of the iSight prototype in improving daily routines and enhancing the independence of visually impaired people. This feedback underscores the system's potential to make a meaningful impact on the lives of its users by providing practical and reliable solutions for clothing management.

QVI.2: To assess whether the use of the iSight prototype increased their feelings of confidence, self-esteem, well-being, and independence through four statements. S1: "The use of iSight increased my sense of confidence". S2: "The use of iSight increased my sense of self-esteem". S3: "The use of iSight increased my sense of well-being". S4: "The use of iSight increased my sense of independence".

The responses indicate a very positive impact of the iSight prototype on these aspects. For S1, 66.7 % of participants strongly agreed, whereas 33.3 % just agreed. For S2, 66.7 % of participants strongly agreed, while 33.3% agreed. For S3, 66.7 % of participants strongly agreed, and 33.3 % agreed. Finally, for S4, 66.7 % of participants strongly agreed, and 33.3 % agreed. There is a high level of consistency in the responses across all four statements, with all participants either strongly agreeing or agreeing that the iSight prototype positively impacted their confidence, self-esteem, well-being, and independence. This suggests a robust and consistent positive perception of the prototype's benefits. All participants who strongly agreed on one statement also strongly agreed on the other statements. Similarly, participants who agreed on one statement also agreed on the other statements. This uniformity in responses indicates that participants consistently experienced an increase in confidence, self-esteem, well-being, and independence through the use of the iSight prototype. The lack of divergent responses further supports the conclusion that the iSight prototype has a comprehensive positive effect on users' lives. The uniform positive feedback across all four statements underscores the significant impact of the iSight prototype on enhancing the quality of life for visually impaired users. The increase in confidence, self-esteem, well-being, and independence highlights the prototype's effectiveness in addressing the everyday challenges faced by these users.

QVI.3: To assess the importance of the iSight prototype in identifying clothes, colours, and stains/dirt.

Participants uniformly recognized the iSight prototype as a crucial tool in their daily lives. For the importance of iSight in identifying clothes, 66.7 % of participants found it extremely important, and 33.3 % found it very important. Similarly, for identifying colours, 66.7 % of participants found it extremely important, and 33.3 % found it very important. Regarding the identification of stains/dirt, 66.7 % of participants found it extremely important, and 33.3 % found it very important. These responses indicate that participants uniformly found the iSight prototype to be an extremely important tool in identifying clothes, colours, and stains/dirt. The high percentage of participants rating it as "Extremely Important" reflects the prototype's significant role in aiding their daily routines and enhancing their independence. This consistency in high ratings across all three areas highlights the comprehensive utility of the iSight prototype in assisting visually impaired people in managing their clothing effectively.

QVI.4: Whether they believe that the iSight prototype would improve their quality of life in relation to clothing management.

The responses indicate that the majority of participants believe that iSight would significantly enhance their quality of life. For the statement, "iSight improves my quality of life in relation to clothing management," 80.0 % of participants indicated that it greatly improves their quality of life, while 20.0 % indicated that it significantly improves their quality of life. These responses reflect a strong consensus among participants regarding the beneficial impact of the iSight prototype on their daily lives. The majority also believes that the iSight prototype greatly improves their quality of life, while the remaining participants still view it as a significant improvement. This indicates that the iSight prototype is perceived as a valuable tool that can substantially aid visually impaired people in managing their clothing more effectively, ultimately enhancing their overall quality of life.

QVI.5: About the specific aspects of their daily lives where the iSight system has a positive impact.

The options included facilitating the choice of clothes for specific occasions, helping to identify the colours of clothes more effectively, enabling the identification of stains/dirt on clothes, contributing to greater autonomy in managing their wardrobe, and other unspecified benefits. The responses were highly positive, with every participant selecting all the options, except for one participant who did not select the first option.

QVI.6 Do you have any specific suggestions or improvements you would like to see implemented in the system to make it even more useful in your daily life?

To provide a comprehensive overview and avoid redundancy, feedback from section IV (Question: "Please share any additional comments or specific suggestions to improve the mobile application based on your experience.") and section V (Question: "Please share any additional comments or specific suggestions to improve the system based on your experience.") were combined. The aggregated responses highlight the innovative nature of the iSight prototype and its potential to significantly enhance the daily life for visually impaired people. Users appreciate the application's ability to aid in clothing selection, identification of characteristics, and facilitating organization, noting that it could help them dress independently and efficiently. Many users suggested making the application faster by including fewer menus to streamline the process. The utility of the application is evident, with participants emphasizing its usefulness in daily routines and expressing eagerness to have such a system at home. Several users suggested enhancements to the application's features, such as including detailed information about clothing fabrics, reading label characteristics, and identifying stains more accurately. The application's ability to distinguish colours and similar items, like shoes, was also highlighted as a critical area for improvement. Despite

some users finding it challenging to use mobile phones, they found the iSight application user-friendly and expressed a strong desire for it to be commercialized and made accessible to a broader community. Participants also provided insights into additional functionalities that could further enhance the application's utility. These include knowing the exact location of stains on clothing and the ability to use the application without the need for additional hardware.

This comprehensive feedback will be analyzed in detail in the next sub-section through a thematic analysis.

6.5 Statistical analysis and relevant findings

This section provides a comprehensive analysis of the user experience with the iSight prototype, focusing on several key aspects, including ease of use, overall satisfaction, effectiveness in identifying features, frequency of technology use, comfort level, and their interrelationships. Due to the nature of the collected data, nonparametric statistical methods were employed, using the SPSS, which are appropriate for samples of small size. The choice of nonparametric statistical methods is particularly appropriate given the sample size of 15 participants, aligning with established practices in behavioural, social sciences, and assistive technology research. Nonparametric methods are well-suited for small sample sizes, as they do not rely on the stringent assumptions required by parametric tests (Chung, 2016). The use of such methods is validated by their robustness to distributional features and their application in studies with similarly small sample sizes in assistive technology research (Barnett *et al.*, 2012; Caine, 2016). Therefore, the statistical approaches employed in this section provide a reliable foundation for analysing the interrelationships between variables in the iSight prototype user experience study. The following nonparametric methods were utilized:

- Spearman's Rank Correlation: employed to measure the strength and direction of the monotonic relationship between two ordinal variables; this test is helpful in determining whether an increase in one variable is associated with an increase or decrease in another variable.
- Mann-Whitney U Test: this test serves as a nonparametric alternative to the independent samples t-test, comparing the differences in distributions between two independent groups. It assesses whether the central tendencies of the groups differ significantly.
- Fisher's Exact Test: utilized for examining the relationships between categorical variables in contingency tables, particularly with small sample sizes and it is an alternative to the chi-square test when the expected frequencies are lower than 5 in any of the cells of a contingency table. It

is commonly used for 2x2 tables, but it can be extended to larger tables, though it becomes computationally intensive.

- **Qualitative Data Analysis:** This method involves the systematic examination of non-numeric data, such as open-ended questionnaire responses. It aims to identify recurring patterns, themes, and insights, thus providing a deeper understanding of user experiences and perceptions.

Given the mixed nature of the data, a mixed-methods approach – integrating both qualitative and quantitative analyses – was adopted. This comprehensive strategy allows for a robust examination of statistical relationships while simultaneously capturing the contextual nuances provided by the participants.

DI: Correlation between ease of navigation, overall ease of use of the prototype and satisfaction

This analysis aims to investigate the relationships between the ease of navigation (QIV.1) within the iSight prototype's mobile application, the user satisfaction (QIV4) and the overall ease of use of the prototype (QV.1). This study explores how these factors interact to influence user satisfaction, providing valuable insights for the enhancement of assistive technologies. To assess these relationships, the following hypotheses were formulated:

- **DI.1:** There is an association between ease of navigation and overall satisfaction.
- **DI.2:** There is an association between the overall ease of use of the prototype and overall satisfaction.

To test these hypotheses the Fisher's Exact Test for Independence was employed. The results for Fisher's Exact Test are summarized in the Table 6.1.

Table 6.1: Fisher's Exact Test results for associations with overall satisfaction.

Hypothesis	Chi-Square	Fisher's Exact Test (2-sided)	Significance Level	Result
DI.1: Ease of Navigation <i>vs.</i> Satisfaction	3.750	0.101	0.05	Not significant
DI.2: Ease of Use <i>vs.</i> Satisfaction	0.536	0.608	0.05	Not significant

For Hypothesis DI.1, Fisher's Exact Test yielded a 2-sided p-value of 0.101, which is above the 0.05

significance level. This result indicates that there is no statistically significant association between ease of navigation and overall satisfaction. Therefore, it can be concluded that the observed differences are likely attributable to random variation rather than a systematic relationship between the variables.

For Hypothesis DI.2, the 2-sided p-value is 0.608, indicating no statistically significant association between the overall ease of use of the prototype and overall satisfaction. The high p-value suggests that the relationship between these variables is weak and not significant, implying that the overall ease of use does not significantly impact user satisfaction within this sample. These findings suggest that while the mobile application meets user expectations and satisfaction levels, the analysis shows that there is no statistically significant association between the overall ease of use of the prototype (including both the mobile application and the wardrobe) and overall satisfaction with the mobile application. This means that, while the introduction of the wardrobe did not show a clear relationship with overall user satisfaction, it cannot be concluded that it worsened the experience either. The data indicate that there is no significant correlation between these variables in the studied sample.

To further explore the relationships between ease of navigation, overall ease of use, and satisfaction, Spearman's Rank Correlation coefficients were calculated as demonstrated in Table 6.2. These analyses aim to measure the strength and direction of the associations between these variables.

Table 6.2: Spearman's rank correlation results.

Relationship	Spearman's Correlation Coefficient (ρ)	p-value	Significance Level	Interpretation
DI.1: Ease of Navigation <i>vs.</i> Satisfaction	0.500	0.058	0.05	Moderate positive correlation, not significant
DI.2: Ease of Use <i>vs.</i> Satisfaction	0.189	0.500	0.05	Weak positive correlation, not significant

For the relationship between Ease of Navigation and Overall Satisfaction, Spearman's correlation coefficient is 0.500, with a p-value of 0.058. This indicates a moderate positive correlation that is not statistically significant at the 0.05 level. This suggests a positive trend where participants who find the prototype easier to navigate tend to report higher overall satisfaction, but the current sample size does not provide strong enough evidence to confirm its significance. Regarding the relationship between Overall

Ease of Use of the Prototype and Overall Satisfaction, the Spearman's correlation coefficient is 0.189, with a p-value of 0.500. This weak correlation is not statistically significant, suggesting that the overall ease of use does not have a significant impact on user satisfaction within this sample.

The analysis reveals a moderate positive correlation between ease of navigation and overall satisfaction, though not statistically significant. This finding emphasizes the need for intuitive and user-friendly navigation within the mobile application to enhance user satisfaction. The close-to-significant result from Fisher's Exact Test for ease of navigation indicates that navigation improvements could lead to higher satisfaction levels among users, warranting further exploration with a larger sample size to validate this trend. Conversely, the weak and non-significant correlation between overall ease of use and overall satisfaction suggests that factors other than ease of use might be more crucial in determining user satisfaction. Again, while ease of use is a valuable component, it may not be the primary determinant of satisfaction, suggesting the necessity for a broader approach to design improvements that considers multiple aspects influencing user experience.

The literature supports the idea that ease of use and navigation are critical factors influencing user satisfaction with assistive technologies. Studies consistently show that users who feel informed and involved in the selection process report higher satisfaction (Martin *et al.*, 2011; Ranada and Lidström, 2019). This is directly relevant to the findings of this study, which suggest a moderate positive correlation between ease of navigation and overall satisfaction, although not statistically significant. The literature indicates that ease of navigation and user-friendly interfaces can lead to higher user satisfaction, reinforcing the trend observed in this study. Moreover, accessibility features and usability in mobile applications, as highlighted by Christy and Pillai (2021) and Darvishy (2014), underscore the importance of intuitive design and user-friendly interfaces. These studies emphasize that while app updates and interface designs aim to improve user experience, they sometimes inadvertently introduce new accessibility challenges, such as incompatibility with screen readers and navigation (Santos *et al.*, 2024; Zaina *et al.*, 2022). These issues resonate with the findings that emphasize the importance of intuitive and user-friendly navigation within the mobile application, even though the correlation between navigation ease and satisfaction was not statistically significant in this study.

The non-significant results in this study could be attributed to the small sample size, which may have limited the statistical power to detect true associations. This is a common challenge in assistive technology research, where specific populations often result in limited sample sizes. Additionally, individual variability in perceptions and experiences with the iSight prototype may have contributed to the non-significant findings. Users' differing levels of technological experience, personal preferences, and specific needs

introduce variability that can dilute the overall effect.

In summary, the literature supports the importance of ease of navigation and user-friendly design in enhancing user satisfaction with assistive technologies. The findings of this study, while not statistically significant, are consistent with broader research trends and suggest that improvements in navigation and overall usability could lead to higher satisfaction levels. Future research should consider larger sample sizes and further explore these relationships to validate and expand upon these findings.

D2: Impact of technology familiarity on ease of navigation and overall experience

This analysis aims to investigate whether participants' comfort with technology (QIII.2) significantly impacts their ease of navigation (QIV.1) and overall experience with the iSight prototype (QIV.4). The data were regrouped into two categories for comfort with technology: "very comfortable" and "comfortable." Responses outside these groups were not considered. Two hypotheses were analysed for this purpose:

- **D2.1:** Different levels of comfort with technology result in different ease of navigation level.
- **D2.2:** Different levels of comfort with technology result in different overall experience level.

To test these aspects, a statistical analysis was conducted using the Mann-Whitney test to compare differences between the two independent groups. The results for each hypothesis are summarized in the Table 6.3.

Table 6.3: Mann-Whitney testing results for ease of navigation and overall experience across different levels of comfort with technology.

Hypothesis	Mann-Whitney U	p- value	Significance Level	Result
D2.1: Ease of Navigation <i>vs.</i> Comfort with Technology	11.00	0.044	0.05	Significant
D2.2: Overall Experience <i>vs.</i> Comfort with Technology	12.00	0.047	0.05	Significant

For both aspects D2.1 and D2.2, the p-values are below the 0.05 significance level, indicating statistically significant differences. The results from the Mann-Whitney test demonstrate that participants' comfort with technology significantly impacts both their ease of navigation and overall experience with the iSight prototype. Specifically, those who are very comfortable with technology tend to rate their ease of navigation and overall experience significantly higher. While all participants generally rated their satisfaction positively, those being very comfortable with technology tended to give the highest possible ratings. These

findings highlight the importance of considering users' familiarity and comfort with technology when designing assistive devices. By addressing the needs of users with varying levels of technological comfort, developers can create more inclusive and user-friendly products.

These findings align with previous research suggesting that familiarity with technology enhances usability and user satisfaction (S. Bhatt *et al.*, 2018; McLellan *et al.*, 2012). For instance, (McLellan *et al.*, 2012) found that users with more technology experience provided higher usability ratings, supporting the idea that comfort with technology is crucial for positive user experiences. Similarly, Bhatt *et al.* (2018) showed that while traditional survey measures might not capture differences in user evaluations, behavioural and neurophysiological measures revealed that comfort with technology significantly influences usability experiences.

To further explore the relationships between technology familiarity and the two variables—ease of navigation and overall experience—Spearman's rank correlation coefficients were calculated using the original data without grouping. The results of these analyses are presented in Table 6.4.

Table 6.4: Spearman correlation analysis results for technology familiarity with ease of navigation and overall experience.

Relationship	Spearman's Correlation Coefficient (ρ)	p- value	Significance Level	Interpretation
D1.1: Comfort with Technology vs. Ease of Navigation	0.572	0.026	0.05	Moderate positive correlation, statistically significant
D2.2: Comfort with Technology vs. Overall Experience	0.627	0.012	0.05	Strong positive correlation, statistically significant

For the analysis labelled D1.1, the Spearman correlation coefficient of 0.572 indicates a moderate positive correlation between comfort with technology and ease of navigation. The p-value of 0.026 suggests that this correlation is statistically significant at the 0.05 level. This finding implies that participants who are

more familiar with technology tend to have better ease of navigation with the iSight prototype. This is consistent with literature highlighting the role of technological familiarity in enhancing navigation and interaction with assistive devices, even though the (Marie-Élise Prémont Claude Vincent & Routhier, 2020) Claude Vincent & Routhier, 2020) discussed how familiarity with geospatial assistive technologies improves usability for wheelchair users, and (Arditi & Tian, 2013) emphasized the importance of user-friendly interfaces in navigation aids for visually impaired users. Both studies underscore the broader principle that technological familiarity enhances user experience and usability.

For the analysis labelled D2.2, the Spearman correlation coefficient of 0.627 indicates a strong positive correlation between comfort with technology and overall experience. The p-value of 0.012 confirms this correlation as statistically significant. This finding implies that participants who are more familiar with technology tend to have a better overall experience with the iSight prototype. This aligns with studies showing that users with higher technological comfort and experience often report better overall satisfaction and ease of use. As highlighted by (Czaja & Sharit, 1998), experience with computers leads to more positive attitudes across multiple dimensions such as comfort, efficacy, and control. Although their study focused on computer use, the underlying principle that technological experience enhances user comfort and perceptions is equally applicable to mobile applications. Similarly, (Goeke *et al.*, 2016) emphasize that expertise, rather than mere experience, significantly enhances ease-of-use perceptions and effective technology utilization.

In summary, these results underscore the importance of considering users' comfort with technology when designing and implementing assistive devices. Both ease of navigation and overall experience are significantly influenced by technological familiarity, highlighting the necessity of enhancing user experience by accommodating various levels of technological familiarity. Developers should prioritize user-centred design approaches and integrate features that are intuitive and easy to learn, as supported by findings from (Tizneem Jiancaro & Mihailidis, 2017) and (Vishnu Nair Greg Olmschenk & Zhu, 2022). Vishnu Nair Greg Olmschenk and Zhu (2022) demonstrated the effectiveness of personalized interfaces and multimodal feedback in improving navigational guidance, safety, and accuracy for visually impaired users. Tizneem Jiancaro and Mihailidis (2017) emphasized the importance of considering learnability, self-confidence, and usability in technology adoption, advocating for a user-centred design approach. Thus, by addressing the needs of users with varying levels of technological comfort, developers can create more inclusive and user-friendly products, ultimately improving the quality of life for visually impaired individuals.

D3: Effectiveness of the iSight prototype in identifying features

This section evaluates the effectiveness of the iSight prototype in identifying various features of clothing items, including categories, colours, stains, and NFC tags (QV.2 and QV.3). Data collected from participants provides insights into the prototype's accuracy and effectiveness in these areas. The analysis focuses on understanding the consistency and agreement in participants' ratings of the iSight prototype's performance across different functionalities.

To quantify the relationships and agreements between participants' ratings for different functionalities, Spearman's Rank Correlation was employed to measure the ordinal correlation between these functionalities. This test helps determine if higher ratings in one functionality (*e.g.*, identifying colours) are associated with higher ratings in another functionality (*e.g.*, detecting stains). Table 6.5 summarizes the Kendall's Tau-b correlation results between different functionalities of the iSight prototype.

Table 6.5: Spearman's correlation results between different functionalities of the iSight prototype.

Relationship	Spearman's Correlation Coefficient (ρ)	p- value	Interpretation
Identifying Colours and Detecting Stains	0.294	0.287	Weak positive association, not statistically significant.
Identifying Colours and Identifying NFC Tags	0.294	0.287	Weak positive association, not statistically significant.
Identifying Colours and Categories	0.612	0.015	Moderate positive association, statistically significant.
Identifying Categories and Detecting Stains	0.480	0.070	Moderate positive association, not statistically significant.
Identifying Categories and Identifying NFC Tags	0.480	0.070	Moderate positive association, not statistically significant.
Identifying NFC Tags and Detecting Stains	0.423	0.116	Weak positive association, not statistically significant.

The correlation between the accuracy in identifying colours and the effectiveness in detecting stains is 0.294, suggesting a weak positive association. However, the p-value of 0.287 indicates that this association is not statistically significant at the 0.05 level. Similarly, the correlation coefficient of 0.294 between the accuracy in identifying colours and the effectiveness in identifying NFC tags also denotes a weak positive association, but with a p-value of 0.287, it is not statistically significant. Moreover, the correlation between the accuracy in identifying colours and the accuracy in identifying categories is 0.612,

indicating a moderate positive association. The p-value of 0.015 for this pair implies that the association is statistically significant at the 0.05 level, which suggests that improvements in the iSight prototype's ability to identify colours are associated with improved accuracy in identifying clothing categories. For the association between the accuracy in identifying categories and the effectiveness in detecting stains, the correlation coefficient is 0.480. This represents a moderate positive association, but not statistically significant, since the p-value is 0.070. The same correlation coefficient of 0.480 is observed between the accuracy in identifying categories and the effectiveness in identifying NFC tags. Again, the p-value of 0.070 also indicates a lack of statistical significance. Finally, the correlation between the effectiveness in identifying NFC tags and the detection of stains is 0.423, suggesting a weak positive association. The p-value of 0.116 shows that this association is not statistically significant.

In summary, the moderate positive and statistically significant association between the accuracy in identifying colours and the identification of categories highlights an area where the iSight prototype excels. The weak and non-significant associations between other functionalities suggest that while there are positive trends, these relationships are not strong enough to be statistically confirmed with the current sample size. These findings provide valuable insights into how the various functionalities of the iSight prototype are interrelated and where targeted improvements could enhance its overall performance. Thus, the iSight prototype demonstrates high effectiveness in identifying categories and colours, detecting stains, and identifying NFC tags. The significant association between accuracy in identifying colours and categories suggests that enhancing one of these functionalities could potentially improve the other. However, further research with larger sample sizes is needed to confirm the observed trends in other functionalities.

D4: Frequency of technology use and comfort level

This study explores the relationship between the comfort level with technology (QIII.2) and the frequency of technology use (QIII.3) among participants. Understanding this relationship is crucial for designing and implementing effective assistive technologies, as frequent use and higher comfort levels can significantly impact the adoption and usability of such technologies. Spearman's Rank Correlation was employed to assess the strength and direction of the association between the frequency of technology use and comfort level, resulting in the following hypothesis:

- **D4.1:** There is a correlation between the frequency of technology use and comfort level.

The results are described in Table 6.6.

Table 6.6: Spearman's rank correlation results for frequency of technology use and comfort level.

Relationship	Spearman's Correlation Coefficient (ρ)	p- value	Significance Level	Interpretation
D4.1: Comfort with Technology vs. Frequency of Technology Use	0.488	0.065	0.05	Moderate positive correlation, not significant.

The Spearman correlation coefficient of 0.488 indicates a moderate positive correlation between the frequency of technology use and comfort level. However, the obtained p-value of 0.065 indicates that this correlation is not statistically significant, suggesting a positive trend where increased frequency of technology use is associated with higher comfort levels. Still, the current sample size does not allow confirming this relationship definitively.

These findings align with previous research suggesting that familiarity and frequent interaction with technology enhance comfort levels and usability. Tizneem Jiancaro and Mihailidis (2017) emphasize the importance of user-centred design and technological familiarity, highlighting that factors like learnability and self-confidence are crucial when designing assistive technologies. This supports the idea that frequent use, which improves familiarity, can enhance comfort and usability. Vishnu Nair Greg Olmschenk and Zhu (2022) demonstrate that personalized interfaces and multimodal feedback can significantly improve user experience, safety, and accuracy in navigation for visually impaired users, suggesting that frequent interaction with well-designed assistive technologies can enhance comfort and confidence. Gagnon-Roy *et al.* (2021) discuss the importance of continuous user experience evaluations in improving the usability and acceptability of assistive technologies, indicating that regular use and feedback loops can enhance user comfort over time. Singh & Gupta (2023) note that familiarity with assistive technologies varies among users, with some devices being more widely understood than others, highlighting the need for frequent use to build comfort and proficiency. Agarwal & Prasad (1999) discuss how individual differences, such as personal innovativeness, affect beliefs and attitudes towards new technologies, suggesting that frequent use can help bridge these differences by increasing familiarity and comfort.

The moderate positive correlation observed between the frequency of technology use and comfort level implies that participants who use technology more frequently tend to be more comfortable with it. However, the p-value of 0.065 indicates that this finding is not statistically significant, suggesting that while there is a positive trend, it cannot be conclusively established with the current sample size.

In summary, these findings emphasize the importance of encouraging frequent use of technology to

enhance comfort levels among users, which can lead to more successful adoption and utilization of assistive technologies like the iSight prototype. The moderate, yet not statistically significant, Spearman's correlation suggests that further research with a larger sample size is necessary to confirm the observed trend. Future studies should consider larger sample sizes and additional variables to further explore this relationship and its implications for the design and implementation of assistive technologies.

D5: Relationship between iSight's functionalities and users' confidence, self-esteem, well-being, and independence

This study examines the impact of the iSight prototype on inclusion and confidence among participants. Specifically, it explores how the functionality of iSight in facilitating the selection of clothing, identifying characteristics and modifications, and organizing clothing, correlates with increases in confidence, self-esteem, well-being, and independence. Understanding these relationships is essential for developing assistive technologies that not only improve practical aspects of users' lives but also enhance their overall sense of inclusion and confidence. Participants' responses regarding the functionality of iSight (QV.1) and their perceived increase in confidence, self-esteem, well-being, and independence (QV.2) were analysed. The functionality of iSight was measured by responses to the questions about how well iSight facilitates the selection of clothing, identifies characteristics and modifications, and organizes clothing. In this context, the following hypothesis was formulated:

- **D5.1:** There is a correlation between the functionality of iSight in facilitating clothing selection, identifying characteristics and modifications, and organizing clothing, and increased confidence, self-esteem, well-being, and independence.

Spearman's Rank Correlation was used to assess the strength and direction of the association between these variables. The results are summarized in Table 6.7.

Table 6.7: Spearman's rank correlation results for iSight functionality and increased confidence, self-esteem, well-being, and independence.

Relationship	Spearman's Correlation Coefficient (ρ)	p- value	Significance Level	Interpretation
iSight Functionality vs. Increased Confidence, Self-esteem, Well-being, and Independence	0.700	0.004	0.01	Strong positive correlation, significant.

The Spearman correlation coefficient of 0.700 indicates a strong positive correlation between iSight's functionality in facilitating clothing selection, identifying characteristics and modifications, and organizing clothing, and increased confidence, self-esteem, well-being, and independence. The p-value of 0.004 is well below the 0.01 significance level, indicating that this correlation is statistically significant. This result suggests that participants who perceive significant improvements in their quality of life due to iSight also report higher levels of confidence, self-esteem, well-being, and independence. Additionally, a Fisher's Exact test was performed to examine the association between the perceived functionality of iSight and the reported increases in confidence, self-esteem, well-being, and independence. The results are presented in Table 6.8.

Table 6.8: Fisher's Exact test results for iSight functionality and increased confidence, self-esteem, well-being, and independence.

Hypothesis	Chi-Square	Fisher's Exact Test (2-sided)	Significance Level	Result
D5.1: iSight Functionality <i>vs.</i> Increased Confidence, Self-esteem, Well-being, and Independence	7.350	0.017	0.05	Significant

The Fisher's Exact test results reveal a statistically significant association between the perceived functionality of iSight and the reported increases in confidence, self-esteem, well-being, and independence. The Fisher's Exact value of 0.017, along with other significant test results, corroborates the findings from the Spearman's Rank Correlation, further emphasizing the importance of the iSight functionalities in enhancing these psychological and emotional aspects of users' lives. Notably, users who perceive the iSight's functionalities as highly important are the ones who report greater increase in confidence, self-esteem, well-being, and independence.

The significant positive correlation (Spearman's $\rho = 0.700$, $p = 0.004$) and the significant Fisher's Exact Test result ($p = 0.017$) highlight the importance of designing assistive technologies that not only address functional needs but also contribute to users' overall psychological and emotional well-being. Technologies that enhance quality of life can play a crucial role in fostering a sense of inclusion and confidence among users, thereby improving their overall life satisfaction and independence.

To support these findings, existing literature underscores the role of assistive technologies in enhancing the self-confidence and self-esteem of visually impaired individuals. Ghafoor *et al.* (2023) highlight that assistive technologies improve social interactions, communication skills, and overall quality of life.

Shinohara & Wobbrock (2016) emphasize that well-designed assistive technologies positively impact self-efficacy and social inclusion. Furthermore, Kinoe and Noguchi (2014) indicate that assistive technologies help visually impaired individuals manage their appearances, which is crucial for building self-confidence. Keshky & yacoub Mohammed (2017) discuss how positive thinking and behavioural therapies, combined with assistive technologies, can further enhance self-esteem. Research indicates that assistive technologies have a significant positive impact on users' self-esteem and confidence in daily activities. Rigby *et al.* (2005) and van Dam *et al.* (2023) show that the use of assistive technologies enhances functional abilities, independence, and psychosocial well-being. Nemek (2021) found that regular sport participation among assistive technology users is associated with higher self-esteem compared to non-participants. Martins *et al.* (2016) note that assistive technologies contribute to increased feelings of competence, adaptability, and self-esteem. Moreover, assistive technologies significantly enhance the independence and autonomy of visually impaired individuals across various aspects of life. Sivan and Darsan (2016) and Biswas *et al.* (2024) highlight the role of computer vision-based systems and real-time object detection in improving navigation and obstacle detection. Ang *et al.* (2016) describe how mobile applications and portable devices, such as the SmartGuide system, further aid independent mobility. Further, assistive technologies significantly impact the ability of visually impaired individuals to perform daily living activities independently. For instance, van Dam *et al.* (2023) emphasize that assistive technologies enable users to execute activities of daily living and increase perceived independence by providing choice, control, and security.

In conclusion, these findings accentuate the critical role of assistive technologies like the iSight prototype in enhancing both the practical and emotional aspects of users' lives. By focusing on improvements in quality of life, developers can create technologies that significantly boost confidence, self-esteem, well-being, and independence among users. Future research should continue to explore these relationships with larger sample sizes and additional variables to further validate and expand upon these findings.

D6: Suggestions for improvement and overall satisfaction

To further explore the nature of the feedback, all comments provided by the users were transcribed uniformly and merged across all open-ended questions. This was done to ensure that duplicate suggestions from different questions were counted only once. The comments were then categorized into common themes, and their frequencies were recorded as stated in Table 6.9. When translating quotations from Portuguese to English for analysis, it is crucial to maintain the accuracy and integrity of the original meaning. It is essential to balance fidelity to the original text with clarity and readability in the translated

version to ensure that the analysis remains valid and meaningful. Special care was taken in translating the comments to preserve the authenticity of the participants' responses and to ensure that the nuances of the feedback were correctly interpreted.

Table 6.9: Thematic analysis of user feedback for the iSight prototype.

Category	Frequency	Example Comments	Translated Comments
Performance Improvements	2	<i>“Está aqui uma ideia muito interessante para usarmos no dia a dia. Apenas colocaria menos menus de forma a ser mais rápido.”</i> <i>“A aplicação é útil mas gostava que fosse mais rápida na escolha, isto é, ter menos menus.”</i>	“This is a very interesting idea for daily use. I would just add fewer menus to make it faster.” “The application is useful but I would like it to be faster in making choices, that is, to have fewer menus.”
Feature Enhancements	5	<i>“Colocar informação como tecido da roupa.”</i> <i>“Ler as características da etiqueta como: lavagem, temperatura de engomar e se pode ir à lixívia.”</i> <i>“Verificar o tipo de tecido da roupa.”</i> <i>“Verificar se existe a troca de sapatos em modelos semelhantes.”</i> <i>“Aplicação útil, pois, tenho baixa visão e antes de usar para mim a roupa era branca e só depois com ajuda da aplicação é que vi que era amarela.”</i>	“Include information such as the fabric of the clothing.” “Read label characteristics such as: washing instructions, ironing temperature, and whether it can be bleached.” “Check the type of fabric of the clothing.” “Check if there is a mix-up of shoes in similar models.” “Useful application because I have low vision and before using it, the clothes looked white to me, but with the help of the application, I saw they were yellow.”
Localization Improvements	1	<i>“Seria interessante saber a localização da nódoa na peça de roupa.”</i>	“It would be interesting to also know the location of the stain on the piece of clothing.”
General Positive Feedback	10	<i>“Com isto já me podia vestir sozinha. É muito útil.”</i> <i>“Está uma boa ideia, ou seja, inovadora. Seria bom utilizar isto todos os dias.”</i> <i>“É uma ferramenta muito útil e inovadora.”</i> <i>“Ferramenta muito útil. Para nódoas que vão para a máquina e acabam por não</i>	“With this, I could dress myself. It is very useful.” “It is a good idea, innovative. It would be good to use this every day.” “It is a very useful and innovative tool.” “Very useful tool. For stains that go into the washing machine and do not come out, it is extremely useful. Innovative and very

<i>sair, acaba por ser extremamente útil.</i>	good idea.”
<i>Ideia inovadora e muito boa.”</i>	“It is useful, I would like the prototype to
<i>“É útil, gostaria que no futuro o protótipo</i>	become a reality in the future, that is,
<i>fosse uma realidade, ou seja,</i>	commercialized and accessible to the
<i>comercializado e estivesse acessível para</i>	community. The idea of the prototype is
<i>a comunidade. A ideia do protótipo é</i>	innovative and well-organized.”
<i>inovadora e está bem organizado.”</i>	“A very innovative and useful idea with a lot
<i>“Uma ideia muito inovadora e útil e com</i>	of potential. I would like the prototype to be
<i>muito potencial. Gostava que o protótipo</i>	commercialized and in the future adapted
<i>possa ser comercializado e no futuro se</i>	to any common wardrobe.”
<i>adaptar a qualquer guarda-roupa</i>	“If it is easy to have this system at home, I
<i>comum.”</i>	would like to have it as it would be useful
<i>“Se for fácil ter este sistema em casa,</i>	in my daily life. I have already worn clothes
<i>gostava de ter já que seria útil no meu dia</i>	with stains and with this, I would detect
<i>a dia. Já me aconteceu utilizar roupa com</i>	them.”
<i>nódoas e com isto já detetava.”</i>	“Although it is not easy for me to use a
<i>“Apesar de não ser fácil ainda para mim</i>	mobile phone, it was very easy to use the
<i>mexer no telemóvel, foi muito fácil utilizar</i>	application. I would like to have this
<i>a aplicação. Gostaria de ter esta aplicação</i>	application on my phone.”
<i>no meu telemóvel.”</i>	“The idea of the prototype is very
<i>“A ideia do protótipo é muito inovadora e</i>	innovative and useful.”
<i>útil.”</i>	“It is an excellent idea, innovative because
<i>“É uma excelente ideia, inovadora dado</i>	I don’t know nothing like it. It will be very
<i>que não conheço nada assim. Será muito</i>	useful to use this when it will be available.”
<i>útil utilizar isto quando estiver disponível.”</i>	

The analysis of Table 6.9 highlights several common themes and areas for improvement as suggested by the participants. In the “*performance improvements*” category, comments emphasized the need for a faster and more streamlined user experience. Users suggested reducing the number of menus to enhance the application's speed and efficiency. Comments such as “*This is a very interesting idea for daily use. I would just add fewer menus to make it faster.*” and “*The application is useful but I would like it to be faster in making choices, that is, to have fewer menus.*” underline a clear demand for optimizing the navigation process. In the “*feature enhancements*” category, participants provided multiple suggestions that aimed at expanding the application's functionality. These include adding detailed information about clothing fabrics, such as care labels (e.g., washing instructions, ironing temperature), and verifying fabric types. Comments like “*Include information such as the fabric of the clothing.*” and “*Read label*

characteristics such as: washing instructions, ironing temperature, and whether it can be bleached." suggest specific features that would significantly increase the utility of the application. Additionally, there were suggestions to check for the interchangeability of similar shoe models and to verify the type of fabric, as noted in *"Check the type of fabric of the clothing."* and *"Check if there is a mix-up of shoes in similar models."*

The *"localization improvements"* category includes feedback on the need for more precise identification of stain locations on clothing. A participant mentioned, *"It would be interesting to also know the location of the stain on the piece of clothing,"* indicating that this feature could enhance the application's practical utility for users dealing with stained garments. *"General positive feedback"* was the most frequent category, with numerous comments expressing satisfaction with the iSight prototype. Many users praised its usefulness and innovative approach. For instance, comments like *"With this, I could dress myself. It is very useful."* and *"It is a very useful and innovative tool."* reflect a high level of appreciation for the prototype's potential. Several participants also mentioned their eagerness for the prototype to be commercialized and to be made available to the public, highlighting its perceived impact on daily life. This sentiment is echoed in comments such as *"It is an excellent idea, innovative because I don't know nothing like it. It will be very useful to use this when it will be available."* and *"A very innovative and useful idea with a lot of potential. I would like the prototype to be commercialized and, in the future, adapted to any common wardrobe."* Overall, the feedback indicates a strong positive reception towards the iSight prototype, with suggestions for performance improvements, additional features, and better localization functionality. The enthusiastic response highlights the prototype's potential as a valuable tool in everyday life. Future development should prioritize enhancing the application's speed, simplifying the user interface, and incorporating more detailed clothing information to further increase user's satisfaction and functionality. A word cloud is depicted in Figure 6.7. The larger the words in the word cloud, the more frequently they were repeated.



Figure 6.7: Word cloud summarizing the visually impaired users' feedback.

The received feedback points out the iSight prototype's promising potential as a transformative tool for visually impaired people. It was well-received for its current capabilities and innovation, with users expressing a clear desire for its future development and wider availability. Moving forward, focusing on user-driven improvements such as optimizing the application's speed, incorporating additional features, and improving stain localization, will be crucial. These refinements will not only enhance user satisfaction but will also ensure that the iSight prototype will meet the diverse and evolving needs of its target audience. As the prototype evolves, maintaining a user-centered approach will be essential to its success and integration into the daily lives of those it aims to support.

D7: Comparative analysis of feedback and satisfaction between users with low vision and users who have always been blind

This study investigates whether there are significant differences in feedback and overall satisfaction between two groups of visually impaired users: those with low vision and those who have always been blind. Understanding these differences is essential for tailoring assistive technologies like the iSight prototype to better meet the diverse needs of visually impaired users. The analysis employs statistical methods, including the Chi-square test for independence and content analysis, to identify patterns in user feedback and satisfaction related to their visual impairment status. Participants were divided into two groups based on their visual impairment status: blind and low vision. Feedback was collected through

structured interviews and open-ended questions, providing both qualitative and quantitative data on their experience with the iSight prototype.

The collected feedback was meticulously transcribed and categorized into common themes: performance improvements, feature enhancements, localization improvements, and general positive feedback. The frequency of comments within these categories was recorded and compared between the two user groups (Table 6.10).

Table 6.10: Distribution of feedback categories by visual impairment type.

Category	Blind	Low Vision
Performance Improvements	2	0
Feature Enhancements	1	5
Localization Improvements	0	1
General Positive Feedback	6	5

Additionally, to provide a visual representation of the feedback, word clouds were generated for each group. These word clouds, Figure 6.8 and Figure 6.9, respectively, highlight the most common terms used by participants, offering insight into their primary concerns and points of interest.



Figure 6.8 - Word cloud summarizing the feedback of blind users.



Figure 6.9 - Word cloud summarizing the feedback of low vision users.

The analysis of the received feedback reveals distinct differences in the usability preferences and needs of blind users compared to those with low vision, as summarized in Table 6.11.

Table 6.11: Usability preferences by visual impairment type.

Usability	Blind Users	Low Vision Users
Simplification and Speed	Preference for fewer menus and faster navigation. Example: "...fewer menus to make it faster."	Less emphasis on simplicity, more focus on additional features.
Confidence in Application	Trust in the prototype compared to other tools like Colorino. Example: "...I use Colorino but sometimes it does not give the correct colours."	Comments indicate appreciation for detailed functionalities but less focus on simplicity.

Blind participants frequently expressed a need for a simplified navigation structure and fewer menus, highlighting their preference for efficiency and ease of use. In contrast, users with low vision were more focused on additional features and detailed functionalities, such as identifying fabric characteristics and reading care labels.

The user feedback also reveals differing expectations regarding the adoption and future development of the iSight prototype, as shown in Table 6.12.

Table 6.12: Expectations for innovations and commercial adoption by visual impairment type.

Expectation	Blind Users	Low Vision Users
Adaptation and Daily Use	Viewed the iSight as an easily integrated, innovative tool for daily use. Example: "...very useful. It would be good to use this every day."	Valued the innovation but expected continuous improvements and enhancements before full adoption.
Impact on Routine	Perceived the prototype as having a significant impact on daily life. Example: "If it is easy to have this system at home, I would like to have it... very useful in my daily life."	Focused on practical use and personalized features.

Blind users expressed enthusiasm for integrating the iSight into their daily lives, once it becomes commercially available and accessible. They see the prototype as a tool that can significantly enhance their autonomy and quality of life. Conversely, users with low vision, while also recognizing the prototype's innovation, emphasized the need for ongoing development and refinement of functionalities to meet their specific needs before full adoption. The nature of improvement suggestions varied notably between the two groups, reflecting their unique priorities and concerns, as detailed in Table 6.13.

Table 6.13: Suggestions for improvement by visual impairment type.

Improvement Area	Blind Users	Low Vision Users
Performance and Simplicity	Focused on reducing complexity and enhancing performance. Example: "...I would add fewer menus to make it faster."	Focused on adding detailed functionalities. Example: "...read label characteristics such as: washing instructions, ironing temperature, and whether it can be bleached."
Feature Enhancements	Fewer suggestions for feature additions. Example: "...fewer menus to make it faster."	Numerous detailed suggestions, including fabric identification and stain localization. Example: "...I would like it to be faster in making choices, that is, to have fewer menus."

Blind participants primarily suggested simplifying the interface to improve navigation speed and reduce complexity, aligning with their preference for straightforward and intuitive usage. On the other hand, users with low vision provided more suggestions for adding detailed features and functionalities, such as reading care labels and identifying fabric types, indicating their focus on comprehensive and detailed information. The feedback from both groups reveals the significant potential impact of the iSight prototype on their daily lives, though their perspectives on its future use differ slightly, as presented in Table 6.14.

Table 6.14: Impact on daily life and future use by visual impairment type.

Impact and Future Use	Blind Users	Low Vision Users
Daily Integration	Believed the prototype would ease daily tasks and increase independence. Example: "...a very useful tool for daily use."	Saw the prototype as a specialized tool that could provide precise assistance. Example: "...for me the clothes looked white and only with the help of the application did I see they were yellow."
Overall Satisfaction	High satisfaction and readiness for future use. Example: "...a very innovative and useful idea."	Positive feedback but with an expectation of ongoing improvements. Example: "...innovative and well-organized."

Blind users generally reported high satisfaction and a readiness to incorporate the iSight into their daily routines, reflecting optimism about its potential benefits. Users with low vision also expressed positive feedback but indicated a need for continued enhancements and more specific functionalities to fully meet their expectations and needs. The content analysis revealed distinct priorities between the groups. Blind participants primarily suggested performance improvements, such as reducing the number of menus to increase the speed of the application. This indicates a preference for a more streamlined and efficient user experience among blind users. On the other hand, participants with low vision focused on feature enhancements. Their suggestions included adding detailed information about the clothing's fabric and care labels, such as washing instructions and ironing temperatures. This demonstrates that users with low vision are more interested in detailed functionalities of the application.

In summary, this comparative analysis highlights the distinct needs and preferences of blind users *versus* those with low vision in the design of assistive technologies. Blind users prioritize simplicity and efficiency, seeking a user-friendly interface with minimal complexity. In contrast, users with low vision tend to value detailed information and additional functionalities, aiming for a more comprehensive tool. For future development of the iSight prototype, balancing these differing needs is essential to create an inclusive and beneficial technology for all visually impaired users. The findings underscore the importance of recognizing the varied requirements of visually impaired users when developing assistive technologies. While blind users emphasize the need for simplicity and efficiency, low vision users demand detailed functionalities and specific information. Both groups express high overall satisfaction with the iSight prototype but have distinct areas for improvement that must be addressed to ensure comprehensive usability and adoption. Future developments should focus on refining the balance between simplicity and

detail, enhancing both the user experience and the practical utility of the iSight prototype. This study highlights the critical role of user feedback in guiding the iterative design process of assistive technologies, ensuring they meet the diverse needs of their intended users.

Chapter Summary

This section provides a comprehensive analysis of the questionnaire results, aiming to understand the iSight prototype's contribution to enhancing users' daily lives, particularly their confidence, self-esteem, well-being, and independence. The study involved 15 participants, predominantly belonging to older demographics, 60 % identifying themselves as female and 40 % as male. A significant majority (66.7 %) were aged 55 or above, and the educational qualifications varied widely, with a notable fraction (33.3 %) having completed only 4 years of schooling. Most participants (60 %) were retirees, highlighting the need to cater to an older demographics' specific needs. Participants reported diverse ages at which the onset of visual impairment occurred, with a significant number (33.3 %) being visually impaired since birth. The causes of visual impairment were split between congenital (40 %) and acquired (60 %) conditions, with *retinitis pigmentosa* being the most common (46.7 %). This information is crucial for tailoring the iSight prototype to meet the specific needs of users based on their experiences with visual impairment. The majority of participants (67 %) did not use applications dedicated to clothing management, indicating an opportunity for the iSight prototype. Among those who did, the Colorino device was the most common. The majority of participants were comfortable using technology, with 40% feeling very comfortable and 53.3% feeling somewhat comfortable. Technological device usage was high, with 93.3 % using devices daily. Participants rated their skills with assistive software from average to very high and believed that technology significantly improved their quality of life (93.3 %) and social/professional inclusion (93.3 %). All participants found technology beneficial for education or training, indicating a strong potential for the iSight prototype's adoption. Feedback on the iSight mobile application was overwhelmingly positive, with 66.7 % finding navigation easy and 33.3 % very easy. Image descriptions and textual alternatives received excellent ratings from 53.3 % of participants, and the clarity of textual content was well-received by 53.3 %. Overall user experience was highly rated, with 66.6 % very satisfied and 33.3 % just satisfied, suggesting that the application meets the high standards of accessibility required by the visually impaired community. The usability of the iSight prototype was highly rated, with 53.3 % finding it very easy to use and 46.7 % just easy. Accuracy in identifying clothing categories and colours was also highly rated, with 60 % and 80 % finding it very precise, respectively. The prototype's ability to detect stains and identify NFC tags was rated highly effective by 86.7 % of participants. These findings emphasize the prototype's effectiveness

and highlight areas for further refinement. Participants rated the iSight prototype quite high for its importance in facilitating clothing selection and organization, with 66.7 % strongly agreeing with its functionality. It was also perceived as significantly enhancing confidence, self-esteem, well-being, and independence, with 66.7 % strongly agreeing on all related statements. The importance of the prototype in identifying clothes, colours, and stains was uniformly recognized, with 66.7 % finding it extremely important. Most participants believed that the iSight prototype significantly improved their quality of life, with 80% indicating a great improvement. Feedback was highly positive, with suggestions for performance enhancements, additional features, and better localization functionality.

The comprehensive analysis of the user experience with the iSight prototype addressed revealed several important findings, highlighting the prototype's potential to significantly enhance the quality of life for visually impaired people, particularly those who are blind. Given the nature of the collected data, nonparametric statistical methods were employed, which are appropriate for small sample sizes and for data that do not adhere to a normal distribution. Qualitative analysis was employed to systematically examine non-numeric data, such as open-ended questionnaire responses, to identify recurring patterns, themes, and insights, thus providing a deeper understanding of user experiences and perceptions.

The obtained findings reveal several insights, indicating that the relationship between ease of navigation, overall ease of use, and user satisfaction, assessed using Fisher's Exact Test, showed no statistically significant associations. However, Spearman's Rank Correlation suggested a moderate positive correlation between ease of navigation and satisfaction, indicating a trend that demands further investigation. The impact of technology familiarity on ease of navigation and overall experience was significant. The Mann-Whitney U Test indicated that participants' comfort with technology significantly influenced both their ease of navigation and overall experience with the iSight prototype. Spearman's Rank Correlation confirmed this, showing moderate to strong positive correlations between technology familiarity and both ease of navigation and overall experience. The iSight prototype demonstrated high effectiveness in identifying clothing categories and colours, detecting stains, and identifying NFC tags. A significant correlation was found between the accuracy in identifying colours and categories, suggesting that enhancing one functionality could improve the other. The relationship between the frequency of technology use and comfort level showed a moderate positive correlation, though not statistically significant. This finding implies a positive trend where increased technology use is associated with higher comfort levels, suggesting the need for further research with a larger sample size to confirm this trend. Users provided valuable suggestions for enhancing the iSight prototype, focusing on performance improvements, additional features, and better localization functionalities. This points out the importance of considering

user feedback comprehensively to guide future developments and increase user satisfaction.

Table 6.15 provides a summary of user feedback and the corresponding affected components discussed in Chapter 4 and 5. This helps identify specific areas for improvement in the iSight prototype, focusing on performance enhancements and feature additions based on user suggestions.

Table 6.15: User feedback and corresponding affected components in chapter 4 and 5.

Category	Feedback/Suggestion	Chapter	Affected Component
Performance Improvements	"This is a very interesting idea for daily use. I would just add fewer menus to make it faster."	5	Mobile application interface
	"The application is useful but I would like it to be faster in making choices, that is, to have fewer menus."	5	Mobile application interface
Feature Enhancements	"Include information such as the fabric of the clothing."	4	AI algorithms (Fabric identification)
	"Read label characteristics such as: washing instructions, ironing temperature, and whether it can be bleached."	4	AI algorithms (Label detection and reading)
	"Check the type of fabric of the clothing."	4	AI algorithms (Fabric identification)
	"Check if there is a mix-up of shoes in similar models."	4	AI algorithms (Object recognition)
	"It would be interesting to also know the location of the stain on the piece of clothing."	4	AI Algorithms (Stain localization)

The comparative analysis between blind users and those with low vision revealed distinct differences in usability preferences and needs. Blind users prioritized simplicity and efficiency, expressing a preference for fewer menus and faster navigation. They also demonstrated high confidence in the iSight prototype compared to other tools like Colorino. In contrast, users with low vision focused on detailed functionalities, such as identifying fabric characteristics and reading care labels, emphasizing the need for continuous improvements and detailed features before full adoption. Both groups expressed high overall satisfaction with the iSight prototype but selected distinct areas for improvement, which need to be addressed to ensure comprehensive usability and adoption.

A strong positive correlation was found between the functionality of iSight and increase in users' confidence, self-esteem, well-being, and independence, underscoring the prototype's potential to significantly enhance these psychological and emotional aspects of users' lives. The iSight prototype

shows significant promise as an assistive technology for visually impaired users, particularly those who are blind. The findings of this study highlight the critical need to balance simplicity and detailed functionality in the design of such technologies to accommodate to the diverse needs of users. By addressing these needs, the iSight prototype can become a valuable tool that enhances the daily lives and independence of visually impaired people.

Although the iSight prototype was primarily designed for blind users, the inclusion of participants with low vision provided additional insights into the broader applicability of the technology. The conducted analysis indicated that while the prototype effectively meets the needs of blind users, it also holds potential benefits for those with low vision, suggesting that the iSight prototype could be adapted to serve a wider audience, further extending its impact and utility.

In conclusion, the iSight prototype has demonstrated significant potential to improve the quality of life of both blind users and those with low vision. The study's findings emphasize the importance of user-friendly design, the impact of technology familiarity, and the need for targeted improvements based on user feedback. As the prototype continues to develop, maintaining a user-centred approach will be essential for ensuring its success and integration into the daily lives of those it aims to support. Future research should continue to explore these relationships with larger sample sizes and additional variables to further validate and expand upon these findings.

Table 6.16 provides a comprehensive summary of the statistical tests conducted, the hypotheses tested, the results obtained, and the significance levels of the findings. This table serves as a quick reference for understanding the key outcomes of the analyses performed in this study.

Table 6.16: Summary of statistical tests, hypotheses, and results *[○○○ corresponds to “Not significant” and denotes none correlation/significance, while ●●● corresponds to “Significant” and denotes substantial impact/correlation].

Test/Analysis	Hypothesis	Result Summary	*Significance Level
Fisher's Exact Test	DI.1: Ease of Navigation vs. Satisfaction	Not significant ($p = 0.101$)	○○○
Fisher's Exact Test	DI.2: Ease of Use vs. Satisfaction	Not significant ($p = 0.608$)	○○○
Spearman's Rank Correlation	DI.1: Ease of Navigation vs. Satisfaction	Moderate positive correlation, not significant ($p = 0.500$, $p = 0.058$)	●●○
Spearman's Rank Correlation	DI.2: Ease of Use vs. Satisfaction	Weak positive correlation, not significant ($p = 0.189$, $p = 0.500$)	●○○

Mann-Whitney U Test	D2.1: Ease of Navigation vs. Comfort with Technology	Significant ($U = 11.00$, $p = 0.044$)	● ● ●
Mann-Whitney U Test	D2.2: Overall Experience vs. Comfort with Technology	Significant ($U = 12.00$, $p = 0.047$)	● ● ●
Spearman's Rank Correlation	D2.1: Comfort with Technology vs. Ease of Navigation	Moderate positive correlation, significant ($\rho = 0.572$, $p = 0.026$)	● ● ○
Spearman's Rank Correlation	D2.2: Comfort with Technology vs. Overall Experience	Strong positive correlation, significant ($\rho = 0.627$, $p = 0.012$)	● ● ●
Spearman's Rank Correlation	Identifying Colours and Identifying Categories	Moderate positive association, significant ($\rho = 0.612$, $p = 0.015$)	● ● ○
Spearman's Rank Correlation	Identifying Colours and Detecting Stains	Weak positive association, not significant ($\rho = 0.294$, $p = 0.287$)	● ○ ○
Spearman's Rank Correlation	Identifying NFC Tags and Detecting Stains	Weak positive association, not significant ($\rho = 0.423$, $p = 0.116$)	● ○ ○
Spearman's Rank Correlation	Comfort with Technology vs. Frequency of Technology Use	Moderate positive correlation, not significant ($\rho = 0.488$, $p = 0.065$)	● ● ○
Spearman's Rank Correlation	iSight Functionality vs. Increased Confidence, Self-esteem, Well-being, and Independence	Strong positive correlation, significant ($\rho = 0.700$, $p = 0.004$)	● ● ●
Fisher's Exact Test	iSight Functionality vs. Increased Confidence, Self-esteem, Well-being, and Independence	Significant ($p = 0.017$)	● ● ●

7 CONCLUSIONS AND FUTURE WORK

Chapter Overview

The following chapter presents the main conclusions obtained with the research described in this thesis and provides an outlook for the future development and use of the iSight prototype for visually impaired users, namely blind people.

6 Conclusions and Future Work

6.1 Conclusions

6.2 Future Work

7.1 Conclusions

Clothing management is one of the most significant challenges blind people face. To execute clothing-related tasks, blind people often rely on family or friends to help them managing their wardrobe, which can impact their independence and self-esteem. The research conducted in this PhD thesis fills a crucial gap in the literature by focusing on the specific needs of blind people for wardrobe management, leveraging advanced technologies such as computer vision and artificial intelligence. Current literature offers limited solutions tailored to assist those who are blind with clothing identification and organization. Many existing systems lack the sophistication required to provide accurate and detailed information about clothing. For instance, technologies for detecting clothing defects or accurately identifying garment types and colours are not widely available or sufficiently advanced to meet the needs of blind users. Additionally, many of these systems are not user-friendly or accessible enough for blind people to use them independently. The challenge addressed by this study was clearly identified by ACAPO, a Portuguese institution that promotes rehabilitation services and fosters independent living and satisfaction while preserving the self-esteem of visually impaired people. ACAPO's involvement highlights the practical necessity of developing tools that cater specifically to the unique requirements of blind people, particularly in managing their wardrobe.

The main goal of this work was to create a system able not only to identify clothing types and colours, but also able to detect clothing modifications, such as stains and holes, thus providing comprehensive support for daily dressing and wardrobe management. The present study aimed at developing an integrated tool combining a mechatronic system (smart wardrobe) with a mobile application that could help blind people managing their clothes, envisaging a significant improvement in their daily lives by increasing self-confidence, self-esteem, independence and well-being.

Based on this premise, the iSight prototype was developed: an automated wardrobe that allows automatically extracting properties of clothing items, as well as identifying defects. Therefore, this work bridges the gap by offering a robust and user-friendly solution that enhances the autonomy and confidence of blind people managing their clothing. The developed prototype integrates computer vision and artificial intelligence to provide accurate and detailed information about clothing items, including their type, colour, and condition. This technology enables blind people to independently select and organize their clothing, thereby improving their quality of life. The importance of this PhD work lies in its potential to significantly impact the daily lives of blind people. The collaboration with ACAPO and the AADVDB provided valuable

insights and feedback that were instrumental in refining the approach and ensuring that the developed system met the needs of its intended users. This collaboration also helped validating the effectiveness of the iSight prototype through real-world testing and user feedback.

In short, this work resulted in a novel solution for the pressing problem of wardrobe management faced by blind people. By leveraging advanced technologies, it was possible to develop a comprehensive and accessible tool - the iSight prototype. To accomplish this, the present work aimed to address specific key objectives, also referred in the first chapter. The main achievements and findings for each of these objectives are summarized below.

G1: Conduct a nationwide survey distributed by ACAPO to assess user interest, needs, and receptivity to the study.

This objective was accomplished by conducting a nationwide survey in collaboration with ACAPO, which was designed to assess user interest, needs, and receptivity of a garment management system for blind people. This assessment involved 26 participants, with 23 providing complete responses for analysis. The survey aimed to gather detailed insights to guide the development of the iSight prototype, ensuring it met the expectations and needs of blind users. The survey was distributed across all ACAPO delegations nationwide in Portugal, ensuring broad geographic coverage and inclusivity.

Participants covered diverse demographics, with a significant majority aged between 45 and 54 years old, being predominantly female. Educational backgrounds varied, with 43.5 % having higher education and 26.1% having, at least, nine years of secondary education. Participants highlighted the critical role of vision in understanding the world and they acknowledged the challenges faced during dressing without visual cues. A significant 73.9 % of respondents frequently sought help in buying clothes, mainly from family members or support professionals. All participants referred to do shopping at physical stores, with 39.1 % also engaging in online shopping. The survey also explored participants' familiarity with existing clothing identification technologies and the corresponding satisfaction upon its use. While 65.2 % were aware of such technologies, only 26.1 % expressed satisfaction with the available options. The majority used smartphones (89 %) and laptops (72 %), with iOS being the predominant operating system. Lastly, the survey investigated the interest and willingness of participants to adopt new technologies for clothing management. An overwhelming 91.3 % agreed on the need for a technology to manage clothing, and 95.7 % were willing to use such technology. Smartphones and laptops were identified as the preferred platforms for implementing this technology.

In conclusion, the survey conducted with ACAPO's blind associates indicated a strong demand for

improved technological solutions in this area, with high receptivity for innovative solutions. These insights have been instrumental in shaping the development of the iSight prototype, ensuring it addressed the specific needs and preferences of blind people. The positive feedback and enthusiasm for new technologies accentuated the importance of continuing this research and development work to enhance the daily of the visually impaired community.

G2: Develop an algorithm for the acquisition, processing, and analysis of images using AI to identify clothing types, colour and detect modifications.

The advanced analysis conducted for clothing type identification and stain detection allowed meeting this goal. Utilizing transfer learning benchmark results, a deep learning model was developed, demonstrating the ability to identify clothing type categories with an impressive F1-Score of up to 91 %, representing an improvement over state-of-the-art solutions for the used dataset. Augmented data showed potential to further enhance these results, although additional tests are necessary to determine the most effective type of data augmentation for the model. In the first experiment, the clothing type recognition was based on images of clothing worn by models, which introduced some limitations due to potential redundancy in categories. To address these limitations, the second experiment extended the first by introducing clothing segmentation. While the first experiment focused on image classification, the second one evaluated the problem as instance segmentation, refining predefined categories to accommodate different backgrounds and enabling the analysis of pixel colours as a result of segmentation. The used dataset is an enhancement and expansion of the one previously utilized, incorporating a refined selection of the most significant categories. In addition to refining the existing categories, new images were sourced from personal wardrobes and included diverse backgrounds to increase the dataset's robustness, merging images from datasets and personal wardrobes. With fine-tuning and data augmentation techniques, the YOLOv8s model effectively segmented various clothing categories, achieving high performance metrics across most categories. The overall performance of the model resulted in a precision of 0.941, a recall of 0.896, and an average precision (AP) for an intersection over union (IoU) of 0.5 of 0.965. These results indicate a high overall performance in segmenting masks, with precision reflecting a low percentage of false positives and recall indicating a low percentage of false negatives. High performance metrics were achieved for most categories, with jackets and shoes attaining near-perfect segmentation results. Nonetheless, there remains room for improvement in categories such as dresses and shorts, where recall rates could be enhanced. For colour analysis, the segmented region's mask was utilized to identify the colours present in the clothing item. The HSV colour space was employed, where nine essential colours

were defined, suiting the needs without detailed colour nuance differentiation.

Detection and classification of clothing defects were also successfully executed using a deep learning approach. An enhanced dataset was created in two iterations, incorporating new types of stains and holes. This dataset, which previously did not exist, was developed using clothing items from personal wardrobes, where various modifications, such as adding stains and creating holes, were deliberately made to enrich the dataset. Later, three experiments were conducted by fine-tuning three models from the YOLOv5 object detector, demonstrating that data augmentation was crucial for better model generalization, resulting in higher precision. Despite achieving maximum precision, recall, and average precision (AP) values of 0.915, 0.543, and 0.747, respectively, with the YOLOv5l6 model, the recall values suggested the need for further improvements to minimize false negatives. Detection of holes proved to be more challenging than stains, highlighting the importance of integrating these findings into an automatic wardrobe system capable of multiple cameras capture from different clothing perspectives. The developed dataset showed that object detection technology could accurately and autonomously detect and classify defects on clothing. This represents the foundational step for creating a mobile application that could effectively detect multiple clothing defects, integrating these findings into an automated wardrobe system as a future step.

In conclusion, the G2 objective was accomplished using computer vision and AI algorithms, whose accuracy was confirmed through user testing, with 60 % of the participants finding the system very precise in identifying clothing categories, and 80 % finding it very precise in identifying colours. The system's effectiveness was extended to the detection of stains, with 86.7 % of participants rating it as highly effective. Additionally, 86.7 % of participants rated the identification of NFC tags as highly effective. These high accuracy ratings across multiple functionalities indicate that the algorithm is not only accurate but also reliable, providing a valuable tool for blind people to independently manage their clothing. The high levels of satisfaction and effectiveness highlight the algorithm's practical applicability and potential to significantly enhance the daily lives of visually impaired users.

G3: Develop user-friendly and accessible software integrated with the wardrobe management system to effectively manage and store all garment characteristics.

This goal was accomplished by developing a software involving a graphical interface for smartphones that communicates with the smart wardrobe. This software was designed to be highly accessible and easy to use, complying with all accessibility standards. Participants rated highly the ease of navigation, with 66.7 % finding it easy, and 33.3% finding it very easy to navigate. The developed software also allows

users to manage their garments by storing detailed characteristics such as type, colour, and condition. It facilitates the navigation and organization of garments, providing an intuitive and satisfying user experience. Additionally, it includes complementary features, such as image descriptions and textual alternatives for visual elements, which were rated as excellent by 53.3 % of participants. The clarity and organization of the textual content was classified as very clear by 53.3 % of participants and as clear by 46.6 %. Overall user satisfaction with the software was high, with 66.6 % referring to be very satisfied and 33.3 % just satisfied. These ratings emphasize the importance of the software in daily clothing management, pointing out the fact of simultaneously being both functional and accessible.

G4: Develop and assemble a mechatronic system (smart wardrobe) prototype to test the proposed methodology.

A mechatronic system, referred as “the smart wardrobe prototype”, was developed to test the proposed methodology for aiding blind people in clothing identification and management, therefore meeting the proposed objective. The prototype was designed and assembled, incorporating several components and technologies to ensure its effectiveness and usability. The in-house developed smart wardrobe is equipped with an image acquisition system, featuring a camera to capture images of clothing items. To ensure the consistent quality of images, the system includes controlled lighting, crucial for eliminating shadows and ensuring uniform illumination across the clothing items, thereby enhancing the accuracy of image analysis by the AI algorithms. The image acquisition system is integrated with the smart wardrobe's internal structure, which is designed to position clothing items optimally. This involves automated mechanisms that adjust the positioning of garments, ensuring that each item is captured from both sides, essential for accurate segmentation and defect detection, allowing the AI algorithms to analyse every aspect of the clothing items thoroughly.

Users interact with the smart wardrobe through the mobile application developed in G3. Through the application, users can command the wardrobe to scan, identify, and categorize clothing items, as well as detect any modifications, such as stains or holes. The application also allows users to manage their wardrobe, including organizing garments and accessing detailed information about each item, such as type, colour, and condition.

The smart wardrobe prototype was tested under real-world conditions to validate the proposed methodology. The user feedback during the testing phase was overwhelmingly positive. Participants found the smart wardrobe to be easy to use, with the application interface being intuitive and accessible. The ability to control the wardrobe through the application was particularly appreciated, as it provided users

with a sense of independence and control over their clothing management.

Hence, the development and testing of the smart wardrobe prototype demonstrated the feasibility and effectiveness of the proposed methodology. The insights gained from the testing phase can guide further refinements and improvements to the prototype, ensuring its readiness for broader deployment and use. This smart wardrobe represents a significant step towards enhancing the independence and quality of life for visually impaired people through innovative technological solutions.

G5: Conduct testing and validation of the prototype with blind users to evaluate the system's effectiveness and usability.

Testing and validation were accomplished through an evaluation carried out by 15 participants from ACAPO, who voluntarily agreed to participate, forming the sample of the study. Most participants (60 %) were female, and the age distribution revealed that a significant majority belonged to older age groups. Specifically, 66.7% were 55 years old or older, 20% were within the 35-44 years age range, and 13.3% were in the 45-54 years age range. This indicates that the feedback and evaluation of the iSight prototype came from predominantly older individuals, with the middle-aged group having a smaller representativeness.

During the testing phase, blind and low-vision participants used the prototype and completed a detailed questionnaire to evaluate their experience. The results confirmed that the prototype was both feasible and effective in improving the quality of life for users, providing greater independence in managing their clothing. Positive feedback included high ratings for ease of use and overall satisfaction. Moreover, statistically significant correlations (Spearman's $\rho = 0.700$, $p = 0.004$) were found between the iSight functionalities and increased users' confidence, self-esteem, well-being, and independence, further validated by the Fisher's Exact Test ($p = 0.017$). This strong positive feedback underscores the critical role of the iSight prototype in enhancing users' psychological and emotional well-being.

Based on the core outcomes on each aforementioned objective, the main research questions can now be addressed, as follows:

RQ1: Is it possible to develop a method, using computer vision technology and artificial intelligence, to identify the type, colour and condition of garments?

The findings of this PhD research suggest the feasibility of developing a method using computer vision and artificial intelligence (AI) to identify garment type, colour, and condition accurately. This method was evaluated through validation and field testing, yielding results for practical application among blind people.

In the initial validation phase, the method's performance in garment type identification and stain detection was tested using deep learning models. Benchmarking results indicated that a fine-tuned GoogleLeNet model achieved an F1-score of up to 91% for garment type classification, suggesting an advancement relative to findings from previous studies. Transfer learning, through fine-tuning all network layers with pre-trained weights, proved effective, and the application of data augmentation techniques, such as random horizontal flipping, further optimized model performance. In contrast, random rotations negatively affected accuracy, underscoring the importance of selecting augmentation strategies carefully. Additionally, the ResNet-18 model demonstrated efficient inference times while maintaining accuracy, supporting its potential suitability for real-time applications in assistive technology.

A subsequent experiment applied the YOLOv8s model to segment clothing items, enabling both garment category classification and colour extraction. This segmentation approach allowed the extraction of pixel-level colour information, using nine predefined colours within the HSV colour space to facilitate simplified colour differentiation. This dual extraction capability achieved high accuracy in most categories, indicating that segmentation may enhance garment identification by enabling both type and colour data extraction. To assess garment condition, a YOLOv5 model was trained to detect and classify specific defects, including stains and holes. Data augmentation techniques were critical in improving the model's generalization, contributing to a high precision of 0.915. Although recall values suggested areas for potential enhancement, these findings indicate that the model performs effectively in identifying garment defects, while also pointing to specific areas where additional refinement could improve reliability, particularly in defect detection.

Following validation, the AI-driven method was integrated into the iSight prototype and tested in real-world conditions by 15 participants, providing feedback on the method's practical usability for visually impaired people. The majority of participants rated colour identification as "very precise" (80%) and garment category identification similarly (60%). Functionalities important for garment condition assessment, including stain detection and NFC tag identification, were rated as "highly effective" by 86.7% of participants. Usability feedback was also positive, with all participants (100%) finding the textual content clear or very clear, further supporting the method's accessibility and suitability for regular use.

Statistical analysis further reinforced the method's effectiveness, revealing a significant correlation (Spearman's $\rho = 0.612$, $p = 0.015$) between the accuracy of colour and category identification, which suggests that improvements in one area may enhance the other. This insight highlights opportunities for iterative refinement to maximize performance.

In conclusion, this research supports the feasibility of developing an AI-driven method for accurately identifying garment type, colour, and condition, addressing essential functional needs for visually impaired users.

RQ2: It is possible to design a mechatronic device integrating computer vision and artificial intelligence technology to support blind people in the identification of type, colour and condition of garments?

The core findings of this PhD work provide robust evidence supporting the feasibility and effectiveness of a mechatronic device (smart wardrobe) integrating computer vision and artificial intelligence technology to assist blind people in identifying the type, colour, and condition of garments.

This strong statement was corroborated by an evaluation that involved 15 participants, predominantly older adults, with diverse educational backgrounds and professional experiences. This demographic diversity ensured that the feedback encompassed a wide range of user experiences, making the results more generalizable to the broader visually impaired community. Notably, the study included both blind participants, for whom the system was primarily designed, and people with low vision, ensuring that the prototype's effectiveness was assessed across a broader spectrum of visual impairment. Participants provided positive feedback on the ease of use, overall satisfaction, and effectiveness of the iSight prototype. The high ratings for ease of navigation (66.7 % found it easy and 33.3 % very easy) and the clarity of textual content (100 % rated it as clear or very clear) underlines the user-friendly nature of the system. The high level of satisfaction with the mobile application (66.6% found it very satisfied, and 33.3% satisfied) further indicates that the interface is accessible and meets the users' needs. The functionality of the iSight prototype in identifying clothing categories and colours was rated highly by participants. These high accuracy ratings suggest that the integration of computer vision and artificial intelligence in the iSight prototype effectively supports blind users in distinguishing garment types and colours. Additionally, the prototype's ability to detect stains and identify NFC tags was rated as highly effective by 86.7% of participants, demonstrating its comprehensive utility in assessing the condition of garments.

The statistically significant findings from the Spearman's Rank Correlation and Fisher's Exact Test further support the device's impact on users' psychological and emotional well-being. There was a strong positive correlation (Spearman's $\rho = 0.700$, $p = 0.004$) between the iSight functionalities and increase in users' confidence, self-esteem, well-being, and independence. The Fisher's Exact Test also confirmed a significant association ($p = 0.017$) between the perceived functionality of iSight and these psychological benefits. This correlation indicates that participants who rated the iSight functionalities as highly important

also reported greater improvements in their quality of life. Several nonparametric statistical methods were employed in the analysis, including the Mann-Whitney U Test, which revealed that participants' comfort with technology significantly impacted their ease of navigation and overall experience with the iSight prototype. Those very comfortable with technology tended to rate their ease of navigation and overall experience significantly higher, underscoring the importance of considering users' familiarity with technology in the design of assistive devices.

The analysis of the effectiveness of the iSight prototype in identifying various clothing features highlighted a significant positive association between accuracy in identifying colours and categories, suggesting that enhancing one functionality could improve the other. However, other functionalities showed weaker correlations, indicating areas for further improvement.

Feedback on the prototype also highlighted several areas for improvement, such as reducing the number of menus to enhance speed, including more detailed information about clothing fabrics, and improving stain localization. These suggestions reflect the participants' desire for a more streamlined and informative system, which can guide future enhancements to further meet the needs of visually impaired users. Participants with low vision also expressed high levels of satisfaction and found the iSight prototype useful, indicating its potential to meet the needs of this group as well. This suggests that the iSight prototype can be adapted to serve a wider audience, further extending its impact and utility.

In conclusion, the evidence gathered from the questionnaire data strongly supports the feasibility of designing a mechatronic device integrating computer vision and artificial intelligence to aid blind people in identifying the type, colour, and condition of garments. The iSight prototype demonstrated high user satisfaction, effectiveness, and significant positive impacts on users' confidence, self-esteem, well-being, and independence. Furthermore, aligning with SDG 10: Reduced Inequality, the iSight prototype contributes to reducing inequality by providing visually impaired individuals with advanced technological support that enhances their autonomy and integration into daily life. These findings highlight the critical role of such technologies in enhancing the quality of life for visually impaired people.

7.2 Future Work

Based on the findings and user feedback from the evaluation of the iSight prototype, several areas for future work and development have been identified.

Future iterations of the iSight prototype should focus on simplifying the user interface to improve ease of navigation. This includes reducing the number of menus, optimizing the layout for faster access to key

features, and incorporating voice commands to facilitate hands-free operation. Additionally, it is essential to incorporate features based on user feedback, such as the ability to read and interpret care labels on clothing, to detect and identify different types of fabric, and to provide detailed information about garment maintenance. Enhancing the prototype's ability to locate and describe stains or other imperfections in clothing items would also be beneficial.

The continuous refinement of the AI algorithms to improve accuracy in identifying clothing types and detecting modifications is crucial. Expanding the training dataset and incorporating advanced machine learning techniques will enhance the prototype's performance. Further, integrating the iSight prototype with other existing technologies for the visually impaired, such as navigation aids, voice assistants, or other wearable technology, could provide a seamless and holistic user experience. Integration with popular personal assistant technologies, such as Amazon Alexa (*Amazon Alexa*, 2024) and Google Assistant (*Google Assistente, Seu Google Pessoal*, 2024), would further enhance ease of use and accessibility.

Future development should also allow for greater customization to meet individual user needs. This includes adjustable settings for voice feedback, personalized recommendations based on user preferences, and the ability to tailor the interface to suit different levels of technical proficiency and visual impairment. Additionally, conducting extensive field tests with a larger and more diverse group of users will provide more comprehensive data on the prototype's performance and areas for improvement. Regularly incorporating user feedback into the development cycle will ensure that the device continues to meet the evolving needs of its users. Moreover, developing educational materials and training programs to assist new users in effectively utilizing the iSight prototype can enhance user adoption and satisfaction. Workshops, online tutorials, and user manuals tailored to different levels of technical ability can support users in maximizing the benefits of the device.

An important alternative direction for future development is its application in the furniture industry. This idea envisions the creation of smart wardrobes, potentially available at major retailers like IKEA, equipped with easy-to-install elements that integrate the iSight technology. Such a system would allow any user to manage their wardrobe efficiently. Users could quickly determine how many pieces of clothing they have in each category, how many t-shirts of a specific colour are in their wardrobe, and more. The capability to identify stains, tears, and other defects would be universally beneficial, not just for the visually impaired. Moreover, associating each piece of clothing with specific washing instructions (temperature, detergent type, etc.) would allow users to cut off inconvenient care labels. By storing this information in the app once, the smart wardrobe could automatically provide these details through its camera system. Additionally, users could link purchase receipts to clothing items, retaining purchase details such as price,

store, and city, even years later. If this feature were endorsed by platforms like Vinted (*Vinted / Vender e Comprar Roupas, Sapatos e Acessórios, 2024*), it would simplify and lend credibility to the process of selling second-hand clothing.

Another alternative direction is the possibility of using just a smartphone for garment inspection, without the need for the wardrobe component. This approach would leverage the smartphone's built-in hardware, such as the camera and sensors, to inspect clothing items in a guided manner. The application could guide the user through the process of taking photos, ensuring proper lighting conditions and positioning for accurate inspection. This would make the iSight technology more accessible and portable, allowing users to benefit from its functionalities without needing a dedicated wardrobe unit. Exploring the application of the iSight technology in other areas, such as personal shopping assistants or virtual wardrobe management for the general population, could increase its market reach and utility. This broader applicability would make the technology beneficial for a wider audience.

Longitudinal studies to assess the long-term impact of the iSight prototype on users' quality of life, independence, and overall well-being will provide valuable insights into its effectiveness. This research can inform future improvements and demonstrate the sustained benefits of the technology. Continued exploration of advanced technologies, such as machine learning and improved sensor capabilities, can further enhance the prototype's accuracy and functionality. Implementing these technologies can ensure that the iSight remains at the forefront of assistive technology.

Furthermore, the iSight prototype contributes to SDG 12 (Ensure sustainable consumption and production patterns) (*Goal 12 / Department of Economic and Social Affairs, 2024*), *i.e.*, responsible consumption and production by promoting more efficient garment management. By helping users maintain their clothing in better condition, the prototype encourages longer use of garments, reduces the need for frequent replacements, and minimizes textile waste. This efficiency not only benefits the environment by reducing the demand for new clothing but also supports a more sustainable consumption model. Aligning with SDG 12, the iSight prototype plays a role in fostering responsible consumption practices and supporting the broader goal of reducing the fashion industry's environmental footprint.

While the iSight prototype has shown promising results in improving the quality of life for visually impaired users, ongoing research, development, and user engagement are essential for its continued success and evolution. By addressing these future work suggestions, the iSight prototype can become an even more effective and indispensable tool for its use.

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APPENDIXES

Materials used in the present thesis:

A.1 Questionnaire to Characterize the Challenges and Technological Needs for Clothing Management Among Blind People (In Portuguese)

Inquérito - Percepção da importância na identificação e combinação do vestuário para os indivíduos cegos

rochacoelho@gmail.com [Switch account](#)

 Not shared

* Indicates required question

Identificação Pessoal

Sexo *

☐ Feminino

☐ Masculino

Idade *

☐ Menos que 18

☐ 18 - 24

☐ 25 - 34

☐ 35 - 44

☐ 45 - 54

☐ Igual ou superior a 55

Habilitações Literárias *

- ☐ Menos de 4 anos de escolaridade
- ☐ 4 anos de escolaridade (1º ciclo do ensino básico)
- ☐ 6 anos de escolaridade (2º ciclo do ensino básico)
- ☐ 9º ano (3º ciclo do ensino básico)
- ☐ 11º ano
- ☐ 12º ano (ensino secundário)
- ☐ Curso tecnológico/profissional/outros (nível III)
- ☐ Bacharelato
- ☐ Licenciatura
- ☐ Pós-graduação
- ☐ Mestrado
- ☐ Doutoramento
- ☐ Curso de especialização tecnológica
- ☐ Habilitação ignorada

Profissão

Your answer _____

Identificação do tipo de deficiência

Desde que idade é deficiente visual? *

- ☐ Menor que 1
- ☐ 2-18
- ☐ 18 - 24
- ☐ 25 - 34
- ☐ 35 - 44
- ☐ 45 - 54
- ☐ Igual ou superior a 55

O que provocou a sua deficiência?

- ☐ Acidente
- ☐ Doença congénita
- ☐ Doença adquirida

Em caso de doença congénita ou adquirida indique por favor o nome.

Your answer _____

Vestuário

Cada vez mais, a estética está presente nas nossas vidas. A forma como nos vestimos, tem tido um grande impacto no nosso dia-a-dia e é crucial no nosso bem-estar. Desde a importância que a sociedade dá à forma como nos vestimos até à importância da escolha do vestuário para o local de trabalho no sentido de ajudar a transmitir a imagem certa e adequada ao contexto em que se está inserido.

Seguidamente serão apresentadas algumas questões em forma de afirmações e é pedido para avaliar considerando uma escala de concordância/importância ou frequência.

A visão é um dos sentidos que domina a vida dos seres humanos. Permite que eles conheçam e tenham a percepção do mundo ao seu redor, enquanto dão significado a objetos, conceitos, ideias e gostos.

- ☐ Discordo totalmente
- ☐ Discordo
- ☐ Indeciso
- ☐ Concordo
- ☐ Concordo totalmente

Como se vestir e o estilo que preferimos para diferentes ocasiões faz parte da identidade de alguém. Pessoas cegas não têm este sentido, e vestir-se pode ser uma tarefa difícil e stressante. Com o avanço da tecnologia, é importante minimizar todas as limitações de uma pessoa cega na gestão de vestuário.

- ☐ Discordo totalmente
- ☐ Discordo
- ☐ Indeciso
- ☐ Concordo
- ☐ Concordo totalmente

O desconhecimento das cores, do tipo de padrão ou do estado das peças de vestuário faz deste um desafio diário, no qual os recursos atuais não são os melhores.

- ☐ Discordo totalmente
- ☐ Discordo
- ☐ Indeciso
- ☐ Concordo
- ☐ Concordo totalmente

Tem preocupação em combinar peças de vestuário? *

- ☐ Sem importância
- ☐ Pouco importante
- ☐ Razoavelmente importante
- ☐ Importante
- ☐ Muito importante

Caso se verifique descreva de que forma o consegue fazer.

Your answer

Com que frequência necessita de ajuda para comprar vestuário? *

- ☐ Nunca
- ☐ Raramente
- ☐ Ocasionalmente
- ☐ Frequentemente
- ☐ Muita frequência

Caso a resposta anterior seja positiva, indique o grau de parentesco.

- ☐ Cônjuge
- ☐ Descendente
- ☐ Ascendente
- ☐ Other: _____

Onde compra as suas peças de vestuário? (por favor assinale uma ou mais hipóteses) *

Por favor assinale uma ou mais hipóteses

- ☐ Em lojas de pronto a vestir
- ☐ Através de lojas online
- ☐ Não costumo comprar

Tecnologia

Com o avanço da tecnologia, é importante evoluir no sentido de minimizar todas as limitações de um cego, tornando-o mais inclusivo.

A definição de ser humano leva-nos a certas interrogações: até que ponto somos diferentes? Será a sociedade capaz de definir a nossa espécie sem interrogações estéticas? Estará a sociedade dotada de capacidades, quer a nível social, psicológico, tecnológico, para auxiliar os cidadãos portadores de deficiências? Será que existe tecnologia suficiente para minimizar os obstáculos enfrentados por estas pessoas no seu dia-a-dia? Certamente, que a tecnologia neste campo tem evoluído bastante, contudo, ainda existem algumas lacunas por preencher.

Tem conhecimento de alguma tecnologia para identificação de vestuário? *

- ☐ Sim
- ☐ Não

Caso se verifique indique a(s) tecnologias que conhece.

Your answer _____

Qual o nível de satisfação com a tecnologia disponível incidente neste tema? *

- ☐ Totalmente insatisfeito
- ☐ Insatisfeito
- ☐ Nem satisfeito nem insatisfeito
- ☐ Satisfeito
- ☐ Totalmente satisfeito

Identifique o tipo de dispositivo que possui: *

- ☐ Telemóvel
- ☐ Smartphone
- ☐ Computador
- ☐ Tablet
- ☐ Nenhum

Se possui smartphone, qual o sistema operativo?

- ☐ Android
- ☐ IOS
- ☐ Windows Phone

Investigação

A estética não só caracteriza a imagem e aparência do nosso corpo, mas também o nosso bem-estar, autoestima e o otimismo no "dia-a-dia". É em busca destas características que surge este projeto, de forma a incutir estas sensações e características num cego, para além de proporcionar maior autonomia à pessoa cega.

A estratégia é criar um protótipo mecatrónico para ajudar diariamente as pessoas cegas com o seu vestuário, para que possam gerir o vestuário autonomamente, substituindo seu guarda-roupa comum.

Seguidamente serão apresentadas algumas questões em que é pedido para avaliar considerando uma escala de importância/probabilidade ou frequência.

Seria importante o desenvolvimento de algo que permitisse identificar e combinar as peças de vestuário? *

- ☐ Sem importância
- ☐ Pouco importante
- ☐ Razoavelmente importante
- ☐ Importante
- ☐ Muito importante

Qual a probabilidade de usar uma tecnologia que inclua o ato de identificação e combinação de vestuário? *

- ☐ Improvável
- ☐ Pouco provável
- ☐ Provável
- ☐ Muito provável

Se sim, gostaria de ver essa tecnologia patente em (por favor assinale uma ou mais hipóteses):

☐ Smartphone

☐ Computador

☐ Tablet

☐ Other: _____

Deixe uma sugestão ou ideia para o âmbito desta investigação.

Your answer _____

Indique se para o preenchimento do questionário recorreu a ajuda. *

☐ Nunca

☐ Raramente

☐ Ocasionalmente

☐ Frequentemente

☐ Muita frequência

Fim do inquérito, obrigado!

Agradecemos o tempo disponibilizado no preenchimento deste inquérito. Com a sua participação iremos adquirir novos conhecimentos que permitiram uma nova abordagem e apoio diário à comunidade cega.

A.2 Informed consent delivered to the ACAPO Members (In Portuguese)

_____ de _____ de 2023

Exmo(a). Senhor(a) Sócio da ACAPO,

A importância da estética para as pessoas cegas é inegável. No entanto, muitas vezes, existe uma lacuna significativa quando se trata da capacidade de selecionar as suas roupas de forma autónoma. É crucial avaliar o desempenho de ferramentas que possam auxiliar nessa tarefa de maneira minimamente invasiva

O projeto **Sistema de Identificação e Combinação de Peças de Vestuário para cegos** surge de uma parceria entre a **Universidade do Minho e Associação de Cegos e Amblíopes de Portugal**, que propõe um novo sistema e metodologia para auxílio aos cegos na componente estética, nomeadamente na gestão das suas roupas. O objetivo deste projeto é desenvolver um sistema mecatrónico com uma aplicação móvel para auxiliar os utilizadores cegos na seleção e avaliação das suas roupas diárias.

O propósito principal é avaliar a utilidade desta ferramenta, através da sua utilização, e analisar o seu impacto na vida quotidiana dos utilizadores. Para atingir este objetivo, planeamos recolher informações sobre como os utilizadores interagem com o sistema e como este os ajuda na escolha e análise das roupas. Além disso, pretendemos realizar um inquérito para obter opiniões diretas dos utilizadores sobre a sua experiência.

Salientamos que a sua participação neste projeto é voluntária e apenas ocorrerá com a sua autorização. Garantimos que os dados recolhidos serão estritamente utilizados para fins de pesquisa e divulgação científica, nunca sendo explorados em outras situações que não estejam relacionadas com o projeto. A sua opinião e experiência serão essenciais para o sucesso deste projeto e para melhorar a vida dos utilizadores cegos na escolha e análise das suas roupas.

Solicitamos, portanto, a sua colaboração e autorização para participar, o que pode ser feito através da devolução do anexo destacável assinado.

Com os melhores cumprimentos,

O aluno de Doutoramento responsável pelo estudo, UM

Daniel Filipe Coelho Rocha

Contactos Daniel Rocha:

✉ id8057@alunos.uminho.pt;

☎ 917 966 638.

Eu _____, membro da ACAPO de Braga,

declaro ter compreendido os objetivos de quanto me foi proposto e explicado pelo investigador, ter-me sido dada oportunidade de fazer todas as perguntas sobre o assunto e para todas elas ter obtido resposta esclarecedora, ter-me sido garantido que não haverá qualquer prejuízo se eu recusar esta solicitação, e ter-me sido dado tempo suficiente para refletir sobre esta proposta.

Declaro também que aceito participar no Projeto de Investigação “**Sistema de Identificação e Combinação de Peças de Vestuário para cegos**” com o Centro Algoritmi da Universidade do Minho. Assim como, autorizo a recolha de dados referentes às minhas interações realizadas durante as sessões de avaliação, desde que as sessões de recolha sejam previamente marcadas e identificadas. As sessões serão filmadas para posterior análise de desempenho do utilizador. As filmagens serão utilizadas única e exclusivamente na divulgação científica do projeto. Os dados pessoais não serão divulgados e os dados obtidos na investigação serão utilizados para divulgação científica do projeto, sendo mantidos por um período de dez anos, ao fim do qual serão destruídos. Todas as informações de caráter pessoal recolhidas no decurso da investigação serão consideradas confidenciais e tratadas de acordo com as regras relativas à proteção de dados e da vida privada. A minha participação ou recusa em participar ou posterior abandono, não prejudicará a relação com a equipa técnica e/ou investigadores.

Não se preveem quaisquer riscos para os participantes durante as sessões. Caso o utilizador demonstre desconforto, a sessão será terminada.

_____ de _____ de 2023

(Assinatura Completa do Participante)

A.3 Compromise Declaration (In Portuguese)



Universidade do Minho
Escola de Engenharia
Centro de Investigação ALGORITMI

DECLARAÇÃO de ACEITAÇÃO

Para os devidos efeitos declara-se que o Centro de Investigação ALGORITMI da Escola de Engenharia da Universidade do Minho, ao qual estão afiliados os orientadores Vítor Hugo Mendes da Costa Carvalho e Filomena Maria Rocha Menezes Oliveira Soares, assume a responsabilidade científica do projeto “Sistema de Identificação e combinação de peças de vestuário para cegos” da investigador Daniel Filipe Coelho Rocha, no âmbito do Programa Doutoral em Engenharia Eletrónica e de Computadores, e assegura as condições necessárias ao bom desenvolvimento do plano de trabalhos.

Guimarães, 12 de dezembro de 2023

O Diretor do Centro de Investigação ALGORITMI

Assinado por: **José Manuel Ferreira Machado**
Num. de Identificação: 09708882
Data: 2023.12.12 14:00:49 +0000

José Manuel Ferreira Machado

A.4 Ethics Committee Documents (in Portuguese)



Universidade do Minho

Conselho de Ética

Comissão de Ética para a Investigação em Ciências Sociais e Humanas (CEICSH)

Identificação do documento: CEICSH 185/2023

Título do projeto: *SISTEMA DE IDENTIFICAÇÃO E COMBINAÇÃO DE PEÇAS DE VESTUÁRIO PARA CEGOS*

Equipa de Investigação: Daniel Filipe Coelho Rocha, Programa Doutoral em Engenharia Eletrónica e de Computadores – Controlo, Automação e Robótica, Centro Algoritmi, Escola de Engenharia, Universidade do Minho; Vítor Hugo Mendes da Costa Carvalho (Orientador) - 2Ai Lab – IPCA & Centro Algoritmi, Universidade do Minho; Filomena Maria Rocha Menezes Oliveira Soares (Orientadora), Centro Algoritmi, Escola de Engenharia, Universidade do Minho

PARECER

A Comissão de Ética para a Investigação em Ciências Sociais e Humanas (CEICSH) analisou o processo relativo ao projeto de investigação acima identificado, intitulado *SISTEMA DE IDENTIFICAÇÃO E COMBINAÇÃO DE PEÇAS DE VESTUÁRIO PARA CEGOS*.

Os documentos apresentados revelam que o projeto obedece aos requisitos exigidos para as boas práticas na investigação com humanos, em conformidade com as normas nacionais e internacionais que regulam a investigação em Ciências Sociais e Humanas.

Face ao exposto, a Comissão de Ética para a Investigação em Ciências Sociais e Humanas (CEICSH) nada tem a opor à realização do projeto nos termos apresentados no Formulário de Identificação e Caracterização do Projeto, que se anexa, emitindo o seu parecer favorável, que foi aprovado por unanimidade pelos seus membros.

Braga, 28 de dezembro de 2023.

O Presidente da CEICSH

Assinado por: EMANUEL PEDRO VIANA BARBAS
DE ALBUQUERQUE
Num. de Identificação: 07089799

(Emanuel Pedro Viana Barbas Albuquerque)

Anexo: Formulário de identificação e caracterização do projeto



Conselho de Ética - Ciências Sociais e Humanas

Universidade do Minho

Formulário de identificação e caracterização do projeto

Identificação do projeto

Título do projeto	SISTEMA DE IDENTIFICAÇÃO E COMBINAÇÃO DE PEÇAS DE VESTUÁRIO PARA CEGOS.		
Data prevista de início:	Dezembro/2023	Data prevista fim:	Maio/2024

Investigador principal e filiação	Daniel Filipe Coelho Rocha - Centro Algoritmi, Universidade do Minho Programa Doutoral em Engenharia Eletrónica e de Computadores – Controlo, Automação e Robótica
Orientador(es) e filiação	Vitor Hugo Mendes da Costa Carvalho - 2Ai Lab – EST, IPCA & Centro Algoritmi, Universidade do Minho Filomena Maria Rocha Menezes Oliveira Soares - Centro Algoritmi, Universidade do Minho

Nota: No caso de projetos de mestrado ou doutoramento deve ser indicado o estudante como investigador principal e o nome do mestrado ou doutoramento

Instituição proponente	Universidade do Minho
Instituição(ões) onde se realiza a investigação	Delegação da Associação dos Cegos e Amblíopes de Portugal de Braga. Testes noutras delegações.

Entidades financiadoras	
--------------------------------	--

Questões relativas ao envolvimento de investigadores exteriores

Estão envolvidos no projeto, colegas de outra (s) Escola(s)/Instituição(ões)?		N
Se sim, este pedido de parecer cobre o seu envolvimento?	-	-

Qualificação dos investigadores

Daniel Filipe Coelho Rocha

Aluno de doutoramento de Engenharia Eletrónica e de Computadores – Área de Controlo, Automação e Robótica, da Universidade do Minho com o tema Sistema de Identificação e Combinação de Peças de Vestuário Para Cegos. Licenciado em Engenharia Eletrotécnica e de Computadores e Mestrado em Engenharia Eletrónica e de Computadores com especialização na área de Automação e Robótica, ambos do Instituto Politécnico do Cávado e do Ave, terminados em 2014 e 2017 respetivamente. Desde 2018 investigador no centro de Investigação Algoritmi na Universidade do Minho. Desde 2018 investigador no centro 2Ai - Applied Artificial Intelligence Laboratory no Instituto Politécnico do Cávado e do Ave. Os principais interesses científicos centram-se na área de visão por computador e inteligência artificial.

Vítor Hugo Mendes da Costa Carvalho

Licenciado em Engenharia Eletrónica Industrial em 2002, mestre em Eletrónica Industrial em 2004 e doutorado em Eletrónica Industrial, na opção de informática industrial, em 2008 – todos os graus pela Universidade do Minho. Atualmente é professor coordenador do Instituto Politécnico do Cávado e do Ave (IPCA), Barcelos, Portugal, investigador integrado do Laboratório de Inteligência Artificial Aplicada do IPCA e colaborador do Centro de Investigação Algoritmi da Universidade do Minho. É também diretor da Escola Superior de Tecnologia do IPCA. Os seus principais interesses de investigação estão relacionados com sistemas de aquisição de dados, jogos sérios e aprendizagem máquina. Publicou mais de 200 artigos, sendo também membro do conselho editorial de várias conferências e periódicos internacionais. Tem um total de 1760 (h índice 23) citações no Google Scholar e 778 (h índice 16) citações no Scopus. Supervisionou vários alunos de mestrado e doutoramento nos campos de interesse relacionados.

Filomena Maria da Rocha Menezes de Oliveira Soares

Professora Associada com Agregação do Departamento de Eletrónica Industrial da UM desde 2020. Concluiu a licenciatura em Engenharia Química da Faculdade de Engenharia da Universidade do Porto em 1986; o Mestrado em Engenharia Eletrotécnica e Computadores pela mesma instituição em 1991; e o Doutoramento em Engenharia Química também pela Faculdade de Engenharia da Universidade do Porto em 1997. Desde 1992, data de entrada na Universidade do Minho, que é investigadora do Centro Algoritmi. Os principais interesses científicos têm-se centrado na modelização e controlo de processos. Tendo como foco especial a utilização da tecnologia como meio de ajuda a pessoas tipicamente envolvidas ou com limitações cognitivas ou motoras, tem investido na área interação humano-computador/robô e *human wellbeing*, destacando-se a utilização de robôs sociais como promotores da interação e comunicação com crianças com perturbação do espectro do autismo. Desde há vários anos que se dedica à área da Educação em Engenharia, novas metodologias e ferramentas de ensino/aprendizagem. É autora de diversos artigos publicados em revistas e conferências internacionais da

especialidade.

Caracterização do projeto e questões de carácter ético relativas à sua execução

Introdução justificativa do projeto e sumário dos seus objetivos

Este projeto resulta da colaboração entre a Universidade do Minho e a Associação de Cegos e Amblíopes de Portugal, com o objetivo de introduzir um sistema inovador e uma metodologia destinados a melhorar a qualidade de vida, autoestima e bem-estar das pessoas cegas no contexto da estética e vestuário. O sistema proposto visa facilitar a identificação de categorias e modificações em peças de vestuário no dia-a-dia.

Para atingir este propósito, utiliza-se um sistema mecatrónico avançado, designado 'armário inteligente', que é capaz de reconhecer as características das peças de vestuário. A interface com este sistema é fornecida por meio de uma aplicação móvel intuitiva, tornando o processo acessível e conveniente para os utilizadores.

Acreditamos que esta iniciativa contribuirá significativamente para permitir que as pessoas cegas tenham maior autonomia na seleção de roupas, promovendo uma sensação de confiança e independência nas suas escolhas de vestuário. O projeto poderá representar um passo importante em direção a um futuro mais inclusivo e igualitário para todos – em particular da comunidade de cegos.

Participantes

- a) A população alvo deste estudo são sócios da ACAPO, de ambos os sexos, com idades compreendidas entre os 18 e os 60 anos-
- b) O número de participantes necessários será de 10, pertencentes à Delegação da ACAPO de Braga (ou de outras instituições).

Recrutamento e triagem

- a) Os participantes serão selecionados pela direção da delegação da ACAPO que considerará o nível dos utilizadores assim como a sua disponibilidade para participarem no estudo, sem que isso interfira com a sua vida social, familiar e escolar.
- b) Aos participantes selecionados serão entregues formulários onde será descrito o objetivo do estudo assim como informação sobre os dados recolhidos durante o estudo e o seu processamento.

Compensação e custos

- a) Não está prevista nenhuma compensação monetária pela participação no projeto de investigação.
- b) Não estão previstos custos ou recursos das instituições participantes para a realização do projeto.

Procedimento

- a) A amostra será constituída por sócios da ACAPO, com idades compreendidas entre os 18 e os 60 anos.
- b) As sessões de recolha de dados serão realizadas nas instalações da ACAPO de Braga, ou em outros locais por si recomendados.
- c) As sessões terão a duração de 30 minutos, onde cada um dos utilizadores realizará a execução de tarefas, previamente selecionadas, que permitirão a recolha de dados.
- d) Pretende-se que número de sessões a realizar com cada um seja 1 (podendo ser superior ou inferior consoante a disponibilidade).
- e) A sessão serão conduzida pelo investigador responsável. Pretende-se que seja o menos invasiva possível de modo a não afetar o desempenho normal do utilizador e permitir a recolha de dados exatos.
- f) Ocorrerá gravação vídeo e áudio das sessões de recolha de dados.

Benefícios, Riscos e Desconforto

- a) Os participantes neste estudo (sócios da ACAPO) podem realizar a monitorização da evolução do seu desempenho, assim como receber indicações para melhorar o seu desempenho, em tempo real.
- b) Não se preveem quaisquer riscos para os participantes durante as sessões. Caso o utilizador demonstre desconforto, a sessão será terminada.
- c) Para minimizar o risco ou desconforto dos participantes, as sessões serão marcadas antecipadamente e será feita uma descrição dos procedimentos a levar a cabo durante a sessão.

Confidencialidade

Não será recolhido qualquer tipo de material biológico.

Serão utilizados ou administrados questionários ou outros instrumentos de auto-relato aos utilizadores. A confidencialidade dos dados obtidos será garantida, na medida em que:

- a) Os dados pessoais e dados obtidos na investigação não serão divulgados e serão apenas mantidos por um período de dez anos, ao fim do qual serão destruídos;
- b) Todas as informações de carácter pessoal recolhidas no decurso da investigação serão consideradas confidenciais e tratadas de acordo com as regras relativas à proteção de dados e da vida privada;
- c) O anonimato dos participantes será garantido em qualquer altura do projeto de investigação, tendo apenas conhecimento destes dados os investigadores e os profissionais que acompanham os atletas;
- d) Cada participante é identificado pela letra A e um número (por exemplo, A01) e cada sessão pela letra S e um número (por exemplo, S01). Assim, em todos os ficheiros associados a cada participante e sessão estes serão etiquetados com por exemplo "A01S01".

Relativamente aos vídeos, estes só serão tornados públicos em eventos de divulgação científica e desde que haja autorização prévia do utilizador e da sua delegação da ACAPO.

Os dados e vídeos, recolhidos e processados durante a investigação apenas serão acedidos pelos elementos da equipa de investigação e serão guardados num único disco duro guardado em instalações da Universidade do Minho, em armário fechado à chave, ao qual apenas os investigadores têm acesso. Os dados serão processados localmente em computadores cujo acesso está limitado aos investigadores e, em caso de ser computacionalmente conveniente, os dados serão processados na nuvem de um proprietário credenciado para o efeito.

Conflito de interesses

Não existe qualquer situação de conflito de interesses, para qualquer uma das partes envolvidas na investigação.

Consentimento Informado

A investigação envolve apenas voluntários saudáveis?	S	
A investigação envolve grupos vulneráveis: crianças, menores, idosos ou outras pessoas com incapacidade temporária ou permanente?	S	
O pedido de parecer inclui a declaração de consentimento informado, livre e esclarecido?	S	

Aqui tem de escolher o formato de consentimento informado

- ☒ Consentimento informado, livre e esclarecido para participação em investigação - de acordo com a Declaração de Helsínquia e a Convenção de Oviedo
- ☐ Consentimento informado não assinado - E.g. formulário para questionários preenchidos online. Deverá adicionar a informação incluída e o modo de os participantes concordarem em participar
- ☐ Consentimento informado alterado - Um formulário de consentimento informado que omite informação requerida. E.g., se não indica o objetivo do estudo para evitar o viés na resposta dos participantes. Deve explicar o racional no procedimento e os processos de *debriefing*
- ☐ Isenção de consentimento – quando não é obtido consentimento informado – esta opção pode ser apropriada para utilização de dados já disponíveis. Justifique

Anexe o formulário de consentimento informado e outro material informativo relevante quando adequado, ou justifique a isenção de consentimento

Assinatura do Investigador Responsável

Assinado por: **Daniel Filipe Coelho da Rocha**
 Num. de Identificação: 14147147
 Data: 2023.12.12 17:01:19+00'00'

Documentação a anexar

- ☒ cópia dos questionários ou formulários de recolha de dados a utilizar, se aplicável;
- ☒ modelo de consentimento informado e outro material informativo relevante;
- ☒ modelo de declaração de compromisso para outros investigadores ou colaboradores na investigação, se aplicável, destinada a documentar o seu envolvimento nas garantias de confidencialidade dadas pelo investigador principal no processo apresentado;
- ☐ cópia da notificação às autoridades nacionais ou internacionais competentes, juntamente com o parecer das mesmas, se emitido; (e.g., Direção Geral de Educação, no caso dos inquéritos em ambiente escolar)
- ☐ informação sobre o enquadramento, apoio e viabilidade do projeto facultada pelo responsável pela unidade/subunidade orgânica onde se vai desenvolver o projeto;
- ☒ *curriculum vitae* resumido de todos os investigadores.

[X] Deverá ser seguido o Regulamento Geral de Proteção de Dados (RGPD), com entrada em vigor em 25 de Maio de 2018, - REGULAMENTO (UE) 2016/679 DO PARLAMENTO EUROPEU E DO CONSELHO, de 27 de abril de 2016, relativo à proteção das pessoas singulares no que diz respeito ao tratamento de dados pessoais e à livre circulação desses dados, que revoga a Diretiva 95/46/CE (Regulamento Geral sobre a Proteção de Dados).

A.5 Questionnaire to characterize the developed prototype (In Portuguese)

Inquérito - Avaliação do protótipo iSight

Exmo. Senhor(a):

O seguinte formulário insere-se no âmbito do Doutoramento em Engenharia Eletrónica e de Computadores, na área de especialidade em Automação, Controlo e Robótica no desenvolvimento de um projeto de investigação com o título "Desenvolvimento de um sistema inteligente de identificação e combinação de vestuário para cegos".

O público alvo deste inquérito são os utentes da ACAPO. O seu preenchimento pode ser feito, caso necessitem, com o devido auxílio.

O nosso objetivo principal é avaliar as ferramentas desenvolvidas ao longo do projeto, analisando o seu impacto na vida quotidiana dos utilizadores por meio da sua utilização. Para alcançar este objetivo, planeamos recolher informações sobre como os utilizadores interagem com o sistema e de que forma este os auxilia na seleção e análise de vestuário, através do preenchimento deste inquérito.

O seu preenchimento terá uma duração aproximada de 20 minutos.

Hi, Daniel. When you submit this form, the owner will see your name and email address.

* Required

Consentimento livre e informado

Os dados recolhidos são confidenciais e anónimos, não sendo possível identificar o participante, pelo que solicitamos que a sua resposta seja tão próxima da realidade quanto possível. Os dados recolhidos serão guardados de forma codificada e analisados de forma agregada unicamente para fins de investigação científica.

As suas respostas são muito importantes para a concretização deste estudo. A participação é de carácter voluntário, não comportando qualquer risco, pelo que poderá interrompê-lo a qualquer momento, sem justificação e sem nenhum tipo de penalização.

Ao preencher está a colaborar para um futuro e, certamente, um bem-estar melhor.

1. Colaboração *

- ☐ Tomei conhecimento e concordo em participar nesta investigação.
- ☐ Prefiro não participar nesta investigação.

2. Identificação Pessoal

Enter your answer

3. Sexo *

- ☐ Feminino
- ☐ Masculino
- ☐ Other

4. Idade *

- ☐ 18 - 24
- ☐ 25 - 34
- ☐ 35 - 44
- ☐ 45 - 54
- ☐ Igual ou superior a 55

5. Habilitações Literárias *

- ☐ Menos de 4 anos de escolaridade
- ☐ 4 anos de escolaridade (1º ciclo do ensino básico)
- ☐ 6 anos de escolaridade (2º ciclo do ensino básico)
- ☐ 9º ano (3º ciclo do ensino básico)
- ☐ 11º ano
- ☐ 12º ano (ensino secundário)
- ☐ Curso tecnológico/profissional/outros (nível III)
- ☐ Bacharelato
- ☐ Licenciatura
- ☐ Pós-graduação
- ☐ Mestrado
- ☐ Doutoramento
- ☐ Curso de especialização tecnológica
- ☐ Habilitação ignorada

6. Profissão ***Next**

Inquérito - Avaliação do protótipo iSight

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Caracterização do tipo de deficiência

7. Identifique o tipo de deficiência

Enter your answer

8. Desde que idade é deficiente visual? *

☐ Menor que 1

☐ 2-18

☐ 18 - 24

☐ 25 - 34

☐ 35 - 44

☐ 45 - 54

☐ Igual ou superior a 55

9. O que provocou a sua deficiência? *

☐ Acidente

☐ Doença congénita

☐ Doença adquirida

10. Em caso de doença congénita ou adquirida indique por favor o nome.

Enter your answer

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Inquérito - Avaliação do protótipo iSight

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Tecnologia

Cada vez mais, a tecnologia desempenha um papel fundamental nas nossas vidas, e é essencial compreender como ela afeta positivamente a experiência das pessoas cegas ou com deficiência visual. A forma como as tecnologias são usadas por essa comunidade pode fazer uma diferença significativa em termos de independência, acessibilidade e inclusão social.

Seguidamente serão apresentadas algumas questões e é pedido que avalie cada afirmação considerando uma escala que reflete a sua concordância, importância ou frequência na sua experiência pessoal.

11. Já utiliza alguma aplicação dedicada à roupa? *

- ☐ Sim
- ☐ Não

12. Em caso de resposta afirmativa indique por favor o nome**13. Em que medida se sente confortável ao utilizar dispositivos tecnológicos, como smartphones e computadores? ***

- ☐ Muito desconfortável
- ☐ Um pouco desconfortável
- ☐ Sem opinião
- ☐ Um pouco confortável
- ☐ Muito confortável

14. Com que frequência utiliza dispositivos tecnológicos no seu dia-a-dia? *

- ☐ Nunca
- ☐ Raramente
- ☐ Ocasionalmente
- ☐ Regularmente
- ☐ Diariamente

15. **Como classificaria a sua habilidade em utilizar software e aplicações específicos para pessoas cegas, como leitores de ecrã? ***

- ☐ Muito baixa
- ☐ Baixa
- ☐ Média
- ☐ Alta
- ☐ Muito Alta

16. **Em que medida considera que as tecnologias melhoram a sua qualidade de vida e independência? ***

- ☐ Não melhoram
- ☐ Melhoram ligeiramente
- ☐ Melhoram moderadamente
- ☐ Melhoram significativamente
- ☐ Melhoram muito significativamente

17. **Com que frequência procura aprender e explorar novas tecnologias adaptadas às suas necessidades? ***

- ☐ Nunca
- ☐ Raramente
- ☐ Ocasionalmente
- ☐ Regularmente
- ☐ Sempre

18. Como avalia o suporte e acessibilidade das tecnologias para pessoas cegas? *

- ☐ Muito insatisfatório
- ☐ Insatisfatório
- ☐ Sem opinião
- ☐ Satisfatório
- ☐ Muito satisfatório

19. Em que medida sente que as tecnologias permitem uma maior inclusão social e profissional na sua vida? *

- ☐ Não permitem
- ☐ Permitem ligeiramente
- ☐ Permitem moderadamente
- ☐ Permitem significativamente
- ☐ Permitem muito significativamente

20. Considera que as tecnologias são uma ferramenta útil para a sua educação ou formação? *

- ☐ Não são úteis
- ☐ São um pouco úteis
- ☐ São moderadamente úteis
- ☐ São muito úteis
- ☐ São extremamente úteis

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Acessibilidade da Aplicação Móvel iSight

A acessibilidade desempenha um papel fundamental na criação de um mundo mais inclusivo e igualitário, onde todos têm a oportunidade de tirar partido das potencialidades da tecnologia. Acreditamos que a acessibilidade não é apenas uma questão técnica, mas sim uma questão de direitos humanos. Todos, independentemente das suas capacidades físicas, devem ter acesso a informações, serviços e lazer através de aplicações móveis.

Seguidamente serão apresentadas algumas questões relativas à acessibilidade da aplicação móvel desenvolvida e é pedido que as avalie considerando uma escala que reflete a sua concordância baseado na sua experiência pessoal.

21. Como avalia a facilidade de navegação na aplicação móvel? *

- ☐ Muito difícil
- ☐ Difícil
- ☐ Sem opinião
- ☐ Fácil
- ☐ Muito fácil

22. A aplicação móvel oferece descrições de imagem ou alternativas textuais para elementos visuais de forma adequada? *

- ☐ Muito inadequada
- ☐ Inadequada
- ☐ Adequada
- ☐ Boa
- ☐ Excelente

23. Como avalia a clareza e organização do conteúdo textual na aplicação móvel? *

- ☐ Muito confusa
- ☐ Confusa
- ☐ Sem opinião
- ☐ Clara

24. Como avalia a experiência global de utilização da aplicação móvel? *

- ☐ Muito insatisfatória
- ☐ Insatisfatória
- ☐ Sem opinião
- ☐ Satisfatória
- ☐ Muito satisfatória

25. Por favor, partilhe quaisquer comentários adicionais ou sugestões específicas para melhorar a aplicação móvel, com base na sua experiência. *

Enter your answer

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Usabilidade do Protótipo iSight

A usabilidade de uma aplicação desempenha um papel fundamental na satisfação dos utilizadores e na eficácia do software. Refere-se à facilidade com que as pessoas podem interagir com a aplicação e atingir os seus objetivos. Uma aplicação com boa usabilidade é aquela que se destaca pela simplicidade, eficiência e satisfação que proporciona aos utilizadores.

A seguir, apresentaremos algumas questões relacionadas à usabilidade do protótipo desenvolvido e pedimos que avalie cada declaração com base na sua experiência pessoal, utilizando uma escala que reflete o seu nível de concordância.

26. A facilidade de utilização do iSight é: *

- ☐ Muito difícil
- ☐ Difícil
- ☐ Sem opinião
- ☐ Fácil
- ☐ Muito fácil

27. A precisão do iSight para identificar *

	Muito imprecisa	Imprecisa	Sem opinião	Precisa	Muito precisa
a categoria das peças de roupa é:	☐	☐	☐	☐	☐
as cores da roupa é:	☐	☐	☐	☐	☐

28. A capacidade do iSight em detetar: *

	Muito ineficaz	Ineficaz	Sem opinião	Eficaz	Muito Eficaz
sujidade ou nódoas é:	☐	☐	☐	☐	☐
em identificar as etiquetas NFC é:	☐	☐	☐	☐	☐

29. Por favor, partilhe quaisquer comentários adicionais ou sugestões específicas para melhorar o sistema com base na sua experiência. *[Back](#)[Next](#)

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Avaliação da importância do iSight

Esta última secção pretende aferir de forma geral o impacto da utilização do protótipo no seu dia a dia e de que forma se torna impactante na melhoria da sua qualidade de vida.

30. O iSight permite: *

	Discordo Totalmente	Discordo	Sem opinião	Concordo	Concordo Totalmente
facilitar o processo de seleção de roupas, ao mesmo tempo que permite identificar características e modificações ao estado original.	☐	☐	☐	☐	☐
organizar as minhas roupas de forma eficaz.	☐	☐	☐	☐	☐

31. A utilização do iSight aumentou a minha sensação de: *

	Discordo Totalmente	Discordo	Sem opinião	Concordo	Concordo Totalmente
confiança	☐	☐	☐	☐	☐
auto-estima	☐	☐	☐	☐	☐
bem-estar	☐	☐	☐	☐	☐
independência	☐	☐	☐	☐	☐

32. O iSight será uma ferramenta importante na minha vida na identificação de: *

	Não é importante	Não é muito importante	Sem opinião	É bastante importante	É extremamente importante
roupas	☐	☐	☐	☐	☐
cores	☐	☐	☐	☐	☐
sujidade/nódos	☐	☐	☐	☐	☐

33. Considera que o iSight iria melhorar a sua qualidade de vida em relação à gestão de roupas? *

- ☐ Não melhora a qualidade de vida
- ☐ Melhora ligeiramente a qualidade de vida
- ☐ Sem opinião
- ☐ Melhora significativamente a qualidade de vida
- ☐ Melhora muito a qualidade de vida

34. Em que aspetos específicos do seu dia-a-dia este sistema tem um impacto positivo? (Pode selecionar várias opções) *

- ☐ Facilita a escolha de roupas para ocasiões específicas
- ☐ Ajuda a identificar as cores da roupa de forma mais eficaz
- ☐ Permite a identificação de sujidade/nódos nas peças de roupa
- ☐ Contribui para uma maior autonomia na gestão do meu vestário
- ☐ Outro

35. Caso tenha selecionado outro, por favor especifique.

Enter your answer

36. **Tem alguma sugestão ou melhoria específica que gostaria de ver implementada no sistema para torná-lo ainda mais útil na sua vida quotidiana? ***

Enter your answer

37. **Indique se para o preenchimento do questionário recorreu a ajuda. ***

☐ Nunca

☐ Raramente

☐ Ocasionalmente

☐ Frequentemente

☐ Muita frequência

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