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Using deep learning to detect the presence/absence of defects on leather: on the way to build an industry-driven approach.

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Abstract. In textile/leather manufacturing environments, as in many other industrial contexts, quality inspection is an essential activity that is commonly performed by human operators. Error, fatigue, ergonomic issues, and related costs associated to this fashion of carrying out fabric validation are aspects concerning companies' strategists, whose mission includes to watch over the physical integrity of their employees, while aiming at enhanced quality control methods implementation towards profit maximization. Considering these challenges from a technical/scientific perspective, machine/deep learning approaches have been showing great skills in adapting a wide range of contexts and, in particular, industrial environments, complementing traditional computer vision methods with characteristics such as increased accuracy while dealing with image classification and segmentation problems, capacity for continuous learning from experts input and feedback, flexibility to easily scale training for new contextualization classes – unknown types of occurrences relevant to characterize a given problem –, among other advantages. The goal of crossing deep learning strategies with fabric inspection processes is pursued in this paper. After providing a brief but representative characterization of the targeted industrial context, in which, typically, fabric rolls of raw-material mats must be processed at a relatively low latency, an Automatic Optical Inspection (AOI) system architecture designed for such environments is revisited [1], for contextualization purposes. Afterwards, a set of deep learning-oriented training methods/processes is proposed in combination with neural networks built based on Xception architecture, towards the implementation of one of the components that integrate the aforementioned system, from which is expected the identification of presence/absence of defective textile/leather raw material at a low-latency. Several models powered by Xception were trained with different tunning parameters, resorting to datasets variations that were set up from raw images of leather, following different annotation strategies (meticulous and rough). The model that performed better reached 96% of accuracy.

1. Introduction

According with recent data made available by the Portuguese official statistics portal [2], in 2019, textile and leather industry was ranked in the top-10 of most economically influent activity fields in

Portugal, contributing with a gross value added higher than 4M €. Pushed by the pandemic advent of COVID-19, a crisis context has been impacting the textile and apparel industry not only in Portugal, but also across Europe, wherein the estimations made up to (this paper) date point out to an overall economic setback of 19%. Solutions towards a solid turnaround must encompass the adoption of state-of-the-art technologies through R&D programmes [3], aiming the modernization of processes, as well as services.

Fabric processes upon raw materials to produce clothes, coatings, among many other outputs with distinct market targets (e.g., household items retail, automotive industry) are prone to originate various types of defects or flaws in the production items – mostly, during knitting activities –, increasing costs through the interaction with textile/leather value chain (for example, due to complains and devolutions or items that were undervalued because of imperfections). This is, precisely, one of the issues that may be intervened by edge information technologies, more specifically, to perform inspection/quality control, which is a task still largely carried out by human operators, who are prone to errors, fatigue, and discomfort from an ergonomic perspective. Following this cogitation line, AOI approaches have been materialized in functional solutions capable of providing consistent and reliable quality control process, with results that indubitably outperform human procedures. Essentially, AOI consists in a set of acquisition devices (RGB sensors, illumination kits, clean chambers if required, etc.), remote or local processing hardware (e.g., workstation) and real-time algorithms for defect detection that, together, establish a powerful combination to deliver valuable quality assessment data to players holding decision responsibilities, in an automatic, effective and timely manner [4].

Fabric defects are anomalies that can be broadly classified as follows [5]: a) critical defects that render an item completely unusable and could cause harm to the user of the product; b) major defects are those that could adversely affect the function, performance, or appearance of a product; and, finally, c) minor defects that can be defined as insignificant issues. At a finest level, more specific categorizations can be found in the literature, as the one proposed by [6], in which 6 classes of defects were identified: a) vertical lines; b) horizontal lines; c) isolated defects; d) pattern defects; e) finishing defects; and f) printing defects. Missing and mixed yarns, broken end, needle line, oil spot, hole, press off, gouts are some of the concrete defects that can be found within the identified types. In terms of automatic inspection systems to address the detection of such defects, several works have been proposed. Concerned with the processing over large backgrounds, Wu et al. [7] combined RetinaNet and focal loss as a strategy to quickly extract features describing flaws in textile. They reached an accuracy of 96%. Hanbay et al. [8] compared the performances of Matlab and C++ with a method for defect detection that consisted in combining histogram oriented gradients (HOG) for feature extraction and artificial neural networks for classification, which reached an accuracy of 93%. It was also possible to conclude that C++ is more than 18 times faster than Matlab in processing the images, while using the same algorithmic approach. The detection of yarn-dyed defects was addressed in [9], in which a patch-based labelling step was carried out for training convolutional neural network (CNN) that, in turn, applies a sliding window strategy to make predictions upon textile images, with better results than traditional computer vision approaches. Resorting to image processing grounded in statistical inference over histogram characteristics for feature extraction, Kolmogorov–Smirnov's sample test for feature selection, a thresholding method feature reduction and several classification approaches, Gan et al. [10] focused in the detection of leather flaws. Accuracies between 99.16% and 77.13% were obtained. Another work that combines traditional and novel algorithms was proposed in [11], more specifically, digital image processing for visual data enhancement and neural networks for fabric defects detection. In most of the works found in literature, validations are carried out with datasets of fabric/leather defects, such as TILDA [12] and MVTec AD [13]. A wider set of works can be consulted in recent reviews [14], [15].

In this work, which aims at the detection of defects in leather (without specific recognition, at the moment), a state-of-the-art CNN architecture – Xception [16] – was adopted to build 24 models for comparison purposes that learned from custom-made datasets variations (DSV), based on representative raw-images. A labelling tool that decomposes images into squared patches of parameterizable size was used to set up the mentioned datasets. Two main labelling approaches were considered: meticulous and rough. Moreover, patch sizes of 71x71px (minimum size supported by Xception) and 128x128px (least common denominator above the minimum size supported by Xception complying with the 1024x1024 pixels size that transversally characterizes raw images) were selected for setting up the datasets. Per patch size mode and labelling approach, 3 datasets variation groups were generated, each one rotating imagery assets between train and validation subsets, but with a fixed test subset (unseen data), aiming to explore models learning potential. Regarding the training itself, two optimizers were integrated in each single session: time-based decay stochastic gradient descendent (SGD) and Nadam.

Regarding this paper organization, besides this introductory section, three more can be found: Section 2 characterizes one of the targeted Portuguese industrial environments for fabric processing as well as relevant issues for implementing real-time defect detection on raw material. Then, a multifaceted architecture proposal adaptable to different fabric industry requirements is revisited from previous proposals [1], to contextualize this work goal, which is to addresses one of its modules, more specifically, the one responsible for performing a binary detection of defects in textile/leather. Afterwards, the procedures carried out to set up datasets and to train the Xception-based CNN are disclosed. Section 3 is devoted to tests and respective accuracy results. Finally, main conclusions and intended lines for future work are presented in Section 4.

2. Quality inspection in textile/leather industry: a brief contextualization

In the context of textile/leather industry, raw material quality standards are getting increasingly tight and meticulous in meeting the requirements demanded by the satellite business models (automotive industry, fashion/clothing commerce, etc.). To be up to the challenge while responding time-effectively, manufacturers have been adapting their inspection strategies differently and in compliance with the needs of their direct consumers. One of the common procedures that can be found inside factory floors relies in a roll trolley of raw material that is unwind to a table at a reasonably fast pace (speeds that can reach 25m/s), wherein a human operator carefully looks for relevant defects. Mainly, but not confined to, the goals are: (1) to avoid logistics additional costs from devolutions and (2) to keep business partners satisfied. However, humans have detection performances around 60-70% [17], proneness to ergonomic issues, among others. Considering these aspects allied to the available technological resources that unlock pathways to AOI, in [1], a defect detection-oriented platform for quality control in the textile industry was proposed, combining computer vision, deep learning, geolocation and communication technologies. Figure 1 depicts, specifically, the computer vision/deep learning system, which is composed of 3 main modules: acquisition, processing, and visualization.

Push-broom scans of raw-material placed in roll trolleys are made through a linear sensor with a field-of-view matching the size of the mat width. Digital representations of mat portions imagery are then reconstructed into 2D wide images. Each resulting image is sliced into patch sets afterwards, which are sent to a non-blocking processing module. A two-queues system composes this module: one to deal with the bottlenecks of patches that are progressively released to a binary predictor, specialized in quickly assessing the presence/absence of defects; and another that articulates with a fine-grade classification capable of estimating the concrete types of anomalies in the patches filtered by the former predictor. Such fine-grade estimations end up in a defects classification database that, depending on a certainty threshold, store concrete classification labels or validation queries (e.g., "Which defect are you seeing?" or "Do you confirm a hole defect?") that are posed to experts (operators) working in the shop floor, in articulation with active learning strategies [18]. Finally, the visualization module implements a set of graphic tools and alarm triggers that interface with the user, aiming to provide highly accurate quality inspection decision support and human in the loop validations for the continuous reinforcement of the deep neural networks in use.

Next section will focus on the technicalities underlying the construction of the deep binary detector proposed in this paper, which is a component in constant burden, since all the acquired images undergo through it, for a preliminary check-in for defects.

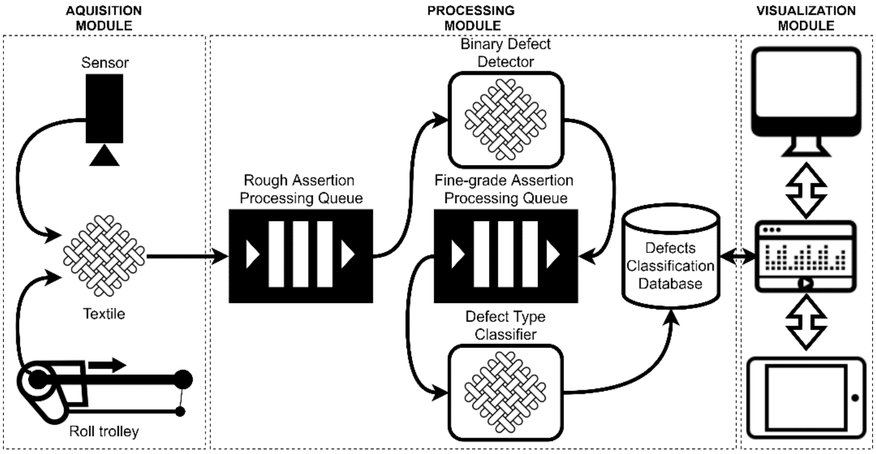

Figure 1. Adapted architecture of the computer vision/deep learning system of the AOI platform presented in [1]. It is composed by three modules – acquisition, processing, and visualization – and it is designed to support dynamic environments that commonly resort to roll trolleys from which textile/leather raw-material are unwind for relatively high cadence inspection.

3. Proposal of a binary defect detector component for textile/leather AOI

Considering the previously presented textile/leather AOI system specification, a process that seeks to build a robust (deep) binary defect detector is proposed in this section, pursuing high accuracies and time-effective operationalization, combined in a preliminary quality screening component (presence/absence of flaws). Such process can be found schematized in Figure 2.

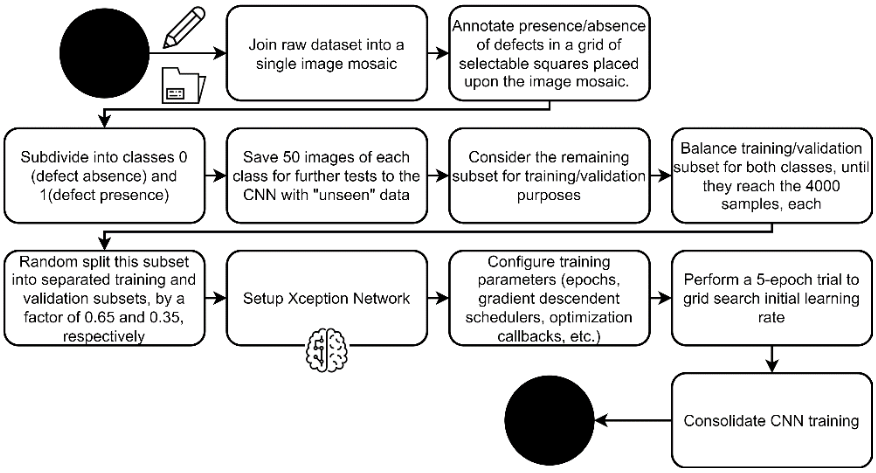

Figure 2. Pipeline for setting up a binary deep model for the preliminary quality screening in textile/leather raw material.

First steps include to gather raw textile/leather images that also include defective regions (stains, rips, etc.) and join them into a single mosaic file. Then, an authoring labelling tool is used to annotate defects, in which a grid approach to divide the mosaics into selectable patches is used. The selected ones are considered as defects. When the annotation is concluded, a first split is performed to separate defects (label 1) from healthy (label 0) parts. To save unseen data for accuracy testing purposes, 50 images of each class are kept in a subset aside, while the remaining images are considered as a training/validation subset, bulked together until this point. Afterwards, resorting to vertical and horizontal flipping, scaling transformation, bright and contrast variation, among other operations, the latter subset is augmented until class 1 reaches 4000 samples, whereas the examples of class 0 - naturally plentiful - are reduced until the same number. Such procedures aim not only to balance data, since healthy patches are present in much greater number, but, also, to increase the number of training and validation samples of defects that end up to support CNNs training. To consolidate the setting up of a given dataset, train and validation subsets are randomly split, using a distribution factor of 65% and 35%, respectively. Regarding the CNN perspective, an Xception architecture is used as the structural template to build the defect detector model. Next, several parameters are configured, as well as a grid search-like process for training optimization and performance enhancement. Some of the most important static characteristics and parameters are:

- batch size of 32;
- 1000 training epochs;
- steps per epoch equivalent to the number of training images divided by batch size;
- validation steps equivalent to the number of validation images divided by batch size;
- checkpoint call-back to store only the best model;
- early stopping call-back configured with 25 epochs of patience, validation accuracy as the monitoring variable, and a threshold that disregards validation accuracy improvements lesser than 0.001%;
- a dropout regularizer weighing 0.25, preceding the dense layer.

On the other hand, a grid search-like process seeks for the more proper initial learning rate (LR) among $1e^{-1}$, $1e^{-2}$, $1e^{-3}$, and $1e^{-4}$ values, by running, for each one, a 5-epoch trial, from which both top validation accuracies and losses are extracted and considered as key performance indicators. Then, LR are ranked based on those metrics – in a way that validation accuracies are of higher importance, while validation losses are only used, if necessary, as tiebreakers – to find the one that showed a better performance in the whole trial, for further usage in the effective training stage. Regarding the optimizers, both time-based SGD – with an LR decay schedule modelled by equation 1 – and Nadam [19] were considered, in isolated training sessions.

$$LR = LR \times \frac{1}{1+decay.epoch} \quad (1)$$

Acknowledging datasets as of major importance in deep learning related challenges, annotation procedures and strategies will be detailed in the next subsection.

3.1. Data gathering and annotation process

Defective samples of leather available in MVTec AD repository [13] were downloaded and used to produce two mosaics of raw-images. To turn these mosaics into structured datasets, an authoring tool (Figure 3) was developed and used for binary labelling purposes.

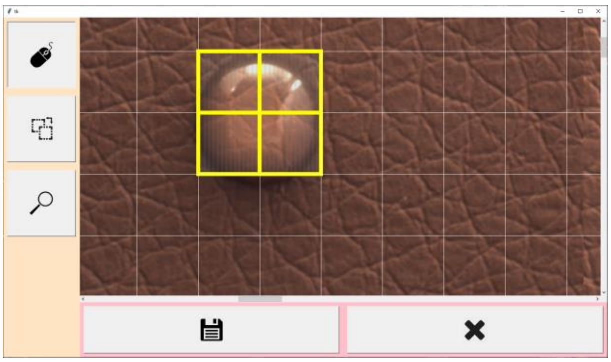

Figure 3. Authoring tool developed for labelling raw images.

It consists of a graphical user interface that allows to import an image, upon which a translucent grid (rule) of definable granularity is placed to orient tagging/releasing actions, as well as to drag, zoom in, zoom out canvas and export labeled grid patches into folders accordingly named. Resorting to this application, two labelling approaches were followed to start outlining the datasets for CNN training:

- a meticulous marking of defects, in which the slightest visual indication of flaw was tagged as a surface fault;
- a rough marking of defects, in which only patches with a substantial area of leather flaw, also determined by visual inference, were considered defective.

While Figure 4 depicts the aforementioned labelling approaches, Figure 5 shows a few examples of healthy and defective leather samples.

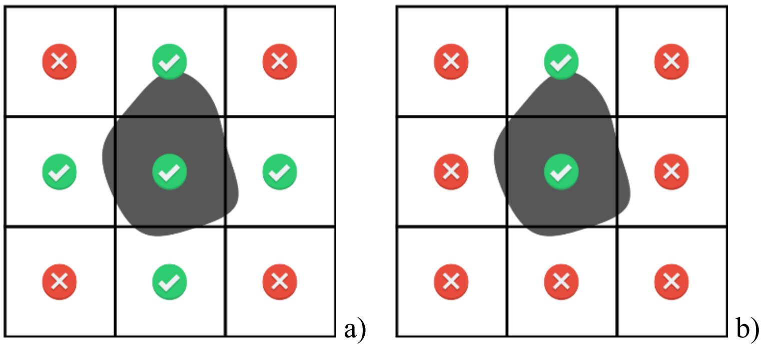

Figure 4. Labelling approach: a) meticulous; b) rough.

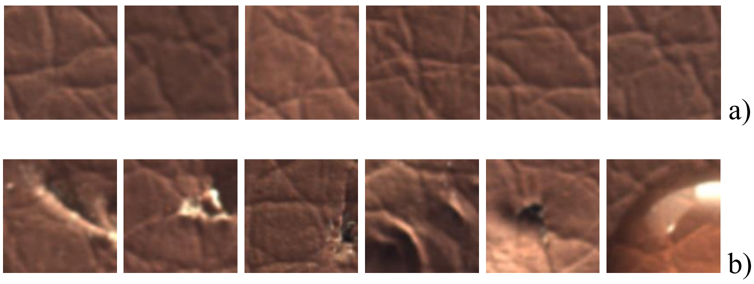

Figure 5. Leather samples: a) represents the absence of defects (class 0); b) depicts examples of defective material (class 1).

With the sample patches properly divided into classes of leather portions with and without defects, the next step is to reserve a testing subset of 50 images per class, foreseeing model's accuracy assessment with "unseen" data, in a post-training stage. Training/validation subset is then balanced – i.e., flaw samples are augmented while examples of healthy patches are decreased, as described earlier in this section – and subdivided into training (65%) and validation (35%) groups. At this point, procedures match steps 1 to 8 of the flow diagram delineated in Figure 2, meaning that datasets are consolidated and ready to undergo through the training stage that shape up the deep learning model for estimating the presence/absence of defects in leather.

3.2. Deep Learning Approach: Xception

Xception [16] combines point-wise convolutions followed by depth-wise separable convolutions and residual connections. By starting of convoluting the points and then the channels and, also, by excluding intermediate rectified linear units (ReLUs) of non-linearity, this deep learning architecture reached state-of-the-art performances in tests with ImageNet dataset [20].

Acknowledging its learning robustness, Xception was considered to the challenge underlying this work, which is to train deep learning models capable of identifying the presence of defects in leather and, thus, starting developing sensibility and structures towards the development of a preliminary but essential screening component to be integrated in a major AOI system [1] for textile/leather quality assessment. Together with representative datasets variations and a couple of LR optimizers – time-based SGD and Nadam – Xception's potential for providing reliable models was explored through tests that will be addressed in a later section.

3.3. Tools and implementation

In terms of tools, Anaconda [21] was used as data science platform, which, in turn, integrates: Spyder [22] development environment, Python [23] programming language and Tensorflow [24] deep learning engine. Xception [16] template was pulled from Tensorflow library and adapted with a dropout layer for overfitting reduction. The solution programming was done taking into account the previously mentioned functionalities and features.

Next section will address the tests performed to the proposed set of deep learning-oriented training methods/processes – turned into a demonstrable solution through Python and Tensorflow – and present the respective results.

4. Tests and results

A benchmark considering Xception architecture, time-based SGD and Nadam LR optimizers, both meticulous and rough labelling approaches – see subsection 3.1 –, and two distinct imagery size modes (71x71 and 128x128 pixels) configuring several datasets variation groups was performed, aiming to explore, mainly, the potential of modern deep learning strategies in the task of binary screening defective leather image patches.

The setting up of DSV corresponds to the range of steps 5^{th} to 8^{th}, defined in the pipeline depicted in Figure 2. A couple of different size modes were considered in the production of such DSVs:

- 71x71 pixels – the minimum accepted by the adopted architecture;
- 128x128 pixels – least common divisor of original raw images dimension (1024x1024 pixels), immediately above the minimum acceptable mentioned in the previous point.

More specifically, by inducing a slight change in the mentioned pipeline (Figure 2) consisting in the repetition of the 8th step, 3 groups of DSVs were generated for each one of the 4 possible combinations pairing size modes (among 71x71 and 128x128 pixels) with labelling approaches (out of rough and meticulous), making a total of 12 variations. Each DSV group results from random splitting operations to set up training and validation subsets, complying with the 65% and 35% factors defined in the previous section, respectively, while maintaining the same testing subset. With the inclusion of Nadam and time-based SGD LR schedulers for comparison purposes, 24 Xception-based models were trained in total.

Regarding the results processing, due to DSVs balancing procedures done before CNNs training stage, the metric selected to assess each Xception-based model in terms of learning and prediction capabilities is standard accuracy, as shown in equation 2.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (2)$$

TP, TN, FP and FN correspond to true positive, true negative, false positive and false negative, respectively.

The computer used to carry out these tests can be classified as a domestic grade market solution, and has the following relevant specifications:

- Processor – 11th Gen Intel(R) Core (TM) i7-11800H @ 2.30 GHz 2.30 GHz;
- Random Access Memory (RAM) – 32 GB @ 2933 MHz SODIMM;
- Graphic Card – NVIDIA GeForce RTX 3080, 16.0 GB GDDR6 RAM (Laptop edition);

- Storage – 1 TB, 3500 MB/R, 3300 MB/W;
- Operative System – Windows 10 Home 64 Bit.

Results are presented in Table 1, from which can be inferred that models trained with Nadam are consistently more accurate than the ones trained with time-based SGD scheduler. It is also possible to conclude that models that relied their learning on roughly labelled datasets performed better, averagely ($\overline{DSV}_{\text{meticulous}} \simeq 77\%$, $\overline{DSV}_{\text{rough}} \simeq 84\%$). Regarding the size modes, the smaller patches allowed to train models with a mean accuracy higher than the bigger ones ($\overline{DSV}_{71\text{x}71} \simeq 90\%$, $\overline{DSV}_{128\text{x}128} \simeq 71\%$). The model with the best performance – reaching 96% of accuracy – follows the tendency of most of these observations, except for size mode, since it belongs to the group of images dimensioned to 128x128 pixels. In Figure 6, more details about the results achieved with this model are provided.

Table 1. Results of the tests done with Xception, considering 3 datasets variation groups, each one dimensioned to 71x71 and 128x128 pixels, and 2 optimizers – Nadam and Time-based SGD (TB-SGD) –, across 2 styles of annotation (meticulous and rough).

	DSV1		DSV2		DSV3	
	TB-SGD	Nadam	TB-SGD	Nadam	TB-SGD	Nadam
Meticulous (71x71)	82%	86%	85%	93%	91%	94%
Meticulous (128x128)	54%	77%	53%	77%	55%	74%
Rough (71x71)	91%	94%	90%	91%	87%	92%
Rough (128x128)	59%	93%	59%	94%	59%	96%

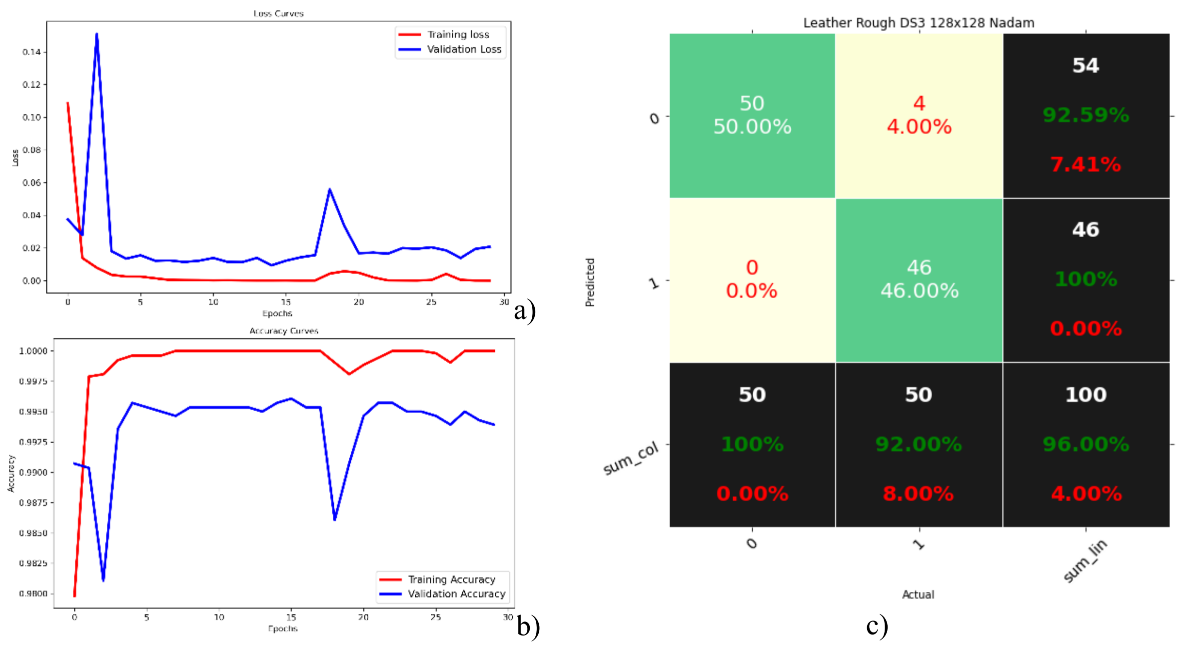

Figure 6. Results achieved with the model that best performed in distinguishing healthy and defective leather portions: a) and b) show the loss and accuracy plots, respectively, with an interesting convergence tendency; c) presents the confusion matrix.

Comparisons with the other works found in the scientific literature (e.g. [6], [7], [8], [9], [10], and [11]) cannot be directly made, inasmuch as this module focuses in the detection of defects, rather than

identification. Even though, one can infer that very promising results were obtained overall, in what concerns to quality inspection accuracy.
In terms of prediction time, the computer in which these tests were performed requires, roughly, 3 seconds to estimate the presence/absence of defects in 100 leather patches, which seems significative for a model that must operate near of real-time rates.

5. Conclusions and future work

Quality inspection is an essential activity for textile/leather industry that is still, however, commonly performed by human operators, with a negative impact in employed collaborators' well-being and companies' financial healthiness. To tackle such conjuncture, AOI approaches have been materialized in functional solutions capable of providing consistent and reliable quality control process.
In this paper, the preliminary binary defect detector component that composes the system proposed in previous work [1] was addressed, with studies and experiments that aim to guide further developments. Pursuing this goal, several combinations involving different raw data labelling styles, dataset variation groups, size modes reflected in images dimensions, as well as training sessions varying optimizers were considered, to build and compare 24 Xception-based models. Accuracies ranging from 53% to 96% were achieved, with emphasis on models created based on datasets roughly labelled, 71x71 pixels size modes and Nadam optimizer, which contributed for higher accuracies, overall. On the other hand, prediction times do not seem to be the most satisfactory to comply with close to real-time processing requirements.
Future activities must encompass the analysis of the variables addressed in this work and, also, others of significant pertinence – including batch size redefinitions, wider sets of optimizers and fine tuning of the respective parameters, alternative labelling strategies and data augmentation methods, etc. –, working with CNN architectures capable of outputting quicker estimations. Moreover, other datasets of public access complemented with acquired ones in shop floors context must be included to consolidate deep learning-based models' reliability and transversality.

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