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Managing Voluntary Interruption of Pregnancy using Data Mining

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Abstract

When a woman aims to terminate an unplanned pregnancy, she must go to a specialized healthcare unit, such as Júlio Dinis Maternity Hospital. In this unit, the procedures of voluntary interruption of pregnancy are done by two kinds of drug administration: the first one is always done by a nursing team, the second one can be performed at home or by a nursing team, depending on patient features. It is important to give the best option to the pregnant. In this paper, it is proposed to predict whether the second drug phase is done at home or at the hospital. The use of Data Mining (DM) helps in performing this step. Throughout this study, DM models capable to make predictions in a real environment using real data were induced. It was adopted the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology. Four distinct techniques were considered: Decision Tree (DT), Naïve Bayes (NB), Support Vector Machine (SVM) and Generalized Linear Models (GLM) to perform classification tasks. Using these techniques it was possible to obtain acceptable results for each model. A value greater than 89% of accuracy and 91% in sensibility was achieved in some models.

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Keywords: Data Minng, Maternity Hospital, Crisp-DM, Voluntary Interruption of Pregnancy, Pregnancy

1. Introduction

Currently, in the information age, organizations are able to respond to new challenges and new requirements as well as constant changes. It is needed to adjust to these new realities, in order to maintain competitiveness in the market and provide quality services. Information and communication technology support information systems, which are a set of procedures that when executed, produce useful information for decision-making process (DMP)

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and organization management [1]. In health sector, the technologies change processes by providing full and reliable information for health professionals and to support the decisions of managers and regulators [1].

The implementation of information systems focused on helping nurses, like the Support Nursing Practice System – SNPNS a.k.a. SAPE, gave the redefinition of activities for the delivery of nursing care to the patient. The SAPE was created with the aim to give visibility to the work performed by nursing professionals, since these are users who more produce, process and provide clinical information [1].

With the storage of all data relating to the processes of patients in the SAPE, it becomes possible to use this information to obtain useful knowledge in practical nursing.

In this case, it is possible the application of Data Mining (DM) on the same data, which allow to obtain predictive models for certain interventions. This works intended, through the techniques of DM, to provide situations for the Voluntary Interruption of Pregnancy (VIP) module, at Júlio Dinis Maternity hospital (MJD) in Oporto.

MJD is one of the four constituent hospitals of Centro Hospitalar of Oporto. The remaining three are the Hospital de Santo António, Hospital Maria Pia and Hospital Joaquim Urbano. This merge of hospitals started in 2007.

In MJD, there is a Voluntary Interruption of Pregnancy module, where pregnant women who wish to abort are addressed. The termination of pregnancy can be medicinal or surgical. The use of medicines to end the pregnancy provides the removal of the fetus and placenta from the uterus of the woman. In the surgical event, it is necessary to perform an operation to terminate the pregnancy. The termination of pregnancy can be accomplished when the developing baby has a birth defect or genetic problem, the pregnancy is harmful to the woman's health (therapeutic abortion), the pregnancy resulted after a traumatic event such as rape or incest, or the woman may not wish to be pregnant (elective abortion)[2]. Portuguese legislation (Law no. º 16/2007 of 17 April) allows the termination of pregnancy for the woman's choice, up to 10 weeks of gestation, and the consequent creation of health services for the care of women who choose this practice[3].

The main goal of this work was achieved using DM techniques to induce classification models in order to predict if a woman in VIP will interrupt pregnancy in the maternity hospital or at home, based on some influential factors. The achieved results were very interesting to the clinical context (sensitivity 91% and accuracy 89%).

Besides the introduction, this article includes six sections. The second is related to the background knowledge, which describes the process of VIP and a brief look is taken about Interoperability and SAPE. Subsequently, section three describes the process of Knowledge Discovery in Databases and the method of Crisp-DM, based on DM techniques and some of the statistical metrics applied. In the fourth section, it is described each stage of Crisp-DM method and the remaining two sections are for discussion and conclusion.

2. Background and Related Work

2.1. Voluntary Interruption of Pregnancy

In the VIP module of MJD is used non-surgical methods to perform the process of termination of pregnancy. More specifically, it was adapted the method recommended by WHO (World Health Organization) that consists in administering specific drugs, because it's a safe and efficient methodology. The medication administered is the combination of *mifepristone* and *misoprostol*.

The VIP process consists of several steps, being the first conducted before the implementation of abortion. It includes a mandatory appointment with a physician, a reflection period of three days and still optional consultations with a psychologist or social worker.

Later, when the patient did not have doubts of its decision, the following three procedures are accompanied by a monitoring of the nursing team. The first is a consultation with a nurse, where it is given the first dose of medication and triage is performed to verify if the patient is able to make the administration of the second dose of medication at home or whether she needs monitoring. If she requires monitoring, the second dose of medication will be applied with the monitoring of a nurse in ambulatory, as set in the protocol.

Finally, after performing the abortion, it's necessary to go to a doctor's appointment to control and there is a collaboration of the nursing team in a family planning consultation [4].

2.2. Interoperability System

This work was possible thanks to the interoperability of existing systems in CHP. The interoperability between Information Systems of Hospital of Porto is guaranteed by the Agency for Integration, Archive and Diffusion of Medical Information (AIDA), which is based on the use of intelligent agents to enable communication between different systems. This multi-agent system enables the standardization of clinical systems and overcomes the medical and administrative complexity of the different sources of information from the hospital. All Medical Information Systems are connected by AIDA, including Support Nursing Practice System (SAPE) [5][6].

2.3. Support System Nursing Practice

The SAPE came under the Nursing Information Systems, as an alternative to the traditional form of paper information and its design in functional terms originated at the Superior School of S. João by Nurse Abel Paiva [1]. The system was developed as a fundamental basis of the CIPE (International Classification for Nursing Practice). Thus, involves the construction of a number of diagnoses and interventions basis, from a set of axes of CIPE, with the frequent focus in each service, which are installed in hospitals within the system [1], [7]. The work of parameterization is performed by the service that uses the app, so a survey of more frequent focus should be done at this same service, later to build, for each focus, interventions that are likely to be used. These interventions parameterized are brought to the nurse, who is in charge of selecting from the set of options, the most appropriate to a particular case. In addition, each focus must be associated with a set of diagnoses that depict the evolution of the same focus in the patient. The system requires that there is at least one diagnosis associated with each patient [1], [7].

3. Knowledge Discovery and Data Mining

3.1. Knowledge Discovery in Database

The Knowledge Discovery in Database (KDD) process is a set of ongoing activities that share the knowledge discovered from databases. According to Fayyad et al. [8] this set consist of five stages, that were followed in this work:

- *Selection* - Occurred the selection of the data set that were needed to perform the Data Mining (DM);
- *Pre-processing* - This step included cleaning and processing of data in order to make them consistent;
- *Transformation* - In this phase the data were worked out according to the target.
- *Data Mining* - At this stage, the objectives to be achieved and the type of result wanted to achieve were defined. According to the type of desired result, was defined the type of task being performed (classification, segmentation, summarization, dependency modelling) and identified the technique to be used (decision trees, association rules, linear regression, neuronal networks, among others). Subsequently, it was applied the selected data mining technique to the data set to obtain patterns.
- *Interpretation/Evaluation* - Consisted in the interpretation and evaluation of the patterns obtained. The validity of the results obtained was verified by applying the patterns found at new datasets [9].

The KDD process refers to the whole process of discovering useful knowledge in data, while data mining refers to the application of algorithms to extract data models. Until 1995, KDD and DM terms were considered interchangeably. Now DM represents a phase of the Knowledge Discovery in Databases process (KDD) and consists in finding patterns or relationships that may exist in the data stored in data repositories.

According to Freitas [10], the knowledge to be discovered must satisfy three properties: it must be correct (as much as possible), should be understandable by human users, and should be interesting useful/new. Still, the method of knowledge discovery must have the following three characteristics: it must be effective (accurate), generic (applicable to various data types) and flexible (easily modifiable).

3.2. Cross Industry Standard Process for Data Mining (CRISP-DM)

The methodology of DM that was addressed was the methodology of Cross Industry Standard Process for Data Mining (CRISP-DM), due to its characteristics:

- Independent Industry - The same process can be applied to analyse business, financial data, human resources, manufacturing, services, etc.
- It is independent of the tool used;
- Has close relationship with the models to proceedings of KDD, previously described.

The CRISP-DM breaks the process of data mining into six major phases as can been seen in to figure 1 [11]–[13].These steps implemented were:

- *Business Understanding*: this initial phase of the project DM focused on understanding the objective of the project from a business perspective, defining a preliminary plan to achieve the goal;
- *Data Understanding:* comprised data collection and startup activities for familiarization with the data, identifying problems or interesting sets;
- *Data Preparation:* in the preparation phase of data were included all the tasks involved in creating cases that were used to build the model table. Data preparation tasks were likely to be performed multiple times, in no particular order. Tasks included building the table of cases, selection of attributes, data cleaning and transformation. Additionally, it was possible add new attributes calculated based on existing ones. The preparation phase of data can significantly improve the information that can be discovered through DM.
- *Modeling:* various modeling techniques (algorithm of decision tree, association rules, linear regression, neural networks, among other) were applied, and their calibrated parameters for optimization. Thus, it was common return to data preparation during this phase;
- *Evaluation*: there was built a model that seemed to have great quality from a perspective of data analysis. However, it was necessary to check whether the model met the business objectives;
- *Deployment:* the knowledge gained by the model was organized and presented in a way that the customer can use.

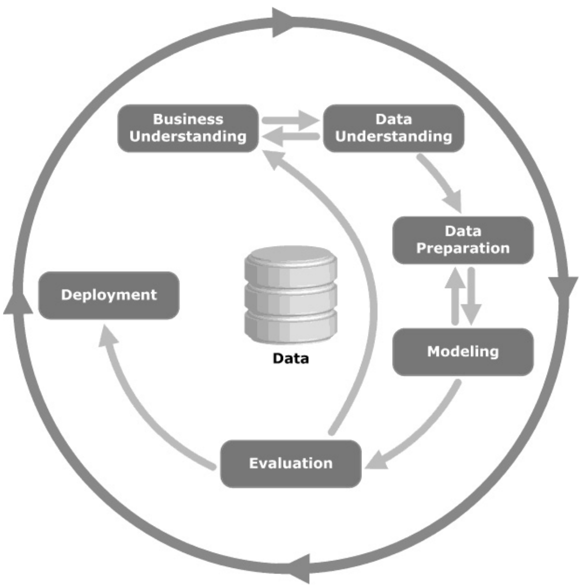

Figure 1 - The Crisp-DM process.

3.3. Data Mining Techniques

In the modeling phase, various DM techniques could be used, but those better mold to the problem were:

- Decision Tree (DT): DT automatically generates rules, which are conditional statements that reveal the logic used to build the tree.
- Naive Bayes: Naive Bayes uses Bayes' Theorem, a formula that calculates a probability by counting the frequency of values and combinations of values in the historical data.
- Generalized Linear Models (GLM): GLM is a popular statistical technique for linear modelling. In Oracle Data Mining is implemented GLM for binary classification.
- Support Vector Machine: SVM is a powerful, state-of-the-art algorithm based on linear and nonlinear regression. In Oracle Data Mining is implemented SVM for binary and multiclass classification.

3.4. Statistical Measures

Using DM techniques it was possible, through the use of Confusion Matrix, obtain four types of results. The first situation could be a true positive (TP) result that corresponds to the number of positive examples correctly classified. We could also get a false positive (FP) result that corresponds to the number of positive examples classified as negative. Still had the status of being a true negative (TN) result, that corresponds to the number of negative examples actually classified as negative and, finally, the false negative (FN), that corresponds to the number of negative examples classified as positive.

From this type of values resulting models, statistical metrics for assessing data quality, in particular, the sensitivity, specificity and accuracy could be estimated.

- *Sensitivity:* is the ability to correctly detect the occurrence of the procedure. It is the result of the ratio of true positive (TP) values on all the values corresponding to positive (TP + FN);
- *Specificity*: on the other hand, it is the ability to correctly identify in a model the non-occurrence of a procedure. It is measured by the ratio of correctly identified as negative values (TN) and all values corresponding to negative (TN + FP);
- *Acuity:* is the total percentage of agreement between the values detected correctly and the actual values. It is measured by the proportion of all the results measured correctly (TP + TN) from the models of all cases liable to be obtained (TP + TN + FP + FN) [14].

Table 1 present the expressions that characterize each of the metrics described.

Table 1. Expressions that define the sensitivity, specificity and accuracy.

	Positive Result	**Negative Result**	**Sensitivity**	**Specificity**	**Acuity**
Positive Value	TP	FP	$\frac{TP}{TP+FN}$	$\frac{TN}{TN+FP}$	$\frac{TP+TN}{TP+FP+FN+TN}$
Negative Value	FN	TN			

4. CRISP-DM /DM

The process is complex, but when done in a methodological context, CRISP-DM becomes easier to understand, implement and develop. In this case study it was intended to apply this methodology to forecast the framework of the VIP. Then it was presented the steps described in section 3.1 following the methodology CRISP-DM and using Oracle Data Miner tool.

4.1. Business Understanding

As was referenced in section 2.1, the process of VIP consists of the administration of two drug, *mifepristone* and *misoprostol* doses, respectively. The first dose is always applied in MJD outpatients with monitoring of the nursing team and the second dose, the same procedure can be performed in MJD or performed by the patient at home.

In this case, a problem was formulated: "*How can it be predicted if a pregnant woman is holding a second drug phase at home or with the monitoring of the nursing team?*" This could be translated into a problem of DM as: *"What is the probability of a pregnant woman carry out the second drug phase with monitoring of nursing staff?"*

A model that predicts where a pregnant woman should perform the second drug phase must be built on data that describes the process of VIP pregnant in the past. Before building the model, one should always choose the data that are likely to contain the relationships between the pregnant and carrying the VIP process (with the accompaniment of the nursing team or domicile).

To induce data mining models it was selected the attributes age, *gesta* (number of pregnancies), *para* (number of births), number of previous VIP's, employment status, use of contraceptive methods and weeks of gestation.

4.2. Data Understanding

In this phase was extracted data from SAPE and AIDA and it was analysed the quality of the possible variables to be used in the process. The sample covers the period between 01.01.2012 and 31.12.2012. 1124 records of VIP cases were registered. Each record consists of fields:

- *Age:* corresponds to the age of the patient who will perform the procedure;
- *VIP number of previous investigations (N_VIP):* this variable sets the number of times the patient underwent the process of VIP previously;
- *Gesta:* corresponds to the number of previous pregnancies of the woman;
- *Para:* corresponds to the number of births that the woman had;
- *Professional Status (PS):* this variable informs if the pregnant woman in question is employed or not.
- *Contraceptive failures (CF):* Corresponds to the failures of the contraceptive method responsible for the occurrence of pregnancy;
- *Local administration of the second dose (LASD):* corresponds to where the administration of the second dose of medication (MJD or domicile) was performed;
- *Contraceptive Method (CM):* the variable informs if the pregnant woman had used a contraceptive method or not;
- *Weeks of Gestation (WG):* corresponds to the weeks of the gestation of the pregnant woman, when she arrived to MJD.

After a surface analysis of the data, it was found that they exhibited quality, but have to be worked so that can be used in forming the problem of DM, since not all required fields are fulfilled in patient's information. In figure 2 is shown the distribution of values of the variable target VIP process local, while in table 2 are represented statistics measures of some numerical variables. Table 3 depicts the percentage of occurrences associated with each of the variables used.

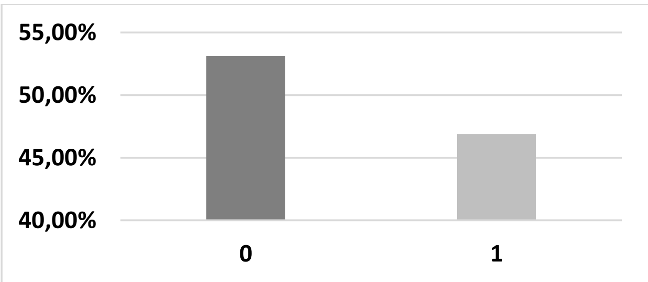

Figure 2 - Distribution of values of the variable target VIP process local, which may take the values MJD (0) or home (1).

Table 2. Statistics measures of N_VIP, WG, Age, Gesta and Para variables

	Minimum	Maximum	Average	Standard Deviation
N_VIP	0	4	0.22	0.53
WG	3	10.4	7.14	1.46
Age	13	46	27.4	6.95
Gesta	1	9	2.1	1.26
Para	0	8	0.8	0.98

Table 3. Percentage of variables occurrences

Number	CM	PS	N_VIP	Gesta	Para
0	38.60	53.00	82.10	42.60	49.70
1	61.40	26.20	14.70	24.80	27.40
2		20.80	2.50	19.60	17.60
3		0.09	0.37	8.95	4.40
4				2.22	0.65
5				1.02	0.09
6				0.46	0.09
8				0.28	0.09
9				0.09	

4.3. Data Preparation

At this stage and having as base the variables mentioned in the previous subsection, it was selected only variables that could model the problem, namely, age, *gesta*, *para*, number of previous VIP's, employment status and place of administration of the second dose of medicines. After selecting data, a pre-processing task was performed, where all data that submit null values or noise were eliminated (targets). Thus, it was eliminated approximately 0.08% of null values of the variable unemployed, about 0.08% of null values of contraception variable, about 0.08% of null values of variable VIP process local and about 0.7% of null values of the variable number of previous VIPs. Were also eliminated approximately 3% of noisy data, leaving only 1082 records at the end.

One of the cases where there was noise in the data was the weeks of gestation, where values with decimal places were separated by a point and sometimes separated by comma. The solution was to use the comma to separate the decimals on all data, and changing the point by the comma.

Besides this procedure, it was also created form classes in order to model the problem accurately and distributions of values were analyzed for each class. Thus were created the following classes, presented in table 4 and 5:

- *Age class 1 (AC_1)*: This division was based on reports built by the nursing team, which conducted the division of the data in these same intervals.
- *Age class 2 (AC_2):* This second division of the ages was performed in order to assess the impact that age can have on results.
- *Weeks of gestation class (WGC):* This division was performed in order to group the pregnant women who come to MJD in three classes, according to the gestational time in order to analyze their impact on the final results.

Table 4. % of occurrences associated with each intervals of class AC_1 and AC_2.

AC_1	% Occurrences	AC_2	% Occurrences
13 - 15	1.20	0 - 18	5.50
16 - 18	7.80	18 - 23	29.50
19 - 21	13.50	24 - 29	28.50
22 - 24	17.50	30 - 35	20.50
25 - 27	14.20	36 - 41	14.00
28 - 30	14.00	41 - 46	2.00
31 - 35	15.80		
36 - 40	12.90		
41 - 46	3.10		

Table 5. % of occurrences associated with each intervals of class WGC.

WGC	% Occurrences
5 - 8	67.70
9 - 12	30.10
0 - 4	2.20

With the transformations, previously mentioned, it was possible to construct a table of cases, where DM techniques were applied.

4.4. Modeling

In Table 6, it can be seen the combination of variables used in each one of the 10 scenarios that gave the best overall result. The only variables that are present in all scenarios is the *LASD*, which is the variable that is intended to predict and *Gesta* and *Para,* which are the variables that have the most influence on the previous.

Table 6 - Representation of the variables used in each of the models.

	LASD	Age	N_VIP	Gesta	Para	PS	CM	WG	AC_1	AC_2	WGC
Scenario 1	X	X	X	X	X	X	-	-	-	-	-
Scenario 2	X	X	-	X	X	-	-	-	-	-	-
Scenario 3	X	-	-	X	X	-	-	-	-	-	-
Scenario 4	X	X	X	X	X	-	-	-	-	-	-
Scenario 5	X	-	X	X	X	X	-	-	X	-	-
Scenario 6	X	-	X	X	X	X	-	-	-	X	-
Scenario 7	X	-	X	X	X	X	X	-	-	X	-
Scenario 8	X	-	X	X	X	X	-	X	-	X	-
Scenario 9	X	-	X	X	X	X	-	-	-	X	X
Scenario 10	X	-	X	X	X	X	X	-	-	X	X

After the construction of the case table in the previous stage, it was used DM techniques in order to obtain the best model to the problem referred in section 3.2. The selection of DM techniques was based in two distinct aspects: interpretability of the models and engine efficiency.

In order to use the GLM model to perform a binary classification, it was necessary to go back to the previous step in order to transform the variable local administration of the second dose in binary, since above this variable contains the following values:

- MJD: If pregnant perform the second drug step at MJD, with monitoring of the nursing team;
- Dom: If pregnant had the ability to self-administer medication at home.

In case of being MJD was assigned a value "1" in the case of DOM, was assigned the value "0". The developed models can be represented by the following expression:

$$M_n = A_f + S_i + TDM_y$$

The model M_n belongs to the approach (A) classification and is composed by a scenario (S) and a DM technique (TDM):

$A_f = \{Classification\}$

$S_i = \{Scenario\ 1 \ldots Scenario\ 10\}$

$TDM_y = \{SVM, NB, GLM, DT\}$

4.5. Evaluation

This task is dedicated to the evaluation of models. To evaluate the results achieved by the DM models, statistical metrics described in section 3.3 were used. In these metrics were evaluated tree parameters: specificity, sensitivity and acuity. During the development phase, 40 models were induced (10 scenarios x 4 DM techniques). Table 7 presents the top 3 scenarios, for each one of the algorithms used.

Table 7 – Top 3 models for each algorithm.

Support Vector Machine				Naïve Bayes			
	Sensitivity	**Specificity**	**Acuity**		**Sensitivity**	**Specificity**	**Acuity**
Scenario 1	0,902	0,870	0,886	**Scenario 2**	0,887	0,880	0,884
Scenario 5	0,902	0,870	0,886	**Scenario 3**	0,900	0,855	0,877
Scenario 7	0,902	0,870	0,886	**Scenario 4**	0,887	0,880	0,884
Generalized Linear Model				**Decision Tree**			
	Sensitivity	**Specificity**	**Acuity**		**Sensitivity**	**Specificity**	**Acuity**
Scenario 2	0,904	0,815	0,856	**Scenario 1**	0,911	0,841	0,874
Scenario 3	0,900	0,825	0,860	**Scenario 3**	0,911	0,841	0,874
Scenario 4	0,889	0,864	0,877	**Scenario 4**	0,911	0,841	0,874

The best cases were selected based on the value of the sensitivity, since MJD wants to follow all the pregnant women who such need support, even though it may occur that there were cases of false positives. Thus, it is preferable that monitoring in MJD occurs without the need, than to run the risk of not monitoring a pregnant and then have problems on abortion.

4.6. Deployment

As mentioned before, after the model validation, the knowledge gained will be organized and presented so that the nurses can use them. Depending on the requirements, the deployment phase can generate a report as simple or complex as the implementation of a process of repeated DM. In this case, these data mining processes will be integrated in Business Intelligence platform, being implemented in MJD.

5. Discussion

The results are quite acceptable based on the assessment carried out for the forecast models. For classification models, the best predictions yielded a higher sensibility to approximately 91%. The top three models that achieved these sensitivity values were models 1, 3 and 4. Curiously, the best models belongs to the same algorithm: DT.

The best scenario that had this sensibility value combined with the highest acuity value was the scenario 3, which is a combination of *LASD, Gesta and Para* variables. Scenario 3 was considered the best scenario because it is present in the top 3 of the best models obtained in three DM techniques used, obtaining the highest sensitivity values in two of them. Thus, it can be concluded that all combinations of variables used in the different models and with different DM techniques, this was the best helped to predict the *LASD* variable.

Table 8 shows the results (accuracy) of the scenario number 3, identifying the number of cases in that the scenario hit and the number of instances where the scenario failed for each of the algorithms used.

Table 8 - Number of cases that the model 3 hit and missed for each of the algorithms used.

	Wrong	**Correct**
Support Vector Machine	48	382
Naive Bayes	53	377
Generalized Linear Model	60	370
Decision Tree	54	376

According to these results, it appears that the most efficient algorithm applied to the scenario 3 was the Support Vector Machine algorithm, since it is the hit a larger number of cases.

In conclusion, the attained results with predictions made to predict where the pregnant effect the second drug phase of the VIP process could be considered satisfactory to support the decision making of the nursing team.

6. Conclusion and Future Work

This study demonstrated that it is possible to obtain classification DM models to predict where a VIP patient should perform the second stage of drug administration. The study was conducted using real data of the VIP process collected in MJD corresponding to one year of activity, namely the year 2012. Acceptable results were achieved in terms of sensibility and accuracy, approximately 91% and 87%, respectively, associated to the model obtained by applying the Decision Tree technique in scenario 3. Thus, it appears that the most relevant factors for determining the location of achieving the VIP process are the number of pregnancies (Gesta) and the number of births (Para) that a woman ever had.

It can be concluded that using the classification techniques and the past personal data of pregnant women, it is possible to predict the future VIP location. The final objective of using DM was achieved; the developed models allow support the DMP and give the better option to the pregnant when she wants to abort.

Finally, this work proves that it is possible to develop models of DM in order to help the pregnant to have the better treatment with good predictive ability. However, this problem of DM addressed in this paper is focused only on VIP and was applied using a specific case in MJD. Models can be translated to other hospitals that have the same problem and use the same approach in dealing with this issue.

Future research will take into consideration some aspects like exploring different types and configurations of data mining techniques, incorporating new variables in the predictive models, repeating experiments with new data and embedding this model in MJD clinical decision support system.

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