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Improvement of the Triage Process using Process Automatization and Machine Learning

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Abstract

From historical times, classification of patients according their priority level has been considered very important. In this aspect, this paper intends to share some experiences in improving the turn allocation process in the emergency room of a hospital using machine learning algorithms. The present work compares several models such as Naive Bayes, Logistic Regression and Multilayer Perceptron in predicting patient classification. The result indicates that machine learning can be a very important tool for decision support in medical fields.

Keywords: Triage, clinical decision support, process improvement, machine learning, data mining, medicine.

INTRODUCTION

The level of maturity of processes in an organization is determinated by the optimization of their activities and involved resources. This is the reason why organizations put their effort in improving their processes by using different methods [1, 2, 17, 18] such as machine learning techniques. In this sense, the optimization of processes using machine learning techniques also has been used in the field of medicine [3]. Worldwide researchers have been put their effort implementing those techniques in medical services such as clinical laboratories [4-10,19, 20] and medical diagnoses; however, machine learning tecnhiques have not been widely used on the triage process yet. This is the reason why this paper intends to apply the mentioned technology to the triage process based on real data of the Emergency Department of a Public Hospital of Ecuador called Armed Forces Specialties Hospital. This research proposes a model to classify the care priority of patients in emergency using machine learning techniques based on medical criteria and predefined variables.

The rest of the paper is organized as follows. First, section 2 reviews briefly the theoretical concepts used in this research. Then, section 3 delivers the current situation of the triage process used in the Hospital (objective of analysis). Later, in section 4, improvement of the triage process using machine learning techniques are explained with details. Finally, analysis of the results of the proposed model and conclusions are described in sections 5 and 6.

THEORETICAL BACKGROUND

For the present work, the following concepts have been considered.

Triage

Triage is derived from the french term “trier” which means "to select or choose / to choose or to classify", and it refers to a system that quickly evaluates the severity of each patient and indicates the best treatment depending on his/her condition [12].

Reference [11] lists the most important triage models i.e. (1) Australian Triage Scale, (2) Triage of the Emergency Department of Canada, (3) Manchester triage system, (4) Urgency severity index, and (5) Triage model Andorra. All of these models have five rating levels, starting from immediate care to treatment after several hours, depending on the patient's symptoms.

Usage of Decision Trees in Public Health

In the last 30 years, different researches have used statistical techniques in the analysis and prediction of information. In this aspect, the field of medicine also have used such techniques to predict infections or diseases, to assign treatment priority, to create decisicon support systems, and so on [4-10, 13, 14].

Machine Learning.

Machine Learning is a technique that allows computers to learn through programs that generalize behaviors from information or a set of patterns of data. It also allows systematizing parts of scientific methods [15]. Machine learning algorithms have existed for two decades, but recently, their application has become popular because of growth of power in computing and data storage. It is also important to indicate that there are several models for resolutions of problems in machine learning. Those models can be classified as Geometric, Probabilistic and Logical; they also can be classified as clustering models when they divide the space of instances into groups or gradient models when means of the representation of a gradient can be differentiated between each instance [16].

ANALYSIS OF THE CURRENT SITUATION OF THE TRIAGE PROCESS OF ARMED FORCES SPECIALTIES HOSPITAL

The intention of this research is to analyze the Triage Process of a real hospital located in Ecuador called Armed Forces Specialties Hospital. For this, we will explain how the hospital has evolved from a manual triage process to a computerized process; to then, we will explain how we applied the machine learning technique to the computerized triage process to enhance the level of precision of patient classification and involved resources optimization.

Evolving from Manual to Computerized Triage Process

Initially, a manual process was used for classification of patients in emergency. First, the patient had to register him/herself in the emergency admission and take a turn. Then, the patient had to wait to be called by the health professional to be attended. Once in the triage room, the nurse took patient's vital signs such as temperature, blood pressure, pulse rate, respiratory rate, and Glasgow Consciousness and Pain Scales. Based on those parameters, the nurse classified the patient using a paper based record and delivered this record to them. The mentioned paper based triage system generated several problems. (1) One of the problems was that lost of records caused new vital signs measurement. (2) Another problem was the assignment of priority levels when various patients had similar values in their vital signs and Glasgow scale; in those cases, an empirical and non-objective classification such as the "Canadian Triage and Acuity Scale (CTAS)" or "Manchester Triage Scale (MTS)" were applied by the specialist based on his/her criteria [11]. (3) Additionally, the manual triage did not control the start/end time of the triage process, which caused incorrect application of the CTAS system. (4) Finally, important indexes such as the number of patients who visited the hospital and critical patients who needed immediate could not be evaluated as they were never stored in a centralized repository. Fig. 1 shows the details of the mentioned manual triage process.

Considering the problems of the manual process, the hospital decided to develop a software application to satisfy the needs of patients' classification in emergency. The application was developed by the internal personnel of the hospital (department of technology) using an agile methodology i.e. SCRUM.

This new computerized triage process starts with the patient registration. The patient must register him/herself (or by the person accompanying to the patient) in emergency admission and wait for evaluation in triage. Then, a health specialist evaluates the pacient by asking some routine questions to know the cause of the emergency and recording vital signs (such as temperature, blood pressure, number of pulsations per minute, respiratory rate and percentage of oxygen saturation in the blood). Additionally, if the patient arrives with multiple trauma or head blow, the medical staff determines the scale of pain without taking the vital signs (if necessary) or uses the scale of Glasgow to measures the value of conscience of the patient based on a simple questionnaire. The patient registration step is omitted only if the patient arrives unconscious, and in such case, the patient is classified directly at priority level 1 (see Table 1).

Once the triage registration is completed, the developed software application classifies the patient and gives him/her a priority level based on the values assigned by the health professionals (data stored in the emergency care record). Fig. 2 shows the details of the mentioned computerized triage process.

ENHANCEMENT OF THE COMPUTERIZED TRIAGE PROCESS USING MACHINE LEARNING TECNHIQUE

Methodology and Hypothesis

This work focuses the enhancement of the triage process of the emergency room using machine learning technique based on several independent variables i.g. vital signs, pain scales and Glasgow coma scale, and dependent variables i.e. classification given to the patient. These process will deliver a level of priority based on the Canadian Triage and Acuity Scale (CTAS), which determines 5 levels of attention (see Table 1).

Table 1. Triage levels used in the Armed Forces Specialties Hospital

Level	Description	Attention
1	Extreme health condition that threatens life of the patient.	Immediate attention
2	Health condition that threatens the life of the patient, but, less serious than level 1.	Within 15 to 30 minutes
3	Critical, but non life-threatening condition requiring valuation in hours	Within 1 to 2 hours
4	Critical, but non life-threatening condition requiring deferred assessment	Within 2 to 3 hours
5	Symptomatic condition requiring deferred assessment	Within 24 to 48 hours

In the improvement of the triage process, real data taken from the Armed Forces Specialties Hospital has been used. We have applied different machine learning algorithms and we also have analyzed the possible correlation among different variables mentioned previously in this section. The intention was to find the best learning machine algorithm with the best combination of variables that allow to predict in best way the classification of patients in the Triage Process.

The hypotheses defined within this research were the following:

H1: Usage of machine learning techniques can improve the accuracy of the emergency patient priority assignment delivered by the current computerized system.

H2: Inclusion of different variables to vital signs such as the Glasgow scale and Pain scale influence positively to the machine learning process of the patients' classification.

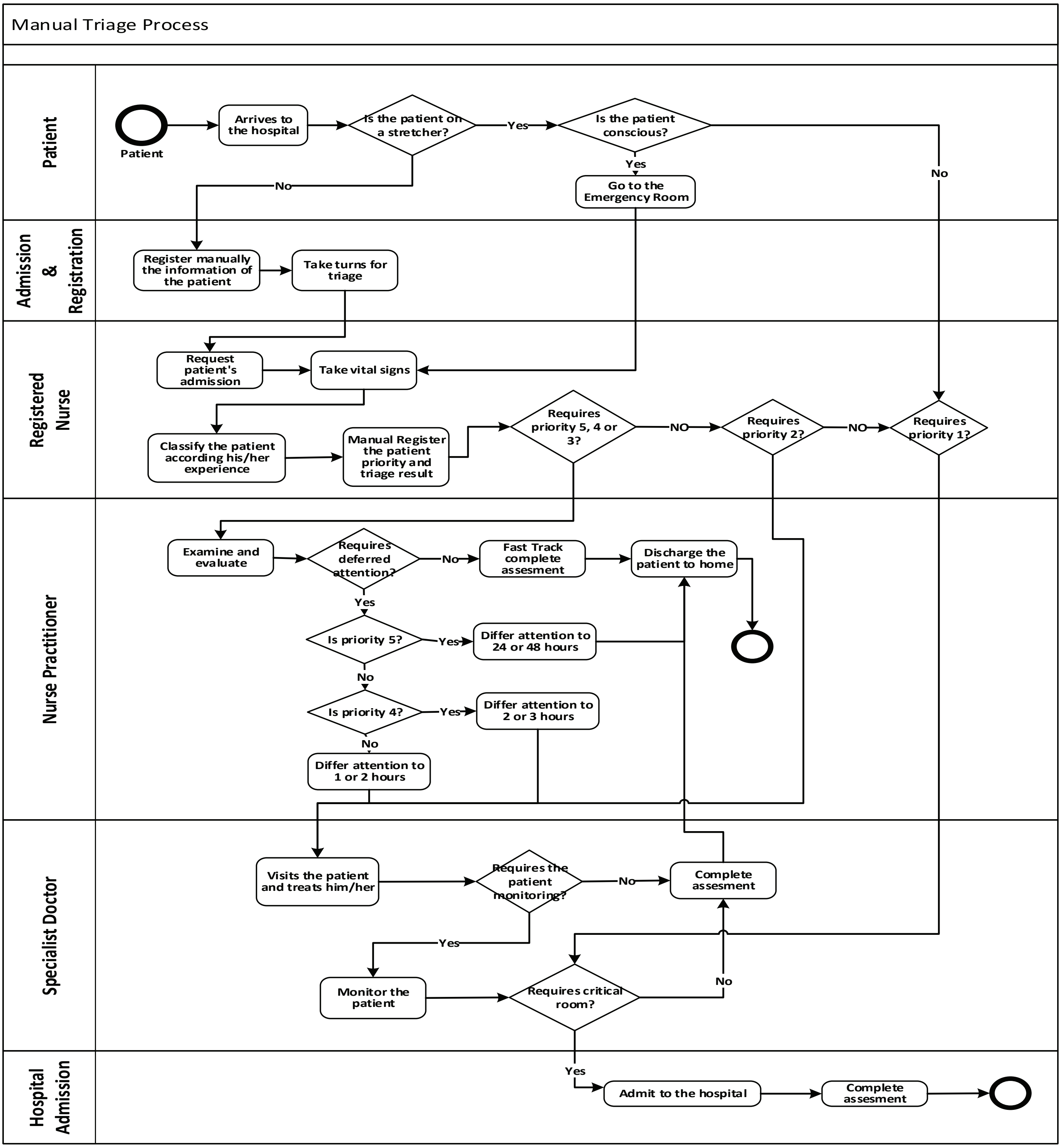

Figure 1. Manual Triage Process

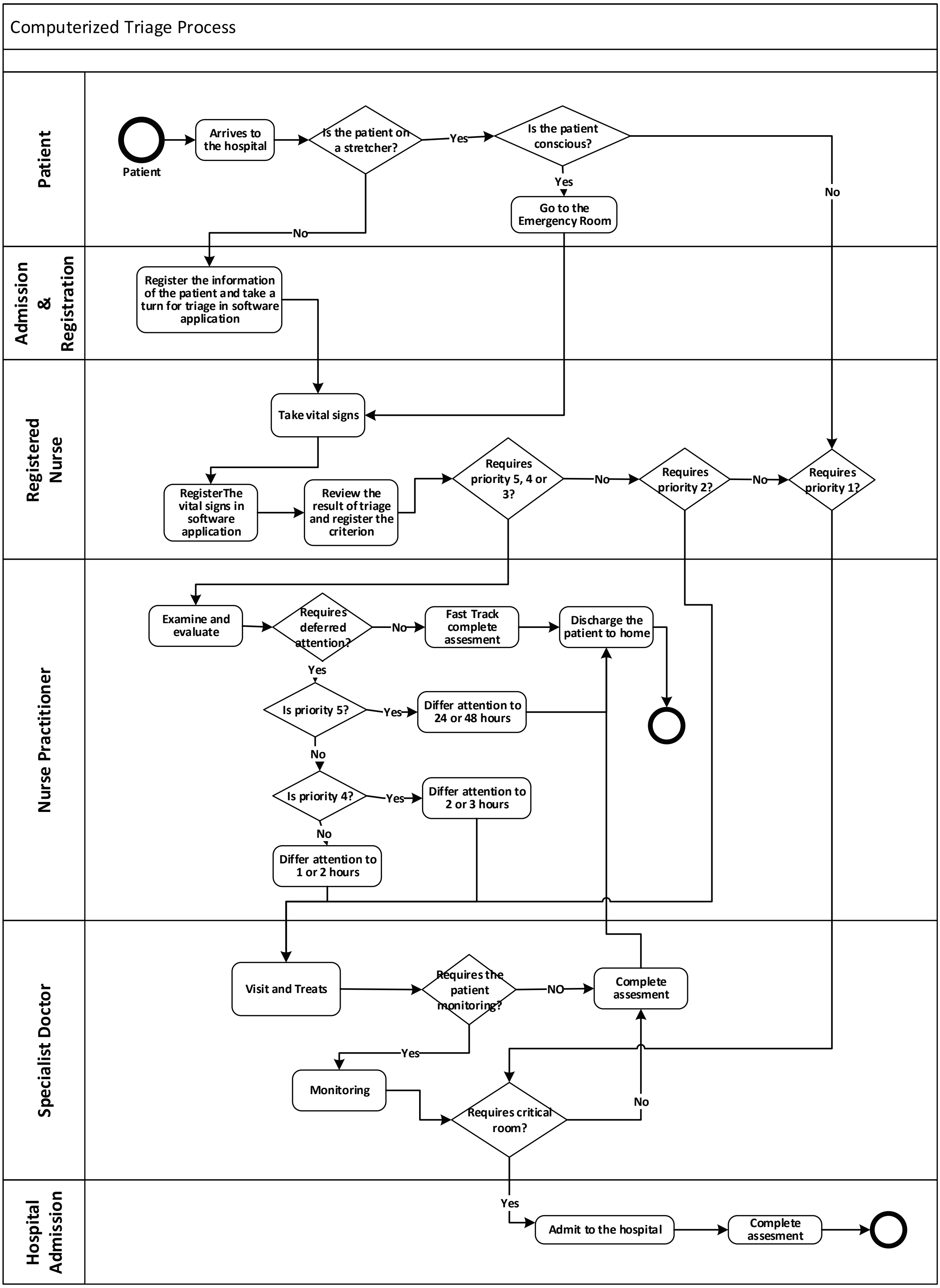

Figure 2. Computerized Triage Process

Improvement of the Triage Process using Machine Learning

Data Gathering

Historical data of triage process of the Hospital, which includes the variables indicated in section 4.1, was used for this research. The basic vital signs included temperature, respiratory rate (measured with a stopwatch counting the number of times the patient's chest is raised), blood pressure (measured with a stethoscope), and oxygen saturation in the blood (measured with an oximeter). In cases of trauma, the Visual Analog Scale and Glasgow Scale were also considered. Additionaly, important data such as age, gender, and gestation state (in case of women) were also added.

Fig. 3 shows the base template which includes the following columns: age, sex (Male = 1, Female = 0), pregnancy state (Yes = 1, No = 0), number of beats per minute, number of breaths in a minute, body temperature, blood pressure, the percentage of oxygen saturation in the blood, pain scale, Glassgow's coma scale and codes indicating the cause of the medical attention.

AGE	SEX	PREG	PULSE	BR	TEMP	SIAST	DIAST	OXYSAT	PAIN	GLASGO	CAUSE	CRITERIO
15	0	0	80	20	36,5	136	89	0	0	0	73	Criterio Médico: 5
15	0	0	82	18	36,7	122	85	96	0	0	71	Criterio Médico: 4
15	0	0	85	16	36	125	97	91	0	0	46	Criterio Médico: 3
15	0	0	86	18	36,8	124	87	94	0	0	46	Criterio Médico: 3
15	0	0	90	18	37,3	130	82	96	0	0	57	Criterio Médico: 3
15	0	0	91	17	37	134	86	97	0	0	50	Criterio Médico: 3
15	0	0	95	18	37,3	123	82	96	0	0	44	Criterio Médico: 3
15	0	0	111	20	37,3	139	91	96	5	0	52	Criterio Médico: 3
15	0	0	144	20	38	0	0	0	0	0	26	Criterio Médico: 2
15	1	0	61	18	36,7	128	80	93	7	15	66	Criterio Médico: 4
15	1	0	68	17	36,8	125	80	92	0	0	57	Criterio Médico: 3
15	1	0	75	13	36,8	140	90	96	0	15	70	Criterio Médico: 4
15	1	0	80	18	37,3	125	86	93	0	0	50	Criterio Médico: 3
15	1	0	100	18	37	125	87	94	7	0	69	Criterio Médico: 4

Figure 3. Triage Data Base Template

For this research, we took a total of 36615 records generated in 15 months. Those records went through a filtering process to eliminate inconsistent data. After, data filtering, we separated 3773 records for the models' testing process. The rest of registers were used for supervised learning process.

Selection of Machine Learning Models for Classification of the Care Priority.

Once gotten the final data to be analyzed, three classification algorithms i.e. Bayesian networks, Logistic Regression and Neural Networks were applied. For the creation of the models, Knime V 3.2.1 was used.

A) Naive Bayes Modeling

For this model the initial probability was defined as 0 and the maximum number of nominal values for each variable was set to 20. The learning node was connected to a Naive Bayes prediction node, where the medical criteria of both the test data and the model prediction are observed. The outputs of the prediction node was connected to enter to a scorer node to show the percentage of hits between the model and the medical criterion. (See Fig. 4).

B) Logistic Regression

The logistic regression model was not executed in the first tests since the learning node had an alert symbol. This alert was because one of the independent variables was too related to the classification level of the triage. After following the advices of Knime documentation i.e. locating a linear mapper and a linear correlator filter node before the input for the learning node, it was possible to complete the tests of this model. (See Fig. 5)

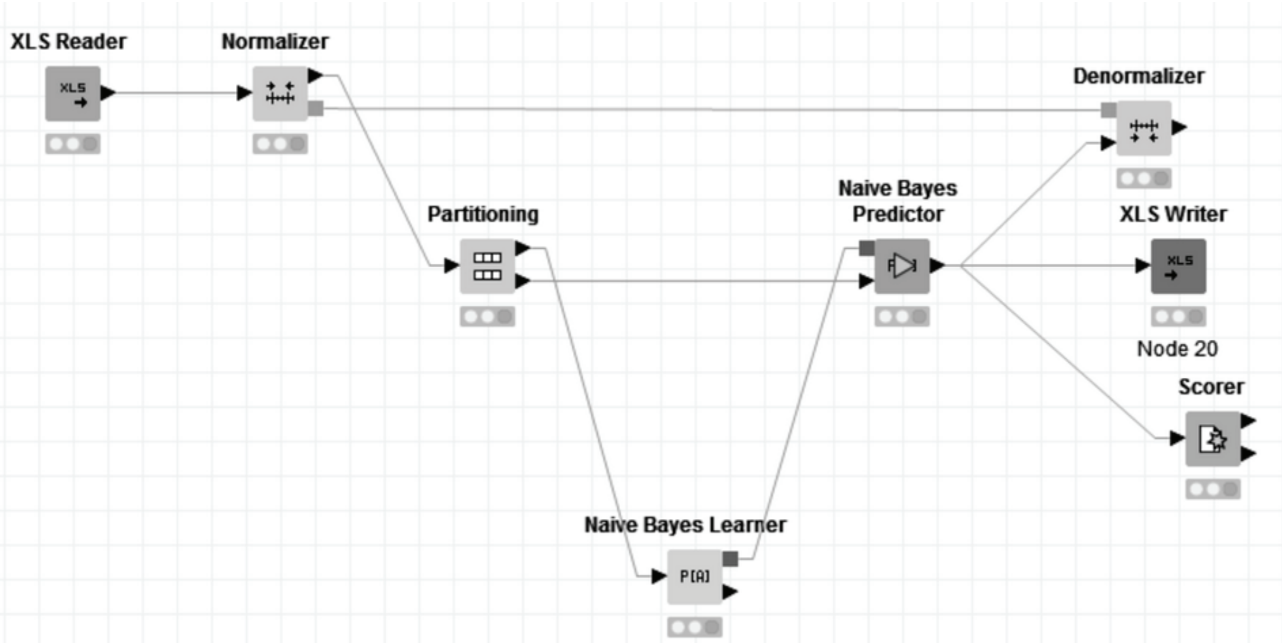

Figure 4. Knime Workflow - Naive Bayes

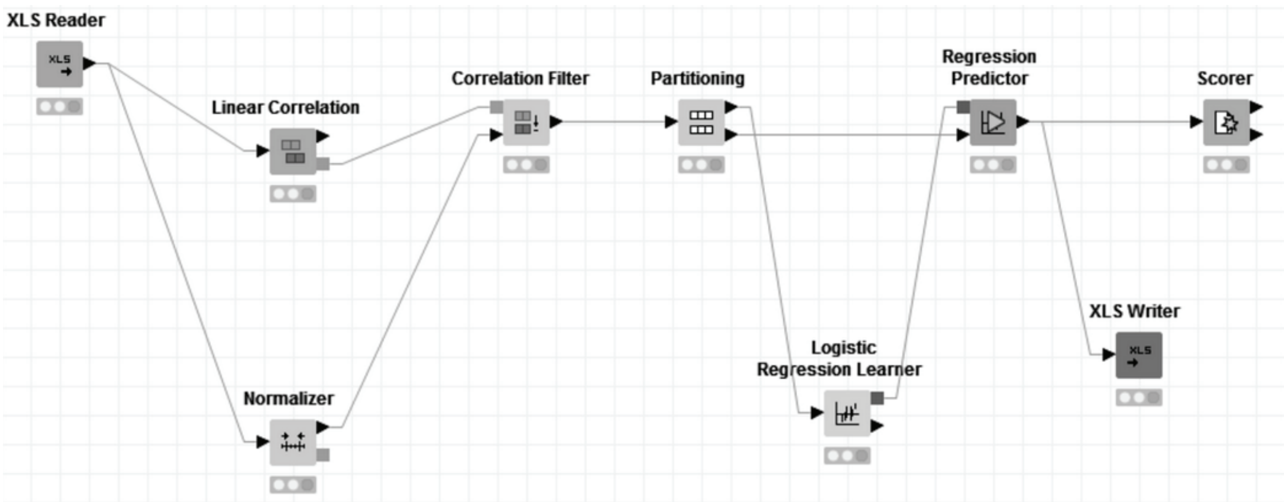

Figure 5. Knime Workflow - Logistic Regression

The logistic regression model allowed to know the possibility of correlating patients' data with triage levels. For this, the tool determined the coefficients with which each independent variable has to multiply and the values to be replaced in a logit (sigmoidal) type function.

C) Multilayer Perceptron

The multilayer perceptron model is generally used when there is no mathematical formula to predict the results based on different input variables [13]. Knime 3.2.1 has two perceptron neural network models: (1) nodes of type MLP and (2) Multilayer Perceptron of Weka 3.7. In this study, we have executed the multilayer perceptron algorithm using both models (see Fig. 6 and 7).

ANALYSIS OF RESULTS.

Before analyzing the results generated by the machine learning models, it is important to mention that the current computerized triage process based on an automated algorithm only has a precision of 17% when classifying patients' priority levels (comparison based on automated algorithm result vs medical criteria registered by the health professionals after computerized triage process).

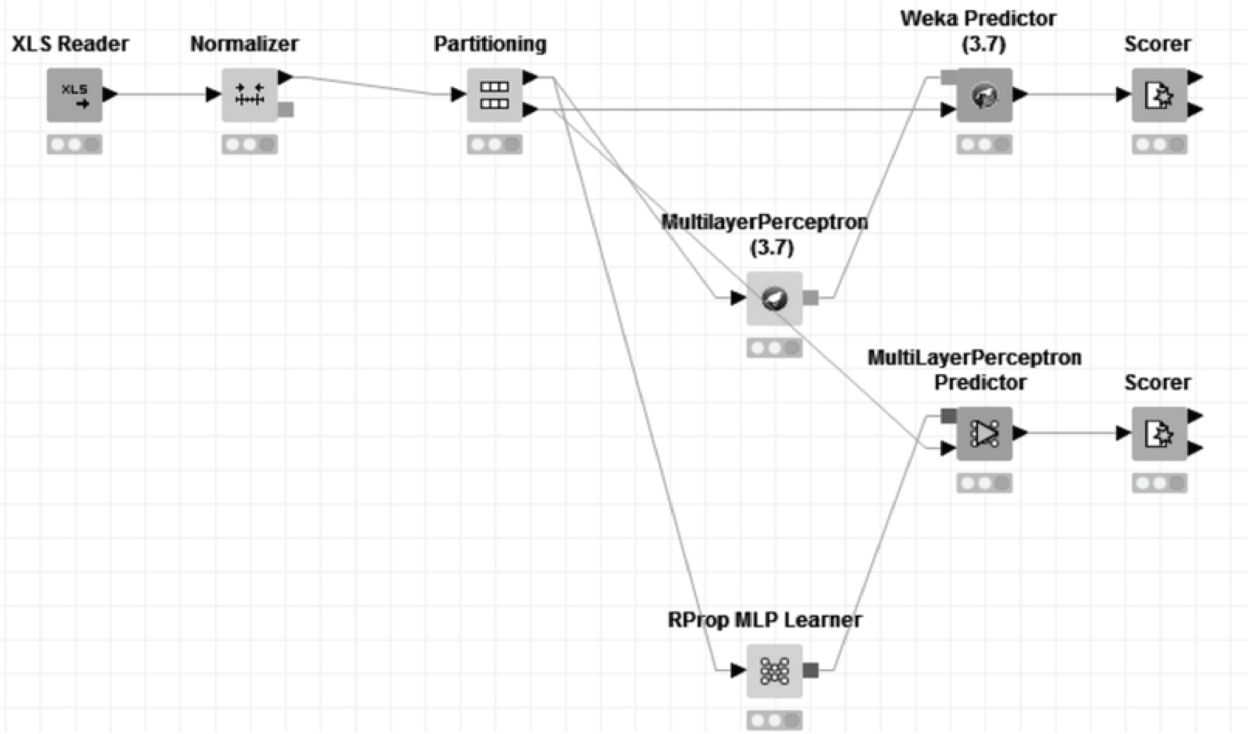

Figure 6. Knime Workflow – Multilayer Perceptron

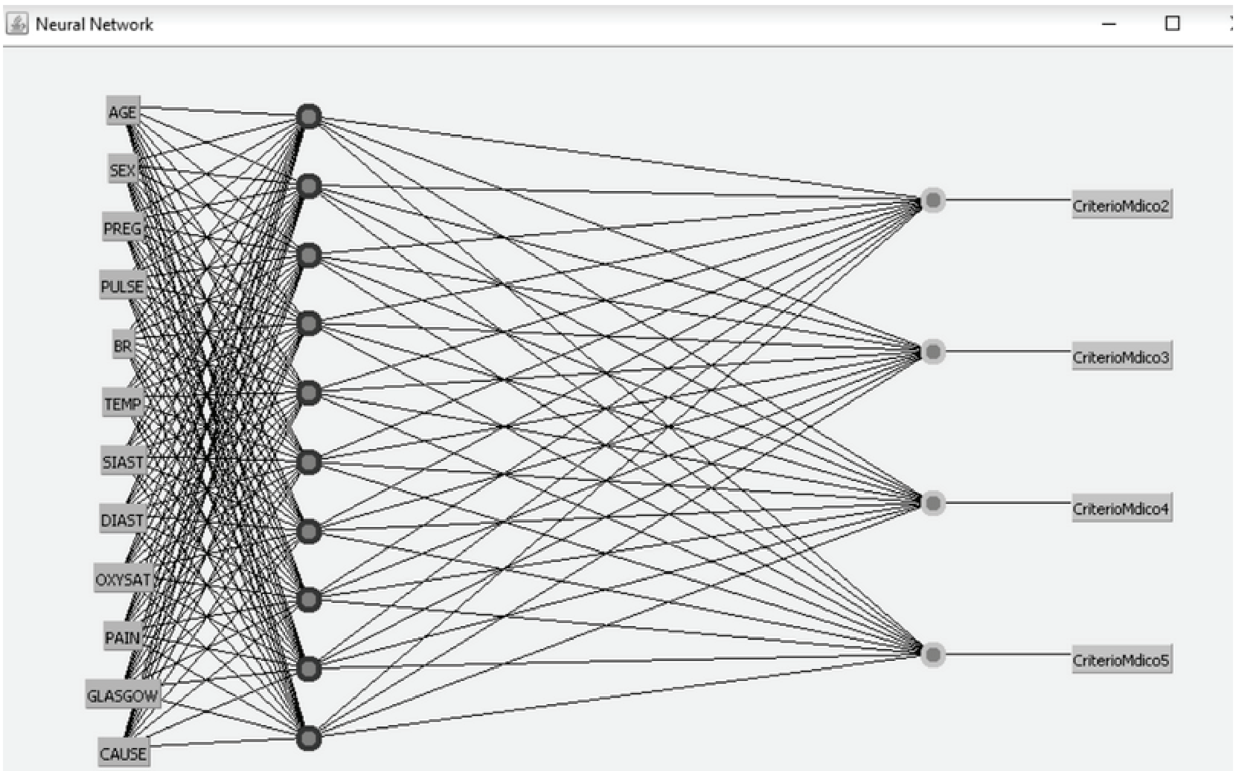

Figure 7. Multilayer Perceptron Weka 3.2.1

As mentioned in previous section, three mechine learning models were applied using the filtered data to improve the current patients' priority level classification system. Normalizer nodes allowed to improve the accuracy level of each model. The comparison of results of different models are shown in Table 2.

Table 2. Results of Machine Learning Models

Model	Accuracy (%)
Logistic Regression	62,99%
Naive Bayes	70,59%
Multilayer Perceptron Weka 3.7	94,17%
Multilayer Perceptron Knime	92,98%

In the logistic regression model, we obtained a prediction accuracy of approximately 63%. (See Fig. 8)

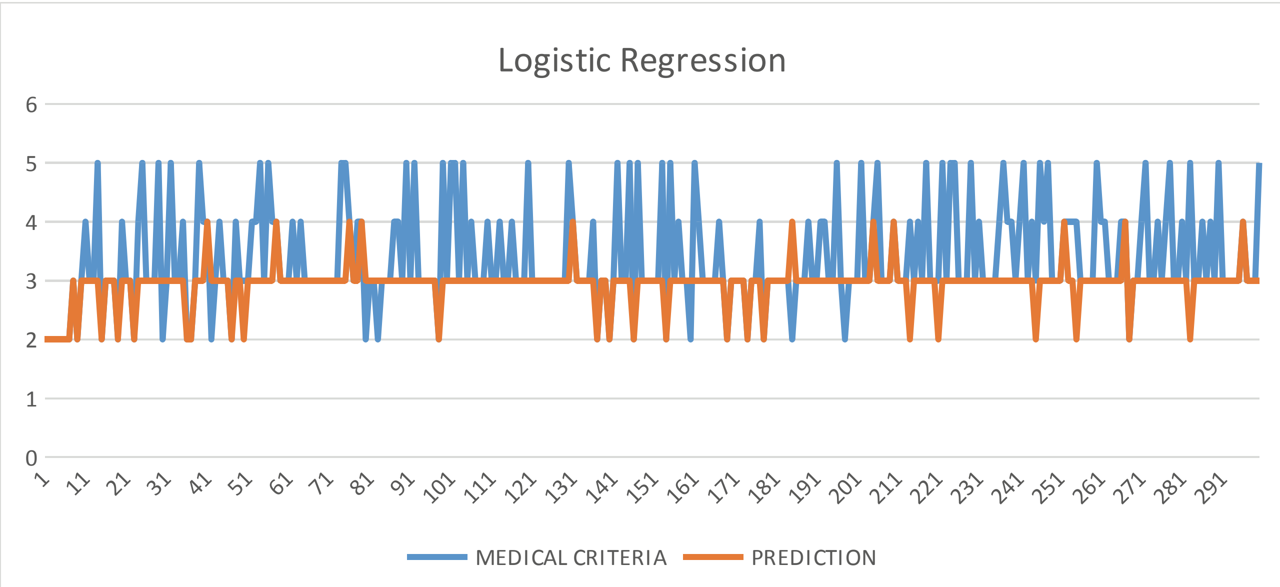

Figure 8. Prediction of Logistic Regression model

For the Naive Bayes model, the data set had to be grouped into output variable (medical criterion) and each variable was totalized by the defined group. Then, the MAP or maximum were calculated after generating the mean and variance. The model determined a success prediction rate of 70.59%. (See Fig. 9)

In the MLP neural network model, two values were obtained: (1) result of Weka based model which generated 94.17% of successful prediction, and (2) Knime MLP based model which generated 92.98% of successful predictions (see Fig. 10).

For the representation of previous figures 300 records were taken. The abcissa axis represents each of the records and in the ordered axis represents the levels of triage. The blue lines represent the test values of the medical criterion and the orange lines represent the result values of machine learning algorithms.

In the logistic regression, it was observed that the orange and blue lines had not many coincidence points. With the model Naive Bayes, the level of prediction was major. But, the best model with high level of overlap was definitely the model based on multilayer perceptrons.

Based on the results, it is important to conclude that the use of machine learning tools can improve significately the processes that require human criteria. The following diagram (see Fig. 11) shows the improved process of assigning emergency turn with Triage in the Armed Forces Specialties Hospital through the use of machine learning technique.

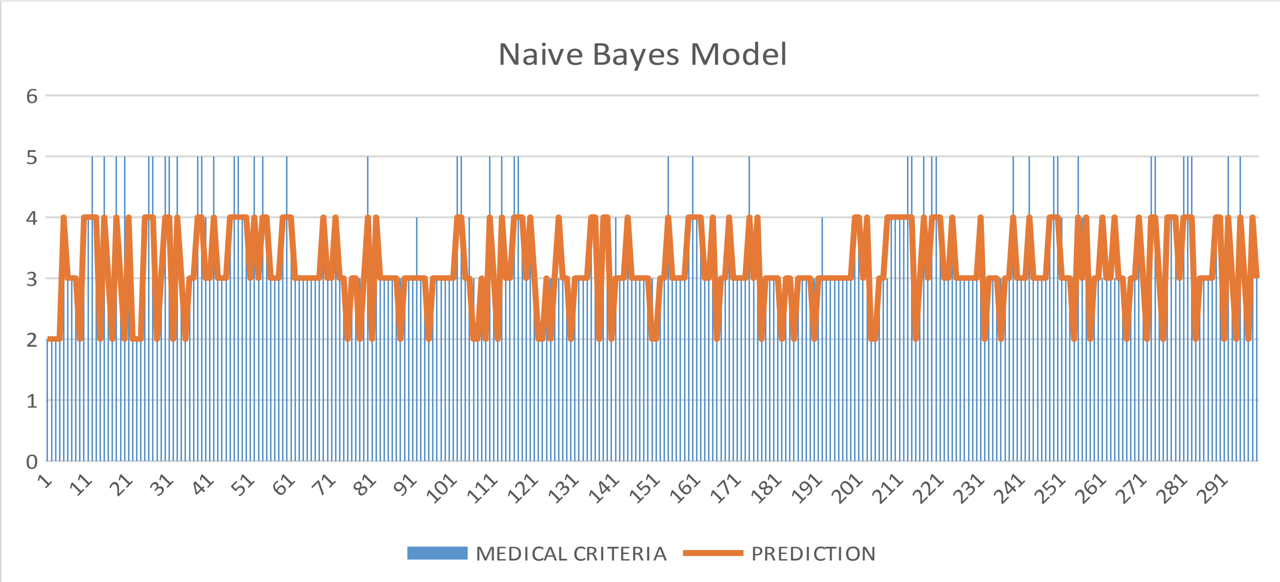

Figure 9. Prediction of Naive Bayes model

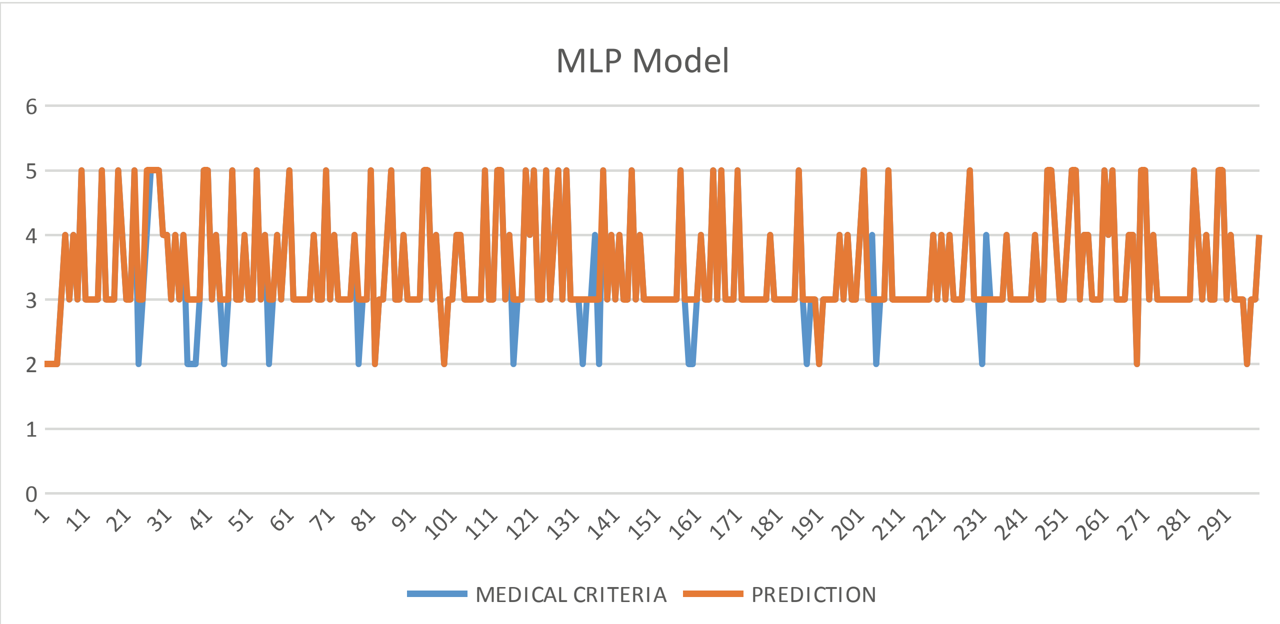

Figure 10. Prediction of MLP model

CONCLUSIONS

Through this research, it was determined that the use of machine learning algorithms such as Naive Bayes, Logistic Regression, and Multilayer Perceptron can improve the success rate of patitent classification in Triage Process. In case of the Armed Forces Specialties Hospital, the application of machine learning models has shown better performance in terms of prediction compared to current solution based on an algorithmic model. This work provides a considerable contribution to the improvement of the level of maturity of the triage process in hospitals since it analyzes a real case. Based on this experience, it can be observed that the machine learning can be a tool to support decision making in the medical sciences.

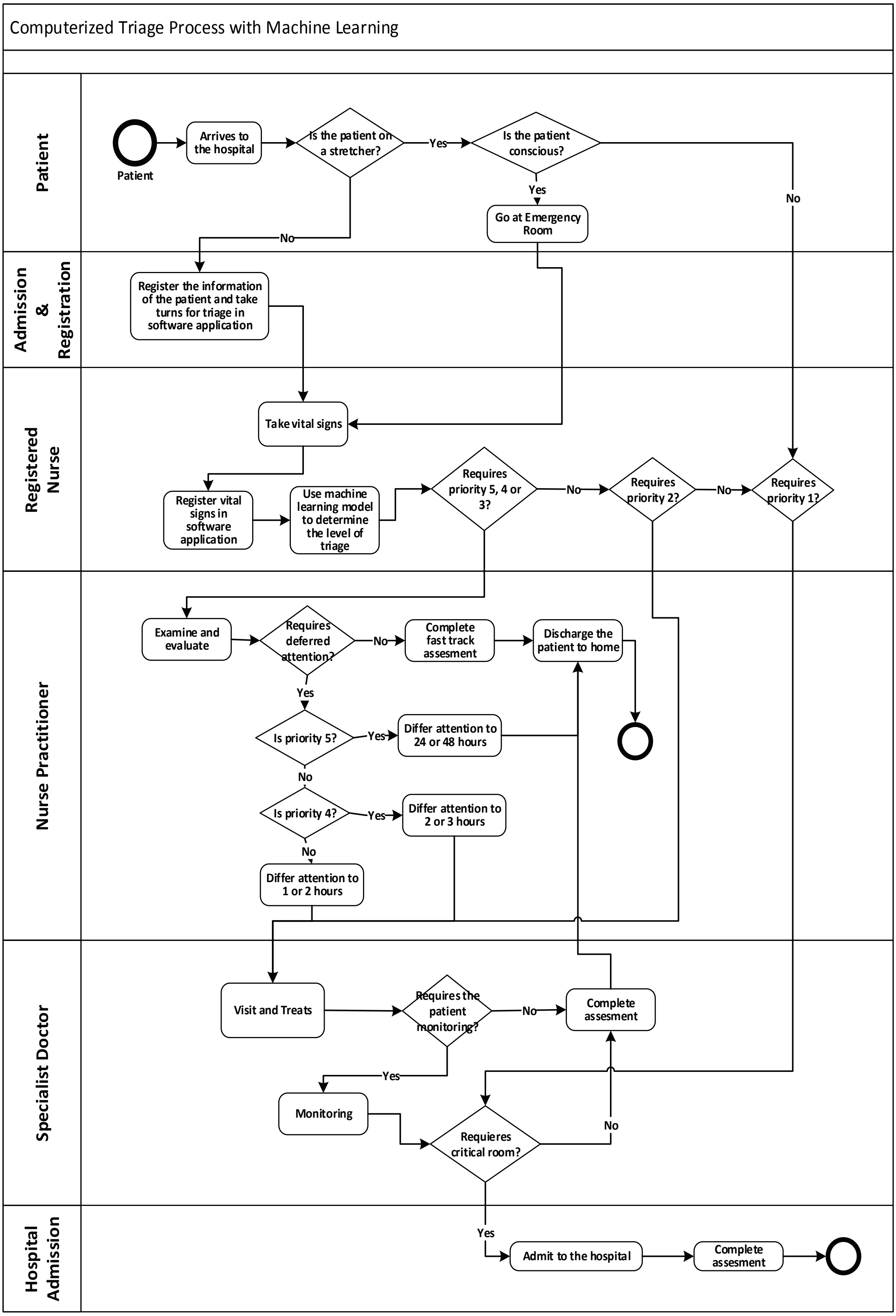

Figure 11. Diagram of Triage Process with Machine Learning.

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