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Machine Learning for E-triage

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Abstract – Due to the rising number of visits to emergency departments all around the world and the importance of emergency departments in hospitals, the accurate and timely evaluation of a patient in the emergency section is of great importance. In this regard, the correct triage of the emergency department also requires a high level of priority and sensitivity. Correct and timely triage of patients is vital to effective performance in the emergency department, and if the inappropriate level of triage is chosen, errors in patients' triage will have serious consequences. It can be difficult for medical staff to assess patients' priorities at times, therefore offering an intelligent method will be pivotal for both increasing the accuracy of patients' priorities and decreasing the waiting time for emergency patients. In this study, we evaluate the machine learning algorithms in triage procedure. Our experiments show that Random Forest approach outperforms the others in e-triage.

Keywords *– Triage, Machine Learning, Emergency Department, Random Forest, Support Vector Machine, Decision Trees, Kth Nearest Neighbor*

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I. INTRODUCTION

The number of people who visits an emergency service in our country and in the world is constantly increasing. Increasing patient volume may lead to the inability to treat in a timely manner for patients who need emergency health care. Therefore, it is important to distinguish between emergency patients and non-emergency patients and determine the treatment priority of the patients. The method that is used for this purpose is called triage [1].

Each country has its own triage system and a triage decision is made by the authorized health personnel at the time of application. In our country, the color-coding determined by the Ministry of Health is applied for the triage [2].

- "*Category 1 (red): Among the patients examined in the main red code, the ones who are unconscious or with no airway safety, respiration and circulation risks will be taken to the resuscitation room immediately.*
- *Category 2 (yellow): Patients examined in this category should be taken directly to the relevant diagnosis/treatment area, with the knowledge of the physician responsible for triage.*
- *Category 3 (green): Patients in this category should be examined in the green area in the emergency department."*

Triage enables the segregation of critically ill patients and thus determines what needs to be done for emergency care. In the patient care area, patient sequence and timing issues are regulated and the decision maker is guided on resource use. Therefore, in crowded emergency rooms, it is important to perform the right triage to quickly distinguish and prioritize those with critical conditions from those with lesser emergencies [3].

Although it seems simple, triage is complex in practice as it relies on limited patient knowledge, time pressure, various medical conditions, and a high degree of intuition and staff experience. Consequently, the predicted clinical course (i.e., triage) is unclear for the majority of emergency room patients. It can differ greatly depending on the assessment of the person performing the triage and poorly distinguishes the various patient groups despite the aim of the triage. The inability of the personnel without adequate training to distinguish this situation creates safety risks for critically ill patients, and the unnecessary use of emergency resources due to over triage of patients, whose risk levels are not clear, causes a decrease in efficiency. Patient safety problems in crowded emergency departments, limitations in applying emergency triage standards, and assessing the need for accurate risk necessitated the development of an electronic triage system using machine learning algorithms. Machine learning acquires patterns in data with a series of computational methods [4].

There are several studies on triage and machine learning in the literature. In the literature studies, triage systems based on machine learning have been implemented on data groups obtained according to different standards in the emergency services of different countries. In [5], Levin et.al. classified emergency department applications with random forest trees and the results were compared with the ESI (Emergency Severity Index). Choi et al. performed a classification using logistic regression, random forest, and XGBOOST with the help of the KTAS system valid in Korea [6]. Bong et al. differentiated high-risk patients from others with the help of deep learning [7]. Kwon et al. used a deep learning method, a multilayer perception, for a retrospective observational study using data from the Korea National Emergency Service Information System (NEDIS), which collects data on all emergency department admissions in real-time [8]. In another study focusing on SVM and KNN, which are machine learning methods, it was aimed at helping doctors identify and treat diabetic diseases. It was concluded that improvements in classification accuracy help machine learning models achieve better results. In addition, it was concluded that the accuracy of the current system is less than 70%, and therefore it was recommended to use a combination of classifiers known as the hybrid approach. The hybrid approach combines the benefits of two or more techniques. It was found that SVM and KNN provide 75.75% accuracy vs. 80% accuracy when using ADA Boost. Therefore, it was concluded that Adaboost was the best option among all classifiers [9].

In this study, with the help of the triage standards of the Ministry of Health of the Republic of Turkey, the methods of machine learning-based triage has been examined. Thanks to the e-triage software developed for this, it is aimed to correctly guide the patients by making correct predictions and right decisions in a short time. In literature studies, triage data were collected according to different standards and classified by different methods; however, there is no e-triage software for the triage process applied in our country.

The Materials and Methods that we used in our study are introduced in the next session. In Chapter 3, the findings of our study are shared. In the last section, the results are discussed.

II. Materials and Method

A. Data set

The data set used in our study was prepared by retrospective sampling from the records of patients who applied to the Izmir Cigli Training and Research Hospital, emergency service. Complaints, vital signs, and basic demographic information of each patient at the time of admission to the emergency department were recorded in the table. When the patients' admission complaints are handled separately, many categories would be formed which could complicate the analysis. For this reason, patients were grouped according to their complaints as much as possible. For example, all extremity traumas that did not affect vital organs and did not involve blood loss were included in the same category.

B. Machine Learning methods used in this study:

Support Vector Machine (SVM): SVM is a classification algorithm that is easy to manage and use. It can be used for purposes of classification and regression. In this algorithm, each point that is a data item is plotted in a dimensional space, also known as the n-dimensional plane, where 'N' represents the number of features of the data. Classification is based on differentiation in classes, where these classes are dataset points located on different planes.

SVM is a very popular research area in machine learning, validated in experiments and successfully put to use across a range of fields. However, traditional SVM is mainly used to solve supervised learning problems, i.e. it handles large amounts of unlabeled data that is too time-consuming to label in real life when it needs to label sample data to train classifiers. This has contributed to taking machine learning to a new level. A study investigated the properties of SVM and searched for a new way to improve the performance of classifiers, a practical approach to classify a small number of labeled samples and a large number of unlabeled samples, and consequently an algorithm was developed [10].

SVM is a kind of method in which the nonlinear problem in low-dimensional space is mapped to a high-dimensional space so that a simple linear classification technique can be considered. SVM is suitable for small sample learning [11].

Kth Nearest Neighbor (KNN): KNN algorithm is an algorithm by which the proximity of the new individual to be classified to k times of the previous individuals is checked [12]. During classification, test samples are compared with each other using training samples. Euclidean distance is used for neighborhood distance. Estimates are based on a majority vote of neighboring samples. Care should be taken as it tends to overfit high k values [13].

Decision Trees: Decision trees not only show decisions, but they also contain explanations of decisions. The training process that creates the decision tree is inductive. The procedure for constructing a decision tree from a set of training objects is called tree induction. The tree induction method is one of the most common methods for self-knowledge discovery. It serves to discover tree-like patterns that can be used for purposes of classification or prediction.

Decision trees try to find the best order to predict the target by performing a variety of tests during knowledge discovery. Each test creates branches in the decision tree, and these branches cause other tests to occur. This continues until the test process ends on a leaf node. The path from the root to the target leaf is called the “rule” that classifies the target. The rules reflect the “if-then” pattern [14].

Random Forest: Random forest algorithm, which is a supervised learning algorithm, is used with classification and regression tasks. The random forest algorithm creates multiple decision trees and combines them to obtain a more accurate and stable prediction. The approach, which combines several random decision trees and averages their predictions, performs better in environments where the number of variables is much larger than the number of observations [15].

Random forest is used in many fields such as banking, commerce, health. In the healthcare field, it is used to identify the right combination of ingredients in medicine as well as to identify diseases and analyze the patient's medical history using a patient's medical records [16].

The random forest classifier consists of a combination of tree classifiers in which each classifier is generated using a random vector that is sampled independently of the input vector with each tree putting in their one unit vote for the most popular class to classify an input vector. The design of a decision tree requires the selection of an attribute selection measure and a pruning method. There are many approaches to the selection of attributes used for decision tree extraction, and most approaches directly assign a quality measure to the attribute. The most frequently used attribute selection measures in decision tree induction are the Information Gain Ratio [17] and the Gini Index [18]. The random forest classifier uses the Gini Index as an attribute selection standard, measuring the purity of an attribute relative to classes.

These overgrown trees are not pruned when a tree expands into maximum depth on new training data using a combination of features. This is one of the major advantages of the random forest classifier over other decision tree methods such as that proposed by Quinlan [17]. Studies suggest that the selection of pruning methods, not attribute selection measures, affects the performance of tree-based classifiers [19-20]. In [18] Breiman argues that as the number of trees increases, the generalization error always converges even without pruning the tree, and overfitting is not a problem due to the Strong Law of Large Numbers. The number of attributes used at each node to build a tree and the number of trees to grow is two user-defined parameters required to generate a random forest classifier. In each node, only the selected attributes are searched for the best split. Thus, the random forest classifier consists of N trees; where N is the number of trees to grow and this can be any user defined value. To classify a new dataset, each state of the datasets is transferred to each of the N trees. In this case, the forest chooses a class with the highest number of N votes [20].

III. RESULTS

The data set is classified into three triage emergency categories. For classification SVM, KNN, Decision Tree and Random Forest classification algorithms were used. All algorithms tested for accuracy with tenfold cross validation. Cross validation is a method applied to a model and a dataset to estimate out-of-sample error. When a model is fitted to a data set, the aim is to minimize the loss function. This most often produces overfitting training or overly optimistic results. In k-fold cross validation, the data set split in to k equal parts. In each iteration, a single part is used as test data while k-1 parts used as training data. This procedure generates k different trained model that tested with different testing data. K=10 is the most widely used cross validation. This is known as tenfold cross validation. The results are shown in Table 1.

Table 1. Tenfold Cross Validation Accuracy Score

Alg.	SVM	KNN	DT	RF
F1	0.7	0.79	0.76	0.74
F2	0.74	0.84	0.86	0.76
F3	0.89	0.86	0.76	0.79
F4	0.81	0.7	0.84	0.84
F5	0.76	0.84	0.79	0.92
F6	0.82	0.87	0.66	0.84
F7	0.68	0.71	0.84	0.95
F8	0.87	0.79	0.86	0.89
F9	0.92	0.76	0.78	0.73
F10	0.82	0.84	0.68	0.78
Avg.	0.80	0.80	0.78	0.82

As we can see in the results, all of the four algorithms scores are close but Random Forest Algorithm yields the best rates. In Figures 1, 2, 3 & 4, results of confusion matrixes of each algorithms for a single fold are given. After the analysis of these tables, data of triage emergency level 1 has the most false-positive and false-negative results.

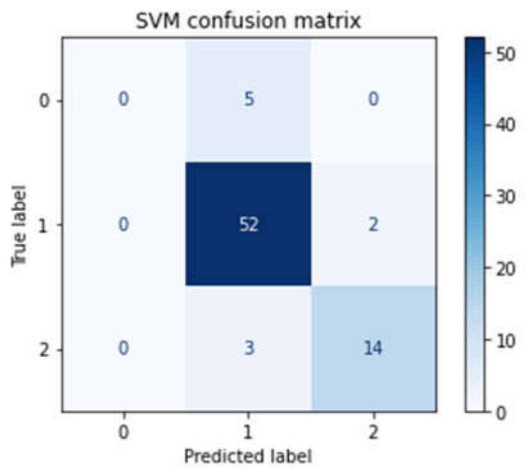

Fig. 1. SVM Confusion Matrix

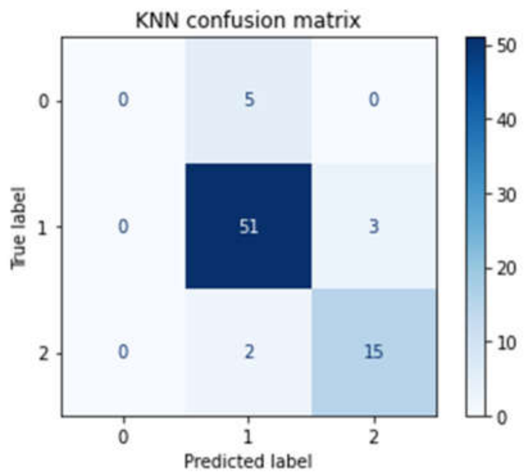

Fig. 2. KNN Confusion Matrix

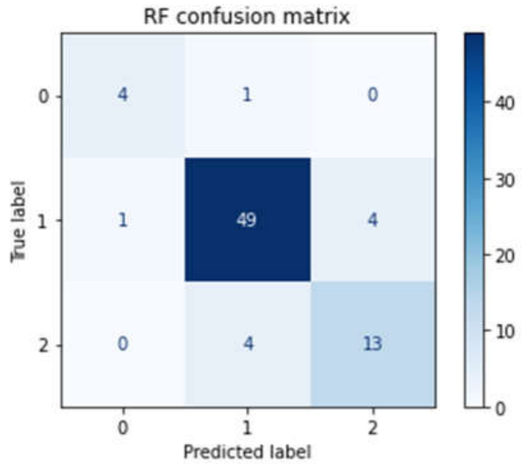

Fig. 3. Random Forest Confusion Matrix

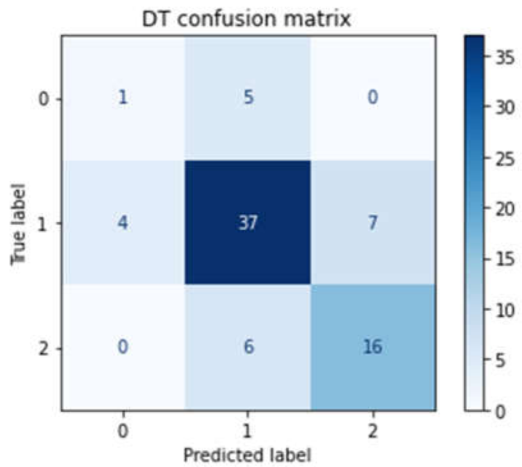

Fig. 4. Decision Tree Confusion Matrix

IV. DISCUSSION

With help of the confusion matrixes, the triage data seems to have a lot of overlapping data. This means that some of the complaints are in a gray area that can be both level 0 and 1 or both level 1 and 2. This can also indicate that some of the targets in this data set might be wrongly labeled. Both of these arguments have its own validating points. Thinking about the emergency service of hospitals, that can have around 1000 patients per day, there have to be mistakes and misinformation.

V. CONCLUSION

The triage, which is the initial evaluation of a patient at the time of admission to the emergency room, determines the urgency of the situation and the priority of treatment, which could draw the line between life and death. In this important decision process, many factors, such as proficiency of the healthcare provider, motivation, and the number of patients at a given time can affect the success. This particular topic is especially important since erroneous decisions during triage could result in increased morbidity or even death. Absolute consistency in triage is not possible because of the human factor. It is predicted that artificial intelligence will increase this consistency when sufficient data is provided; therefore, it will be increasingly used in emergency triage. The results we obtained in this preliminary study have played a decisive role in determining the methodologies we will use both for the acquisition of patient data and for learning algorithms.

Our study shows that Random Forest Algorithm has better results in classifying the triage data. The results are promising for better results. With the collection of more local data, a more detailed analysis will be provided and it will be possible to use methods that require a large amount of data such as deep learning. In future studies, in addition to the triage area, the probability of patients being hospitalized, discharged or sent to intensive care after the emergency department can be estimated.

Authors' Contributions

The authors' contributions to the paper are equal.

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The authors declare that this study complies with Research and Publication Ethics

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