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Using Machine Learning for Predicting the Hospitalization of Emergency Department Patients

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Abstract. Artificial intelligence processes are increasingly being used in emergency medicine, notably for supporting clinical decisions and potentially improving healthcare services. This study investigated demographics, coagulation tests, and biochemical markers routinely used for patients seen in the Emergency Department (ED) concerning hospitalization. This retrospective observational study included 13,991 emergency department visits of patients who had undergone biomarker testing to a tertiary public hospital in Greece during 2020. After applying five well-known classifiers of the caret package for machine learning of the R programming language in the whole data set and to each ED unit separately, the best performance regarding AUC ROC was observed in the Pulmonology ED unit. Furthermore, among the five classification techniques evaluated, a random forest classifier outperformed other models.

Keywords. Artificial intelligence, machine learning, emergency department, R programming language, predict hospitalization

1. Introduction and background

One of the greatest challenges that most Emergency Departments (ED) have to face daily is the sudden surge in patient volume and the limited medical resources capacity. The current COVID-19 pandemic exacerbates the problem making the delivery of basic services ineffective [1]. Fast recognition of emergency problems requiring direct admission to the hospital is of utmost importance to have an efficient triage workflow [2]. Patient prioritization according to medical acuity is the main purpose of a triage plan that aims to improve healthcare services and reduce patient mortality rates. In the ED setting, the medical and nursing staff need to act quickly by deciphering clinical information to arrange patients and foresee results. This is crucial for emergency medical decisions and directly affects cost, effectiveness, and patient outcome [2].

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Artificial Intelligence (AI) tools have been recently implemented in several medical fields, including emergency medicine, aiming to improve decision-making [3,4]. In the Covid-19 era, some useful applications have been introduced, such as predictive models to forecast future demands in beds, equipment, and staff [4]. Machine learning (ML) approaches might be utilized to help medical staff settle on quicker and more suitable decisions, decline superfluous testing, and reduce ED overcrowding [3-5]. Fast triage leads to reduced length of hospital stay, having potential economic benefits. One US hospital, for example, estimated that lowering ED congestion through expedited transfers to inpatient settings may save $3.9 million per year [6].

2. Methods and Materials

This retrospective observational study was performed at the Emergency Department of a tertiary public hospital and approved by the corresponding Institutional Review Board (IRB). For the purposes of this analysis, we used the caret package [7] in R [8], a well-known framework for building ML models. The caret package offers functions that make model training for complex regression and classification tasks easier. During one year, from January until December 2020, there were recorded 13,991 ED visits from patients who had undergone routine laboratory testing.

In our study, we investigated coagulation tests and biochemical markers, routinely used for patients visiting the ED concerning the ED outcome. The biochemical markers were used along with their medians are Creatine Kinase (CPK) (84.0), Creatinine (CREA) (0.900), C-Reactive Protein (CRP) (7.10), Lactate Dehydrogenase (LDH) (203.0), serum levels of Urea (UREA) (36.00), activated partial thromboplastin time (aPTT) (30.50), D-Dimer (654.3), International Normalized Ratio (INR) (1.020), hemoglobin (HGB) (13.10), lymphocyte count (LYM%)(20.40), neutrophil count (NEUT%)(70.60), platelets (PLT) (247.0), including white blood cells (WBC) (9.05). The data set under consideration also included age, gender, triage disposition to the ED unit, and the corresponding ED outcome that can be either admission or discharge. The ED units along with the corresponding frequencies are Pathology (5128), Pulmonology (2787), Cardiology (2313), Surgical (1295), Urological (1173), COVID (717), Vascular Surgical (242), Thoracic Surgical (121), Triage (109), Otolaryngology (61), Psychiatric (34), Ophthalmology (11). The descriptive statistics for Age, Gender, and Admission are summarized in Table 1 below.

Table 1. Descriptive statistics for Age, Gender, and Admission

Age		Gender		Admission	
Mean	61.85	Male	7586 (54.22%)	Yes	6303 (45.05%)
St.deviation	20.82	Female	6405 (45.78%)	No	7688 (54.95%)
Range/IQR	84/33	Total	13991	Total	13991

Multiple Imputations by Chained Equations (MICE) method [9,10] for missing data imputation was implemented and used with the R programming language. The classification problem that we had to deal it consisted of two classes of patients; the patients who visited the ED and were admitted and the rest who were discharged.

We applied and evaluated the following classification models: linear discriminant analysis (method: lda), Recursive Partitioning and Regression Trees (method: rpart), support vector machines (method: svmRadial), k – nearest neighbor (method: knn), and random forests (method: rf) to try to predict hospitalization. The caret package uses the *train()* function to build any predictive model. We trained our models through a 10-fold cross-validation (CV) procedure to avoid overfitting in our analysis. The performance metrics of the ML techniques that were evaluated in this study were the Sensitivity, Specificity, and the Area Under the Receiver Operating Characteristic Curve AUC ROC from prediction scores. Apart from applying the classifiers to the whole data set, we also examined their performances separately for each ED unit to determine the best-performing case.

3. Results

Among several classifications algorithms that were tested through 10-fold CV, a random forest model with *mtry=14* outperformed other models in terms of AUC ROC, where *mtry* denotes the number of variables that are randomly collected to be sampled at each split time. The random forest algorithm works by aggregating the predictions made by multiple decision trees [11], and it can be used for both classification and regression tasks. After performing the five classifiers in the whole data set and in each ED unit separately, the best performance regarding AUC ROC was observed in the Pulmonology ED unit. The performance of the five classifiers in the whole data set are close overall to those in the Pulmonology ED unit, which are summarized in table 2 alongside the corresponding ROC curves which are shown in figure 1.

Table 2. Performance metrics of the five classifiers in the Pulmonology ED unit

Metric/Method	lda	rpart	knn	svmRadial	rf
Sensitivity	0.7168	0.5834	0.6778	0.7013	0.6969
Specificity	0.7184	0.7617	0.6800	0.7687	0.7757
AUC - ROC	0.7834	0.6989	0.7307	0.7961	0.8054

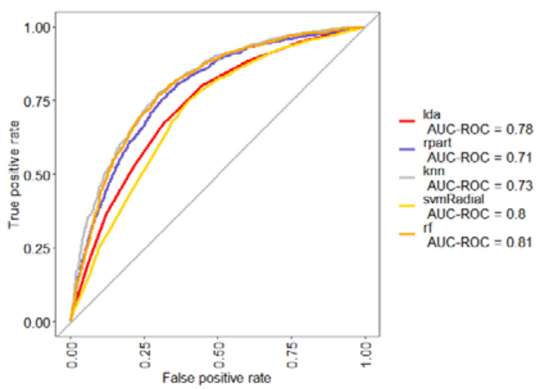

Figure 1. ROC curves of the five classifiers in the Pulmonology ED unit.

Furthermore, the six most important variables sorted in descending order were D.DIMER, CRP, Age, LYM, NEUT, and LDH.

4. Discussion

Artificial intelligence processes are increasingly being used in emergency medicine, notably for supporting clinical decisions and potentially improving healthcare services

[3, 4]. The rapid advancement of AI has introduced the possibility of using healthcare data to create reliable ML models that can automate clinical decisions in a timely and dynamic manner [12-14].

In this study, we evaluated five classifiers to predict hospitalization in the ED. A random forest model outperformed other models in the whole data set and had the highest performance in the Pulmonology ED unit with respect to AUC ROC and it showed promise in terms of aiding in the prediction of hospital admission of the patients who visit the ED.

Among the limitations of the study are the following: there is a single point of data collection (i.e., we only collect data at one hospital), the relatively short period examined, as well as the proposed ML model's limited explainability. We primarily expect to include data on patients over substantially longer periods in future studies. Using such an approach, focusing on one institute is less of a problem and may improve the odds of such technology-acquaintance experiments being successful by capitalizing on the knowledge shared by physicians who work together in the same ED. It is extremely interesting to note that the transformative capability of AI technologies can be felt even without fielding AI at the production level.

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