CLASSIFYING EMERGENCY PATIENTS INTO FAST-TRACK AND COMPLEX CASES USING MACHINE LEARNING

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ABSTRACT

Emergency medicine is a lifeline specialty at hospitals that patients head to for various reasons, including serious health problems, traumas, and adventitious conditions. Emergency departments are restricted to limited resources and personnel, complicating the optimal handling of all received cases. Therefore, crowded waiting areas and long waiting durations result. In this research, the databases of MIMIC-IV-ED and MIMIC-IV were utilized to obtain records of patients who visited the Beth Israel Deaconess Medical Center in the USA. Triage data, dispositions, and length of stay of these individuals were extracted. Subsequently, the urgency of these cases was inferred based on standards stated in the literature and followed in developed countries. A comparative framework using four different machine learning algorithms besides a reference model was developed to classify these patients into complex and fast–track categories. Moreover, the relative importance of employed predictors was determined. This study proposes an approach to deal with non-urgent visits and lower overall waiting times at the emergency by utilizing the powers of machine learning to identify high-severity and low-severity patients. Given the provision of the required resources, the proposed classification would help improve the overall throughput and patient satisfaction.

KEYWORDS

Emergency Medicine, Triage Enhancement by Machine Learning, Emergency Patients Classification, Identifying Fast-Track Patients. Identifying Severity of Emergency Cases.

1. INTRODUCTION

Patients visit the emergency department of a hospital for various reasons. While some individuals visit emergency departments based on a personal perception of the need to be examined by a physician, the scarcity of a nearby primary care facility, or following a friend's suggestion, others may be referred to the emergency by a healthcare provider [1]. As a result, nurses and physicians in emergency medicine usually treat various conditions ranging from life-threatening, such as strokes and heart attacks, to minor ones, including localized pain and obtaining a medication refill. Patients who head to the emergency expect to attain efficacious patronage, provided without delays and reachable in alignment with their locations and schedules [2].

Several systems were established in developed countries to guide healthcare professionals on triaging received cases based on the level of their acuity, such as the Emergency Severity Index (ESI) and the Australasian Triage Scale [3][4]. However, previous studies pointed to constraints in emergency triage, including the inconsistency of staff performance and limited accuracy of assessment, which indicate that existing triage approaches efficiency is insufficient, including their abilities to identify lower-severity cases that can subsequently be fast-tracked [5][6].

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Moreover, a few obstacles manifested in emergency units, particularly long waiting times and being overloaded by cases exceeding the available personnel and resources [7][8]. Various factors lead to such impediments, including unsound triage appraisal besides non-urgent emergency visits, which exerts extra pressure on personnel at emergency departments [9]. A significant proportion of emergency visits in the USA were comprised of such non-critical visits [10].

Consequently, these issues negatively reflect on the level of care provided to received patients and impact the satisfaction level of these people as they must wait for a longer time to be examined and treated at the emergency room [7][8]. Artificial intelligence (AI) technologies are changing the scenes in several fields. They seem promising in healthcare, where they can be implemented in different use cases, including data extraction, diagnostics, prognostics, and development of drugs [11][12].

In emergency medicine, most previous studies focus on predicting outcomes and length of stay rather than improving the triage process itself [13]. While Chang et al. utilized tree-based algorithms and boosting methods to identify low-severity cases among level III patients in Taiwan, they excluded levels IV and V in their study. Moreover, they did not incorporate neural network algorithms, which are prominent in different classification scenarios [14]. To our knowledge, no study has explored categorizing emergency patients comprehensively into fast-track and complex cases based on the composite of the length of stay, disposition, and triage score outcomes by implementing machine learning (ML) algorithms, including artificial neural networks.

Building on these considerations, this research proposes a ML-based model that can classify emergency cases thoroughly into fast-track and complex cases. This research proposes four different classifying models, including a neural network model, and compares these models to a reference one. The models were developed from a clinical dataset of a medical center that implements the ESI system for emergency triage scores. Cases assigned to levels III, IV, and V were eventually discharged after spending less than four hours in the emergency division, and they were considered fast-track cases. As a result, they require fewer resources from emergency care providers due to being less critical. On the contrary, complex cases necessitate a different handling approach since they require more attention and resources. This paper starts with an abstract and an introduction, followed by the research methodology. Then, the results are elaborated and discussed thoroughly. Finally, the paper is wrapped up with conclusions and relevant future work.

2. METHODS

2.1. Aim, Design and Setting of the Study

This study aimed to harness healthcare big data along AI's exceptional pattern recognition and predictive capabilities to lay the foundation for optimizing workflow in emergency departments. Therefore, it aimed to develop a model based on ML approaches that can help identify low-severity cases besides demanding ones among emergency patients. Furthermore, it purported to verify the performance of the developed model on a subset that was not engaged in the training phase as well as to present an illustration of how the predictors function regarding the classification outcome.

To accomplish the objectives of this research, a clinical dataset containing patient information that is collected at the time of triage in the emergency was sought. Moreover, past health records concerning demographic details and registration information for the same individuals were required to obtain a broader perspective of the studied population. Preferably, retrospective data from a healthcare institution that implements a renowned triage system, such as the Canadian Triage and the Acuity Scale and Emergency Severity Index scale, were desired where they are utilized widely worldwide. Such systems guide emergency nurses and providers on the acuity level of received cases, considering their physiological status, perceived pain and reason for the visit.

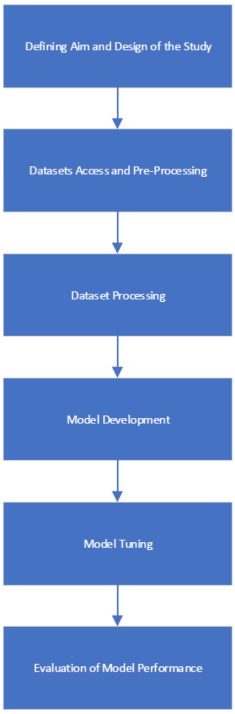

Figure 1: Methodology steps followed in this research.

To carry out this research, two clinical databases were harnessed, which had retrospective data pertaining to patients who visited the emergency department of Beth Israel Deaconess Medical Center in the USA for the period from 2011 to 2019. The respective databases were MIMIC-IV-ED (v2.0) and MIMIC-IV (v2.0), where the first one included the information gathered at emergency, including triage score and vital signs. On the other hand, demographic data were debriefed from the latter one, such as age and race. The respective health institution is a tertiary academic medical center which provides healthcare and research services besides being involved in Academia and teaching in affiliation with Harvard Medical School. The center is in Boston, MA where it has approximately 750 beds and receives approximately 50,000 emergency visits yearly.

2.2. Characteristics of the Participants

The records extracted from the two databases were for patients aged 18 and older. The conditions varied largely from simple grazes and medicine refills to life-threatening heart disorders. Clinical symptoms of the reported visits exceeded 60,000, which were entered as free texts, while some of them included two or three different symptoms. Cases with unavailable triage scores were omitted from the dataset, while cases with missing vital signs or pain values were replaced so that we could have a greater deal of samples available for training and testing of the ML models. A considerable portion of the documented cases were assigned to the acuity levels of two and three by the triage nurse at the time of assessment.

2.3. Dataset Access and Pre-Processing

Accessing the data was carried out through the website of **Physionet.org**. Subsequently, they requested completing specific requirements to grant access to both databases: signing up as a credentialed user, signing a consent regarding data usage, and finishing an online human ethics-focused course. The requested data became available accordingly.

Data analysis and machine-learning models were developed using R language software (v 4.2.1) besides the RStudio (v2023.06.1 + 524) for Windows 11. Three different datasets files were employed: patients.csv, triage.csv, and edstays.csv. The first dataset was drawn from the MIMIC-IV (v2.0), while the other two datasets were pulled from the MIMIC-IV-ED (v2.0). Hence, the three files were combined where first patients.csv and triage.csv were incorporated by subject_id. Then, the edstays file was merged with the consequent file according to the identifiers: stay_id and subject_id.

2.4. Dataset Processing

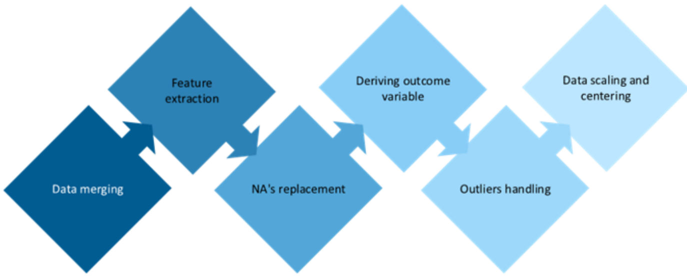

Figure 2: Data pre-processing and processing steps.

Following the merging step, specific columns were omitted. As a result, this research excluded the columns of date of birth (dod) along with hospital admission identifier (hadm_id) for non-relevancy. The same process was applied to the duplicate gender column. Next, in-time and out-time data points were employed to extract the year of the emergency visit. After that, the age of the recorded cases was concluded with the assistance of the in_Year variable according to the following equation: $age = in\_Year - anchor\_year + anchor\_age$. Moreover, the length of stay for documented cases was calculated by subtracting the intime from the outtime column. It was also converted into hours format and rounded to two decimal places. The names of columns were amended to facilitate the handling of variables during the coding process.

A few modifications were made to the dataset where categorical variables were transmuted into factors, and the **Pain** and the **Acuity** were made as numerical variables to facilitate data handling and feature extraction. Then, NA's values were replaced using the *K-Nearest Neighbors method*, which imputes such values using the closest observations in the dataset, replacing these values more accurately. The identifiers of both stay and patient were removed. In addition, the race and in-year variables were excluded from the dataset to avoid any potential bias in the model due to the former and the latter did not reflect the actual year of emergency visit. Further, a classifying column was created to group patients into Fast-track and Complex. Cases with a length of stay shorter than four hours in the emergency were considered fast-track, which is considered the standard length of stay for emergency patients and applied in different developed countries such as Canada and Australia [15][16]. Furthermore, incorporated cases should be assigned to acuity levels III, IV, or V and discharged at the end of the emergency visit. The categorization was carried out using the **Dplyr** library's functions. The Disposition, Acuity and Length of Stay columns were omitted after that as they were partly involved in inferring the two categories.

Major accompanying symptoms for the fast-track cases were identified to provide some insights into the characteristics of these patients. Furthermore, to narrow down the tremendous variety of complaints in the dataset. As a result, the most frequent ten complaints and the top thirty corresponding from the subgroup of fast-track – level III and the subgroup of fast-track – level IV & V were utilized to bring about a more balanced dataset. The **Forcats** library's functions were applied to combine similar symptoms. Next, the outliers of numerical predictors were converted into NA's and replaced using *K-Nearest Neighbors method*. Following the outliers handling, the remaining data were centered and scaled to lay the ground for effective classifying models.

2.5. Model Development

A reference model was established based on the variables of vital signs, pain, chief complaints, arrival mean and age to act as a baseline model in this research. Logistic regression (LR) was selected for this purpose, considering the simplicity of this algorithm and the nature of the outcome as a binary one. The **Caret** package was utilized for its variety of algorithms to establish ML-based classifying models. Four different models were created by using the algorithms of *Random Forests (RF), Stochastic Gradient Boosting (SGB), Multi-Layer Perceptrons (MLP), and Classification and Regression Trees (CART)* [17][18][19]. Prior to the training step, a data split was carried out where 80% of the data set was assigned to the training set, and the rest was allocated for the testing procedure. Furthermore, the predictor column was excluded from the training set. Moreover, the *five-fold cross-validation technique*, which encompasses splitting the data into five similar parts, where four are utilized for training while the remaining part is held for validation, was incorporated into the training process to produce more generalizable predictive models. This process is repeated for the five parts, and the model performance is computed as an average of the five predictions. *One hot encoding technique* was also applied to the categorical variables of the dataset to convert them into numerical ones. In turn, it facilitates running the algorithms of MLP and CART. For reproducibility purposes, two seeds were set to values 12345 and 1234 for data segmentation and algorithm training, respectively.

2.6. Model Tuning

Hyperparameters of the four employed algorithms were adjusted prior to the validation stage. Hyperparameters refer to the parameters through which we can control how an algorithm runs and learns an assigned task. Consequently, various parameters were passed into the **Tunegrid** to optimize the resulting models' performance. These parameters included the number of hidden layers and neurons for the MLP, complexity parameter for the CART algorithm, interaction depth and number of trees for the SGB algorithm, besides minimum node size and number of features sampled at a split for the RF algorithm. The activation function that was employed in the MLP algorithm is the logistic regression function. Moreover, the number of hidden layers that were experimented with was from one to three layers during the tuning phase. Node numbers were increased gradually, starting with one node in a single layer and concluding with fifteen nodes in the whole for the three hidden layers, taking into consideration the computational cost of having multiple hidden layers for such models. The below figure illustrates the basic structure of an MLP network.

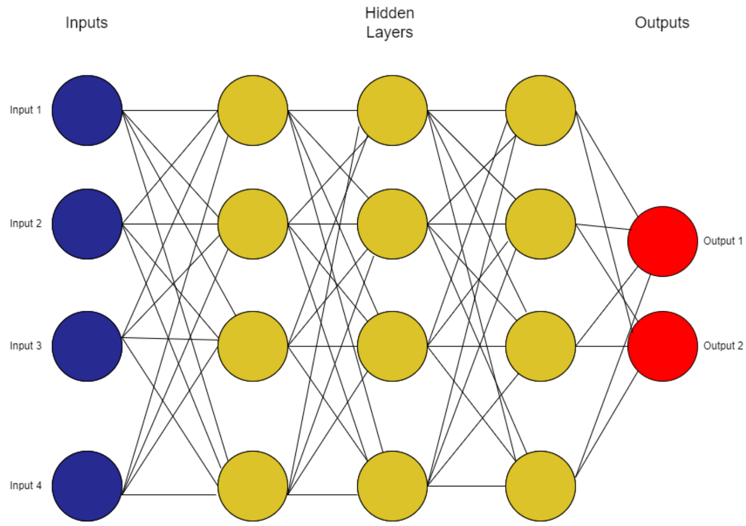

Figure 3: Schematic representation of an MLP network.

2.7. Performance Evaluation of the Model

After completing the development phase, the model was set to classify the new data in the test set. Then, these outcomes were compared to the actual ones, and performance measures of area under the curve (AUC), sensitivity and precision were computed to assess how well the models' identified cases. AUC, which is the area under the receiver operating curve, represents the overall performance of the predictive model, while sensitivity and precision evaluate the model's capability for fast-track case detection, where sensitivity refers to the probability of predicting a positive outcome when the actual one is positive, and precision is the ratio of correctly predicted positive instances to the total predicted positive instances. Confidence intervals were determined by applying the DeLong method to compare statistically the AUC of the models with respect to the reference model. Evaluation metrics were calculated for each of the five models. To provide some insight into features that are significant for the developed models, the Variables' importance was determined by employing relative predictors' importance attribute of the SGB model.

3. RESULTS

After combining both required datasets, the resulting dataset had 400,443 complete cases. The merged dataset had the needed specifics, including vital signs readings at triage, demographic characteristics of the received patients, length of stay of the visits, and the ultimate endpoints at emergency for the respective individuals. Further information on the attributes of the utilized dataset is demonstrated in the table below.

Table 1: Demographic and triage characteristics of the merged dataset.

Variable	Mean ± SD/Count
Temperature (°F)	98.01±3.75
Heart rate (Beat per minute)	84.91±17.62
Respiratory rate (Breath per minute)	17.55±23.02
Oxygen saturation (%)	98.51±16.86
Systolic Blood Pressure (mmHg)	135.17±47.60
Diastolic blood pressure (mmHg)	81.10±1058.99
Pain (0-10 scale)	4.42±4.05
Age (year)	52.31±20.46
Acuity level	
Level 1	13107
Level 2	132681
Level 3	224739
Level 4	28827
Level 5	1089
Chief complaint	
Abdominal pain	17810 (4.45%)
Chest pain	13479 (3.37%)
Dyspnea	6711 (1.68%)
Status post fall	6676 (1.67%)
Headache	5143 (1.28%)
Gender	
Male	181279
Female	219164
Race	
White	215392
Black/African American	73888
Other	19568
Hispanic/Latino - Puerto Rican	13760
White - Other European	8724
Arrival Mean	
Ambulance	137892
Helicopter	68
Other	1225
Unknown	11259
Walk in	249999

The subset derived from the primary dataset had 104,014 records and 12 variables, including the outcome. These rows comprised 79,048 *complex* cases and 24,966 *fast-track* cases. Additionally, the chief complaints of these patients constituted 42 manifestations. After replacing the outliers using the *K-Nearest Neighbor* imputation, the observations' count remained the same. The following figure illustrates the two outcome groups and their corresponding number of cases, stratified by the acuity scores.

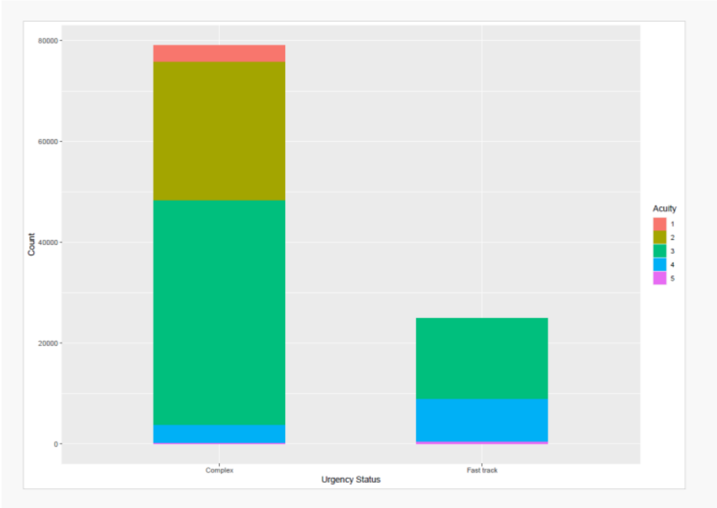

Figure 4: Distribution of outcome classes in the subset stratified by acuity levels.

Following the construction of the classifying models, the importance of predictors was attained and scaled to be from zero to one hundred. The *complaint* came first as the most crucial factor in the prediction process, followed by *arrival transport mean* and *age*. The least influential factors in terms of contribution to the predicted response were *diastolic blood pressure, respiratory rate*, and *gender*, respectively. The descending order of the influential variables is indicated in the below figure.

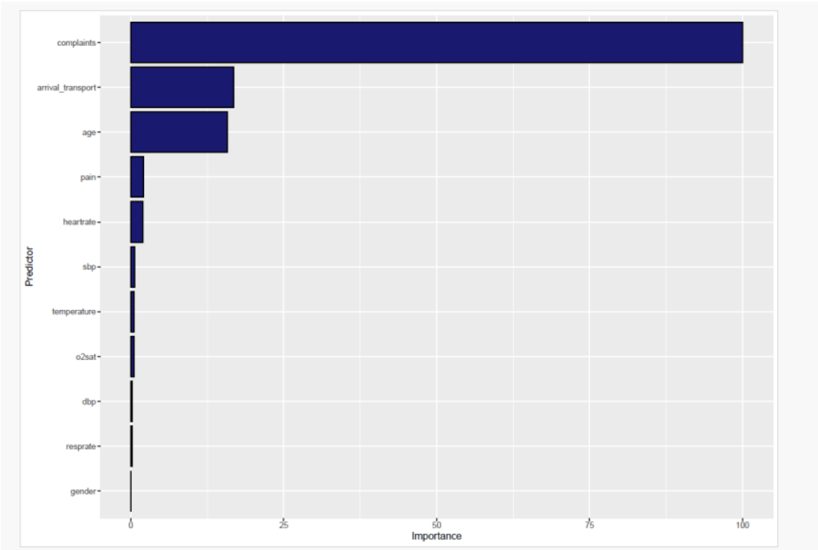

Figure 5: Ranking of relative importance of predictors according to the SGB model.

The performance of the predictive models varied when they were validated during the testing phase; the **MLP** algorithm statistically outperformed the reference model by scoring an AUC of 0.7594 (95%CI: 0.7523-0.7665), where it correctly classified the highest percentage of fast-track cases among the five models. However, the other models could not surpass statistically the reference model in terms of AUC. The following table demonstrates the performance assessment for the generated ML models and the reference model followed by a figure for the receiver operating curves of the five models:

Table 2: Comparison of the Performance of the classifying models.

Model	AUC (95% CI)	Sensitivity (95% CI)	Precision (95% CI)
MLP	0.7594 (0.7523-0.7665)	0.6399 (0.6264-0.6532)	0.6252 (0.6118-0.6385)
CART	0.7177 (0.7104-0.7249)	0.5185 (0.5046-0.5325)	0.6632 (0.6481-0.6780)
RF	0.7223 (0.7151-0.7296)	0.5245 (0.5106-0.5385)	0.6747 (0.6597-0.6894)
SGB	0.7309 (0.7237-0.7381)	0.5394 (0.5254-0.5533)	0.6872 (0.6724-0.7017)
LR (Reference Model)	0.7221 (0.7149-0.7294)	0.5199 (0.5060-0.5339)	0.6846 (0.6695-0.6994)

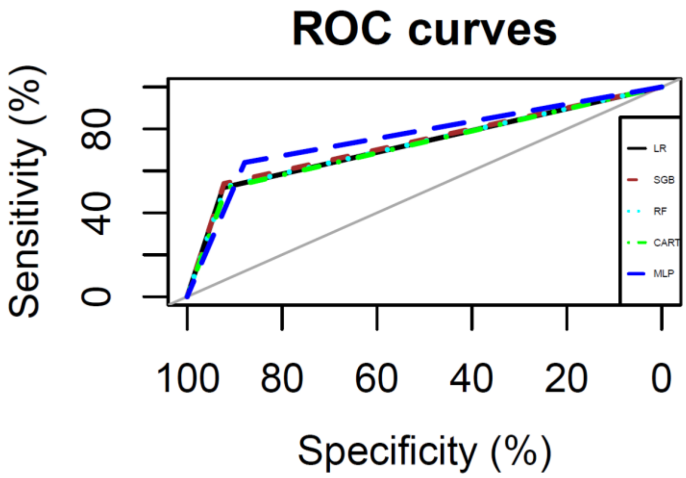

Figure 6: Receiver operating curves of the developed ML models and the reference model.

4. Discussion

This research aimed to devise an enhancing strategy so that the flow of care inside emergency departments is expedited for stable cases – urgent and non-urgent by harnessing the ML algorithms' predictive capacities. This method, in turn, would reflect on the contentment of patients as it may make for receiving efficacious treatment within shorter periods. As a result, this study presents four ML-based classification models besides a reference model developed from two retrospective patient databases of the same healthcare facility, besides providing some insights on the most significant factors for such classification. In this study, the **MLP** algorithm, which had two hidden layers of nine and seven nodes, respectively, yielded leading outcomes compared to the reference model.

MLP algorithm is a multi-layer neural network that comprises an input layer, an output layer, and a variable number of hidden layers. Initial weights are set to the inputs and are utilized to predict the outcome. This prediction is followed by iterative weight adjustments to decrease the mean error and optimize the accuracy of the predicted results. The superiority of the **MLP** model compared to the reference model could be attributed to the presence of hidden layers in its network structure, which enables the neural network to learn complex tasks, including composite health outcomes predictions. The classification outcome of this study was inferred based on the acuity score, disposition and length of stay, which in turn might have limited the performance of the other algorithms utilized in this study due to the complexity of this outcome. Concerning the most influential predictors, the leading position gained by *complaints* could indicate how significant the ailment patients have, whether in triaging them or appending them into the fast-track cases lane. Individuals with less severe symptoms are more likely to be identified as fast-track patients. The second factor on the list was *arrival mean*, where a substantial portion of the Complex group arrived by ambulance to the emergency department. *Age* predictor, which came third, also plays a significant role in identifying the complexity of the received patient. The subset revealed a significant difference between the suggested complex and fast-track categories, with age specifics of 52.98±20.41 and 41±17.82, respectively.

Integrating such models into clinical decision-aid tools would help in the data-driven classification of received cases based on their likely outcomes in terms of length of stay at the emergency and the conceivable destination at the end of their visit. Implementing these tools and setting up the required resources for faster emergency care for low-severity cases would reflect on patients' waiting time and satisfaction with the service catered to them. Fast-tracking stable patients in an emergency is a concept that has been investigated in a few studies, which in turn indicated favorable consequences. Chrusciel et al. found that recognizing minor emergency cases gave rise to a drop in the overall length of stay for patients. Moreover, it reduced the rate of cases who departed the emergency before being examined by a provider [8]. The impact of this strategy on older patients' health was researched by Gasperini et al., where the fast-track group demonstrated a significant drop in length of stay compared to the control group, besides a faster discharge following the end of physician's inspection [20]. However, harnessing the emerging AI technologies for this purpose is hardly examined in the existing literature since there was only one study on this topic for a dataset in Taiwan. Chang et al. suggested differentiating the low-severity patients assigned to level III at the emergency by utilizing five ML algorithms, including the **XGBoost** and the **CatBoost**. They established their model based on data from two health institutions that employ the TTAS triage system in Taiwan [14]. Another study in Iran inspected the possibility of navigating the workflow of emergency cases through simulation modelling and ML algorithms, where they evaluated the impact of a few factors relevant to resources, numbers of providers, and available inpatient beds on the waiting time of triage-run units and fast-track units. Consequently, their assessment found a prominent enhancement for both outcomes [21].

Despite the presence of urgent care units in some developed countries, for instance, Canada, their impact on relieving some of the pressure put on emergency may be limited due to the absence of a comprehensive understanding of the differences between the two divisions and where to head in case of unexpected illnesses [22]. This phenomenon aggravates the situation in societies challenged by immigration waves and homelessness as these individuals tend to struggle to select the proper healthcare facility that they should visit in case of ailments, preferring emergency care over other healthcare services, which in turn exerts additional pressure on emergency departments [23]. A previous study in the UK indicated that non-urgent visits to emergency departments are more common among adults and young adults compared to seniors [24]. Hence, these factors may hinder providing care to high-severity cases in emergency units as well as vulnerable patients, for instance, the elderly population. In light of such challenges, streamlining cases at emergency units using cutting-edge technologies, including artificial intelligence systems, would help improve the flow of patients in emergencies. In turn, it could assist in better serving both severe and non-severe cases, provided that the needed resources are assigned.

5. CONCLUSIONS AND FUTURE WORK

This study proposes classifying emergency patients into complex and fast-track. The indicated categorization was based on utilizing ML algorithms and harnessing retrospective emergency data. As a result, the results of testing four ML-based models besides a reference model on a validation set that was not engaged in the development phase were presented. MLP model statistically demonstrated a better performance compared to the reference model. Moreover, the significance of the predictors and how they contribute to the outcome of predictions was determined from the SGB model. Considering the inadequate performance of current triage approaches, Implementing ML algorithms in emergency departments may help identify high-severity and low-severity cases in an emergency based on arrival means, vital signs, complaints, and age besides pain. Consequently, it would help mitigate left-without-being-seen rates and diminish waiting times for low-severity cases, given it is integrated into a decision aid tool and applied along the required resources for rapid care of such categories, positively reflecting on patient satisfaction with provided services and overall emergency throughput.

Since the Caret package provides limited hyperparameter tuning for neural networks through the methods utilized, other packages that offer more extensive tuning will be explored in the future. Moreover, deep learning models will be established and compared to the results of this paper. The source code employed in this research can be accessed at [25].

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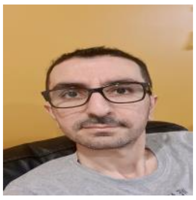

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