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ORIGINAL ARTICLE

The utilizing of machine learning algorithms to improve triage in emergency departments: a retrospective observational study

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ABSTRACT

Background: Machine learning in the healthcare sector represents a group of technologies in all aspects of medicine, and it appears promising, especially in emergency medicine. Hence, this study aims to utilize emergency department (ED) records to train machine learning algorithms and assess medical performance and outcomes.

Methods: This is a retrospective observational cohort study utilizing emergency patient records acquired from the Emergency Department of King Faisal Specialist Hospital & Research Centre in Riyadh City. Also, different machine learning models were evaluated, including regression, instance-based, regularization, tree-based, Bayesian, dimensionality reduction, and ensemble algorithms.

Results: A total of 149,513 emergency patient records were acquired. Due to many outliers and mislabeled data, clinical knowledge and a confident learning algorithm were used to preprocess the dataset. This resulted in only 84,970 patient records being kept. We observed that ensemble algorithms outperformed the others in all evaluation metrics, achieving an F-1 score and quadratic weighted kappa of 93.1% and 0.8623, respectively, in the case of CatBoost. In addition, the model never classified an emergent patient as nonurgent, nor did it classify a nonurgent ED patient as emergent. Optimizing the healthcare center workforce while ensuring that all critical patients are treated immediately is vital.

Conclusion: Machine learning-based triage models are feasible, highly accurate, and provide an in-depth assessment of the patient's risk profile, which may not be found in routinely used emergency triage systems. A prospective study to evaluate the potential efficacy of machine learning-based triage models in predicting emergency visit outcomes needs to be conducted.

Keywords: Machine learning, artificial intelligence, emergency medicine, triage.

Introduction

For many years, overcrowding in the emergency department (ED) has been considered a worldwide public health problem [1,2]. For this reason, many health organizations have put effort into improving their processes using different methods. Among various healthcare methods, other triage systems used in ED present the first opportunity to assess the patient's risk and the ability to urgently identify high-risk patients, determine treatment priority on arrival at the ED, and efficiently allocate ED resources [3-5].

Although these triage systems help classify patients' care priorities in the ED, they have some critical limitations, including that triage systems depend entirely on clinicians' decisions and subjective assessments. As decisions can differ for each clinician, the frequency of under- or over-triage of patients will increase, leading to high variation and low reliability in clinical outcomes [6]. Also, the equivocal nature of this subjective information

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can lead to a delay in patient flow in the ED. Moreover, as subjective information is based on clinical expertise, the time required to make a clinical judgment can be dependent on the experience of the provider, which is a risk to patient safety [7-10]. Therefore, it is a key challenge for health organizations all over the world to optimize triage systems to provide high-quality and timely care to achieve efficient resource allocation in the ED. As such, great effort has been put into developing a rapid, low-cost, and accurate screening tool that can be used to help medical staff accurately differentiate and prioritize patients. In this sense, nothing has been better developed to improve predictive ability in various triage conditions than the application of machine learning models [11-13].

The advantage of a machine learning system is its ability to process complex and large amounts of clinical information while considering the importance of every single piece of information. Conversely, humans might not be able to quickly identify the proper relationships and meaningful interactions between the different elements to make an accurate decision that will improve outcomes [14,15]. In addition, machine learning systems can continuously improve accuracy and efficiency each time more data are entered. Allowing machines to learn will enable them to make improvements to their algorithms by themselves. However, machine learning systems have not yet been widely used in the triage process for many reasons. Although it is simple in concept, applying machine learning systems to emergency triage is challenging and has limitations.

Machine learning systems are trained, not programmed, which means that they require huge amounts of data to carry out complex tasks at the human level. These massive data sets are not simple to create or obtain in the medical field; consequently, collecting them as part of routine clinical care is infrequent. Also, as these algorithms are deployed, there will likely be more instances in which potential bias finds its way into algorithms and datasets, leading to unintended negative consequences. In this paper, we used large quantities of recorded ED data at King Faisal Specialist Hospital and Research Center (KFSH&RC) to develop a machine learning model to accurately predict clinical outcomes after triage.

Subjects and Methods

This section describes this retrospective observational cohort study dataset, preprocessing techniques, machine learning algorithms, and evaluation metrics. Brief mathematical details are demonstrated in this context, while more complex algebraic formulations are referenced accordingly. In this retrospective study, no patient identification data were involved. All patient data were de-identified and only used for research purposes. The study was approved by the Institutional Review Board of KFSH&RC to ensure the protection of patient privacy.

The study dataset consisted of 149,513 adults (age ≥18) emergency patient records acquired from KFSH&RC from 2016 to 2019. Each patient record included administrative, demographic, and clinical data. We excluded patients who were dead upon arrival, were referred to another hospital, were discharged to a psychiatric facility, or left without being seen or before treatment was complete. Other patient records were also dropped to eliminate missing information and maintain data clinical consistency, including the following: $0 \leq$ pain ≤ 10; 33°C $\leq$ temperature ≤ 50°C; $0 <$ systolic blood pressure ≤ 250 mmHg; $0 <$ diastolic blood pressure ≤ 150 mmHg; $0 <$ respiratory rate ≤ 80/minute; and $0 <$ pulse rate ≤ 240/minute. Consequently, the dataset size was reduced to 123,510 adult patient records in total.

As for input features for the machine learning model, we used information that is routinely available in ED triage settings—gender, age, mode of arrival, number of ED visits during the past 72 hours- as a proxy measure of acuity, time of arrival, temperature, systolic blood pressure, diastolic blood pressure, respiratory rate, and pulse rate. Note that this dataset did not contain oxygen saturation or the patient's reasons for the visits. While many studies have been limited to developing binary machine learning models (discharge *vs.* admission or ICU *vs.* hospitalization), this study investigates the development of a more integrated model that classifies ED patients as either nonurgent, urgent, or emergent. The acquired dataset provides the nurse emergency severity index (ESI) (scale of 1-5), which we used to prepare the model output, such that nonurgent, urgent, and emergent imply ESI levels of (5 or 4), (3), and (2 or 1), respectively. Triaging is a subjective decision in which variations are expected to be observed from one nurse to another, despite the defined ESI standards that healthcare staff recognize and follow. Hence, lumping the ESI scale into three categories aims to reduce subjective inconsistency and uncertainty in triage records. For convenience, we denote the model outputs of nonurgent, urgent, and emergent as "A", "B", and "C", respectively.

Before training machine learning models, it is critical to visually observe trends and preprocess the dataset. Figure 1 shows the binary correlation and distribution plot of the quantitative input features. Most binary correlation plots show a nearly Gaussian distribution of the three output classes (A, B, and C), where nonurgent records are closer to the center. Observing the distribution of each feature solely (plots across the diagonal), we noticed that the probability density distribution of each triage outcome was only differentiable in some features. This reflects how properly triaging a patient often requires correlated information across two or more features.

It is cumbersome and infeasible to task senior ED physicians with screening and cleaning the data; hence, an automated approach is required. We utilized confident learning, proposed by Northcutt et al. [16], to identify mislabeled records. Confident learning is a model-agnostic, principled framework that uses machine learning to statistically detect whether a label in the dataset is more appropriate for a record than its given label. Confident learning is based on pruning (searching for) noisy data, counting to estimate noise, and ranking training records. As seen in Figure 2, this technique aims to estimate a joint distribution between the given/noisy labels and the unknown/uncorrupted labels, assuming a class conditional classification noise process [17]. In this

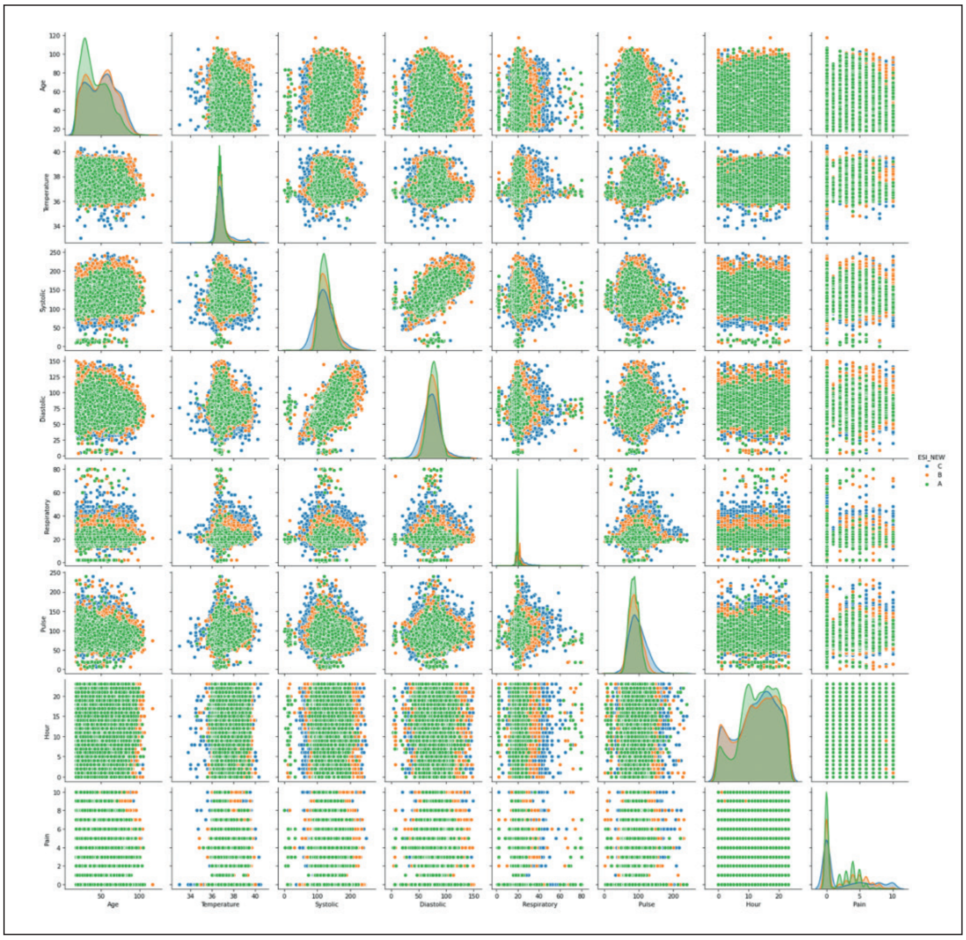

Figure 1. Binary correlation and distribution plots of model input features based on the raw patient records with respect to the three emergency triage outcomes of a, b, and c.

supervised learning task of ED triage, the inputs are the out-of-sample predicted probabilities and noisy labels. We trained a Gaussian Naive Bayes with four-fold cross-validation on all 123,510 patient records to construct the out-of-sample predicted probabilities [18].

This process resulted in the elimination of 38,540 records, reducing the dataset size to 84,970. This accounted for uncertain and incorrectly labeled records in the dataset. Figure 3 shows the binary correlation and distribution plots of the quantitative input features after eliminating these records. We observed that using confident learning to clean this dataset improved information consistency and outlier elimination. Figure 4 shows a comparison of the quantitative feature distributions before and after cleaning the dataset using confident learning. This confirms that the feature distributions were not altered after applying confident learning to clean the dataset.

Before training the machine learning models, we label-encoded the categorical features (gender, mode of arrival, and number of ED visits during the past 72 hours). We further normalized the numeric features, which reduces the time required to find the optimal parameters while training, as it limits oscillation before reaching the loss minimum [19]. It reshapes the cost function into a circle in two dimensions and a sphere in three dimensions, allowing the optimizer to converge in a smaller number

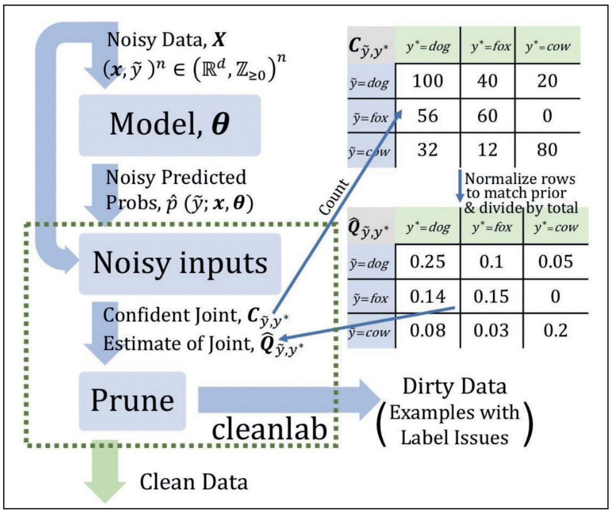

Figure 2. Confident learning process which is utilized to identify and eliminate the mislabeled emergency triage outcomes in the study dataset [16].

of iterations [20]. The input features are normalized and scaled using their corresponding mean and SD. Note that the training data means, and SD were also used to transform the validation and testing data.

We compared the performance of different families of classification machine learning algorithms on

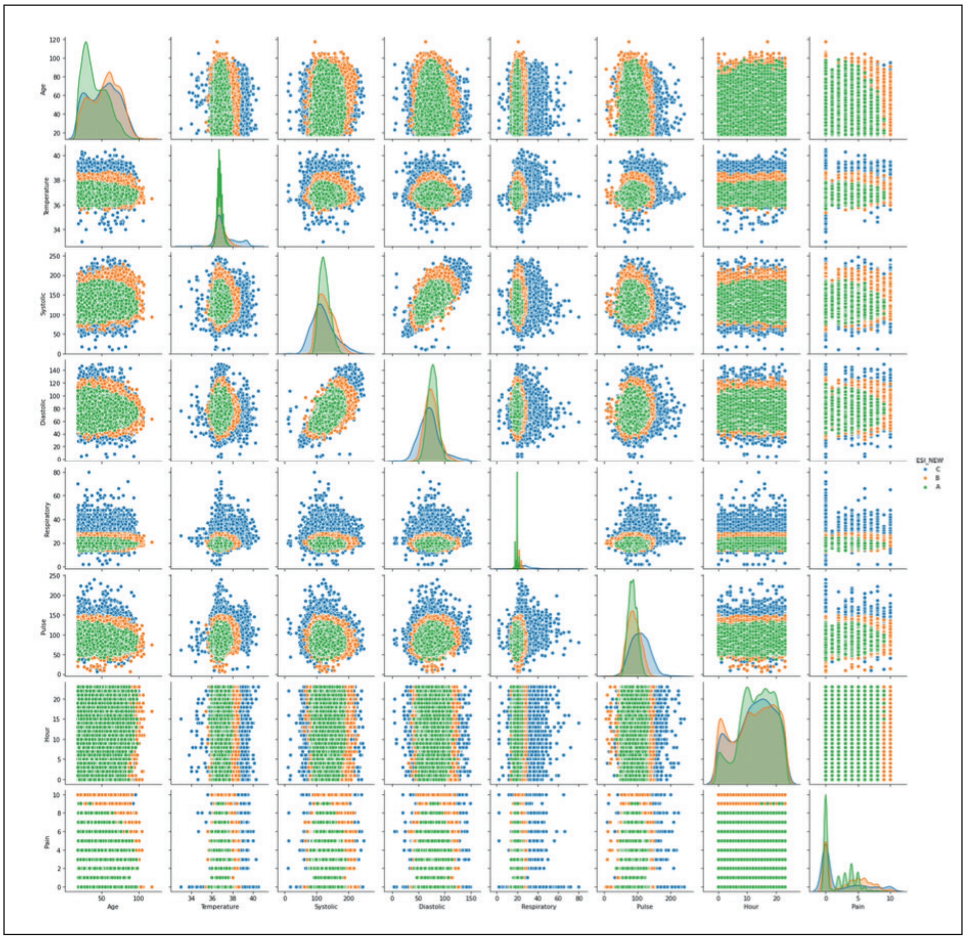

Figure 3. *Binary correlation and distribution plots of model input features based on the preprocessed patient records with respect to the three emergency triage outcomes of a, b, and c.*

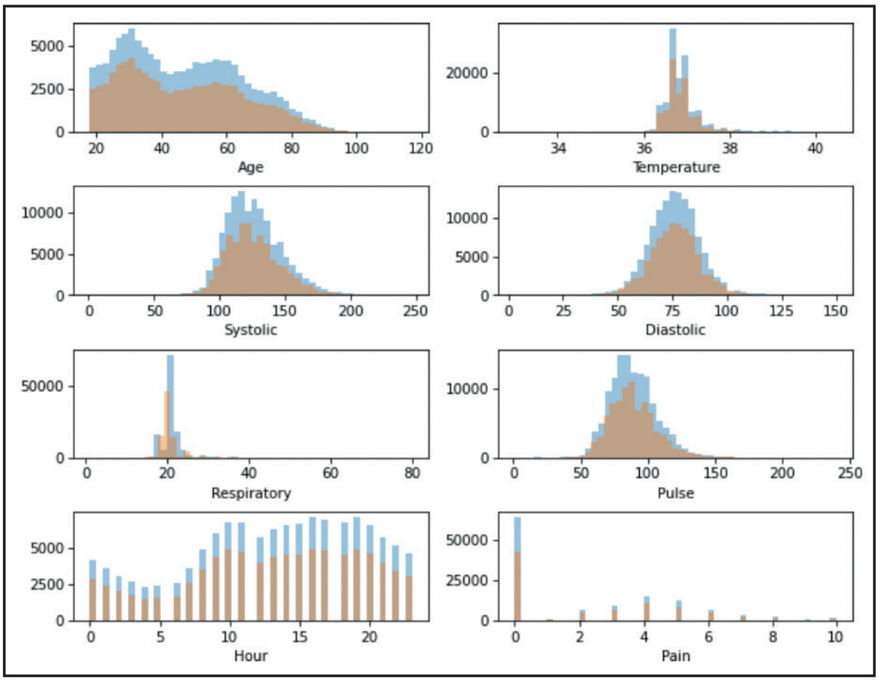

Figure 4. *Comparison of the distribution of the major triage prediction features before (blue) and after (orange) applying the confident learning algorithm. Note that the univariate distribution is maintained for each feature which indicates that this step did not result in any form of statistical alteration of the original dataset.*

the prediction of ED patient triage. These included regression (e.g., logistic regression), instance-based (e.g., *k*-nearest neighbors and support vector machines), regularization (e.g., ridge classification), tree-based (e.g., decision trees), Bayesian (e.g., naive Bayes), dimensionality reduction (e.g., linear discriminant analysis and quadratic discriminant analysis), and ensemble algorithms (e.g., random forest, extra trees, boosting, Ada Boost, and gradient boosting machines). Given that this dataset was imbalanced, we evaluated the models using accuracy, recall, precision, F-1 scores, and quadratic weighted kappa. The best model was found by tuning its hyperparameters using the F-1 score as the optimization metric of interest. Furthermore, we computed the quadratic weighted kappa metric to evaluate how close the model prediction is to the ground-truth triage [21].

Results

Of the 84,970-emergency patient dataset, we allocate 90% (76,473 records) and 10% (8,497 records) for training and unseen hold-out testing, respectively. In training the machine learning model, we perform 10-fold cross validation to enhance the model's ability to generalize to unseen emergency patient records. different machine learning algorithms. As seen in Table 1, we trained multiple machine learning algorithms and compared them using 10-fold cross-validation metrics. We observed that ensemble algorithms outperformed the others in all evaluation metrics, achieving F-1 scores as high as 93% in the case of CatBoost. We further tuned the CatBoost hyperparameters for a slight improvement and achieved a 93.1% F-1 score and 0.8623 quadratic weighted kappa. Figures 5 and 6 show the evaluation metrics for each class and the confusion matrix, respectively, on the unseen hold-out test records. Note that the model performed best in triaging nonurgent and emergent ED patients. In addition, the model never classified an emergent patient as nonurgent, nor did it classify a nonurgent ED patient as emergent.

Discussion

This is a pilot study to evaluate the visibility of the application of the machine learning model in triaging ED patients. To our knowledge, this is the first study investigating the utility of machine learning models in clinical settings utilizing Saudi data. The machine learning model is aimed to reproduce the ESI triage levels by the ED registered nurse. This was achieved with high accuracy, specifically in extreme presentations (low and high acuity presentations). While a large subset of ED visits ends up being discharged and non-critical, it is very important to recognize patients with high acuity who can decompensate to prioritize their care and allocate resources [22].

We applied different families of classification machine learning algorithms to the prediction of ED patient triage, which includes regression (e.g., logistic regression), instance-based (e.g., *k*-nearest neighbors, support vector machines), regularization (e.g., ridge classification), tree-based (e.g., decision trees), Bayesian (e.g., naive Bayes), dimensionality reduction (e.g., linear discriminant analysis, quadratic discriminant analysis), and ensemble algorithms (e.g., random forest, extra trees, boosting, Ada-boosting, gradient boosting machines) using the available data at triage. The models were evaluated using accuracy, recall, precision, F-1 score, and quadratic weighted kappa. The CatBoost model is clinically plausible and was developed using multiple triage information as follows (gender, age, mode of arrival, number of ED visits during the past 72 hours, time of arrival, temperature, systolic blood pressure, diastolic blood pressure, respiratory rate, and pulse rate).

The main aims of ED triage are to precisely discriminate high-risk patients from more-stable patients and to deal with the frequency of under- or over-triage of patients, which could lead to high variation and low-reliability outcomes. Previous studies and clinical observation documented that conventional triage approaches have incommensurate predictive potential. Furthermore,

Table 1. *Performance comparison of different machine learning algorithms.*

Algorithm	Accuracy	Recall	Precision	F-1 score	Kappa
CatBoost classifier	0.930	0.915	0.930	0.930	0.860
Light gradient boosting machine	0.928	0.909	0.928	0.928	0.855
Random forest classifier	0.917	0.895	0.917	0.917	0.834
Ada boost classifier	0.914	0.882	0.914	0.913	0.825
Gradient boosting classifier	0.911	0.871	0.910	0.910	0.818
Extreme gradient boosting	0.910	0.864	0.910	0.908	0.815
Extra trees classifier	0.909	0.848	0.909	0.908	0.814
Decision tree classifier	0.870	0.876	0.890	0.876	0.753
Logistic regression	0.813	0.696	0.809	0.806	0.605
Linear discriminant analysis	0.813	0.713	0.813	0.802	0.596
Ridge classifier	0.795	0.611	0.797	0.778	0.548
SVM - linear kernel	0.793	0.669	0.814	0.774	0.557
K neighbors classifier	0.783	0.663	0.777	0.772	0.534
Naive Bayes	0.730	0.584	0.752	0.677	0.368
Quadratic discriminant analysis	0.728	0.495	0.748	0.677	0.345

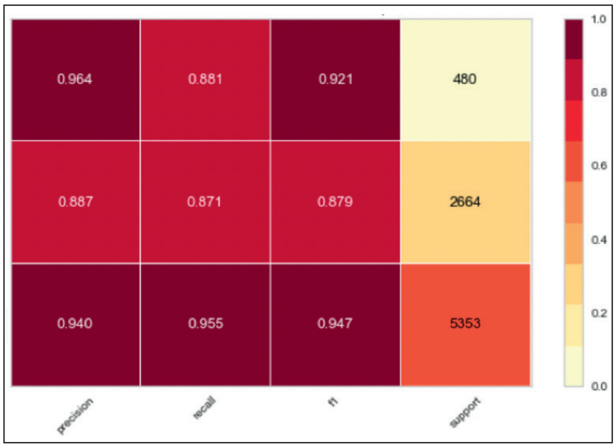

Figure 5. *Model evaluation metrics (precision, recall, and F-1 score) on the test set with respect to each of the three emergency triage outcomes. Based on the F-1 score, we observe that the model performs best with respect to outcomes A and C.*

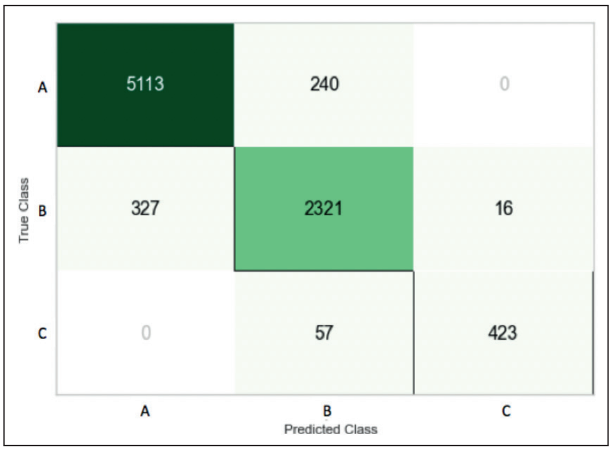

Figure 6. *Confusion matrix resulting from evaluating the trained model on the unseen test set. It is evident that the model never confuses cases A and C, which is a critical component of this model.*

they reported the need for a more dependable ED triage approach [23-25]. The use of machine learning models has been proven to be more accurate than the regular approaches. Recently, medicine witnessed a significant emphasis on the application of machine learning models to tackle many challenges in different medical fields. For instance, predicting breast cancer diagnosis, predicting kidney diseases, predicting cardiovascular diseases, predicting mortality in patients with sepsis, and predicting the diagnosis of cardiac ischemia in patients with chest pain [26-33]. The current study investigates the development of a more integrated model that classifies ED patients as either nonurgent, urgent, or emergent.

The reasons for developing predictive potentials noticed in the machine learning models are likely multifactorial. In addition, machine learning models have many strengths over conventional approaches. One of the advantages of machine learning is that it can be applied simply to carry out iterative recalibration of models over time as new data become available. Secondly, the ESI approach could lead to insufficient performance and high fluctuation between providers, as it excessively depends on subjective clinical assessment of expected ED resource use [23].

While triage aims to risk-stratify patients and anticipates ED resource utilization, the lack of clinical outcomes based on the available data set is a limitation of this study. We have developed a model to reproduce the ESI triage levels by the ED registered nurse. This placed a restriction on the accuracy of the triage level based on the accuracy of the performed by ED registered nurses. However, we could reproduce the triage levels to a high level of precision and reproducibility. Another limitation is utilizing a machine learning model to identify miss-label records that were excluded. The data were obtained from a single large referral tertiary center with a large unique oncology population and a transplant patient. This cohort of patients might not reflect the general population. Even though this is a retrospective analysis of the output data, clinician team members review us to assure consistency and reproducibility.

Conclusion

Machine learning models appear promising to provide new tools that will improve the physician's ED triage decision-making, which will, in turn, allocate resources utilization, enhance patient care, and control overcrowding in the ED. Our study shows that machine learning-based triage models are feasible, highly accurate, and provide an in-depth assessment of the patient's risk profile which may not be found in the routinely used emergency triage systems. A prospective study to evaluate the potential efficacy of machine learning-based triage models in predicting emergency visit outcomes need to be conducted.

Acknowledgment

None.

List of Abbreviations

ED Emergency department
ESI Emergency severity index
KFSH&RC King Faisal Specialist Hospital and Research Center

Conflict of interest

The authors declare the absence of any conflict of interest.

Funding

No source of funding was required to conduct the study.

Consent to participate

Not applicable.

Ethical approval

This study was approved by the King Faisal Specialist Hospital & Research Center-Riyadh (KFSH&RC) Internal Review Board (IRB number: 2190019), dated: October 17, 2019.

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