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A Review Article on Applications of Machine Learning Techniques in Emergency Medicine

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ABSTRACT:

The application of artificial intelligence and machine learning methods in several medical specialties, particularly emergency medicine, is expanding quickly. The use of artificial intelligence in emergency care has been the subject of current research, which has been compiled and evaluated in this study. These investigations fell into three categories: disease prediction and detection, admission, discharge, and mortality need predictions, and machine learning-based triage systems. The most significant studies in each of these categories have been selected, and the algorithms' accuracy and outcomes have been briefly reviewed by citing machine learning methodologies and relevant datasets.

Keywords: emergency medicine; emergency service, hospital; triage; artificial intelligence; machine learning.

INTRODUCTION:

Artificial intelligence has been applied in various health and medical disciplines. Particularly, several artificial intelligence and machine learning techniques have drawn interest lately. Among the most crucial areas of every hospital are the emergency department (ED) and triage, where diagnostic and therapeutic interventions should be carried out quickly and efficiently. Common standard procedures might not be enough when the number of ED referrals rises. Therefore, various artificial intelligence techniques such as data mining, natural language processing, clustering, and classification algorithms should be applied to dramatically improve the effectiveness of hospital emergency systems. Artificial intelligence will have some benefits; it will decrease human errors, as well as time and costs, and speed up the delivery of services. Additionally, compared to hospital medical staff, machine learning approaches typically have a comparable or even higher accuracy. Numerous research

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have evaluated the use of artificial intelligence in ED triage from various angles. However, the majority of them may be categorised into three groups, which will be covered in more detail below.

Studies on computerised triage strategies based on a basic survey of machine learning techniques has been done. Patients are given priority depending on studies mentioned in this section various machine learning methods, which are typically both quicker and more precise than conventional techniques and emergency severity index (ESI) (1). Quicker triage is not only raises patient satisfaction but also enhances ED efficiency and avoids overcrowding.

TECHNIQUES FOR MACHINE LEARNING AND THEIR VARIOUS FORMS:

An essential component of artificial intelligence that allows machines to learn and perform specific jobs is machine learning. In actuality, machine learning refers to a collection of methods and algorithms that can categorise or predict certain future events by identifying patterns in the past data. Logistic regression, support vector machines (SVM), Naive Bayes algorithm (2), decision trees, random forests, gradient boosting, and deep learning are some of the most significant methods in this area.

By fitting a line to the curve of the provided data, the machine learning technique known as logistic regression attempts to create a linear model of the relationships between variables (3). It may also be employed to classify things. SVM algorithm is one of the regularly utilised data categorization algorithms (4). Finding the optimal data classifier for the supplied data has been demonstrated to work. SVM has very strong generalisation capabilities.

Another method for modelling data is the decision tree, which classifies judgments using tree-like structures and outputs a category for the given data. An ensemble learning technique called random forest is created when several decision trees are used (5). Additionally popular in various machine learning issues is the gradient boosting technique (6). By using a few weak models, it creates an ensemble model of the data. This method's capacity to lessen the model's bias and variation is one of its benefits.

REVIEW OF STUDIES:

The three most crucial challenges in the ED—prediction and identification of disease; prediction of need for admission, discharge, and also death; and electronic triage—will be covered separately in the sections that follow by reviewing the most significant studies.

1. Identifying and predicting diseases

The Electronic Health Record (EHR), nursing reports, laboratory test results, and patient profiles are some of the sources of information in EDs that provide extensive details about patients' demographic traits, symptoms, and illness appearance. Machine learning approaches

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may use this data to forecast and identify various diseases so that quick and efficient medical interventions can be made.

Acute kidney injury

Acute kidney injury (AKI) is a condition that can develop between a few hours to a few days and, if not treated effectively, can result in kidney failure. Patients with AKI will require dialysis for the rest of their life and may even pass away from kidney failure. However, if this illness is discovered quickly, it can be swiftly managed to prevent consequences. Techniques for machine learning and artificial intelligence can aid in achieving this goal.

A approach based on boosted ensemble of decision trees was proposed in 2018 and was capable of detecting AKI at the moment of commencement as well as 12, 24, 48, and 72 hours beforehand (8). Two databases were employed in this investigation, both of which provided data on patients older than 18 years old. Patients' data from all hospital wards are included in the Stanford Medical Center dataset, and Beth Israel Deaconess Medical Center has data on ICU patients from the readily accessible MIMIC-III database. This algorithm's effectiveness was evaluated in comparison to the Sequential Organ Failure Assessment (SOFA) technique.

The accuracy of this approach in predicting AKI at the time of initiation is 87%, according to area under the curve (AUC). Additionally, this method's accuracy is 80%, 79%, 76%, and 72%, respectively, for the 12, 24, 48, and 72 hours prior to the beginning of AKI. Another study examined clinical notes from the MIMIC-III dataset that were taken within the first 24 hours after intensive care unit (ICU) admission (9). Meaningful words and representations of concepts and embedding were generated through natural language processing, and the model was created using a variety of supervised classifiers, including Multinomial naive Bayes (MNB), L1-/L2-regularization, SVM, Logistic Regression (LR), Random Forest (RF), Gradient Boosting and Decision Tree (GBDT), and architecture knowledge-guided deep learning. Among them, LR had the highest accuracy at 77.90%.

Influenza

Every year, influenza, an infectious disease that is highly contagious, affects a large number of people. Thus, early detection and forecasting of influenza can stop outbreaks, save lives, lower healthcare costs, and decrease the number of patients who need to visit the emergency department. In this regard, a study has suggested an automatic technique for EHR-based influenza diagnosis in which symptom extraction, feature selection, and classification for influenza diagnosis have all been carried out methodically (10).

In fact, the automatic diagnosis of influenza sickness based on EHRs has been achieved by combining natural language processing and various classifiers. More precisely, we can say that in this method, the crucial information concerning influenza is extracted from free-text ED reports utilising Topaz, MedLEE, and an expert, among other language processing

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parsers. The Bayesian network classifier then employs BN-EMTopaz, BN-EM-MedLEE, or expert-defined-BN to estimate the probability of influenza. Finally, nine experiments were run on three parsers and three classifiers to evaluate this strategy, and the outcomes were compared to the industry standard. When an expert analysed the reports and extracted data relating to the flu, BN-EMTopaz classifiers were utilised; their AUC value, which was 0.79, was the highest among the nine experiments.

Urinary tract infection (UTI)

Since a urine culture is not accessible until 24 to 48 hours after the initial visit, urinary tract infections are a common condition in emergency departments with a high probability of diagnosis mistake. Based on symptoms, physical exam findings, and laboratory test results, doctors make diagnoses and decide which medications to prescribe. This can lead to antibiotic misuse and antibiotic resistance. Previous research has demonstrated that individual forecasts and the diagnostic effectiveness of laboratory testing are insufficient.

Sepsis

Severe infection sepsis has a high fatality rate and expensive medical treatments. As a result, early detection and treatment of sepsis can lower patient fatality rates and lower the cost of treating these patients. It has been suggested to use machine learning to detect and diagnose sepsis, which will help patients receive better care (11). Three stages of sepsis are identified using the gradient tree boosting technique. Values of six vital signs in emergency rooms, general wards, and intensive care units are among the features employed in this method. Eventually, the area under the ROC value for sepsis and severe sepsis is 0.92 and 0.87, respectively.

Chronic obstructive pulmonary disease (COPD) and asthma

Patients with asthma and chronic obstructive lung disease run the daily risk of worsening their conditions. When necessary, sophisticated techniques can be used to significantly lower the likelihood of a disease aggravation. Some approaches that can be utilised to diagnose illness exacerbations early have been proposed using machine learning techniques.

In several research, the severity of asthma and COPD exacerbation in EDs has been evaluated using a variety of machine learning techniques, including Lasso regression, random forest, boosting, and deep neural networks. Some models have also been created based on the data that has been collected. The Random Forest method had the highest efficacy with 84% accuracy when these methods were compared using the C-statistic score (12).

Appendicitis

One of the most frequent reasons why people visit the ED with stomach pain is appendicitis. The incorrect or delayed diagnosis of appendicitis and subsequent perforation present a significant diagnostic problem. Consequently, it's important to identify appendicitis early and

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accurately (13). Major elements are automatically pulled from ED clinical notes and laboratory test data by a system that has been developed. This model divides the risk of paediatric appendicitis into three categories: high risk, low risk, and equivocal (14). This approach is built on machine learning strategies and natural language processing, both of which make use of structured data taken from EHRs (lab results) and ED clinical notes. First, using natural language processing techniques, the data regarding the risk of appendicitis is extracted. The risk of appendicitis was then divided into three categories using a rule-based approach (high risk, low risk, and equivocal). The effectiveness of this system was then contrasted with the gold standard method, which is created manually by doctors. This system's average recall and precision were 38% and 86%, respectively.

2. Prediction of disposition and mortality

Due to the overcrowding and rising demand, boarding of patients admitted to the ED is a problem. To enhance this procedure, automatic discharge and admission prediction can be carried out on patients. Supervised machine learning techniques and readily available health data are utilised to aid in the admittance of new patients in order to accomplish this goal. The provision of resources and beds to the patient can be accelerated using early admission prediction, cutting down on boarding periods. On the other hand, the findings suggest that, in some situations, nurses are unsure when forecasting patient admission and perform worse than machine learning techniques (15). Machine learning techniques can thus save time, enhance the results of medical procedures, increase patient happiness, and lower hospital expenses.

Various models have been suggested for early patient admission prediction. In this study, a model based on a mixed generative-discriminative approach was created (16). Naive Bayes was used to reduce the number of variables (generative) before a discriminative regression model was applied to the output of the first model. This model is able to predict 73.4% of admissions with a specificity of 90% and 35.4% of admissions with a specificity of 99.5% (AUC=91%) in the first 30 minutes using data from accessible EHRs.

A model to forecast risk level at the time of admission is suggested by a study. This algorithm evaluates data from all triaged patients with any ailment and also uses data gathered from routine exams conducted at the time of triage (17). In order to allocate resources to individuals who need to be admitted and relieve ED congestion, this approach aids nurses in triage in reaching conclusions about whether a patient should be admitted or not more quickly. This approach was developed using logistic regression, which has a specificity of 96.8% and a sensitivity of 33.4%. Additionally, the findings of a study demonstrated that the logistic regression method with an AUC of 0.80 to 0.89 may be used to hospitals with various patient populations (18).

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3. Machine learning based triage systems

Due to the overcrowding in EDs, the key challenge in triage is to quickly and accurately categorise patients depending on the severity of their illnesses in order to offer the best care. When compared to conventional ways, using machine learning techniques can speed up and increase the effectiveness of patient management during triage.

A study was recently undertaken to offer suggestions for a system for correctly classifying patients in triage into 5 groups based on the level of disease (19). In this paper, a brand-new technique called Randomly Occurring Distributed Delayed Particle Swarm Optimization (RODDPSO), based on PSO evolutionary algorithms, is recommended for clustering ED data for patient classification. Finally, the effectiveness of this strategy was assessed using the mean silhouette value and two clustering algorithms, K-means and FCM. According to the reported findings, RODDPSO has a better efficacy than the other two approaches, with a value of 0.31 for the aforementioned index. Clinical decision support systems (CDSSs) may be used in place of traditional triage methods, which are mostly based on disease symptoms.

Models with supervised machine learning algorithms have been proposed in another study on the electronic triage of ED patients, and they have been compared (20). Naive Bayes, Support Vector Machine, Decision Tree, and Neural Network classifiers have all been used, however Support Vector Machine and Decision Tree had the highest accuracy (84%). Another study suggested a calculative algorithm that classifies patients in emergency department triage using fuzzy logic and decision trees (21).

CONCLUSION:

Artificial intelligence and machine learning tools can be utilised in medicine, particularly in emergency care, to anticipate diseases, predict admission or discharge, and prioritise patients, among other critical challenges. Early detection and diagnosis of high-risk illnesses like AKI, sepsis, pneumonia, and contagious illnesses like influenza allow for more fast performance of critical therapies in the ED and the prevention of various disease-progression consequences. In this context, a variety of machine learning techniques, including deep learning, Bayesian networks, and logistic regression, have been used. These techniques have generally demonstrated high accuracy levels between 70% and 90%. These algorithms and other techniques can also aid in patient triage improvement and admission prediction.

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