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Towards the Application of Machine Learning in Emergency Informatics

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Abstract. Emergency care is one of the cornerstone parts of the world health organization's action plan. Rapid response and immediate care are considered in agile emergency care. Artificial intelligence (AI) and informatics have been applied to fulfill these requirements through automated emergency technology. Machine learning (ML) is one of the main parts of some of these proposed technologies. There are various ML algorithms and techniques which are potentially applicable for different purposes of emergency care. AI-based approaches using classification and clustering algorithms, natural language processing, and text mining are some of the possible techniques that could prove useful for investigating models of emergency prevention and management and proposing improved procedures for handling such critical situations. ML is known as a field of AI which attempts to automatically learn from data and applies that learning to make better decisions. Decision-support tools can apply the results of either supervised or various semi-supervised or unsupervised learning methods to tackle the how decisions about emergency situations are typically handled by the best professionals at the scene of an emergency, in the pre-hospital, and in healthcare facility settings. Enhanced and rapid communication at the moment of emergency, with the most effective decision making for triaging to estimate the acute nature of injuries and possible complications, how to keep a patient stable on the way to the care facility, and also avoiding adverse drug reactions, are some of the possible directions for exploring how ML can help to gather the data and to make emergency management more efficient and effective. The wide range of scenarios present in emergency situations and the complexity of different legal and ethical constraints on what responding personnel are allowed to perform on an injured subject before reaching a hospital makes for a most challenging set of problems for investigating the components of "intelligent" decision support that could help in these highly interactive and humanly tragic situations.

Keywords. Machine Learning, Emergency Care, Artificial Intelligence, Informatics

1. Introduction

Emergencies may occur at any time, often without warning, and even though the latest technologies are used. Even in a perfect world, it's crucial to be prepared for handling emergencies. Accident and emergency management is a synchronized activity involving

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numerous agents [1]. According to the 2019 report from the United Nations (UN) office for disaster risk reduction (UNDRR), there were 7,348 cases of major recorded disaster events affecting 4 billion people in the last 20 years [2]. To tackle these situations, at the societal level, risk reduction approaches are required. We propose a multisector professional approach aiming at avoiding emerging risk types and circumstances, addressing pre-existing types of emergencies, sharing information between those that are involved, and proposing good alternatives to tackle a particular type of situation, as already considered in [1, 2]. According to the definition provided by the American College of Emergency Physicians, emergency care is a medical field focusing on the diagnosis and treatment of acute and severe illnesses or injuries. It has a fundamental role in providing care to patients seeking urgent medical care [3]. Emergency informatics emphasizes the application of informatics for managing accidents and emergencies. Informatics has the potential to improve effectiveness of emergency responses and theircompetent and ethical handling with rapid information updates, providing prompter reactions from possible preplanning by using simulators, and estimating possible possible outcomes in accidents and emergencies

Informatics has been defined as the interdisciplinary study of the design, development, adoption, and application of information technology-based innovations in healthcare services delivery, management, and planning [4]. It is closely related and sometimes taken as synonymous with computer science but mainly known as the application of computing technologies as a profession, according to Association of Computing Machniery (ACM) Europe and the Informatics Council [5]. It is applied to various real-life problems providing novel and effective solutions. Computer systems and computational processes technologies have various subfields in which artificial intelligence (AI) is an emerging one composed of computer science methods and reliable datasets [6]. Machine learning (ML) is a major subfield that is frequently mentioned in conjunction with AI. This discipline is comprised of algorithms seeking expert systems creation for predicting or classifying available data to develop models for decision-making support. There are various applications of ML in everyday life. The popularity of the implementation of these systems is dramatically growing due to the increase in the availability of data in our society[6]. Recently, ML techniques have become popular in various fields to define algorithms based on the use cases for patterns extraction in big data [7].

The clinical practice of emergency informatics encompasses the initial assessment, diagnosis, treatment, coordination of care among different physicians, and stabilization of cases such as injuries and infections, heart attacks and strokes, asthma, and acute complications of pregnancy. The care may vary based on the degrees of acuity for any given patient [8]. An integrated view of emergencies from early recognition to rapid management of cases can save lives. This view has been addressed by the World Health Organization (WHO) and the output is a visual summary drawing the essential functions of an agile and responsive emergency care system (Fig. 1). The key human resources, equipment, and information technologies are considered in three main sections [9]. In an emergency, necessary activities in the scene, prehospital, and in hospital setting must be conducted, as precisely and quickly as possible. Proper technologies such as AI might be a good support to achieve this crucial aim.

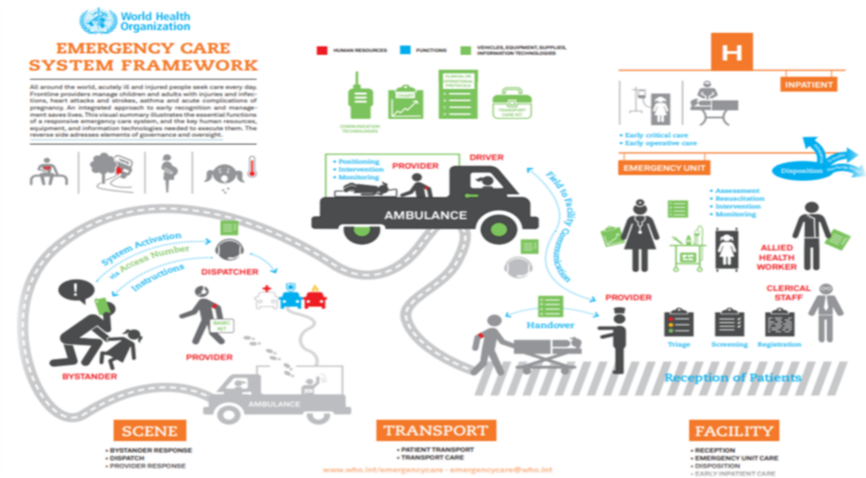

Figure 1. The WHO framework for emergency care [9].

2. Intelligent Emergency Informatics

Intelligent emergency informatics implies the usage of AI in technology-based emergency care and support. This application has been in various usages, such as automated triage and dispatching system using intelligent resources to detect medical emergencies, optimize planning, and improve prioritization [5, 10]. To understand the use-cases of AI for emergency care in detail, the survival chain may work well, as the staging of emergency care addressed in Fig. 1 by WHO is general. The chain encompasses triaging of emergency calls, provision of emergency medical services, treatment in the emergency department, inpatient and intensive care treatment (if needed), and the discharge of patients or transfer to long-term care. Technology has been applied to each component (Fig. 2). Provided technology may improve the speed and quality of care for each emergency-based solution on the given step.

As an example, intelligent triage centers detect cardiac arrests and help dispatchers to detect out-of-hospital cardiac arrests with an average of 30 seconds faster than human operators [11]. At the emergency department, AI has been applied for predictive modeling, patient monitoring, and day-to-day running of emergency departments. These intelligent tools may support health care providers in reducing waiting times in the emergency department, decreasing errors, and increasing the efficiency of care [12]. The impressive progress of AI to support emergency care has been enhanced by applying improved computing methods, integrated databases, and algorithm development. AI composed of the theory and computer systems development can perform tasks that normally require human intelligence such as visual perception, speech recognition, decision-making, and translation between languages [13]. ML is a key component of AI enabling emerging technologies to provide services in practice. It is well known as a field of AI with the ability to automatically learn from the data and applies that to make better decisions. Fig. 3 presents the applications and use-cases of AI as an emerging technology for intelligent emergency care [10]. They are mainly conducted by applying ML algorithms.

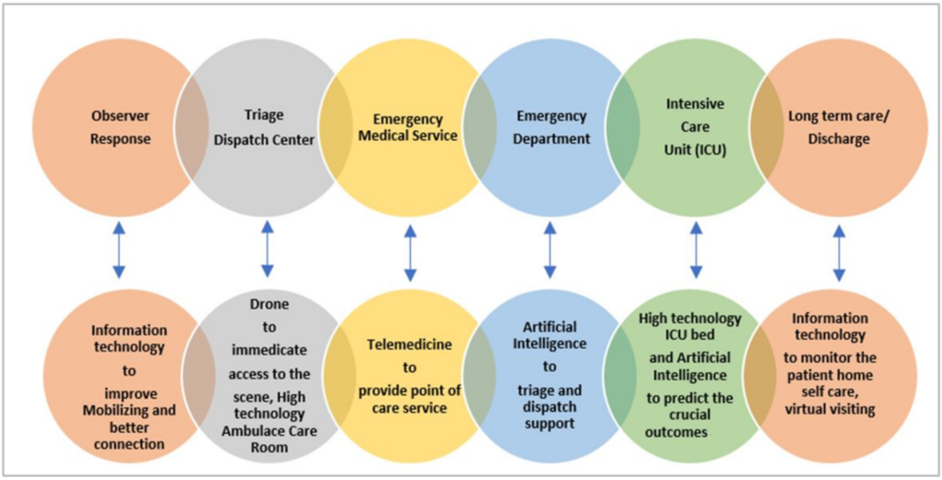

Figure 2. Available emergency technologies for each step of the survival chain in emergency care.

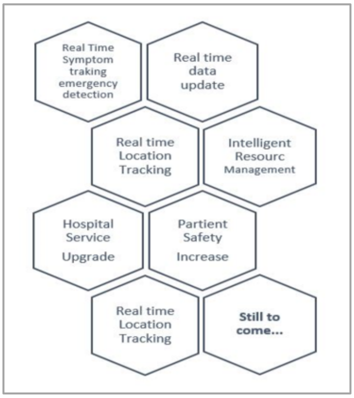

Figure 3. The artificial intelligence applications in emergency care.

3. Machine Learning for Emergency Informatics

With the rise of Al and ML, monitoring of information during emergent situations and decision-making under time-sensitive conditions have significantly enhanced. This achievement has created the potential for the spread of disease prediction, more efficient evacuation plans development, and effective distribution of resources to areas in need [5]. ML models are typically trained on large quantities of representative data for the target task and subsequently applied to unseen test data without a requirement for explicit programming and handcrafted decision boundaries. During the training process, these algorithms normally perform iterative updates to parameters of the model, which is then used to make predictions and improve at achieving the desired task over time. Comparatively, ML is similar to statistics as both fields can be used, in principle, to make inferences or predictions [14].

The utilization of computer science and statistics concerned with automatic improvement over time, leads ML to support the user including the clinicians in decision-making under uncertainty [6]. ML is an inductive process that automatically creates a classifier tool. It is conducted via learning the characteristics of classification categories from a set of pre-classified documents. The major ML approaches fall under the category of supervised learning, unsupervised learning, and semi-supervised learning. Supervised learning algorithms build a mathematical model by using a set of historically labeled data known as the training data; however, in unsupervised learning, no label is available for each record of the dataset. Using the training data and supervised learning algorithms, a model is developed; it is then tested on test data with the goal of output prediction based on input. Supervised learning algorithms include classification and regression [7, 12]. Some of the most important algorithms in this field are logistic regression, support vector machines (SVM), naive Bayes algorithm, decision trees, random forest, gradient boosting, and deep learning.

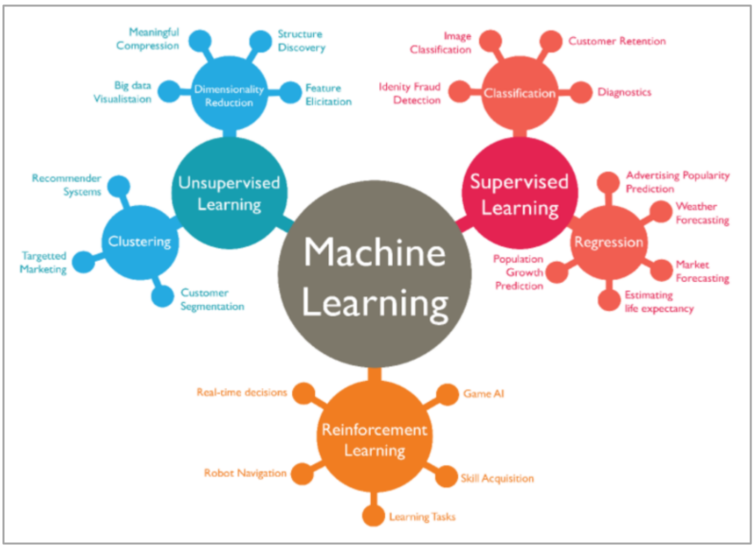

Figure 4. Machine learning area of application for data analysis and model development comprising three main categories [6, 7].

Logistic regression is a ML algorithm, which discovers a linear model of the relations between variables by fitting a line on the curve of the given data. It can also be applied for classification. One of the frequently used algorithms for data classification is SVM; it is an algorithm to discriminate the best data classifier for the data. SVM can achieve a very good generalization performance. A decision tree is another algorithm for mapping data using tree-like structures, classifying the decisions to output as classes or boundaries. Ensemble learning method applied if several decision trees are deployed, producing random forest. Moreover, the gradient boosting method is also widely used in some ML problems, producing an ensemble model of the data by employing some weak models [7]. The primary advantage of this method is its ability to reduce bias and the variance level in the model. Deep learning is a more recently introduced algorithm that is successfully applied to some complex tasks. It is a part of another class of ML methods named artificial neural network (ANN) in which a network of cells is produced and the connections between the cells, adjusted in a way that the resulting network can learn the structure of the training data. Usually, the number of layers in the network in the deep learning method is much higher than in an ordinary ANN. Thus, in deep learning, there are higher-level extracted features from the input data [15].

ML algorithm usage may allow assessing the collected historical data and provide the required information to improve emergency medical processes [12]. Through the available sophisticated algorithms, the analysis process may lead to useful knowledge for reducing the workload of medical staff, avoiding possible human fatigue, leading to fewer errors in healthcare.

Table 1. The most applied ML methods definition for emergency-related outcome prediction [16]

ML Method	Definition
Random Forest	An ensemble ML algorithm combining multiple learners in the form of nodes and predictors.
Deep learning	A method of ML that makes use of large neural networks. The adjective "deep" comes from the use of multiple layers in a network.
Ant colony optimization (ACO)	A population-based optimization algorithm where artificial agents work to solve problems as efficiently as possible by mimicking the behavior of real ants.
Reinforcement learning	A learning paradigm that is concerned with how intelligent agents ought to take actions in an environment to maximize the notion of cumulative reward.
Adaptive boosting	A ML meta-algorithm that combines other learning algorithms into a weighted sum that represents the final output of a boosted classifier.
Gradient boosting	A ML technique for regression and classification problems. Produces a prediction model in the form of an ensemble of decision trees.
Ensemble learning	Multiple learning algorithms were used to obtain a better predictive performance than could be obtained from a single constituent learning algorithm.
Constraint programming model	A paradigm is used to solve combinatorial search problems in which the user establishes constraints and the constraint solver finds a solution to them.
Hierarchical task network planning	An Al approach to automated planning in which a hierarchically structured network can give actions to solve a series of tasks.
Active learning	An approach to ML in which the learning algorithm can interactively query a user to label new data points with desired outputs.
Semi-supervised learning	An approach to ML that combines labeled data with unlabeled data during training.
Binary decision tree	A structure that serves as a compressed representation of sets or relations. It is often associated with 'Boolean functions' in computer science, or a graph with several nodes.
Supervised learning	An approach to ML that uses labeled data.

4. The Use-Cases of Intelligent Emergency Informatics

The framework of WHO presented in Fig. 1 encompasses three main sections of an emergency: the scene, prehospital and EMS, and hospital and care facility. In this section, the use cases of emergency management using machine learning methods based on these three sections are demonstrated.

4.1. Emergency Informatics Applications in the Scene

In the scene of an emergency, rapid response for quick and optimum decision-making is essential and requires efficient communication of information between governmental agencies, corresponding organizations, and healthcare facilities.

During natural disasters, emergency evacuations are very important. Machine learning-based modeling is often used to predict the best evacuation routes and provide useful insights to develop more effective evacuation plans. Ant colony optimization (ACO) algorithm has been a common algorithm used for evacuation route computation. The best route for an evacuation in a crisis is the output of the model after validation [16]. ACO algorithm has also been used for emergency management to distribute resources in disaster situations to overcome the vehicle routing problem. There is a mathematical optimization model which incorporated the idea of a virtual central "depot" or resource distribution center for distributing emergency resources from a stock center during an emergency. The proposed algorithm performed more efficiently than previous vehicle routing problem optimization models, calculating the best routes without traffic blockages or other disruptions considerations that could affect the results of the model [17]. Furthermore, a decision support system (DSS) was developed to allocate the resource and human force in case of emergencies with the highest level of efficiency [18].

ML algorithms have been useful in establishing DSSs aiding the response plans and embedded into an emergency. Hierarchical task network planning is a technique to train a model to search for a solution to obtain an initial task network in the early state. This tool coordinates the agencies involved in disaster scenarios and prepares standard operating procedures. This decision-making model was dynamic and able of dealing with temporal uncertainty in emergency response situations. Another agent-based decision-making system, working without the staff presence, is under progress. It will work based on reinforcement learning, a method in ML that enables an agent to learn from experimenting [18, 19] shown in Fig. 4.

Using ML, a classification model for survival prediction was built to quickly and precisely triage victims by wearable devices application in the emergency scene with the absence of medical personnel. Logistic regression, random forest, and neural network algorithms were all found to outperform using the datasets collected from patients sustaining accidents in daily life rather than in a disaster context. The deficiency of samples collected from the patients in a disaster is a key limitation of this study[20]. Furthermore, a game module has been developed to directly train on how to supervise the students during an active shooter scenario on commands. The model applied for the game was trained by the data of real-world scenarios that have already occurred. The game is used for training real related experiences to users and put them in the roles such as teachers, staff and administrators, law enforcement officers, school resource officers, and the suspect role [12].

With the crisis, reports of casualties might be limited due to infrastructure damage. The urgent use of social networks such as Twitter and Facebook can provide important information in the first few hours of an event, helping significantly to reduce both human loss and economic damage. An ML approach was used to tag and label data derived from tweets that were shared during emergency scenarios. Using this system, they were able to identify tweets that were relevant to disaster response efforts [16]. Furthermore, ML algorithms such as Adaptive Boosting, Gradient Boosting, and Random Forest were used to analyze heterogeneous social media data, including various types of emergencies and disasters[15]. Also, a project named Evolution of Emergency Copernicus services (E2mC) addressed that satellite imagery can be enhanced by social media data. The ML component can preprocess the social media posts to decipher slang and predict the relevancy of the post generating a damage assessment that may not be available from the satellite. Using ML techniques for analyzing the data obtained from temporal and spatial information derived from social media using digital volunteers and local eyewitness reporters has created a witness system to depict the emergency scenario at hand with as few gaps in information as possible [21].

Moreover, social media data have been applied for text and images analysis driven from social media posts in crisis and emergencies. The developed classifier was applied to detect notifying words in messages written in the tweets to identify the informative tweets using a supervised ML classifier such as SVM. There is also a keyword-based data-retrieval method and modeled the data during the training stage using SVM with an AUC of 0.937. This model to detect alarming posts of social media such as Twitter has been improved using deep learning methods such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN)[22-24].

Furthermore, machine learning-based matching models support effective communication between the disaster victims and the emergency teams immediately following a disaster event. These models help in clearly identifying the useful availability of resources and aid for those who need support stated in a post. Automated matching of resource requests and offers for emergency relief coordination has been explored [23, 24]. Furthermore, the problem-solution approach was developed by Varga et al. [25] to enhance emergency coordination via discovering the match between two sides: victim who requests support and aid provider.

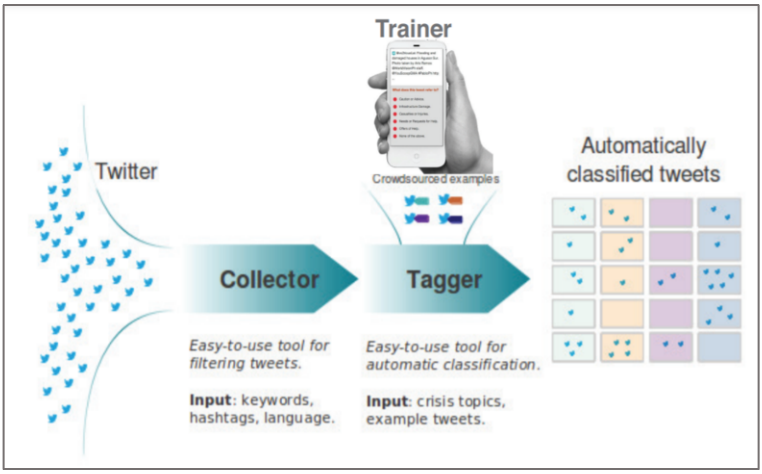

Figure 5. The diagram of social media (Twitter posts) classification using ML methods [26].

Deep learning also has been used for images classification taken from social media posts. the domain adaptation approach called Domain Adversarial Neural Network (DANN) was used to classify the images of a disaster event in a real-time setting[27]. Further work is required for this purpose to improve the model for analyzing the picture when it composes some other features which make it vogue or not clear enough to be processed.

4.2. Emergency Informatics Applications in Pre-Hospital Setting

In prehospital settings and emergency medical service (EMS), the need or not for critical care has been the focus of researches. Classification models using learning methods have been developed. This early identification may save patients' lives by helping clinicians to make quicker and more accurate decisions regarding the patients' transfer. ML algorithm and deep learning algorithms are applied for training and validated [14]. If the patient is expected to require critical care, the EMS technician must pass through the nearest low-level ED to a high-level ED. Accurate tools for predicting prognosis play an important role in communication between the prehospital EMS technician and hospital medical staff through providing online medical directions and preparing in-hospital management [28].

Furthermore, for deterioration prediction in the prehospital setting and need for critical care, different tools such as emergency severity index (ESI), Korean Triage and Acuity System (KTAS), Modified Early Warning Score (MEWS), and National Early Warning Score (NEWS) were compared. These tools became more improved through intelligent model development [19]. As can be seen in Fig. 6, ensemble methods of a convenient scoring system and ML algorithms outperformed the convenient scoring system with a higher level of the area under the receiver operating characteristics curve and the proposed method can more accurately predict the need for critical care in a prehospital EMS situation[14].

Moreover, patient prioritization and categorization in prehospital settings were conducted. That is, a triage decision for traffic road injured patients at three main levels using ANN and adaptive neuro-fuzzy inference system (ANFIS) was made. This was a requirement due to the excessive road traffic accidents in many countries and several referrals of injured people to ED. The system may support caregivers to focus on life-threatening conditions as they cannot provide emergency service to several cases simultaneously; that is, the shortage of resources does not allow caring for all of them at the same time. Therefore, injured individuals should be prioritized at triage by EMS. The models were built with a data set of 3015 data designed by Iranian medical experts and were based on patients` general status, vital signs, and chief complaints. Results showed less triage time and a shorter queue of patients, and the out-performance of the overall ANFIS model [29].

4.3. Emergency Informatics Applications in Hospital and Care Facility

4.3.1. Triage Improvement

Applying ML for emergency care of a case in hospital-based setting in various studies has been considered [14, 30]. Optimal emergency department (ED) for patient care depends on quick and accurate clinical decisions based on limited information. The number of emergency visits in ED is increasing over the past 20 years [31]. The increased level of ED crowding raised costs, and delays in care may result in more adverse consequences such as elevated morbidity and mortality for patients.

There are different clinical prediction tools, such as the Canadian CT Head Rule and Quick Sequential Organ Function Assessment score which have been developed to support decision-making under these demanding circumstances. However, these tools are limited to specific clinical scenarios. Their development requires substantial time and resource investment [10, 14, 15]. ML-based tools and models have emerged to support ED decision-makers in the triage the emergency cases, prognosis analysis, emergency detection, and early management and adverse drug event prediction [10].

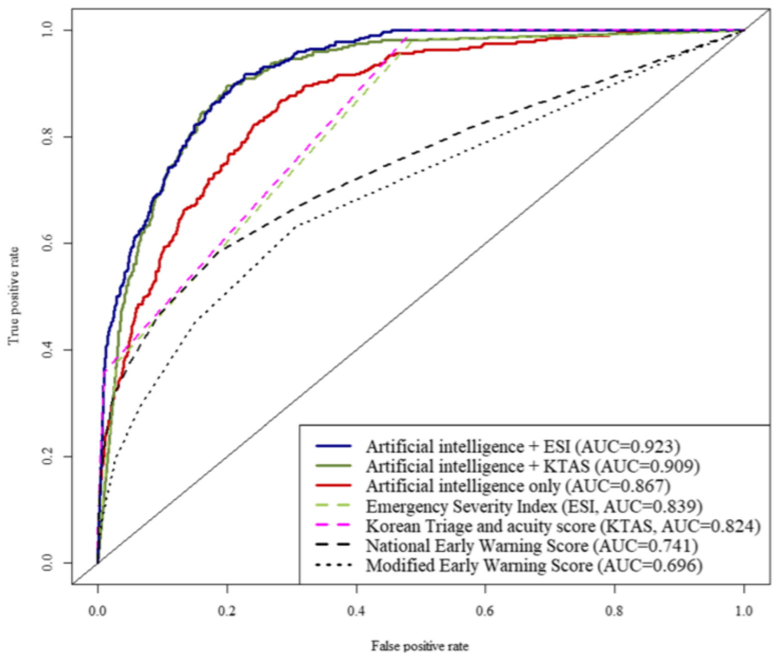

Figure 6. The receiver operating characteristics curve for predicting critical care needs to be enhanced with AI methods [14].

4.3.2. Probable Outcome Prediction

A study addressed the application of ML algorithms to develop a predictive model for clinical deterioration in hospitals. The tool, which is called Mayo Clinic Early Warning Score (MC-EWS) was developed using 2-year data of tertiary care of hospitals trained by gradient boosting and feature engineering. The occurrence of inpatient deterioration, including resuscitation call, intensive care unit (ICU) transfer, or rapid response team call during the next 24 hours was considered. The model demonstrated excellent discrimination in both the internal and external validation datasets with a high level of sensitivity analysis. The developed model had lower alert rates but was more accurate in discrimination cases. This might be due to applying more MC-EWS as it includes both nursing assessments and extensive feature engineering. The superior performance of MC-EWS to predict general care inpatient deterioration using more nursing-related variables and sophisticated models using ML algorithms, resulting in a reduced rate of alert and higher efficiency [32].

An emergency chest pain has always been significantly considered an alarming symptom. However, the level and quality of this symptom are challenging. ML methods were used to predict the critical care requirement in patients with chest pain, and simultaneously compare its performance with available scoring tools such as HEART, GRACE, and TIMI. Having considered different possible outcomes after chest pain, including cardiac arrest, transfer to ICU, and death during treatment in ED, the predictive model developed. LASSO regression model significantly outperformed the available tools regarding the metrics of accuracy, sensitivity, and specificity presenting an accurate model providing substantial support to clinicians' decision-making at ED [33]. Besides, ML outperformed the convenient statistical method to assist emergency physicians to classify the undifferentiated chest pains and promptly diagnose the life-threatening causes such as acute myocardial infarction (AMI) and prognosis of a major adverse cardiovascular event (MACE) with a higher level of accuracy. ANN, random forest, SVM, and gradient boosting studies have been the most common applied algorithms outperforming the existing risk stratification scores [34].

Due to uncertain decisions regarding the medical intervention related to a drug, an adverse drug event (ADE) may occur. It includes adverse consequences such as medication errors due to inappropriate use of drugs or adverse drug reactions (ADR) due to harm caused by drugs at normal doses, allergic reactions, and overdoses [35]. Predicting and preventing ADRs in the early stage of the drug development pipeline enhances drug safety and decreases financial costs. To prevent ADEs in an emergency department, informatics-based technologies such as CDSS and CPOE have been applied [36]. ML also has been used to automate the systems and give the ability of detection and prediction to these systems. As drug prescription is an important task of daily work of doctors to be done for each patient, it needs more attention and accuracy. The drug prescription must be done considering all potential drug sides. Deep learning methods were utilized to accurately detect and professionally identify unreported drug side effects using widely available public data. The dataset of 10,000 reviews was gathered from WebMD and www.drugs.com. It was manually labeled by utilizing a hybrid transfer learning from pre-trained BERT representations and sentence embeddings. The proposed model achieved a highly satisfying AUC score of 0.94 for ADE detection and an F1 score of 0.97 for ADE extraction. This approach can be applied to multiple healthcare and information extraction tasks and to be used for solving the problem that doctors may face over medication prescribing. Overall, this research introduces a novel dataset using social media health forum data demonstrating the viability and capability of using deep learning techniques in ADE detection and extraction. The model may be applied to other multiple healthcare and information extraction tasks, including medical entity extraction and entity recognition [37]. Also, a deep learning algorithm was used to early predict adverse drug reactions (ADRs) which are unintended and harmful reactions caused by normal uses of drugs. The applied algorithm was convolutional deep learning to simultaneously construct chemical fingerprint features and assess their associations with ADRs [38]. The AwareDX algorithm has been created to use ML to predict sex risks for ADRs. The algorithm mitigates the biases and minimizes adverse events by modifying drug prescription and dosage to gender [39].

5. Emergency Informatics Challenges and Solutions

There are various challenges in using ML algorithms for emergency care. The main challenges are dataset access, data integration, information delivery, and network connectivity [17]. To overcome current limitations, a systematic method with defined regulations is required to share the available datasets. To develop an experimental model leading to higher performance, free access to available data to all interested researchers should be supported, equally. Furthermore, the possibility of sharing the information among emergency related systems through applying interoperability standards may lead to enhanced operational processes. It is achieved provided that access and use of automated data be guaranteed for both humans and machines. Data combination from various sources such as electronic medical records (EMRs), social media data, data collected by sensors, or even satellites may lead to synergy and consequently more accurate solutions. This creates a synergy to benefit from different sources of data, collected by various platforms resulting in quicker and more accurate decision making and service in emergencies; the E2mC project by the usage of satellite imagery and social media data is an example [21].

Besides, the restrictions of ML methods corresponding to the large-scale distributed data sources should be addressed. Some algorithms are limited in terms of speed, tackling with the high dimensional big data, and susceptibility to bias [40]. The uncertainty associated with many of these algorithms besides other pitfalls has prevented them from being widely used in medical applications and health care [41]. Applying the ML models may encounter some limitations such as overfitting. It occurs when the learning algorithm performs well the training and testing data of the same dataset and delivers poor performance on a new dataset upon external dataset validation. A statistical method such as the goodness of fit test can measure how closely the model's predicted values match the observed (true) values. Cross-validation and partitioning the example randomly into training and validation sets are useful techniques to tackle the overfitting and prove the internal validation. Employing a simpler algorithm with less complexity may be a solution to deal with overfitting provided that the desired result might be achieved [7].

There are researches regarding the application of ML in public health-related emergency care and the ED at the hospital [5, 15, 17]. Although the applied ML algorithms outperformed the current approaches, there is still a need for a standardized method of ML application in terms of minimum data requirement, feature analysis, learning process, and reporting guidelines. Further progress is required to improve the reliability and accuracy of ML and AI applications in the management of critical care in an emergency through the development of clinical decision-making support, focusing on patient-orientated outcomes, and patient and physician acceptability improvement.

6. Conclusion

Emergency medicine has been a major focus for study and solution development with the advent of artificial intelligence. Technological advances have brought various tools that have great potential to improve processes and will improve the operational efficiency and quality of healthcare service delivery. ML and deep learning encompass different algorithms used for predictive and regression models developed for emergency-related outcomes including public health and the prehospital scene or in the emergency department. The validated outcome may support decision-makers to be much quicker and more efficient. The available data for training the algorithms differ from image, satellite, social media, individual data, or historical data of casualties or former emergencies. The approach of combining the available data to overcome the knowledge deficiency has also been applied and needs to be more considered.

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