Artificial intelligence in emergency medicine

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Abstract: Emergency medicine has witnessed increasing interest in the use of artificial intelligence (AI) and machine learning algorithms for numerous applications. This paper provides an updated summary of recent development in AI in emergency medicine. We categorize the studies into three domains, namely AI in predictive modeling, AI in patient monitoring, and AI in emergency department operations. Though this categorization is not meant to be exhaustive, it captures most of the AI applications in emergency medicine. Many AI methods such as classification and clustering algorithms, natural language processing, and text mining have been well investigated, but image understanding, computer vision, and robotics are yet to be explored. This leaves enough space for future endeavors in emergency medicine on applying AI and machine learning techniques to solve clinical problems.

Keywords: Artificial intelligence (AI); machine learning; emergency medicine

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Introduction

Artificial intelligence (AI) in medicine has a long history (1). AI has been an active subfield of computer science for more than 60 years, while medicine is even a much older field, which can trace back to thousands of years. Researchers from both AI and medicine communities have been interacting to create novel solutions for better patient care and enabling more efficient healthcare systems (2,3). Collaborations between both communities were either technology-driven or problem-driven. In technology-driven research, innovations are mainly the development and validation of new AI algorithms for selected clinical problems where the algorithms are generic and not necessary to be optimal in solving real-world problems. In problem-driven research, AI algorithms are customized to fit in specific clinical problems to deliver the best solutions, which however may not have excellent generalizability to other problems. Over the years, the gap between technology-driven and problem-driven research is getting smaller and smaller.

Development of an efficient informatics infrastructure has been instrumental in the field of AI in medicine. The advancement of computational power and storage capability enables processing massive amount of healthcare data with sophisticated AI algorithms. Large-scale image understanding and real-time patient monitoring data analysis become reality. Boosted by the computing power of the latest graphics processing unit (GPU), techniques such as deep learning (4) has gained fame in handling complex clinical data including medical images (5,6) and electronic health records (7). AI solutions have been traditionally popular in intensive care (8) and cardiology (9). Handelman and colleagues (10) have well described the state-of-the-art of AI in medicine and its future directions. However, due to the width of medicine and the breadth of AI, it is not possible to describe every innovation in the interactions between AI and medicine. In this paper, we aim to summarize several AI applications in emergency medicine. We categorize these studies into three domains, namely AI in predictive modeling, AI in patient monitoring, and AI in emergency department (ED) operations. Subsequently, we will elaborate the discussions on AI for emergency medicine and make concluding remarks.

AI in predictive modeling

One natural application of AI in medicine is predictive modeling. Numerous AI systems have been built to predict risk of disease and adverse outcomes. Notably, in emergency medicine, AI has been well explored for creating predictive models. Graham *et al.* (11) used AI algorithms and data mining tools to predict hospital admissions with patient data collected at the ED, where logistic regression, decision trees and gradient boosted machines (GBM) were implemented. Hu *et al.* (12) developed a real-time web-based tool to assess the risk of future ED visit where multiple data mining and machine learning methods were adopted for prediction. This study demonstrated that data from not only hospital or ED but also outpatient clinics could be valuable in enabling population-based risk assessment where AI played an important role. In the study by Lee *et al.* (13), a clinical decision tool was proposed to predict patients who will return to the ED within 72 hours. This tool could enable ED staffs and administrators to use patient specific values to assess the probability of ED revisit within 72 hours, which provides an opportunity for improving care and offering additional guidance to reduce ED readmissions.

Among various AI tools and algorithms, artificial neural network is one of the most popular. The study by Walsh and colleagues (14) showed the feasibility of using artificial neural network ensembles to predict ED disposition for infants and toddlers with bronchiolitis, although the prediction of length of stay was found not good. Bektaş *et al.* (15) developed a predictive model using artificial neural network for predicting craniocervical junction injury in trauma patients. Harrison and Kennedy (16) proposed a predictive model of acute coronary syndromes using artificial neural network and clinical data at the ED presentation. Jenny *et al.* (17) assessed predictability of routinely collected variables for mortality and acute morbidity by building models with 17 statistical and AI methods including neural networks. Another example is Eken *et al.* (18) where artificial neural network and genetic algorithms (a metaheuristic inspired by the process of natural selection) were adopted to predict renal colic in the emergency settings.

The availability of massive amount of data in the electronic health records enables the use of large, complex dataset for predictive modeling. However, traditional logistic regression will not be feasible when there are more independent variables than observations (9). To address this issue, variable selection is effective and efficient. Liu *et al.* (19) created a ranking algorithm to select a few variables to achieve comparable predictive performance with the full set of variables in assessing the risk of major adverse cardiac events for ED patients with chest pain. Taylor and colleagues (20) used established random forest algorithm to rank variables according to their computed importance and demonstrated the power of AI and machine learning over clinical scores in predicting in-patient mortality for ED sepsis patients.

AI in patient monitoring

Facilitated with advanced sensor technologies and the rise in computing power, continuous acquisition and analysis of large-scale patient physiological data are no long in imaginations. Curtis *et al.* (21) presented an integrated wireless system to monitor unattended patients in the ED. In this study, a prototype of scalable medical alert response technology (SMART) system was piloted and a small-scale deployment was conducted. In a recent study by Clifton *et al.* (22), an integrated patient monitoring system was developed and validated in large-scale in the ED. The integrated system interfaced to a peer-to-peer network of bed-side monitors and hand-held PDAs. The authors compared two early warning systems (EWS) that developed on the integrated system and traditional manual system. The reported large clinical trial also evaluated automatic methods for assessment of patients based on electronic health records augmented with AI techniques. Generally, integrated patient monitoring systems are paired with AI components for assistive decision making. There were other research studies investigating the use of AI tools for handling physiological data such as electrocardiography in the emergency setting (23,24).

AI in ED operations

Resource planning and crowd management are important tasks in the ED. In Sun *et al.* (25), the authors used time series analysis technique called the autoregressive integrated moving average (ARIMA) to develop models for prediction of workload at the ED. Their research showed evidence on using forecasting models for the arrangement of staff roster and resource planning. In the study by Jones and Evans (26), the authors addressed ED overcrowding in terms of evaluating the impact of physician staffing configurations by developing an agent based simulation tool. The feasibility of such a tool has been evaluated at a single hospital ED.

Diagnostic decision tools are essential in the ED to screen and stratify patients. Haug *et al.* (27) proposed a system for diagnostic modeling, which could potentially automate the creation of diagnostic decision support applications. The system was validated in the ED and has demonstrated feasibility of extending it to other departments. Similarly, Grigull and Lechner (28) used data mining techniques to support diagnostic decisions in a pediatric emergency department.

AI and machine learning tools have also been widely adopted for various operational purposes in the ED. For example, Zmiri *et al.* (29) implemented several data mining methods including Naïve Bayes and C4.5 algorithm for triaging ED patients by measuring their severity grades. Comparably, Goto *et al.* (30) used several machine learning approaches to predict ED dispositions to facilitate the triage of asthma and chronic obstructive pulmonary disease (COPD) patients. Yadav and colleagues (31,32) proposed automated outcome classification of ED computed tomography (CT) reports for both adult and pediatric patients, where hybrid natural language processing (NLP) and machine learning systems were built. NLP played an important role in another study (33) where the authors proposed an automated subjective, objective, assessment, plan (SOAP) framework for emergency department reports.

Discussion

The amount of complex health data including images, texts, videos, genomic sequences and structured electronic health records, continues to grow. The needs of AI and machine learning are increasing to analyze these heterogeneous data as traditional biostatistical solutions are unable to handle. AI has been proven effective and useful in augmenting physicians in terms of enhancing operational efficiency for healthcare systems. As summarized in *Table 1*, the studies investigated earlier have shown evidence on how ED physicians and the department could benefit from AI and machine learning technologies. Many researches on using AI for emergency medicine have been well reviewed in (34) and (35). Our paper aims to analyze this field from different perspectives, by categorizing AI applications in emergency medicine into three domains, namely predictive modeling, patient monitoring, and ED operations. Apparently, there are more AI applications beyond the above-mentioned areas. For instance, Ni *et al.* (36) developed an automated system to prescreen clinical trial eligibility in the ED to improve the efficiency of patient identification.

So far, the intersection of AI and emergency medicine is under-developed. Both areas have sophisticated development and rich individual sub-fields. The ED sees a big variety of patients and thus provides many opportunities to treat and study heterogeneous patient cohorts, such as trauma, sepsis, cardiovascular, among others. Likewise, AI has broad fields that study robotics, image, audio, video, text, genomics, and various applications. Given the fact that increasing number of technological innovations are available for real-time patient monitoring and system integrations, AI will play an instrumental role in the ED, in areas such as intelligent monitoring, clinical outcome prediction, and resource planning.

In this paper, we are not aiming to elaborate AI and machine learning algorithms, which has been done in many review articles (8-10); instead we emphasize on several specific AI applications in emergency medicine. We further categorize these applications into three domains, to which we believe most AI applications in the ED would belong. Even though AI solutions seem to be effective and useful in many applications, they are not universal. Customizations of AI algorithms to fit into specific clinical problems and needs are essential. This demands close collaborations between ED physicians and computer scientists. Therefore, building a culture and platform of knowledge sharing is a crucial step moving towards widespread adoption of AI and machine learning in emergency medicine.

Table 1 Summary of the applications of artificial intelligence (AI) in emergency medicine

Application	Study	Study aims	AI methods
Predictive modeling	Graham *et al.* (11)	Create a model to predict hospital admissions from the emergency department (ED)	Decision tree, gradient boosted machines
	Hu *et al.* (12)	Develop a real-time web-based tool to assess the risk of future ED visit	Decision tree, principal component analysis, k-means clustering algorithm
	Lee *et al.* (13)	Develop a clinical decision tool to predict patients who will return to the ED within 72 hours	Particle swarm optimization, discriminant analysis model
	Walsh *et al.* (14)	Predict ED disposition for infants and toddlers with bronchiolitis	Artificial neural network, ensemble learning
	Bektaş *et al.* (15)	Predict craniocervical junction injury in trauma patients	Artificial neural network
	Harrison and Kennedy (16)	Develop a machine learning model for diagnosis of acute coronary syndrome with clinical and ECG data at the presentation of ED	Artificial neural network
	Jenny *et al.* (17)	Evaluate the predictability of routinely collected variables for mortality and acute morbidity	17 state-of-the-art statistical and machine learning methods
	Eken *et al.* (18)	Predict renal colic in the emergency settings	Artificial neural network, genetic algorithm
	Liu *et al.* (19)	Select a subset of variables in assessing the risk of major adverse cardiac events for ED patients with chest pain	Random forest, support vector machine
	Taylor *et al.* (20)	Predict inpatient mortality for septic patients in the ED	Random forest, classification and regression tree
Patient monitoring	Curtis *et al.* (21)	Implement and evaluate an integrated wireless system to monitor unattended patients in the ED	Physiological signal analysis
	Clifton *et al.* (22)	Conduct a large-scale trial on an integrated patient monitoring system in the ED	Kernel method, k-means clustering algorithm, support vector machines
	Liu *et al.* (23)	Develop a scoring algorithm to predict cardiac arrest in ED chest pain patients	Support vector machine, k-nearest neighbor algorithm
	Liu *et al.* (24)	Develop a scoring algorithm with imbalanced clinical data to predict acute cardiac complications in ED chest pain patients	Ensemble learning, support vector machine, synthetic minority over-sampling technique
ED operations	Sun *et al.* (25)	Develop time series analysis models to forecast daily attendance at ED for the prediction of workload	Autoregressive integrated moving average (ARIMA) model
	Jones and Evans (26)	Develop a simulation tool to evaluate associations between ED physician scheduling and patient waiting time	Agent-based model
	Haug *et al.* (27)	Develop a system for diagnostic modeling for automating the creation of diagnostic decision support applications	Bayesian network, natural language processing, random forest
	Grigull and Lechner (28)	Use a computerized diagnosis tool created by combined data mining procedures to support diagnostic decisions in a pediatric ED	Support vector machine, artificial neural network, fuzzy logics, voting algorithm
	Zmiri *et al.* (29)	Categorize ED patients into severity grades with data mining approaches	Naïve Bayes, C4.5 algorithm
	Goto *et al.* (30)	Predict ED dispositions to facilitate the triage of asthma and COPD patients	Random forest, gradient boosted decision tree, deep neural network
	Yadav *et al.* (31)	Validate the performance of a hybrid natural language processing for automated outcome classification of CT reports in the ED	Natural language processing, decision tree
	Yadav *et al.* (32)	Validate the performance of a machine learning system for automated outcome classification of brain CT imaging reports for pediatric traumatic brain injury	Natural language processing, decision tree
	Mowery *et al.* (33)	Build an automated subjective, objective, assessment, plan (SOAP) framework for emergency department reports	Natural language processing, text mining, support vector machines

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Footnote

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