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Review Article

Artificial Intelligence and Machine Learning in Emergency Medicine

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ABSTRACT

The advent of Artificial Intelligence (AI) has resulted in development of novel applications in a multitude of fields, such as in Medicine, to aid medical professionals in clinical diagnosis. Specifically, the field of Emergency Medicine has been of immense interest to researchers, with vast untapped potential for AI solutions to improve operational efficiencies and quality of healthcare. Aside from primary healthcare facilities, the Emergency Department serves as the first line of contact to patients, who often present with varying and undifferentiated symptoms. Several challenges faced by clinicians and patients alike, such as waiting times and diagnostic dilemmas, present opportunities for application of AI solutions. In this paper, we aim to summarise the applications of AI in the field of Emergency Medicine by reviewing recent developments in Emergency Department operations and in the clinical management of patients.

1. Introduction

Emergency Medicine (EM) is a growing specialty and plays a critical role in society for receiving patients in need of urgent medical attention. These patients often present with a myriad of presenting complaints. In the US, there were 137 million Emergency Department (ED) visits in 2015, accounting for almost 14% of all hospital visits [1]. Multiple concerns have been brought up by patients. For example, long waiting

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times is one of the known factors contributing to decreased patient satisfaction in the ED [2,3]. In the UK, one study has shown that the median waiting time for decision making in the ED between April 2008 and April 2013 was almost 3 h, with up to 10% having wait times of more than 4 h [4]. Along with other factors, another study has shown that this had led to as much as 7.4% of patients leaving the ED without receiving treatment [5]. Recent advancements in technology has brought into the field a suite of tools, with great potential of improving processes and overall quality of healthcare in EM. With further evidence presented, it is believed that AI can seek to improve patient experiences in the ED. In this review, we aim to study the evidence to support the potential of AI in EM.

1.1. Definition of Emergency Medicine

According to the American College of Emergency Physicians, EM is defined as the 'medical specialty dedicated to the diagnosis and treatment of unforeseen illness or injury' [6]. ED physicians and nurses are tasked with enormous responsibilities of providing initial evaluation, diagnosis, rapid treatment and stabilization of cases with varying degrees of patient acuity. Medical decisions, resuscitation, treatments and stabilisation are often made within minutes of a patient's arrival with potentially life changing implications [7].

1.2. Definition of Artificial Intelligence, machine learning and deep learning

While there are many definitions and interpretations of the terms written by researchers over the years, the essence of AI, machine and deep learning is the incorporation of human intelligence into machines. This broad definition aptly defines AI, with its subsets of machine learning and deep learning being techniques utilized to train machines to mimic human intelligence with subtle differences in the way data is being parsed and inferred. To illustrate, machine learning uses algorithms on a user defined feature set to detect and make predictions. Structured data highlighting unique characteristics in a dataset are used for training of the model which is then used for inference upon training. Deep learning utilizes artificial neural networks (ANN) to emulate how neurons in the brain function. Feature definitions are automatic with different levels of representation: low-mid-high being extracted at various stages as inputs for learning. The process of learning first begins with the nonlinear transformation of input data at each node of the input layer to produce intermediate outputs called features. These features, each carrying an associated weight relative to adjacent nodes, is collectively summed up and utilized as inputs in the next layer. This process continues until the output layer, where the inference is made. The weights of the neurons are refined with every epoch - the process of data being passed through the entire neural network during training. This is done through process of back propagation using techniques such as gradient descent to reduce its associated cost function – the difference between the actual and predicted values. Such refinements illustrate the process of learning [8,9].

1.3. Key differences between machine and deep learning techniques

Apart from the differences in the way data is processed by machine and deep learning techniques, there are also a couple of subtleties that should be noted as points for consideration. These subtleties are grouped under two broad scopes of (1) data requirements and (2) training and hardware requirements:

- Under (1) data requirements, while the efficacy and performance of both machine and deep learning techniques are highly dependent on the quality and quantity of datasets fed into the models, there comes a stagnation point in machine learning where model performance stops scaling with quantity of data [10,11].
- Under (2) training and hardware requirements, owing to many layers of complex matrix calculations required to be solved, deep learning requires significantly longer periods of time for training compared to machine learning. They would also require more specialized hardware such as Tensor Processing Units (TPU) to aid in performing such non-linear transformations.

1.4. Why we require Artificial Intelligence in Emergency Medicine

The main challenge of EM involves the timely provision of medical triage defined as the process of sorting patients according to urgency and severity. This is required owing to the unpredictable nature of emergencies and conditions present where resources (e.g. staffing/beds) are sometimes limited and stretched [12,13]. Relevant literature on department crowding and patient flow have shown impacts to quality of patient care. To a grimmer extent, such instances are also linked to increased mortality levels [14–16]. The use of machine learning and deep learning can potentially help discern patterns of data gathered over the years and shed insights for improvement in ED processes. It can aid in ongoing medical trials and research based on merits of its inherent strengths in areas such as data pattern and trend recognition, image analysis and classification tasks and result in reduced workloads for medical professionals involved in ongoing studies [17,18].

As increasingly utilised in other disciplines of medicine such as oncology and radiology, it may also be used to provide near accurate predictions and diagnoses, if in the event of the absence of trained specialists [19–22]. There is also potential for AI to be used in targeted and tailored treatment options for better patient outcomes [23]. In this paper, we will be reviewing the various machine learning and deep learning techniques that are utilized in Emergency Medicine as well as the impacts such techniques have in improving quality of healthcare. The typical flow of the ED is illustrated in Fig. 1.

1.5. Search terminologies

The main goal of this paper is to consolidate relevant publications over the past six years on machine learning

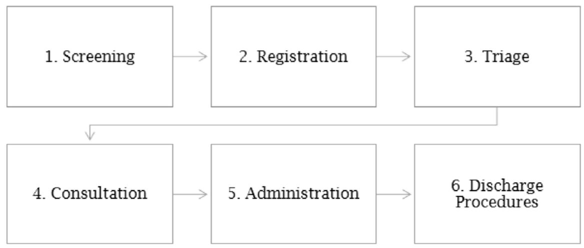

Fig. 1 – Typical process flowchart for ED cases [24].

and deep learning in Emergency Medicine. The keywords utilised in search for relevant literature are: Machine Learning, Deep Learning, Artificial Intelligence, Emergency Medicine, Emergency Departments, Triage and Management. Papers are collated from Google Scholar, PMC, PUBMED, ScienceDirect using the abovementioned keywords, between the year of 2014 and 2020. A summary of the papers that utilised machine learning techniques for Emergency Medicine is given in the Supplementary Information Appendix: Table A.1, while a summary of the papers that utilised neural networks and deep learning techniques is given in Table A.2. Fig. 2 presents an overview of the various studies listed in this review paper.

2. Review

With reference to Tables A.1 and A.2, this review will be covering four main applications on the use of machine and deep learning techniques in Emergency Medicine. These four main applications are: (1) Pre-hospital emergency management, (2) Patient acuity, triage and disposition, (3) Prediction of medical ailments and conditions, and (4) Emergency department management. It is not possible to cover all applications of AI in Emergency Medicine, hence in this review, we aim to cover several applications which we believe accurately represent and summarize the improvements AI has brought to the ED.

2.1. *Application 1: Pre-hospital emergency management*

Pre-hospital emergency medicine refers to emergency care given to patients before arrival to the ED upon activation of Emergency Medical Services [25]. The application of machine and deep learning techniques in this domain serves two-fold; one, to identify medical conditions for immediate medical intervention and two, to aid in prediction of critical medical conditions requiring additional preparation and mobilization of medical resources prior to patient arrival.

Kang et al. [26] developed a deep learning algorithm to predict need for critical care in such settings, to ensure that patients can be classified accordingly en route and brought to emergency departments with appropriate medical facilities. A feed-forward neural network comprising of 5 hidden layers and 89 nodes was utilized and trained on the Korean National Emergency Department information system dataset. With factors of age, sex, chief complaint, symptom onset to arrival time, trauma, and initial vital signs, the algorithm performed well in predicting the need for critical care with an area under the receiver operating characteristic curve (AUC) of 0.867. This is higher than other triage algorithms namely the Emergency Severity Index (AUC: 0.839), Modified Early Warning Score (AUC: 0.696), National Early Warning Scores (AUC: 0.741) and the Korean Triage and Acuity System (AUC: 0.824), illustrating the effectiveness and applicability of deep learning in triage prediction.

Blomberg et al. [27] utilized a machine learning framework (Corti.ai) on raw emergency dispatch audio recordings to detect and identify out of hospital cardiac arrest (OHCA) cases. Recordings were binary labelled with and without the presence of OHCA and evenly split for training using k-fold

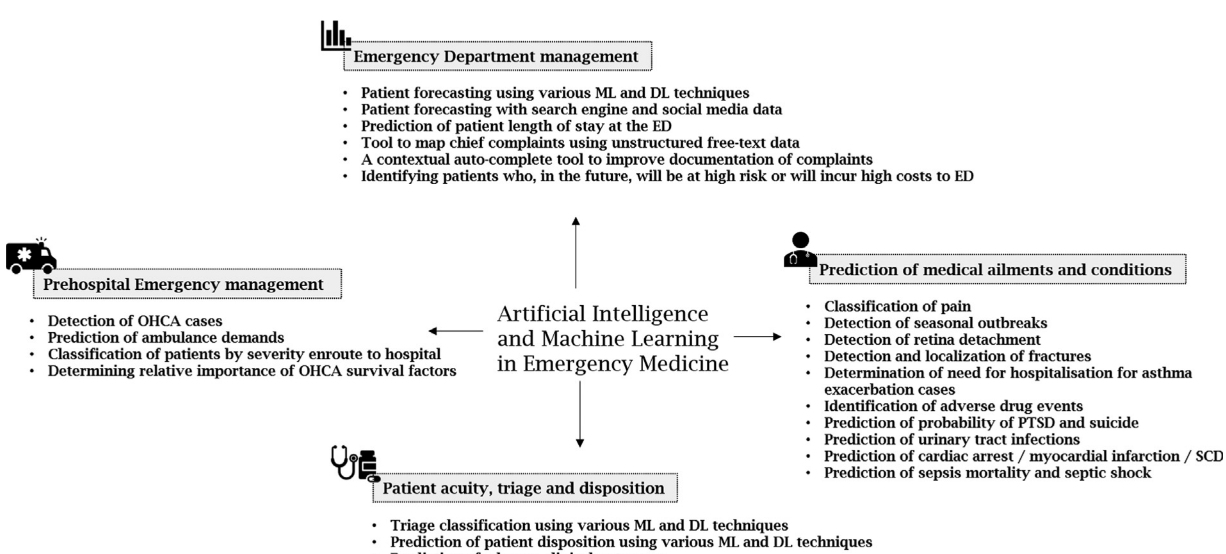

Fig. 2 – Overview of studies presented in this review paper.

cross validation. Out of 918 calls with OHCA, the machine learning framework was able to accurately recognize 84.1% of the cases ($p < 0.001$) verses 72.4% by a trained medical dispatcher. In the study, only 10 calls constituting 1.1% of all cases were picked up by the dispatcher and missed by the trained framework. The median time taken for the machine learning framework to recognize an OHCA for all cases was also significantly shorter at 44 s verses 54 s ($p < 0.001$).

Al-Dury et al. [28] employed a random forest (RF) approach to determine the order of relative importance of 16 key-factors linked to 30-day survival in OHCA cases. The study looked at the relative importance of these key factors through three different analyses: (1) on patients with shockable rhythm, (2) on patients with non-shockable rhythm and (3) the overall picture. Overall findings highlights the importance of initial rhythm, age, time taken before cardiopulmonary resuscitation was rendered, time taken for emergency medical services arrival and location of cardiac arrest in predicting survival while shedding new light and reducing importance of other factors such as gender and time of cardiac arrest when viewed holistically. Insights gained from this study paves way for further research to be conducted to determine survival rates, types of care to be rendered, and medical resources required enroute and to be readied at the ED.

Lin et al. [29] evaluated various machine learning techniques on real-world ambulatory and demographic datasets to extract greater insights and aid in the prediction of ambulance demands – an important metric required for pre-hospital emergency service operators and emergency departments to anticipate, deploy and better cater to the needs of the population it serves. Such predictions are predominantly hard to achieve owing to the complex multi-nature factors involved and non-linear dynamics of ambulance service demands. To overcome such challenges, a selection of datasets consisting of historical demands, spatial and demographic information were feature engineered and compared using six different machine learning classifiers: Regional Moving Average (RMA), Linear Regression (LINR), Support Vector Regression (SVR), Multi-layer Perceptron (MLP), Radial Basis Function Network (RBF) and Light Gradient Boosting Machine (LightGBM). Results from the comparison crowns LightGBM as the best performing model while also shedding light on the importance of total demand figures (over the past 7 and 30 days) as key features required for accurate next-day demand prediction.

2.2. *Application 2: Patient acuity, triage and disposition*

The application of machine and deep learning techniques in this domain serves to aid medical professionals in determination of patient triage severity and requirements for nursing care [30,31]. This also relates to patient disposition, defined as the next location a patient is headed to based on clinical outcomes.

We first discuss the AI techniques used to determine patient acuity and triage. A study by Levin et al. [32] showed that a machine learning electronic triage tool based on the RF model was equivalent or better in terms of performance as compared to the US Emergency Severity Index (ESI). In particular, it excelled in further refining and classifying patients in ESI level 3. The implementation, tested at several Emergency Departments, had identified over 14,326 (approximately 10% sampled) of ESI Level 3 patients who required higher levels of care based on their conditions. This illustrated effectiveness of the e-triage tool developed and highlights room for improvements on current methods of classifying triage.

Choi et al. [33] developed and compared multiple machine learning models to determine if they could be used to accurately predict Korean Triage and Acuity Scale (KTAS) levels. A combination of clinical data and written free text notes were utilized for the training of three machine learning algorithms: logistic regression (LR), RF and extreme gradient boosting (XGBoost). The comparison found that all three models could be used to accurately predict KTAS levels with an interesting point noting that the RF and XGBoost models, which were trained only on clinical data, outperformed the LR model trained on a combination of both clinical and free text data (AUROC 95% CI, RF: 0.913, XGBoost: 0.912, LR: 0.905), highlighting the complex non-linear relationships underlying structured data.

Kwon et al. [34] developed a deep learning triage and acuity score based on a 5-layer multilayer perceptron (MLP) model. The intention of the study was to identify patients at high-risk of in hospital mortality, need for critical care and hospitalization. The study involved a large dataset consisting of 11,656,559 patients from 151 ED across the Korean National Emergency Department Information System (NEDIS).

Only basic input parameters consisting of age, sex, chief complaint, time from symptom onset to ED visit, mode of arrival, trauma, initial vital signs, and mental status were required to be fed to the model - a contrast to complex scoring methods and data requirements of conventional triage tools.

The study also highlights the strength of the model in being able to be redeployed in different settings such as in pre-hospital emergency medical services.

Yu et al. [35], similarly utilized both machine and deep learning techniques to develop an initial nursing assessment-based triage system for the prediction of adverse clinical outcomes such as mortality or intensive care admission, which outperformed existing triage systems. The results illustrate that the outcome of the machine learning technique of LR is comparable to neural networks if the dimensionality of the dataset used is kept low.

Farahmand et al. [36], developed a web-based interface with machine and deep learning underpinnings to relate acute abdominal pain to an emergency severity index score. A total of 6 initial models were individually assessed before subsequently being ensembled together; where outputs from one model are used as inputs for the second model. This resulted in improved AUC scores with greater accuracy.

For cases utilizing AI to predict patient outcomes and disposition, Kim et al. [37] utilized machine learning to determine the key patient presentation factors for prediction of hospital admissions. Hong et al. [38], conducted a comparison between 9 machine and deep learning techniques to predict hospital admissions from patients' medical records and parameters collected at triage. It conclusively demonstrated that AI can reliably predict hospital admission.

Raita et al. [39] and Goto et al. [40] both utilized the same methods of lasso regression, RF, gradient-boosted decision tree, and deep neural networks in their studies and demonstrated applicability of the use of machine learning to predict clinical outcomes in both adults and children over conventional triage approaches. Findings indicate higher discriminatory abilities in both machine and deep learning models, which help to reduce over or under-triaging.

Roquette et al. [41] conducted a comparison and evaluation of deep neural networks on structured and unstructured triage textual data for the early prediction of admissions in the pediatric ED with results indicating a 1.9% improvement in AUC with the use of textual data. This once again highlights the value of incorporating textual data into models.

Zhang et al. [42] did a comparison study between LR and multi-level neural networks (MLNN) on a variety of structured and non-structured free text data sources to predict hospital admission or transfers in the ED. The results highlighted that the use of unstructured free text data, extracted using natural language processing, resulted in improved prediction values. Without unstructured free text data, LR achieved AUC of 0.824, and MLNN AUC of 0.823, whereas for combinations of both structured and unstructured data, LR achieved AUC of 0.846 and MLNN AUC of 0.844. Chen et al. [43] utilized deep neural networks on clinical narratives and structured data to predict patient disposition. Their approach used a deep neural network model with word embeddings based on a hybrid bidirectional long short-term memory (LSTM) and convolutional neural network architecture.

Xu et al. [44] proposed a protocol using ensembles of decision trees for the development of Early Warning Score (EWS) models. Traditionally, EWS models are developed based on clinical judgement and iteratively optimized through tentation to detect adverse outcomes. The proposed protocol serves to provide a quick means for the development of cost effective EWS models while additionally aid in the evaluation, comparison and validation of existing ones – in aspects such as predictive performance and feature prioritization.

To conclude this section, Sterling et al. [45] and Fernandes et al. [46,47] both utilized AI methods and natural language processing (NLP) in the determination of patient disposition. The paper written by Sterling et al. [45] does this by using a 3 layer ($200 \times 40 \times 10$) neural network regression model on free-text triage data extracted using NLP with the model demonstrating that nursing triage notes, created at the start of an ED visit can be used as sole inputs for prediction of patient disposition. Fernandes et al. [46] approached this problem using a machine learning and natural language approach that converted semi-structured data in combination with medical data collected at triage, yielding higher recall in identifying patients at ESI level 3 who may be at higher risk of intensive care admissions. Fernandes et al. [47] developed a risk stratified, machine learning and NLP approach to identify patients at high risk of mortality and cardiac arrest 24 h after triage. A series of machine learning models (XGBoost RF, LR) were employed and trained on data collected at triage. Non structured data via the chief complaint component, subsequently added to the models, showed improved performance in XGBoost and LR with XGboost coming up top amongst the three models developed. When compared with a Manchester Triage System (MTS) based reference model, the developed XGBoost performed better overall, with lesser instances of false classifications at MTS-1 and MTS-2 (denoted as Immediate and Very urgent with 0, 10 min waiting times respectively) and higher recall at MTS-3.

2.3. Application 3: Prediction of medical ailments and conditions

The application of machine and deep learning techniques in this domain serves to aid clinicians in the detection of medical ailments and conditions. Board certified specialists may not always be available for consult. This is especially applicable after office hours or in developing countries with shortage of trained specialists in fields such as Cardiology and Ophthalmology [48–50]. This would mean that patients may occasionally be attended by medical personnel who are not specialized for their conditions. Machine and deep learning models can be used to ease such situations by providing expert knowledge in their absence.

With regards to pain, which is one of the most common chief complaints from patients, Vu et al. [51] conducted a comparison of machine and deep learning techniques on free text fields found in electronic health records to identify and classify patients into two main binary labels, with or without pain. Results from their study highlighted the applicability of use of AI with a macro-average F1 score (standard evaluation metrics for classification tasks) of 90.96%.

On the detection of novel and seasonal outbreaks, López Pineda et al. [52] conducted an evaluation of several machine learning classifiers on free-text ED reports to determine the best classifier for the detection of Influenza cases. Eight classifiers were trained on 31,268 ED reports collated from four hospitals over a span of four years. It was compared with an expert-built Bayesian classifier which served as a baseline. While expected that the expert-built Bayesian classifier should be comparable with the machine learning models, it was outperformed by all eight classifiers - identifying huge potential for the use of AI in early detection of developing epidemics or pandemics.

On predictive applications related to Mental Health, Papini et al. [53] developed an ensembled machine learning model (XGBoost) on psychological and contextual features, in addition to information routinely collected during hospitalization, to predict probability of developing Post-Traumatic Stress Disorder at three months. Obeid et al. [54] conducted a study to evaluate traditional and deep learning text classifiers to identify altered mental status from ED clinical notes, whereas Sanderson et al. [55] utilized a machine learning model (Optimal gradient boosted trees) on administrative healthcare data to predict death by suicide following an ED visit for parasuicide.

On using AI to diagnose various common medical conditions at the ED, Taylor et al. [56] did a comparison of machine and deep learning models trained on electronic health record parameters generated from ED visits to predict urinary tract infections.

Lindsey et al. [57] developed convolutional deep neural networks based on U-net on radiographs to detect and localize fractures with bootstrapping and data augmentation techniques utilized to improve model training time and prediction accuracies. It was shown that ED personnel, when aided by the model, had a 47% decrease in misinterpretation when detecting fractures from radiographs. Olczak et al. [58] demonstrated that it is possible to classify wrist, hand, and ankle radiographs into four classes using freely available deep learning models with diagnostic performances similar to that of senior surgeons. It highlights the applicability of deep learning for screening purposes in the absence of radiologists or orthopedic surgeons.

Jang et al. [59] examined different artificial neural networks on electronic health records to predict the development of cardiac arrest 24 h prior. Lindhom et al. [60] similarly developed a GBM classifier on electronic health records including laboratory work data and vital signs to detect myocardial infarction in patients who present at ED with chest pain. Archarya et al. [61] employed a 9 layer deep convolutional neural network on electrocardiogram signals to identify 5 classes of heartbeats, Kwon et al. [62] developed a deep learning early warning system based on a 3-layer recurrent neural network with long short-term memory unit. It outperformed traditional machine learning techniques and track-trigger-systems in accurately and reliably detecting in-hospital cardiac arrest - with lesser instances of false alarms, higher sensitivities and the capability to detect more than 50 percent of in hospital cardiac cases 14 h before the event thereby allowing for, timely medical intervention and care to be rendered for improved survival rates. Johnsson et al. [63] developed a set of supervised artificial neural network models to aid in the early prediction of long-term functional outcomes and risk of poor outcomes, at 180 days, on OHCA cases using patient gather gathered from Targeted Temperature Management trials. Results from the study indicated an AUC value of 0.891 on the first ANN model trained with 54 variables and 0.852 when trained with only 3 variables (age, time to return of spontaneous circulation and first monitored rhythm) selected based on relative importance. Both models performed better against a prior LR based study conducted on the same cohort/dataset and highlights the ability of ANN models to detect correlation patterns in complex datasets while also showing how models need not necessarily require large amounts of variables and data to perform well. Liu et al. [64] on acknowledging the limitations of traditional scoring systems in detecting cardiac arrests, developed a novel manifold risk scoring system to predict cardiac arrest within a 72-h time frame while Fujita et al. [65], Shi et al. [66], Rohila et al. [67] and Devi et al. [68] each developed AI techniques to aid in the analysis of Heart Rate Variability (HRV) signals to predict mortality and sudden cardiac death (SCD) before onset. With the human heart being one of the most vital organs and SCD a life changer, to those left behind, there has been increased research focused on the use of AI as well as other novel techniques, with potential for AI incorporation, in the domain of cardiology to address this problem [69–74].

Kim et al. [75], Perng et al. [76] and Taylor et al. [77] developed machine and deep learning techniques on sepsis. Kim et al. [75] compared various machine learning algorithms to predict septic shock in patients within 24-h upon arrival. Perng et al. [76] focused on the prediction of in-hospital sepsis mortality within a 72 h and 28-day timeframe, with Taylor et al. [77], in a proof of concept study, demonstrating the effectiveness of a local, big-data driven machine learning approach over traditional analytical methods and clinical decision rules in the prediction of in-hospital sepsis mortality.

Koh et al. [78] developed a hybrid novel classification system using support vector machine (SVM) classifiers on 2 classes of ultrasound images to detect retinal detachments, and distinguishing it from posterior vitreous detachment, its common mimicker, achieving high classification accuracies of 99.13%. This demonstrates the potential of AI to be used in ED for ocular emergencies.

Patel et al. [79] tackles the problem of pediatric asthma, a leading cause of pediatric admissions, by developing and conducting studies on different machine learning approaches (Decision trees, RF, GBM and Lasso LR) to predict disposition for cases of asthma exacerbation at time of triage. This is a step up from the conventional method of prediction which is often only done after hours into an ED visit. A similar study was also conducted by Goto et al. [80] who investigated the various machine learning approaches in predicting the need for hospitalization or critical care in cases of exacerbation of asthma and chronic obstructive pulmonary diseases after triage. Both approaches highlight the potential of machine learning methods in predicting the clinical course of diseases by the virtue of its ability of being able to account for non-linear and higher-order interactions over traditional statistical modelling methods.

Lastly, Ouchi et al. [81] published preliminary research on the use of NLP and machine learning (RF) on electronic health records to identify elderly patients presenting at the ED at high risk of adverse drug events (overdose, allergic reaction) for proactive interventions in their prescriptions.

2.4. *Application 4: Emergency Department management*

ED management refers to an all-encompassing field that handles matters (e.g. operational, logistical, contingency, etc.) related to smooth running of the ED. The demand for ED services has risen significantly in recent years, causing many problems of overcrowding and poor allocation of resources and manpower, degrading the general quality of services provided. This demand is also partly fueled by transient and seasonal events such as air pollution and haze which have been linked to chronic and acute health impacts that leads to increased demand for medical services [82–84]. The highly variable and random nature of these occurrences makes prediction of demands using traditional statistical methods hard. AI techniques have shown the potential to help better estimate the volume of patients in ED. The application of machine and deep learning techniques in this final domain serves to, one, aid ED managers in forecasting patient numbers for better planning and management of medical resources, and two, provide the necessary tools and framework required to aid in improving operational efficiencies to deliver best care to patients.

To address the issue of congestion at the ED, Whitt et al. [85] conducted a study of different methods to forecast daily arrival totals and hourly occupancy levels in real time. These methods consist of a prior developed aggregate stochastic model, a regression method, Seasonal Autoregressive Integrated Moving Average (SARIMA) time series model, Seasonal Autoregressive Integrated Moving Average with exogenous factors (SARIMAX) time series model and a MLP neural network model were trained on 200 weeks of daily arrival totals with relevant calendar and weather-related metrics. Results indicate that the SARIMAX time series model was the best in forecasting daily arrival totals as it was best able to utilize weather and calendar related data to form correlations with past daily arrival totals. It was also capable of accurately forecasting hour occupancy levels 1 hour ahead of time with low error rates.

Khaldi et al. [86] utilized artificial neural networks on historical data to aid in the forecasting of weekly patient visits to the ED. In the first documented combination of its kind, a MLP feedforward artificial neural network was paired with an Ensemble Empirical Mode Decomposition (EEMD) signal decomposition technique with good effect. It outperformed a plain vanilla feed-forward neural network, a feed-forward neural network with discrete wavelet transform decomposition and an Auto Regressive Integrated Moving Average model (ARIMA). This illustrates the effectiveness of signal decomposition techniques in helping to improve generalization performance and prevent overfitting.

Yousefi et al. [87] investigated the various factors that affected ED demand and developed a forecasting tool with LSTM underpinnings capable of forecasting patient visits up to 7 days in advance. The use of LSTM outperformed other well-known techniques used for patient forecast predictions such as multiple LINR, ARIMA, SVR, generalized linear models, generalized estimating equations, SARIMA and combined ARIMA and LINR. Promising results were also similarly seen in LSTM patient forecasting studies conducted by Kadri et al. [88]

Leveraging on the huge amounts of data generated by prevalent use of search engines and social media, Ho et al. [89] demonstrated promising results by using Google Trends Search data and a multiple regression model to forecast the volume of patients visiting the ED. Ram et al. [90] utilized big data comprising of historical health records, air quality indexes, search engine interests and social media data for the prediction of asthma-related visits to the ED. Preliminary results from the study observed higher prediction accuracies across various classification methods (Decision tree, Naive Bayes, SVM, and ANN) employed when air quality indexes were used in tandem with Twitter data. Both approaches indicate the applicability of using social media trends for early identification of high-risk individuals and for timely interventions to be deployed. The use of big data from search engines and popular social media platforms such as Facebook, Instagram and Twitter may provide new out of the box approaches in garnering and associating non-diagnostical data trends for patient forecasting.

Another factor that needs to be considered, apart from volume of patients, is the length of time each patient remains in the ED. Kuo et al. [91] utilized machine learning algorithms with system thinking elements for personalized waiting time predictions in the ED. Four machine learning algorithms, stepwise multiple LINR, ANN, SVM, and GBM were compared with a baseline LINR model with results indicating reduction of 15 to 20% Mean Squared Error (MSE) compared to the baseline with the use of machine learning, and a further 2% reduction in MSE with the use of systems thinking.

In the aspects of productivity improvement and operations support, Greenbaum et al., [92] developed a domain specific ontology and machine learning driven user interface to optimize ED quality and workflow. The interface, which is powered by a multi-class support vector algorithm utilized top 5 suggests and contextual auto-complete to aid nurses in the documentation of presenting complaints. The results from the implementation indicated a 95% reduction in keystrokes required to be typed in per presenting problem (prior implementation: 11.6 keystrokes, post implementation: 0.6 keystrokes), as well as an estimated annual man-hour savings of 87.7 h from typing.

Tootooni et al. [93] sought to improve the mapping of chief complaints at the ED and the first set of information gleaned from patients, by developing a heuristic natural language processing algorithm and tool (CCMapper) that maps free-text symptoms and problems collected at registration or triage to a structured list of chief complains using bag of words. Such a method allows for the classification of problems to aid in ED operations while also paving the way to transform and pre-process unstructured free text data into one that is structured for use in other machine learning prediction algorithms.

The prediction of repeat ED visits is also of interest to ED planners as high repeat visit rates increases congestion at the ED and incurs higher system costs. Frost et al. [94] utilized a LR model on free text mined from emergency medical records to identify patients who were predicted to be at high risk for frequent ED visits (classified as 3 or more ED visits per year) and/or would incur high costs to the healthcare system when revisiting the ED. Such pre-emptive efforts allow for early interventions to be conducted, which firstly, increases the quality of healthcare to identified patients; secondly, reduces ED visits and lastly, reduces the amount of costs incurred on the overall by the healthcare system.

Vest et al. [95] utilized two-class boosted decision trees on electronic health records and electronic information exchanges to predict repeat ED visits. The intention was to look for methods to reduce repeated ED visits to improve healthcare costs and quality, similar to Frost et al. [94]

Summing up this section is a paper written by Rahimian et al. [96] whose team utilized a RF and gradient boosting classifier on a 56 variable electronic health record to quantitatively predict the risk of ED admissions over a 12, 36, 48 and 60-month time frame.

3. Discussion

3.1. *Limitations and challenges*

Some challenges highlighted in the reviewed literature mention the ''black box'' nature of neural network models, making it hard for practitioners to understand and explain the rationale for prediction results generated. There are also limitations on the transferability and deployability of models from one healthcare institution to another owing to differences in aspects of standardization, operating procedures and availability of dataset parameters. Even with available dataset parameters, its values may differ due to the different demographics and locale. Such limitations can affect overall accuracy and predictive performance of the Artificial Intelligence model which poses a risk to patients if used wholesale. Further studies and trials are required to be conducted to ascertain the effectiveness of the developed model.

3.2. *Gaps and opportunities*

The current state of research is primarily focused on the use of AI for the prediction of patient triage levels, acuity, disposition and in the detection of acute conditions such as sepsis and myocardial infarction. While nearly all encompassing, there are still gaps that can be filled. Further opportunities exist for AI to be expanded to lesser researched domains of ED management, such as neurological, endocrinological or vascular emergencies [97].

The first gap identified is with regards to the use of AI on patients who are awaiting medical attention. This is often a crucial time period whereby patients may be unattended to for hours and whose medical conditions may further deteriorate beyond initial assigned triage levels, eventually requiring the need for immediate medical assistance. Cameras aided by trained convolution neural networks and embedded sensor technologies can be deployed to help track and monitor patients identified. They may serve as additional pairs of eyes that can for one, track ED patient numbers, and two, keep a lookout for patients with signs of potential deterioration. Data gathered can be beamed over to a central data lake and analytics or alert dashboards for close to real-time analytics such as ED forecasting for hospital executives to make operational, logistical and manpower deployment decisions based on predicted trends and to augment and alert medical professionals of patients in critical condition amongst an often chaotic sea of other patients. Recent advancements in convolutional neural networks show that these underlying frameworks are already present but have yet to be adapted to an ED-related setting [98]. The system can also be linked to a national healthcare system for use by the general public to understand ED crowds for consideration of alternative healthcare options such as primary healthcare facilities or 24-h clinics for non life-threatening ailments. It can also be used by emergency services dispatchers to divert non-emergency ambulatory cases to hospitals with lower patient loads. Such systems, if implemented, can potentially aid in reducing crowds, waiting times and improve the overall quality of healthcare provision.

Further research on the use of search engine and social media data in conjunction with validated medical diagnoses can provide a bigger picture of ongoing trends or events (such as developing outbreaks) and aid ED in forecasting manpower and preparation of resources required [99].

3.3. *Future predictions of Artificial Intelligence in Emergency Medicine*

Looking at progress by researchers in the field of EM the authors predict that the use of natural language processing and unstructured free-text data on health records (paper and electronic) can potentially play a larger role in improving triage classification or diagnosis prediction and improve overall prediction accuracies. Archived paper based patient records which were often being used in parallel with electronic medical records during the transitional phase towards electronic health records in the early 2000 to mid-2000s could contain additional information such as annotations or sketches that can be extracted to supplement models trained on text based electronic health records.

The maturity of cloud-based solutions and technologies will see more AI developments move from the local environment to the secure cloud. This brings about numerous benefits of an envisioned unified training-inference-visualisation environment which overcomes many of the current "early adopter" problems such as the management of environments, libraries, command line interfaces and requirements of high-powered computing hardware required for the training of complex models. It ultimately results in greater user acceptance owing to ease of access to available tools and resources and by consequence, wider adoption of AI in EM and beyond.

Tools developed on the cloud can be further extended and easily shared with medical facilities in the heartlands to aid physicians in the diagnosis and prediction of ailments requiring hospitalization while at the same time, feed information back to a central hospital repository for enhanced

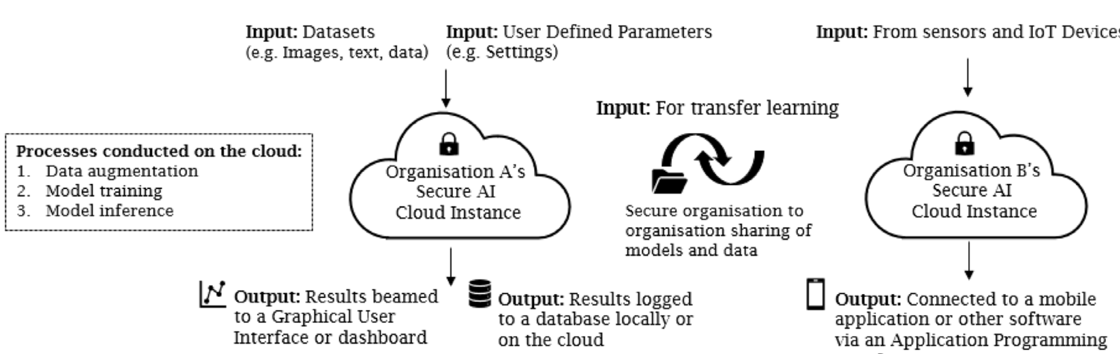

Fig. 3 – Proposal for cloud technologies and solutions.

monitoring of communicable disease outbreaks and medical conditions specific to the locale. Such early detection nets cast wide can provide health authorities and ED with early warnings and a clearer picture on the state of their population's health, as well as aid in informed planning of medical resources required in the short, mid and long term. It will also open up opportunities for myriad of personalized healthcare solutions to meet the population's needs. Some of these possibilities are illustrated in Fig. 3.

4. Conclusion

The use of AI in EM, through machine and deep learning, have seen an increase in recent years. Recent developments in computational capabilities as well as the increasing amount of data that can be collected, allows researchers to utilize Artificial Intelligence in ways that were not possible before, leading to an increase in accuracy and efficiency of ED treatment. Even so, it is our belief that there is vast room for improvement, making this an exciting field with huge potential for improvements in the current technology and new innovations to lead the way. In this paper, we have reviewed the existing research and technology that has been produced from the intersection of AI and EM, as well as the gaps and opportunities moving ahead. We believe that further integration of deep learning within this field can lead to significant gains coupled by computer vision and natural language processing.

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Conflict of interest

The authors declare no conflict of interest.

Appendix A. Summary tables

Table A.1 – Summary of machine learning techniques applied to emergency medicine.

Study	Aims	Method	Application
Blomberg et al. [27]	Using machine learning on raw emergency dispatcher audio recordings to identify out of hospital cardiac arrest cases	Machine learning framework developed by (Corti.ai)	Pre-hospital emergency management
Lin et al. [29]	Evaluation of different machine learning techniques on ambulatory and demographic datasets to forecast next-day ambulance demands	Regional moving average, Linear regression, Support vector regression, Multi-layer perceptron, Radial basis function network and Light gradient boosting machine	Pre-hospital emergency management
Al-Dury et al. [28]	Determining relative importance of 16 key factors to predict survival in OHCA cases	Random Forest	Pre-hospital emergency management
Levin et al. [32]	Using machine learning on triage data to classify triage severity levels by predicting needs for critical care, emergency procedures and inpatient hospitalization	Random forest model	Patient acuity, triage and disposition
Fernandes et al. [46]	Using machine learning and natural language processing to identify patients with high risk of ICU admission	Logistic regression with L2 regularization, RUSBoost and Random forests regression	Patient acuity, triage and disposition
Fernandes et al. [47]	Using machine learning and natural language processing to identify patients at high risk of cardiac arrest and mortality within 24 h after triage	Logistic regression, random forests regression bootstrap aggregation of decision trees and XGBoost	Patient acuity, triage and disposition

Table A.1 (*Continued*)

Study	Aims	Method	Application
Kim et al. [37]	Using machine learning to determine key factors for the prediction of hospital admission.	Logistic regression	Patient acuity, triage and disposition
Xu et al. [44]	Protocol for comparing and validating EWS models with decision tree generated EWS models	Decision trees	Patient acuity, triage and disposition
Choi et al. [33]	Using machine learning on clinical and text data to predict KTAS levels	Logistic regression, Random forest, and XGBoost	Patient acuity, triage and disposition
Shi et al. [66]	Using machine learning on EEMD-based entropy and classical linear features derived from heart rate variability signals for early detection of sudden cardiac death	k-Nearest Neighbor	Prediction of medical ailments and conditions
Rohila et al. [67]	Using machine learning on normal and abnormal heart rate variability signals to detect sudden cardiac death	Decision trees, Support vector machine	Prediction of medical ailments and conditions
Devi et al. [68]	Using machine learning on heart rate variability signals for early detection of sudden cardiac death	k-Nearest Neighbor, Support vector machines, Decision trees	Prediction of medical ailments and conditions
Fujita et al. [65]	Using machine learning on non linear heart rate variability signal features for early detection of sudden cardiac death	k-Nearest Neighbor, Support vector machines, Decision trees	Prediction of medical ailments and conditions
Ouchi et al. [81]	Proposed methodology on the utilization of machine learning on electronic health records to predict, identify older patients (above 65) who are at high risk of adverse drug events for timely intervention	Random Forest and Natural Language Processing	Prediction of medical ailments and conditions
Lindholm et al. [60]	Using machine learning on electronic health records including laboratory data and vital signs to detect Myocardial Infarction in patients	Gradient boosting machine and Logistics regression	Prediction of medical ailments and conditions
Sanderson et al. [55]	Using machine learning on administrative healthcare data to predict death by suicide after a parasuicide ED visit	Optimal gradient boosted trees	Prediction of medical ailments and conditions
Kim et al. [75]	Using machine learning on electronic health records to predict event of septic shock 24 h upon arrival at the Emergency Department	Support vector machine with radial basis function kernel, Gradient-boosting machine with bernoulli loss, Random forest, Multivariate adaptive regression splines, Least absolute shrinkage, Selection operator and Ridge regression	Prediction of medical ailments and conditions
Taylor et al. [77]	Using machine learning for prediction of sepsis mortality	Random forest model, Logistic regression model and Regression tree (CART) model	Prediction of medical ailments and conditions
Patel et al. [79]	Using machine learning to predict hospital admissions for pediatric asthma at triage	Classification trees, Logistic regressions with L1 regularization, Random forests, and Gradient boosting machines	Prediction of medical ailments and conditions
Papini et al. [53]	Using machine learning on psychological and contextual features in addition to information routinely collected during hospitalization to predict probability of developing Post-Traumatic Stress Disorder at three months	XGBoost	Prediction of medical ailments and conditions
Koh et al. [78]	Using machine learning on 2 classes of ultrasonic images to accurate distinguish and detect retinal detachment	Support vector machine	Prediction of medical ailments and conditions
Liu et al. [64]	Using machine learning to predict cardiac arrest	Manifold ranking	Prediction of medical ailments and conditions

Table A.1 (*Continued*)

Study	Aims	Method	Application
Rahimian et al. [96]	Using machine learning on electronic health records to predict risk of emergency department admissions within a 12,36,48,60-month time frame	Random forest and Gradient boosting classifier	Emergency Department Management
Greenbaum et al. [92]	Using domain specific ontology and machine learning driven user interface to optimize emergency department quality and workflow.	Multi class support vector machine	Emergency Department Management
Frost et al. [94]	Using machine learning on free text mined from emergency medical records to identify patients predicted to be at high risk for frequent emergency department visits / or will incur high medical costs	Logistic regression	Emergency Department Management
Vest et al. [95]	Using machine learning on electronic heath records and health information exchanges records to predict emergency department revisits by patients	Two-Class Boosted Decision Trees	Emergency Department Management
Ho et al. [89]	Using search engine data to forecast patient visits to the hospital	Multiple Regression	Emergency Department Management
Tootooni et al. [93]	Using natural language processing and bag of words to map free-text data to a structured list of complaints	Natural Language Processing	Emergency Department Management

Table A.2 – Summary of deep learning techniques applied to emergency medicine.

Study	Aims	Method	Applications
Kang et al. [26]	Using AI to identify vulnerable and high-risk patients for appropriate care and hospital resource preparation	Feedforward Neural Network	Pre-hospital emergency management
Hong et al. [38]	Using deep learning to predict hospital admission from patient's medical records and parameters collected at triage	Logistic regression, XGBoost and Deep Neural Networks	Patient acuity, triage and disposition
Farahmand et al. [36]	Using AI in determining ESI-4 score for patients with acute abdominal pain in lieu of conventionally required hardware	Association Rules, Clustering, Logistic Regression, Decision Tree, Naive Bayes, Neural Networks	Patient acuity, triage and disposition
Kwon et al. [34]	Using deep learning to identify high risk patients	Multilayer perceptron	Patient acuity, triage and disposition
Yu et al. [35]	Using machine and deep learning for prediction of adverse clinical outcomes that results in mortality / ICU admission.	Multivariate logistic regression and a deep learning model based on Keras	Patient acuity, triage and disposition
Goto et al. [40]	Using machine and deep learning to predict clinical outcomes and disposition for children under the age of 18	Lasso regression, Random forest, Gradient-boosted decision tree, and Deep Neural Network	Patient acuity, triage and disposition
Raita et al. [39]	Using machine and deep learning to identify patients requiring critical care and hospitalization and comparison of performance with a five level ESI model	Lasso regression, Random forest, Gradient-boosted decision tree, and Deep Neural Network	Patient acuity, triage and disposition
Chen et al. [43]	Using deep neural networks on clinical narratives and structured data to predict patient disposition	Deep Neural Network model with word embeddings based on a hybrid bidirectional long short-term memory and convolutional neural network architecture	Patient acuity, triage and disposition

Table A.2 (*Continued*)

Study	Aims	Method	Applications
Zhang et al. [42]	To compare different modelling methods with and without natural language processing to predict hospital admission or transfer in the Emergency Department	Logistic regression, Multi-level Neural Networks, Natural Language Processing	Patient acuity, triage and disposition
Sterling et al. [45]	Using natural language processing for prediction of inpatient admission on Nursing triage notes	3-layer (200 by 40 by 10) Neural network regression model	Patient acuity, triage and disposition
Roquette et al. [41]	Using deep neural networks on structured and unstructured triage textual data for the prediction of admission	Support Vector Machine, ElasticNet, Deep Neural Network, XGBoost, Catboost	Patient acuity, triage and disposition
Lindsey et al. [57]	Using convolution deep neural networks on radiographs to detect and localize fractures	Convolutional neural network based on U-net	Prediction of medical ailments and condition
Taylor et al. [56]	Comparison of machine and deep learning models trained on electronic health records to predict unitary tract infections	Random forest, Extreme gradient boosting, Adaptive boosting, Support vector machine, Elastic net, Neural network and Logistic regression	Prediction of medical ailments and condition
Kwon et al. [62]	Using a developed deep learning model to detect in-hospital cardiac arrest	3 layer recurrent neural network with long short-term memory unit, logistic regression, random forest	Prediction of medical ailments and condition
Johnsson et al. [63]	Using a supervised artificial neural network to predict long term functional outcomes and risk of poor outcomes in OHCA cases	Artificial neural network	Prediction of medical ailments and condition
Obeid et al. [54]	Evaluation of text classifiers to identify altered mental status from clinical notes comparing performance between deep learning-based models with traditional ones	Convolutional neural network, Naive Bayes, Lasso, Single Decision Tree classifier, Random Forest, Support Vector Machines and Multi-layer perceptron	Prediction of medical ailments and condition
Vu et al. [51]	Using machine and deep learning on free text fields to classify patients into two main groups (in pain / no pain)	Support Vector Machine, Random Forest, Recurrent Neural Network and Convolution Neural Network	Prediction of medical ailments and condition
Perng et al. [76]	Use and comparison of different machine learning algorithms for prediction of in-hospital septic mortality within a 72 h/28-day timeframe	k-nearest neighbor, Support Vector Machine, SoftMax, Random forest, Autoencoder, Convolution Neural Networks, and Principal component analysis	Prediction of medical ailments and condition
López Pineda et al. [52]	Comparison and evaluation of several machine learning classifiers on free-text Emergency Department reports to detect Influenza cases	Random Forest, Support Vector Machine, Artificial Neural Networks, Logistic regression, Efficient Bayesian Multivariate Classification, Bayesian network with K2 algorithm, Naive Bayes and Expert-MLE	Prediction of medical ailments and condition
Jang et al. [59]	Using artificial neural networks on electronic health records to predict the development of cardiac arrest 24 h before one.	Multilayer perceptron, Long short-term memory, Hybrid Artificial Neural Network, Logistic regression, Random forest and a conventional Modified early warning score method	Prediction of medical ailments and condition
Olczak et al. [58]	Using deep learning on skeletal radiographs to determine the feasibility of the method in an orthopedic setting	BVLC Reference CaffeNet network, VGG CNN S network, VGG CNN, Network-in-network	Prediction of medical ailments and condition
Goto et al. [80]	Using machine learning techniques to compare and predict the clinical course of obstructive airway disease exacerbations	Lasso regression, Random forest, Boosting, and Deep Neural Network	Prediction of medical ailments and condition

Table A.2 (Continued)

Study	Aims	Method	Applications
Acharya et al. [61]	Using deep convolutional neural networks on ECG signals to identify 5 different classes of arrhythmia	Deep Convolutional Network (9 Layer)	Prediction of medical ailments and condition
Khaldi et al. [86]	Using deep learning on historical visitation data to predict weekly patient visitation numbers	Multilayer perceptron with ensemble empirical mode decomposition compared with, Artificial Neural Network with discrete wavelet transform, Vanilla Artificial Neural Network and ARIMA.	Emergency Department management
Whitt et al. [85]	Comparison and evaluation of different methods including neural networks to forecast emergency department crowds	Multilayer perceptron, Regression, SARIMA time series model and SARIMAX time series model	Emergency Department management
Kuo et al. [91]	Using machine learning algorithms for real time with system thinking elements for personalized waiting time prediction in the emergency room	Stepwise multiple linear regression, Artificial Neural Networks, Support vector machines and Gradient boosting machines.	Emergency Department management
Yousefi et al. [87]	Investigation of factors affecting daily demand and development of a forecasting tool capable of forecasting up to 7 days in advance	Long short-term memory	Emergency Department management
Ram et al. [90]	Using multiple data sources on multiple machine learning classifiers to determine which works best to forecast asthma related emergency department visits	Decision tree, Naive Bayes, Support vector machine, and Artificial neural network	Emergency Department management
Kadri et al. [88]	Using deep learning to predict when patient arrives at emergency department	Long short-term memory	Emergency Department management

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