Application of artificial intelligence techniques in the intensive care unit

Prabhudutta Ray[1], Sachin Sharma[2], Raj Raval[3]
[1]Institute of Advanced Research, Gandhinagar, India
[2]School of Cybersecurity and Digital Forensics, National Forensic Sciences University, Gandhinagar, India
[3]Gujarat Pulmonary and Critical Care Medicine, Ahmedabad, India

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ABSTRACT

Intensive care unit deals with data that are dynamic in nature like real time measurement of health condition to laboratory test data that are continuously changes accordingly with time. Artificial intelligence (AI's) potential ability to perform complex pattern analyses using large volumes of data. Generated pattern discovers the new symptoms of the disease in the Intensive care units (ICUs), helps the doctors to prescribe the new drug discovery which is helpful to intelligent use. Currently research work has been focused in the ICU making more efficient clinical workflow by generation of high-risk patterns from improved high volumes of data. Emerging area of AI in the ICU includes mortality prediction, uses of powerful sensors, new drug discovery, prediction of length of stay and legal role in uses of drugs for severity of disease. This review focuses latest application of AI drugs and other relevant issues for the ICU.

Corresponding Author:

Sachin Sharma
School of Cybersecurity and Digital Forensics, National Forensic Sciences University
Gandhinagar, Gujarat, India
Email: sharma.f@gmail.com

1. INTRODUCTION

In the hospital setting there are several opportunities to apply different types of artificial intelligence (AI) techniques. Intensive care units (ICUs) are overflowing with different kinds of dynamic data due to variety of patients are admitted with different kinds of diseases. In order to verify severity in diseases several kinds of real-time physiological measurements require with laboratory test to classify the patients diversity in terms of age and co-morbidities [1]. Since data are constantly in flux and collected daily with plethora of information requires uses of AI techniques to enhance decisions regarding patients care. As mentioned the term "severity of disease", requires some kinds of patient's classification systems (PCS) in the health care as tool for optimizing resource allocation in terms of nursing, medicine, cleaning of ICUs and managing patients with sepsis kind of diseases. ICUs are dedicated for critically ill patients who need high treatments during critical situations by the necessary use of advanced equipments for medical purposes.

A PCS can helps in improving the circulation of nursing manpower to increase performance. Timely and accurate predictions regarding mortality are highly in demand before rapid deterioration of the patients in the ICUs. The unpredictability of the critically ill patients may involve several factors in terms of cost; obstruct the introduction of new nursing care, evaluation of impact of medicines and also doctors knowledge about the treatment. Developing new critical care in practice has significant interests within ICUs through the implementation of a PCS. Plenty of heterogeneous data from ICU requires uses of machine learning algorithm (ML) to determine groups of patients with similar kinds of trajectories [1]. Patient's evaluation in the ICUs depends on the classification of patient's dependency regarding similar kinds of diseases, severity of illness and measurement of nursing intensity. Regarding cost effective resource allocation in the ICU this one dimensional care models are not enough. Impact of scoring systems also plays an important role for the ICU outcome and resource allocation.

2. THE PROPOSED PROCEDURE SPECIFICALLY DESIGNED FOR ANALYSIS

2.1. Impact of scoring system

Diseases severity, age, nutrition, co-morbidities, inflammation biomarkers, artificial ventilation support and infection status are also the important factors for determining the survival rate of the patients in the ICU. Several scoring systems have various purposes and measures important parameters. For examples outcome of models cannot be used to measures the intensity of individual organ dysfunctions or to monitor progress of the patients in the ICU for time.

Organ abnormality scores shows connectonwith outcomes but this is not for they were developed [2]. Because disease severity scores finalize the picture by contributing information regarding how patient disease will point out on staffing necessities and resource uses [3]. As mentioned term "disease severity" on admission for that various diseases severity scoring system is used like acute physiology and chronic health evaluation (APACHE), simplified acute physiological score (SAPS) and mortality probability model (MPM) are helps to improve prognostic decision to increase the outcome of an ICU in the hospital. For example, some studies shows that APACHE II score was helps to identify the severity of patients' diseases and management of classification of patients was implemented.

Though glasgow coma scale (GCS), mean arterial pressure, level of potassium and sodium in the blood, level of sugar (fasting and PP) and other variables are direct impact as compared to impact of nursing workload on patients or was ignored largely [4]. A critical care patients are highly dependable on the critical condition of illness and nursing workload score as these scores are indispensible to each other for the diagnoses of the patients care where as a PCS does not account for these factors. As such case valuable resource allocations are wasteful and inefficient also. Comprehensive evaluation of PCS requires reliability and validity as key factors that are absents in majority of the PCS. Therefore uses of AI based application are still open for the ICUs [5].

3. METHOD

3.1. Perspective of AI in critical care

AI based algorithms are highly based on the uses of statistical techniques starting from correlation, regression, factor analysis, mean, median, mode which can helps to interpretation of complex data in a easy mathematical way from the clinical point of view. There are other simple steps apart from the complex deep learning algorithm that can helps to take better decision in critical care by better assessment of available data in the ICU [6]. First, scoring system consists of several variables that are directly or indirectly influence the outcome of the ICU. A measurement scale allows us to collect the data that helps us to provide the information about the variables that our interest to measures. Measurements scales having one of four distinct levels of measurements like nominal, ordinal, interval, and ratio. Higher the levels of measurements are helps to gather more information about the variables. As severity scoring systems are consisting of several variables, so measuring such variables are necessary to determine what level of analysis can be done with these generated data in the ICU [7]. AI models are correlated with prediction based on the kinds of input data are given during the training with adjusted bias. For examples, if the unit size is very small or not relevant to the general community then outcome prediction may be different. Further capturing of freely available clinical data is an important issue to determine whether AI model works correctly on several sets of data as compared to exclusively on a single dataset. Preprocessing and reorganization of data before analysis is an important issue to examine wrongly identified physiological relationships not to affect the clinical decision making. How accurately the input data are organized may influence in the validity and reproducibility of model's prediction regarding the ICU outcomes [8].

Second, separate uni-variate frequency analysis do not helps us very much as it is impossible to assess whether there is a strong relationships exists between two variables. A bi-variate contingency table allows us to investigate how two variables are clinically related. Differences in diagnostics accuracy significant enough to give signal for introducing AI based clinical techniques in the ICU. Suppose two to 3% improvements are not sufficient reasons for transferring critical patients from ICU to a general word [9]. Creation of new base line model when there is no base line model available for assessment is major area for introducing AI techniques for assessment based on clinical utility such as selected classification schemes helps or affect the clinical outcomes and innovation related to incorporate the variables that are not recognized earlier for prediction [10].

Third, selection of sample size from the clinical point of view is another important factor ICU outcome. Sometimes non-parametric tests are employed when most of the times data are not normally distributed and samples are small in size. In that case ordinal data or interval/ratio data which is not normally distributed are in consideration like ratings for uses of new medicine for the heart attack patients. Different kinds of test like one sample t-test, one-sample wilcoxon sign rank test are used to identify before-after situation, pre-post situation or data is taken from the same observations from two different time points for measuring the ICU outcomes [11]. Further diagnostic AI related model's performance are measured with receiver operating characteristic curve (ROC) where area under the curve (AUC) measures the true positive rate compared with false positive rate by using an index of validity. If the AUC value near to 1 means classification done by the model is perfect like stay in ICU or not. Though AUC measures the model classification but does not provide any significant information regarding optimization related to cost of false cases [12].

4. APPLICATION OF AI IN THE ICU

Different surveys have been conducted for the applicability of AI technology to provide the special care for the critically ill patients. Using large datasets not only for the severity of diseases to organ dysfunction scores and many other relevant information also to predict length of stay (LOS), readmission in the ICU, mortality rates, medical complication or conditions and associated risk evaluation such as sepsis. Another studies also conducted for generated small dataset regarding physiological and clinical data regarding ventilation support and nursing care [13].

4.1. Mortality rate in the ICU

Well known mortality prediction models and severity scoring systems like APACHE III and MPM0 have some direction for predicting mortality but have some limitations also regarding missing data points during admission or unstable only after 24 hours to 48 hours of admissions. AI methods can help regarding this area to provide the solutions by using machine learning algorithms that can learn from continuously generated data. In a study performed by Awad *et al.* [14] using MIMIC-II database of 11,727 patients of first admission with features like demographic, physiological and laboratory test data are used regarding mortality prediction by using machine learning algorithms like, random forest, decision trees and naive Naïve Bayes theorem. One major observation regarding that using the same models for standard scoring systems like APACHE–II, SOFA and SAPS for time series analysis for the same dataset performance are not good [15]. Random time sampling scheme are used for a single hospital study using gradient boosting method it is found that AUC of 0.92 was achieved to predict individual patient mortality [16]. Early prediction regarding mortality within 24 hours after ICU admission is highly in demand [17]. Artificial neural networks (ANNs) based approach are applied for the more than 200,000 patients in a Swedish hospital system for first-time ICU admissions, that shows better performance regarding predicting mortality as compared to SAPS-3 scoring system [18]. ANNs accurately predicted 30-day mortality using data collected within the first hour of ICU admission. Regarding trauma and pediatric patient's machine learning based models are also proposed to predict mortality [19]–[22].

Major concerns are to assessment of potential complications on admission of patients in ICU. Previously several deep learning methods have been applied to multi factorial patient data on admission which includes vital signs, demographics, coagulation, bleeding characteristics, renal failure all to predict mortality. Significantly deep learning models provided accurate predictions for the outcomes for vital signs, coagulation and bleeding characteristics as compared to standard clinical reference tools [21]. Further improving global outcomes where staging criteria for acute renal failure also includes the clinical rules for post-operative bleeding, SAPS-II and kidney disease. Utilizing the above mentioned model can help to rapidly assess which patients are at greater risk and allocate the resources subsequently [23].

4.2. Length of stay

Another important area for application of AI/ML techniques regarding management of space and resources in the ICU is the prediction of length of stay (LOS). In a study by Houthooft *et al*. [2] data for 14,480 patients are used to forecast survival of patients and length of stay (LOS) by a trained support vector machine model. The model shows significant results in area under the curve (AUC) for predicting 0.82 as prolonged length of stat. In contrast to a clinical study which shows accuracy level to be only 53% by the physician when predicting length of stay in the ICU [24]. Another study shows using Gaussian process (GP) model can help regarding predictions for both on probability for day of discharge for non emergent cardiac surgery patients and day of discharge after surgery. The model only used patient data from the first 4 hours after admission. This analysis proves the capability of AI technique to provide useful information with early data [25]. In another study for predicting length of stay with reasonable accuracy in the ICU by using a hidden Markova model framework was applied to measure physiological parameters taken during the first 48 hours of ICU admission [26].

4.3. ICU re-admission

AI modeling can help in this area by identifying which physiological variable are mostly contributed to re-admission decisions. Prior to patient discharge it is mandatory for the physician to analyze the patient conditions for calculating risk to reduce the preventable readmission. Though neural network based modeling approach are applied to compare between models predicted versus actual predicted readmission rate but these prediction are only assist the doctors and clinicians to identifying the patient's condition using follow up data. The problems related to ICU readmission was investigated by many researchers using neural network based algorithm with available MIMC-III database but the outcome shows risk related to patients readmission with 0.74 sensitivity only and AUC of 0.79 [27].

4.4. Sepsis predictions

To rationalize the ICU beds facility and quantity demands proper work management by the multidisciplinary teams of the hospitals. Objectives is to provide ICU facilities to those who need close monitoring and proper nursing care with optimizing cost and positive outcomes though other critical patients are more frequently allowed. But sepsis is another kind of diseases that are very costly to manage with an increasing number of patients over the last decades [28]. To reduce the complications from sepsis as early as possible using other than traditional methods demands application of machine learning techniques for evaluation of sepsis diseases to rapidly yield an accurate diagnosis. Preventing from sepsis is another major challenge and much effort has been done regarding this also via digital alerts that are specifically designed like systematic inflammatory response syndrome (SIRS), quick sepsis organ-related failure assessment (QSOFA) and modified early warning score (MEWS).

These mentioned scores are helping the modern AI techniques regarding mortality predictions of sepsis related patients [29]. Timely prediction of sepsis disease is continuously improving. Another study with only 6 vital signs to predict sepsis 4 hours before with an AUC of 0.96 validated a commercial sepsis predictor (InSight developed by Dascena) [30]. Further an observational study shows that a clinical recognition was able to predict sepsis accurately from 4 to 12 hours before using AI sepsis experts while producing a list of the most contributing factors [31]. Another study shows that long short-term memory model (LSTM) architecture model that predicted sepsis with greater accuracy as compared to InSight [32]. Integrating ML algorithms into real time scenario for critical care such as in a study validated Insight's positive effect on patient outcomes like rate of decrease mortality, LOS for sepsis related, 30-days readmission rate related to sepsis diseases when compared with the results to twice-daily systematic inflammatory response syndrome screenings [33]. Further utilizing the AI ability to analyze the patient data continuously shows remarkable decrease in mortality rate and length of stay (LOS) as compared to for prospective randomized controlled trial using Insight [34].

Integrating AI/ML techniques in day to day critical care for improving sepsis related treatment requires utilization of commercial product or by using open source code related to machine learning algorithm that are found in many research paper. Utilization of commercial product has several commercial pros and cons related to security, reliability and validation issues. For open source codes are tested on the freely available database like MIMC-II, MIMC-III and many other databases also. Several pilot studies have been performed using the above mentioned databases for the traditional methods before incorporating fully functional AI in the critical care to smooth the ICU workflow.

4.5. Mechanical ventilation

AI research addressing another important area in the critical care is when to use or remove mechanical ventilation for the cardiovascular patients. Present situation ventilators work extremely well in delivering fresh air to the lungs diseases patients, they are open loop or "feed-forward" systems in nature where the mode of ventilation or input signal is largely unaffected by its output, which result in the adequacy of ventilation. Lack the capacity of ventilators to assess the patient's response to the delivered breadth. Due to the shortage of capacity a development of autonomous ventilator a desirable solution that continuously monitor the patient's response to ventilation by adjusting ventilator conditional parameters to provide the patient with an optimal and comfortable delivered breadth. Making of this kind of ideal device in reality is a significant challenge. In this issue one important parameter that focus on the degree of coupling or response of the patients during ventilator support [35].

Machine learning algorithms are developed to asynchronously detect the patient-ventilator based on morphological changes of the noted pressure with available flow signals [36]. Due to different kinds of patients requires admission in the ICUs regardless of the type of surgery, risk prediction is another important criteria to manage the costs and provide first line of treatment for the severely ill patients through the mechanical ventilation units [37]. A study has been performed with an incorporated predictive AI tool upon real time data for ICU admission patient's shows comparable results to clinical experts by the use of machine learning algorithm like random forest shows results with specificity 80.3% [38]. Respiratory surgery patients are common with the continuous mechanical ventilation in the ICU, though it is very difficult to predict mortality rate after performing the surgery based on the available patient data [39]. Development of classification system for slowly removing a patient from the ventilators with the use of AI experiments for creation of predictive models to predict the removal of a tube that has been put into a patient's body before the wearing process in the view of management strategy [40].

5. APPLICATION OF AI IN NEONATAL ICU

Managing neonates is very critical, involves high risk also for correct decision in the neonatal ICU. Vast amount of physiological data populated in the neonatal ICU where uses of AI techniques can continuously providing information for the neonates regarding greater risks and complications [41], [42]. Several researches is currently going on for introduction of AI applications in the NICU related to mortality prediction and appropriate suggestions related to level and duration of interference [43]. Several ANN based models are used regarding child mortality prediction where learning from existing patient data and provide correct prediction from the available data [44], [45]. In this case developed ANN can helps to analyze the relationship between age, weight during pregnancy and other scores can helps to predict mortality of the newborn child. Besides of these parameters other factors like physiologic and clinical experiment parameters also need to consider during development of models for calculating the estimated length of stay, ventilation support duration in the neonatal ICU [46]. Further combination of natural language techniques with AI also helps to processing the doctor's documents to predict the mortality outcomes in the ICU. AI techniques give flexibility to the physician to simulate the real time effects of adding or subtracting the variables according to the interest for mortality predictions. Utilizing physiologic parameters with natural language processing create better input to the AI based model to work as a potential way to check mortality in the surgical intensive care unit (SICU) [47].

6. ICU MANAGEMENT THROUGH AI SENSORS

Internet of things (IoT) based devices are used several areas to continuously monitors and receiving of proper messages in time where sensors are specifically used to collect data to help decision making. AI based models are used in critical care with continuously monitoring patient data by several sensors for decision making by the utilization of sensor collected data. A study has been conducted with 17 SICU patients with wearable accelerometers, sensors for sound and light to check the uses of AI with the help of sensor technology can be used applied to monitor the patient's condition in the ICU [48]. To maintain the standard regarding diagnosis the confusion assessment model (CAM-ICU) in the ICU are used [49]. Several kinds of extensive measurement techniques are used to monitors different kinds of patient's despites of gender and physical capability by the named AI techniques like face recognition and detection, facial expression management, posture management for extremely movement analysis, detection of sound pressure level for paralytic patients, light level detection of blind patients and visualization of frequency detection.

These AI techniques shows after analysis of the captured data there was major differences in patientsworkings in the ICU area between demented and non demented patients [50]. Analyzing numerical data related to monitoring blood pressure, oxygen saturation level which is traditional in nature to accounting human observations through medical techniques, as well as integrating heterogeneous forms of extracted features data from XRAY, USG images and laboratory experiment data where AI techniques can helps very much for decision making [51]. Another study shows that usage of AI based glucose controller provides good resultscorresponding to other controllers like Yale protocol or Gluccomander [52]. Improvement of hygienic condition for ICU patients several AI based smart technology has been used starting from the smart toothbrush to consumable medical items like unpackaged gauze, oxygen tube to significantly reduce the health care costs though materials with absence of identification number or radiofrequency tags are excluded from the cost calculation [53]. A novel optical detection system based on ML techniques shows tracking of various consumable medical items in the ICU area [54].

7. COMPARISON FOR RELIABILITY VERSUSACCURACY OF AI TECHNIQUES

The performance of the learning algorithm is measured by its capability to how accurately it predicts the results from the available data sets. Models are created first, then trained with the labeled data sets and validated with samples available from the same data sets of population; it is found that performances regarding ML algorithms are very high in accuracy. Judiciously extracted features with corresponding characteristics from a good number of smplesand correctly selection of algorithm shows very high accuracy regarding the model. As the collected data are correct in nature, also verifiable then modelsoutcomes are also bound to be accurate and reliable. There are many situation, ICU generated data are unseen in nature and generation of patterns from these unseen data are challenging. When the models are trained with label data but tested with unseen data or faulty data, the prediction may be accurate but not totally reliable [55].

The basic question is coming up at what extent the models are reliable. These AI models are considering several variables, uses minimum bias in data classification but models reliability cannot be ensured. Therefore major challenge is to develop a model with respect to ICU patients with good classification ability. Prediction regarding mortality and readmission in the ICU is another major criterion for checking performance of the models [56]. It is very difficult to conclude that in every cases AI is superior to humans because some of the unseen situations in the ICU human brains are more capable to take correct decisions. AI can help the doctors to provide information in much shorter time from huge data by performing complex calculations. Another important emerging area in the ICU is the collection of accurate data with the help of AI technique to monitor patients. Currently human-made algorithms are very much used with AI technology regarding critical decision making. Regarding medical judgment and decision making AI techniques are not so much capable because AI application are not sensitive, independent and lack of self-aware entities [57].

8. CONCLUSION

Real strength of AI lies in its capability to extract useful information from the updated real time data and manage the constant inflow of data. Implementation of AI techniques are highly demandable in the ICU environment due to generation huge volume of data and the prioritization of patient care based on illness/injury, prognosis, limited physical and human resource availability. Areas in which AI techniques has been used considerably are sepsis prevention and mechanical ventilation. For prediction regarding re-admission, length of stay, mortality where AI techniques are contributed more and more. Day by day AI algorithms are fine-tuned, tested with large volume of data with improved technology can help the doctors to provide the treatment to the patients with better care. Currently major focus on the validating ML algorithms but it is also remember the other factors are also responsible for integrating of AI techniques into the clinical settings practically like training of clinical staff and patients, the legal issues, principles of AI in the care unit and representation of task into intellegient systems. Further receiving of continuous response from the patients during treatment, observing face-to-face care by the physician during ICU stay for the patients are now a day's more improving. Still several AI research is going on to enhance the clinical workflow, minimizes the resource costs and enhance patient care for better reputation of health care industry.

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BIOGRAPHIES OF AUTHORS

Prabhudutta Ray received his Master degree in computer science and engineering. Currently work as a full-time research scholar at Institute of Advanced Research, Gandhinagar. He can be contacted at email: prabhuduttaray.phd2020@iar.ac.in. and phdrayprabhu@gmail.com

Dr. Sachin Sharma is a NVIDIA DLI University Ambassador, Mentor of Change at AIC-GTU, Member of BOS (Faculty of Computer Science) Sankalchand Patel University Ahmedabad, Gujarat, India. He can be contacted at email: sharma.f@gmail.com.

Dr. Raj Raval is a Critical Care Specialist (MD), Ahmedabad, but what really sets us apart is also the personalized attention and care he devote to his patients. With a strong, committed highly qualified team of doctors and state-of-the-art facilities. It is our goal to set new standards in healthcare with an unwavering focus on quality patient care, service excellence and protocol-based delivery. He can be contacted at email: drrajrawal@gmail.com.