ICU MORTALITY PREDICTION

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Abstract - *Patients admitted to an Intensive Care Unit (ICU) have life-threatening health problems or are in poor health and require considerable care and surveillance in order to recover quickly. An early ICU mortality prediction is critical for identifying patients who are at a higher danger and for making better therapeutic decisions for the patient. Using Deep Learning-based approaches, an early Mortality Prediction can be used to support this analysis. The Medical Information Mart for Intensive Care (MIMIC-II), which is freely available, is being used for the evaluation. The F1 score, area under the receiver operating characteristic curve (AUC), and precision predictions show the model's ability. Two models, the recurrent neural network-long short term memory (RNN-LSTM) and the convolution neural network (CNN) are employed and evaluated in order to produce the best mortality prediction utilizing the SAPS-I score and related parameters.*

Key Words: Morality prediction, Deep learning, SAP-I, MIMIC-II, Recurrent neural network, Convolution neural network.

I. INTRODUCTION

Intensive care units (ICUs) are the department in-hospital which is used to treat people who are terminally ill, had major surgery, accidents, trauma or serious infection. The patient who is admitted in ICU is closely monitored and provided medical aid from skilled physicians, nurses, respiratory therapist, physical therapist, community worker and also provides medications in order to ensure normal. Therefore, quick and dependable prediction implementations in support of delicate medical conditions would be useful for aiding. The greatest task in critical care research is Mortality Prediction (MP). The use of mortality prediction can not only identify the high threat and can also make sure that the available ICU bed is given to the patient who is more in need of it. During the ICU stay, different biological parameters are checked and analyzed each day. In scoring systems these parameters are measured and examined to gauge the ferocity of the patients [6]. Since the technology is advancing rapidly and can be comprehended with healthcare. In ICUs, accurate mortality prediction is critical for assessing the severity of illness and determining the value of novel treatments and interventions that may help to improve clinical outcomes [2]. To track a patient's clinical progress, Electronic Health Record (EHR) is used to facilitate enhanced health care decisions and contribute evidence-based care. Keeping patients data stored safely, easily, in less space and for an uncertain amount of time and also being in digital format, it decreases the number of records off track.[4] However, internal data constraints such as sparsity, irregularity, heterogeneity, and noise make modeling and evaluating EHR data more difficult. For simulation, an available to the public clinical dataset called Medical Information Mart for Intensive Care MIMIC-II was used, which covered broad, diverse, and granulated data that was accepted and is used for improved clinical prediction or as a data source for constant validation among most published machine learning literature [2-3]. For the ICU different types of severity, scoring has been developed which are the acute physiology and chronic health evaluation system (APACHE II), the simplified acute physiology score (SAPS II), the Sequential Organ Failure Assessment (SOFA) score. The challenge faced in severity scoring the accuracy rate of mortality prediction is less accurate and so to attain precise mortality prediction we are using intelligent tools ie; deep learning. This paper introduces deep learning (DL) based models for the Mortality Prediction (MP) in ICU patients. The models rely on classification techniques based on Recurrent neural network (RNN) and Long Short-Term Memory (LSTM). This paper aims to build a deep learning model that can predict mortality of a patient within the ICU based on EHR database and the model will utilize the unstructured data to derive relevant clinical events, vital signs data and lab events to predict mortality. The remaining paper is categorized as follows: We include the literature evaluation on relevant investigations in section 2. The MIMIC-II dataset's basic data are provided in Section 3. We discussed the preprocessing method we used to extract the features and the RNN models we presented in Section 4.

II.RELATED WORK

Intensive care units are departments that deal with patients who have decrepit health and are dealing with multiple diseases simultaneously. The medical data collected during their ICU stay is feasible for predicting the mortality which can help doctors to make optimal decisions for further treatment of patients related to their condition. From the collected data, prediction can be done easily by using different scoring techniques and ML or DL models. Early work [3][7][8] illustrates a comparison between different ml algorithms, indicating that SVM, DT, and GMB outperformed other ML models using several scoring techniques including APACHE and SAP-II for the freely available database Medical Information Mart for Intensive Care (MIMIC-III). In [4] stack ensemble algorithms combine the prediction of multiple ML models on the same dataset to produce an optimal mortality prediction. Yuanfei Bi. [1] presented that the RNN-LSTM model can firmly surpass the accuracy of the traditional logistic regression (LR) model. Researchers recently made a concerted effort to apply deep learning-based methodologies to EHR in order to take advantage of the system's ability to learn complexity from data. The LSTM algorithm is widely used to handle longitudinal data.

III. DATASET

A. MIMIC-II

The data comes from the Massachusetts Institute of Technology's Medical Information Mart for Intensive Care (MIMIC-II), a freely accessible critical care database (MIT). It includes EHR data from patients admitted to the Beth Israel Deaconess Medical Center (BIDMC) in Boston's ICUs. The data selected is a subset of MIMIC-II for simulation idea which is a dataset consisting of 1544 ICUstay of adult patients in the first 48hrs. Within the first 48 hours after admitting the patient to the ICU, 42 variables are assessed at least once, six of those are basic signifiers. These six regular signifiers which are collected after the admission of the patient for the first time are age, gender, weight, ICU type, and height. The remaining 37 variables are time series that could be acquired through numerous tests. Each examination will include an accompanying period indicating the time lag since ICU admissions are in hours and minutes.

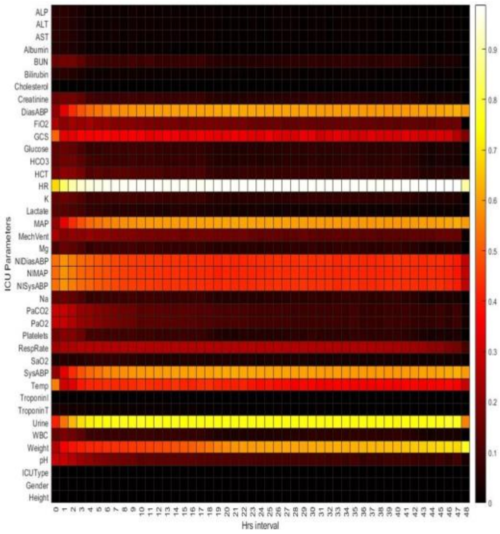
B. SAPS-I

We have selected Simplified Acute Physiology Score-I (SAPS-I) as our scoring system which is one of the many ICU scoring systems. We have also selected a related set of features as used in calculating the SAPS-I score. SAPS-I is a scoring tool advanced to estimate the severity of the disease of a patient who is above the age of 15 years and is admitted to ICUs.

IV. DATA PREPROCESSING

This step focuses on modifying raw data and cleaning the state of gathered medical data in order to increase the performance of the deep learning process. After surveying the dataset, we have clustered the data of variables in every hour that were repeated multiple times or not in an hour during the ICUstay of 48 hours and then took the mean of the variable values and we did the same for every hour which will further help the model to predict mortality more easily and accurately.

Table -1: Heatmap of parameters



V. PROPOSED MODEL

The proposed system's flow chart, given in fig.1, illustrates a dataset picked from MIMIC-II, with the data acquisition stage of a subset of the MIMIC-II dataset taken into account. Since the dataset for DL experiences missing value and is noisy and so the dataset was pre-processed to attain prominent results. During the data splitting phase, the data is divided into two portions. One of the portions is used for training the data and the other portion is used for testing the data. The data is utilized to train the model 70percent of the total, while the remaining 30 percent of total is used to test the model.The training data is trained using Deep learning models based on RNN-LSTM and CNN techniques. Once the model testing is completed the trained model is used for mortality prediction and the performance is evaluated using different performance metrics.

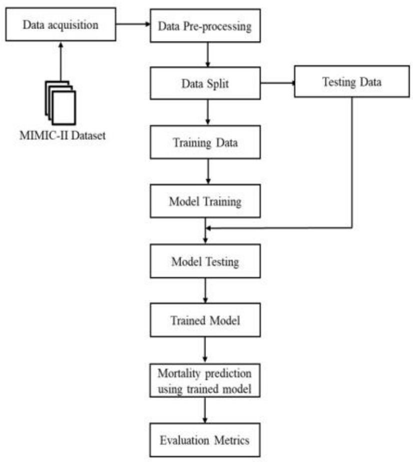


Fig -1: Flow chart of the proposed model

A. IMPLEMENTATION

In this case, we used MATLAB to run a six-layer LSTM model. With a learning rate of 0.01 the LSTM model was trained. The batch size is 120 and the maximum epoch number is 30. During training, the smallest weight possible is used to come to an early stop. We've also randomly shuffled the dataset, using 30 percent of the patients as a test set and 70 percent of the patients as a training set.

B. EVALUATION METRICS

Since ICU mortality is a supervised learning model, we chose Precision, F1, and AUC for evaluating our predictions.

Table -2: EVALUATION METRIC OF DIFFERENT MODEL

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	Precision	F1	AUC
RNN-LSTM	0.83	0.93	0.90
CNN	0.97	0.97	0.97

VI. PREDICTION RESULTS

The RNN-LSTM-based model was compared to the CNN model in Deep Learning. The last hour of the 48-hour timeframe is used to time the model's input parameter values. The metrics findings for the LSTM and comparison CNN models are documented in (Table II), and the CNN models receiver operating characteristics (ROC) are shown in Fig.2. The CNN model consistently outperforms the RNN-LSTM model in terms of accuracy (Table II). On the test dataset, the CNN model has a higher AUC than the RNN-LSTM model. Fig.2. Infers that a basic CNN model may achieve superior execution in mortality prediction, implying that such models have a bright future in health-related tasks.

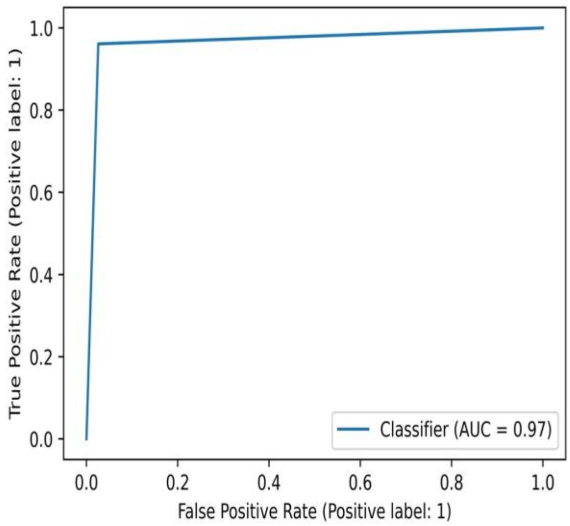

Fig -2: ROC curve of CNN model

VII. CONCLUSION AND DISCUSSION

Given that when it comes to dealing with sequential and time series death parameters, Deep Learning models like RNN-LSTM and CNN have the upper hand. In this paper, we used the MIMIC-II dataset to predict ICU patient mortality using deep learning models. We pre-processed the data and extracted the SAPS-I-compatible parameters. These values were found in both sequential and non-sequential data, indicating that patients' psychological circumstances were improving. Then we create and train a CNN model, which we compare to the RNN-LSTM model's prediction performance. In terms of accuracy, our data reveal that a CNN model regularly outperforms an RNN-LSTM model. We may be able to broaden our efforts in the future. For instance, further study of the huge MIMIC-II dataset can be done, and improved model pretreatment methods can lead the characteristics of MIMIC-II datasets.

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