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Hybridized deep learning model with novel recommender for predicting criticality state of patient using MIMIC-IV dataset

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ABSTRACT

The contribution of machine learning towards prediction of critical state of patient is the prime focus of the current study. The review of current approaches of machine learning has been witnessed with various shortcomings. Hence, the proposed study adopts medical information mart for intensive care (MIMIC-IV) dataset in order to develop a novel analytical model that can predict the criticality state of patient in their next visit. The model has been designed by hybridizing convolution neural network (CNN) and long short-term memory (LSTM) which takes the discrete input of hospital and individual patient information in each visit. The concatenated feature is then subjected to a newly introduced recommender module which offers implicit feedback by assigning a ranking score. The final predictive outcome of study offers criticality rank. The study model is benchmarked with existing machine learning approaches to find 54% of increased accuracy and 70% of reduced processing time.

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1. INTRODUCTION

There is a significant level of contribution made by machine learning towards the healthcare system that has successfully transformed healthcare management, medical research, and patient care [1]. The core technological advancement of machine learning can be realized by its highly improved medical imaging and diagnostics that contributes towards detection of various diseases in its early stages. Further, hospital operations are substantially optimized using machine learning right from inventory control and staff scheduling to bed management. At the same time, various types of patient data, e.g. lifestyle factors, genetic information, clinical history, can be used by machine leraning towards predicting probability of various ranges of diseases [2]. The prediction of progression of diseases can be now possible by investigating the patterns of data over time using machine learning. This also assists in offering personalized treatment for various patient suffering from chronic diseases e.g., asthma, hypertension, and diabetes. Considering real-time data from clinical setting (e.g., electronic health records), machine learning can assess the risk pertaining to specific patient, offer drug interaction, and generate alert system for potential issues. However, mortality prediction is still one of the challenging topic within machine learning in healthcare sector [3]. The prime reason behind this is absence of high-quality longitudinal data, noisy data, imbalanced data, and missing data.

Apart from this, the inheritance of bias from the medical data is quite possible in machine learning while they undergo training operation. Hence, such trained model offers more amplification of biases that finally leads to outliers. At the same time, introduction of biasness is also feasible during selection of feature in order to carry out predictive analysis. Another bigger challenge associated with machine learning is narrowed scope of generalization, which means model designed using one scenario of patient and disease may not be applicable when some of the potential dependencies changes. Because of all these issues, developing a reliable machine learning model for mortality prediction, especially for patient admitted in intensive care unit (ICU) is still a potential challenge [4]–[6]. This reduces the reliability attribute over various settings of healthcare units. In order to address all these impending issues, there is still a better chance to work on it. One way to do so is by adopting a highly comprehensive and enriched medical dataset that is universally accepted and have diversified information that can assists the researcher to develop a model and work on flaws on machine learning models. This research work uses medical information mart for intensive care (MIMIC) dataset of version latest version 4 signified as MIMIC-IV dataset [7]. This benchmarked dataset consists of real-world data from over 40,000 ICU admitted patients charecterized by diverse clinical data, temporal data, and multimodal data. Apart from this, MIMIC-IV is open access data that encourages collaboration with higher supportability for research work in machine learning ideal for model development and evaluation of model towards stratification and prediction of risj, early detection of critical condition, and mortality prediction. Apart from this, it also offers clinical text mining that contributes towards enhanced diagnosis and prognosis. The insight extracted from MIMIC-IV data assist in identifying factors that has potential impact for readmission to hospital and capacity of ICU. It also assists in estimating overall cost of healthcare unit assisting to shape policy decision for better cost-effective care.

In order to ascertain the implications of machine learning approaches, various related work has been reviewed. Pang *et al*. [8] have used machine learning for predicting mortality risk for patient admitted in ICU. The study has used MIMIC-IV dataset where multiple learning models viz. decision tree (DT), support vector machine (SVM), logistic regression (LR), and extreme gradient boosting (XGBoost) has been used. Similar direction of mortality prediction is also carried out by Chiu *et al*. [9] considering topic modelling approach. The model has used latent dirichlet allocation (LDA) for text classification considering MIMIC-III dataset to find gradient boosting to excel better predictive performance. Cogollo *et al*. [10] have designed a model for predicting sepsis on early stage using MIMIC-III dataset considering mutliple machine learning models towards assessing organ failure possibilities. Aden *et al*. [11] have presented a classificatioin framework using multiple deep learning models and natural language processing (NLP). The framework has used various combination of long short-term memory (LSTM) and bidirectional encoder representations from transforms (BERT) to improve upon their predictive accuracy on MIMIC-III dataset. Bozkurt and Aşuroğlu [12] have presented a predictive model using machine learning and feature analysis towards patients suffering from cancer using MIMIC-IV dataset. A unique modelling towards risk prediction is discussed by Ogasawara *et al*. [13] for assesing patient undergoing surgery. The model has used a brute force mechanism towards the determination of new disease. Cao *et al*. [14] have discussed a specific validation framework for XGBoost algorithm towards forecasting mortality rates in hospital using regression model. Adoption of similar XGBoost is also noted in study of Hidayaturrohman and Hanada [15] where the idea is to assess the predictive performance improvement using preprocessing. Ko *et al*. [16] have presented a mortality prediction model for terminally ill patient considering multiple dataset. Chung *et al*. [17] have used XGBoost model for predictive analysis of heart attack. Hence, convolution neural network (CNN), LSTM, DT, SVM, LR, and, XGBoost are identified to be frequenly adopted machine learning towards solving prediction problems associated with critical patients [18]–[24]. After reviewing the related work, there are various identification of research problems:

i) Existing system has identified potential of CNN as well as LSTM to excel better predictive performance. However, they cannot be considered as optimally preferred solution for diagnosis problems.
ii) There are few research models which has actually focussed on chronic disease as the core part of research emphasis is mainly given to critical diseases only.
iii) Existing study has mainly adopted the dataset as a whole; however, less emphasis is given to extract the commonalities, unique traits, and patient-specific features that could attribute to high performing predictive modelling.
iv) Existing system is also witnessed to emphasize more on introducing machine learning algorithms in its sophisticated form and hence the higher accuracy has come up with increased computational cost that has been not much emphasized upon.

Hence, the aim of the proposed study is to present a novel predictive model that can realize the severity degree from chronic to critical disease of a patient with optimally higher predictive accuracy. This model is an extension of our prior work [25]–[27]. The value-added contribution of this study are as follows: i) the proposed scheme introduces a simplified hybridization of two deep learning models (CNN and LSTM) to offer better predictive score, ii) a novel recommeder module is introduced which computes and assign severity score followed by further optimization using deep learning, iii) the study uses MIMIC-IV dataset where demographic information, current status, biological state of patient, are evaluated using simplified analytical model, and iv) the study outcome has been benchmarked with existing methods to prove the effectiveness of study model. The next section presents discussion of the solution in the form of adopted research method.

2. METHOD

The prime aim of the proposed study is to develop a simplified and yet efficient predictive model towards analyzing state of criticality of a patient on the basis of analyzed score of biological state considering MIMIC-IV dataset. Figure 1 showcase the adopted architecture for this purpose which shows multiple underlying processes involved in proposed study. The primary step of this mechanism is to obtain the information of hospital-based data associated with the patient to understand the visit information of all the patient. The idea is to perform forecasting of evaluated value of biological state associated in upcoming visit. The system then acquires the actual information of the patient's biological state in their next visit by predicting the biological state of all the prior visits. The consecutive step performs concatenation of information of patient's biological state noted in initial and current visit in order to acquire the resultant score of prediction. The next operation in architecture of Figure 1 is associated with diagnosis where a simplified recommender system has been designed that generates ranks associated to critical state of patient. This recommender system is initially trained by obtaining information of biological state and demographic information for the patient witnessed with both severe critical disease as well as chronic disease. The trained recommender system further takes the input of predicted biological state and demographic information in order to generate the final outcome of prediction.

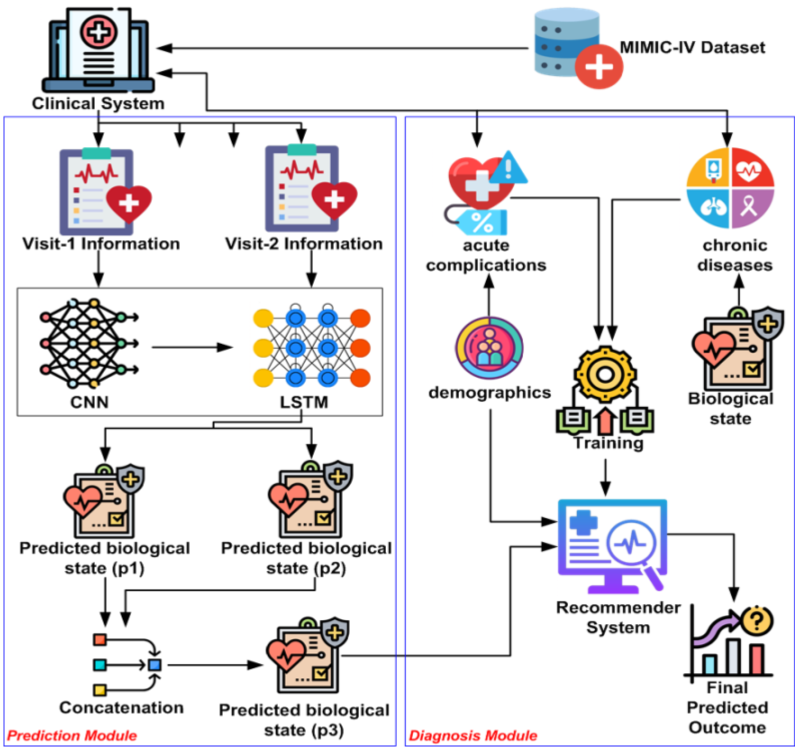


Figure 1. Architecture of proposed system

Adoption of MIMIC-IV dataset offers access to various essential information e.g. patient demographics, clinical notes, medication, and lab results. Hence, a better form of predictive modelling can be carried out as this dataset offers better likelihood estimation of mortality as well as other critical complications. Apart from this, being a part of open access community, it offers wider supportability of assessing AI model toward studying disease progression, mortality rates, and critical care. Hence, adoption of MIMIC-IV dataset offer a wider scope of evaluation for the proposed study model towards predicting state of criticality adopting deep learning model. The elaborated operation of the architecture are as follows.

2.1. Integrated deep learning module

From the practical scenario, a real-state of the patient is analyzed by a physician who recommends for further stages of treatment. This process is automated by adopting CNN where the MIMIC-IV dataset is considered as an input argument followed by extracting the latent attributes in i) data related to medication and ii) data related to physical symptoms. The final score of attributes are obtained from concatenating various layers in order to acquire a high-level abstractive form of attributes. This finally obtained attributes undergo further processing using LSTM using three discrete gate system (forget, input, and result). Figure 2 showcase the flow of the internal operation of this module, where it can be seen that information from both individual and hospital associated with clinical state of an individual is considered which are subjected to CNN layers to generate features. The generated features are then subjected to LSTM followed by concatenating them where the concatenated features are further subjected to dense layers. The determination of demands of forgetting associated with previous cell is carried out by forget gate followed by determining the necessary features to teh cell for updating state of cell in input gate. At the end, the exact state of result is decided at output gate of LSTM.

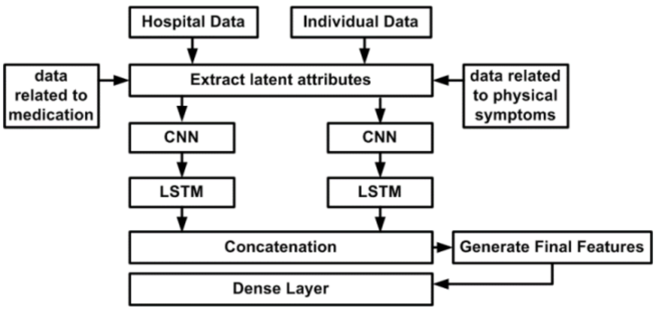


Figure 2. Integrated deep learning module

2.2. Recommender module

This module is responsible for determining the liklihood of occurance of any critical state of a patient on the basis of their demographic data as well as evaluated information of physical attributes Figure 3. Adoption of MIMIC-IV dataset in proposed study defines particular disease that is found to be evolving as well as a set of regular chronic disease. For this purpose, an objective function is empirically set as (1).

$$\Phi = \pi\lambda d \tag{1}$$

In expression (1), the variable Φ represents an objective function depicting possible value of specific number of parient possessing manifold disease, variable π represents weighted matrix, and variable λ represents state matrix considering d duration of time. The weighted matrix π is obtained by product of disease information in MIMIC-IV dataset and current state while state matrix λ is obtained from product of information of patient in MIMIC-IV dataset and current state. It is necessary that weighted matrix must cater up objective function bearing state matrix in order to predict the rank of criticality matching with patient information and disease information.

This challenge of prediction is solved using a simplified recommender system which is capable of generating a rank of the criticality state by learning the model using stochastic gradient descent for better optimization. This mechanism is used for computing the weighted matrix. For this purpose, this module constructs a matrix (δ, P_1, P_2) where δ represents disease to construct a logic that patient P_1 has higher probability to demand criticality screening in contrast to patient P_2. The computation of this probability Pr is carried out empirically as (2).

$$\mathrm{Pr(hp)} = \sum_{i=1}^{m} A^1 \tag{2}$$

In (2), probability Pr is computed with respect to hyperparameters hp and is obtained by summation of parameter A^1 where A^1 represents product of individual weight and cumulative information from MIMIC-IV dataset pertaining to symptoms of patients and their associated demographics. It will eventually mean that if patient P_1 has confirmed and increasing value of evolving diseases compared to already existing values of diseases in MIMIC IV dataset than this respective patient information is predicted to exhibit that specific disease in future. Figure 3 showcase the mechanism of proposed recommender module.

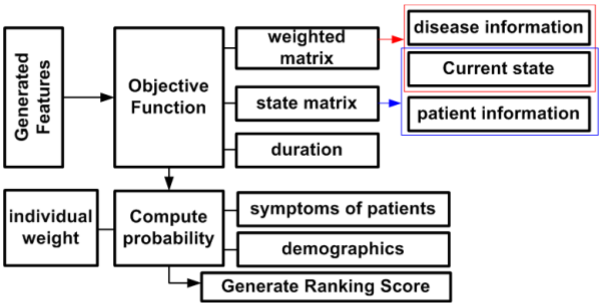


Figure 3. Proposed recommender module

2.3. Symptom prediction module

The outcome of the previous module acts as an input for the current module to predict severity. Various layerwise operation is carried out considering combined CNN and LSTM as shown in Figure 4. The MIMIC-IV dataset is used where the hospital data and individual patient information were obtained using integrated deep learning module. The features associated with both individual information and common information were appended together in concatenation layer. The accomplished outcome is then forwarded to fully connected layer in order to forecast the biological state of the patient which are likely to be exhibited by the patient in their upcoming visit or follow-ups. The predicted values of biological state is fed to the prior recommender module in order to identify and assess the liklihood of severe critical state in upcoming visit for the particular patient. This is more valid for both patient with chronic and evolving diseases. It is necessary to understand that values of clinical settings for hospital-based information will differ from that of patient-based information as well as cardinality of biological state of features. The proposed system considers items of biological state as well as items of medicine associated with various critical conditions related to keoacidosis (X_1), respiratory failure (X_2), pancreatitis (X_3), renal failures (X_4), heart failure (X_5), and cerebral hemorrhage (X_6). Apart from this, the system also considers various preexisting set of diseases of chronic form associated with each critical conditions. The final outcome of this prediction module is the optimal ranking score of biological state of patient which is anticipated to be in higher proximity to the actual state when the patient visits next for follow up.

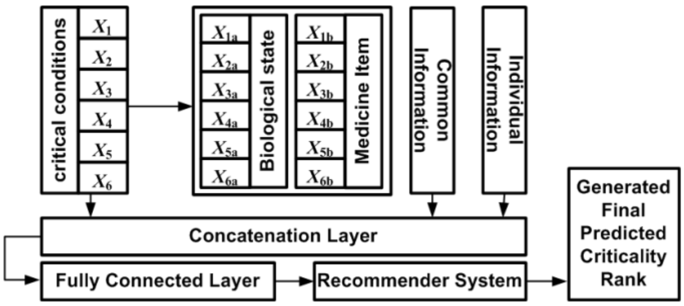


Figure 4. Severity prediction module

3. RESULT

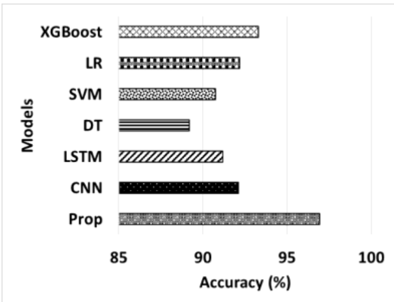
The scripting of the proposed model is carried out in python in Jupyter environment consists of dual convolution layers where there are 32 filters for first layer and 64 filters for second layer. The length of filter is 3 while rectified linear unit is used as activation function. The length of pool is considered as 2 in MaxPooling layer of CNN while three different layers of LSTM is considered. The first and second layer of LSTM has 64 each as hidden units while the third LSTM layer has 32 hidden units. The study chooses 24 biological states from MIMIC-IV dataset. The numerical outcome of study is analyzed using standard performance metrics of accuracy, precision, recall, and F1-score as exhibited in Table 1. The outcome showcases similar consistency for almost all the target screening associated with critical diseases.

The proposed study model (Prop) has also underwent a comparitive analysis considering the frequently adopted machine learning models as shown in Figure 5 with respect to predictive accuracy and processing time. The outcome in Figure 5(a) showcases that proposed study model offers approximately 54.7% of higher accuracy in contrast to existing machine learning models. Interestingly, proposed model using CNN and LSTM is found to excel approximately 5% and 6% of increased accuracy in contrast to standalone version of CNN and LSTM respectively. In perspective of processing time as shown in Figure 5(b), proposed system is witnessed to show approximately 70% reduced processing time in contrast to mean value of all existing models. The study model is found to exhibit 19 and 45% of reduced processing time in contrast to standalone CNN and LSTM respectively. Other models like XGBoost, LR, and SVM is found with nearly similar trend with respect to both the performance metric.

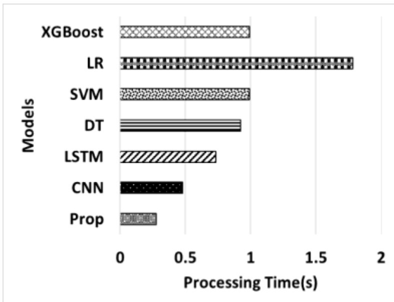
The analysis offers various manifold learning outcomes. The primary learning outcome is to understand that a better predictive modelling demands hybrid modelling which could actually curtain the operational and resource demand cost in perspective of machine learning approaches. The secondary learning outcome is to realize that MIMIC-IV dataset has undeniably enriched set of informationi; however, not all the informations are demanded for performing predictive modelling. As the proposed system targets towards minimizing the effort of physician to diagnose the patient in every upcoming visits, so the demographic information and actual state information obtained from predictive operation in just three steps can overcome the challenge. Hence, proposed study model is proven to offer a cost-effective architectural design that not only customize the clinical settings for critical patient care but also offer faster and simplifed operations.

Table 1. Numerical outcome for various disease targets

Target screening	Accuracy	Precision	Recall	F1-score
X_1	97.9	0.993	0.951	0.978
X_2	98.6	0.899	0.992	0.991
X_3	96.9	0.942	0.975	0.961
X_4	98.8	0.984	0.984	0.987
X_5	93.1	0.992	0.928	0.933
X_6	96.3	0.811	0.935	0.999
Average	96.93	0.9368	0.9608	0.9748



(a)



(b)

Figure 5. Result of comparative analysis of (a) accuracy and (b) processing time

4. CONCLUSION

The proposed study investigates different contributions of machine learning approaches towards critical care of patients suffering from either chronic disease as well as newly evolving diseases. The proposed scheme offers a hybridization of CNN and LSTM, the two powerful deep learning model, in order to predict the possible state of criticality in upcoming visits. Unlike existing approaches, proposed scheme doesn't demand any iterative training operation, nor does it involve intensive analytical processing that is witnessed from its accomplished numerical outcomes. The scheme has introduced a novel recommendation system which works in two modes — prior performing deep learning operation and after performing deep learning operation — thereby ensuring highly validated criticality score as predictive outcome. The study outcome is assessed on standard performance metric to find proposed scheme to excel better performance on multiple set of critical disease attributes in contrast to existing frequently adopted machine learning approaches.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Sarika Khope	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Deepali Kotambkar		✓				✓		✓		✓	✓	✓		
Rama Vasantha Adiraju		✓	✓		✓					✓		✓		
Smita Suhas Battalwar	✓	✓		✓		✓		✓	✓		✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [SK], upon reasonable request.

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