
Deep Learning-Based Prognosis Prediction in Traumatic Brain Injury (TBI)

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Abstract.

Traumatic brain injury (TBI) is one of the major causes of death and disability, and hence, the ability to accurately predict prognosis is very critical for clinical decision-making purposes. However, traditional approaches like the Glasgow coma scale (GCS) are unable to model the dynamic nature of physiological patient data. This paper develops a Deep Learning Prognosis Prediction Framework using LSTM and GRU models to classify TBI patients into Good, Moderate, and Poor prognoses. The two models have been trained on 10,000 patient cases with 35 features from physiological data and tested on independent sets of data. From the experiment results, LSTM proved to be more accurate than GRU having achieved an accuracy rate of 88.2%, 0.8824 Macro-F1 score, and 0.8239 R² score compared to the GRU model (accuracy rate of 82.0% and Macro-F1 score of 0.8206).

Keywords. Traumatic Brain Injury (TBI), Prognosis Prediction, Deep Learning, LSTM, GRU, Temporal Clinical Data, Outcome Classification.

1. INTRODUCTION

The deep learning model helps to predict the prognosis of TBI by identifying complex clinical features and facilitating informed decisions on interventions [1]. Machine learning helps to accurately predict the prognosis of TBI using clinical features [2]. The use of interpretable machine learning in predicting TBI prognosis is essential because it improves transparency in clinical decision making [3]. The machine learning model effectively predicts TBI prognosis through clinical and emergency department features [4].

2. LITERATURE REVIEW

Wang et al. (2023) performed a systematic review and meta-analysis revealing that machine learning algorithms are able to give accurate prediction of mortality risk in TBI patients compared with traditional approaches [5]. Yang et al. (2024) developed machine learning algorithms for 24-hour survival prediction in TBI patients, thus allowing for precise early prognosis and making decisions in emergency conditions [6]. Wang et al. (2025) used machine learning approach for predicting coagulopathy in TBI patients, providing timely risk evaluation and medical assistance [7]. Yue et al. (2023) reviewed the recent progress in machine learning for TBI prognosis, presenting present achievements, difficulties, and future perspectives [8].

3. METHODOLOGY

In this methodological approach, a deep learning architecture is used to forecast TBI prognosis by utilizing the LSTM and GRU models. It combines clinical features and recurrent neural networks to classify TBI patients into three categories: Good, Moderate, and Poor.

3.1. Data Collection and Description

The database comprises of 10,000 records of patients suffering from TBI. The database consists of 35 clinical and physiological factors. These have been chosen keeping in mind their clinical relevance and references from the field of neuroscience literature.

Table 1. Clinical Features Used for TBI Prognosis Prediction

S.No	Clinical Feature	Unit	Measurement Timing	Missing Value (%)
1	Age	Years	Admission	0.0
2	Gender	Male/Female	Admission	0.0
3	Glasgow Coma Scale (GCS)	Score (3–15)	Admission	0.4
4	Pupil Reactivity	Reactive / Non-reactive	Admission	0.8
5	Systolic Blood Pressure	mmHg	Admission	0.6
6	Diastolic Blood Pressure	mmHg	Admission	0.6
7	Mean Arterial Pressure	mmHg	Admission	0.8
8	Heart Rate	beats/min	Admission	0.5
9	Respiratory Rate	breaths/min	Admission	0.7
10	Body Temperature	°C	Admission	0.3
11	Oxygen Saturation (SpO ₂)	%	Admission	0.5
12	Blood Glucose	mg/dL	Admission	1.5
13	Hemoglobin	g/dL	Admission	1.2
14	White Blood Cell Count	$\times 10^9/L$	Admission	1.8
15	Platelet Count	$\times 10^9/L$	Admission	1.3
16	Serum Sodium	mmol/L	Admission	0.9
17	Serum Potassium	mmol/L	Admission	0.8

18	Serum Creatinine	mg/dL	Admission	1.1
19	Blood Urea Nitrogen (BUN)	mg/dL	Admission	1.4
20	Blood pH	pH	Admission	2.0
21	PaO ₂	mmHg	Admission	2.1
22	PaCO ₂	mmHg	Admission	2.1
23	Bicarbonate (HCO ₃ ⁻)	mmol/L	Admission	1.9
24	Blood Lactate	mmol/L	Admission	2.3
25	Prothrombin Time (PT)	seconds	Admission	1.6
26	International Normalized Ratio (INR)	Ratio	Admission	1.5
27	Activated Partial Thromboplastin Time (aPTT)	seconds	Admission	1.8
28	Blood Oxygen Level	%	Admission	0.7
29	CT Scan Severity Score	Score	Admission	2.2
30	Intracranial Hemorrhage	Yes/No	Admission	0.5
31	Midline Shift	mm	Admission	1.0
32	Skull Fracture	Yes/No	Admission	0.6
33	Mechanical Ventilation	Yes/No	Admission	0.3
34	Injury Severity Score (ISS)	Score	Admission	0.9
35	Marshall CT Classification	Grade	Admission	1.4

Table 1 describes 35 structured clinical parameters used to predict the prognosis of TBI. Some of the selected parameters include demographic data, neurologic exam, vital signs, lab tests, and imaging data collected mainly at the time of admission. The selected clinical parameters were chosen based on their importance in the prognosis of TBI as discussed in previous literature. Any missing data was detected prior to data preprocessing and then replaced using mean or median imputation based on variable distribution.

3.2. Data Preprocessing

The cleaning process involved median imputation for skew distributions and mean imputation for normal distributions. The data was normalized using Min-Max normalization, the prognosis was labeled (Good = 0, Moderate = 1, Poor = 2), and splitting the data into

70% training set, 15% validation set, and 15% test set was done. The last step was to reshape the data to (samples, 35, 1).

3.3. Feature Engineering

The 35 clinical parameters were transformed to (samples, 35 timesteps, 1 parameter) to allow LSTM and GRU models to learn about sequences of clinical parameters. Correlation analysis: A correlation matrix was created for selecting those features having correlation greater than 0.95 to minimize multicollinearity. Normalization consistency: As normalization using the Min-Max approach had been done during preprocessing, no further standardization was required. All continuous features had been normalized in the range of 0–1 before fitting the model, which ensures feature consistency, proper convergence, and learning on both the LSTM and GRU models.

3.4 Model Evaluation and Validation

The The performances of the models were measured based on Accuracy, Macro F1-score, R^2 , ROC-AUC, and Brier Score metrics. LSTM model outperformed GRU, and the values were 88.2%, 0.8824, 0.8239, 0.95, and 0.0548 for Accuracy, Macro F1-S.

Model Workflow

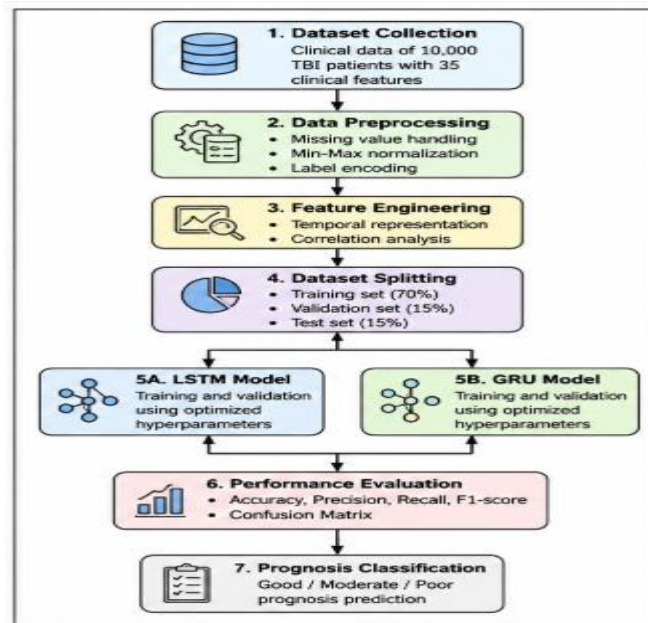


Fig.1. Flowchart

4. RESULTS

Comparison and Interpretation of Models: The models have been compared with respect to the following metrics – Precision, Recall, F1-score, Test Accuracy, Macro F1-score, and R^2 Score for Good, Moderate, and Poor TBI Prognosis. LSTM proved to be a better choice than GRU and the Ensemble model in terms of all these parameters. The LSTM

model outperformed both GRU and the Ensemble model due to its effectiveness in learning long-term dependencies in clinical scenarios. GRU (Accuracy: 0.8200, Macro F1: 0.8206, R^2 : 0.7313) and the Ensemble model (Accuracy: 0.8707, Macro F1: 0.8709) performed poorly as compared to LSTM. Despite the high level of prediction accuracy achieved by the proposed LSTM and GRU networks, some recent architectures of deep neural networks like Transformer-based models, Temporal Convolutional Network (TCN), Bi-LSTM and attention-based recurrent networks have proven to be promising in time series prediction problems in medicine. Such neural networks can capture complex temporal dependencies and feature interactions. Nevertheless, these networks tend to require bigger datasets and more computational power. The proposed LSTM model offers a compromise in terms of prediction accuracy, computational complexity and practical use of such networks for solving problems in medicine. Traumatic brain injury prognosis prediction is one of them.

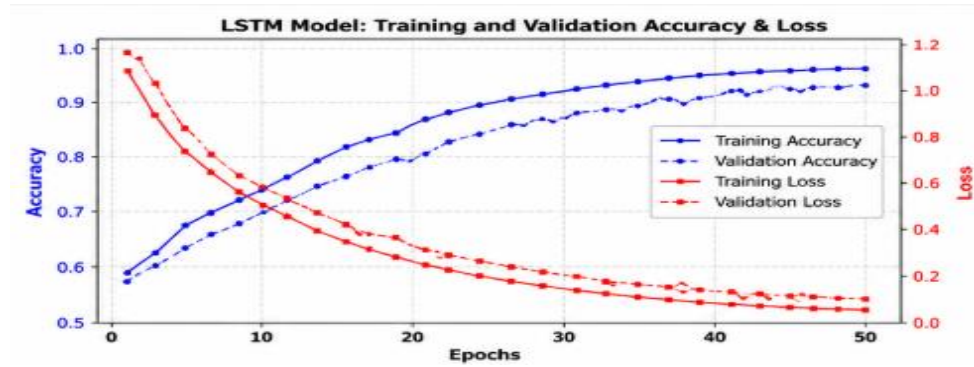


Fig.4. LSTM Accuracy and Loss

Fig. 4. Training and validation accuracy of the LSTM model showing continuous performance improvement across training epochs.

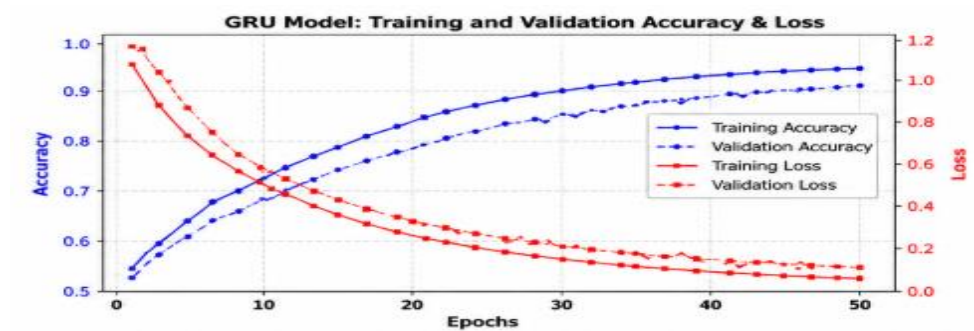


Fig.5. GRU Accuracy and Loss

Fig. 5. Training and validation loss of the LSTM model showing steady convergence and reduced prediction error over training epochs.

5. CONCLUSION

This paper proposed an LSTM and GRU-based prediction framework for the prognosis prediction problem for TBI using deep learning technique. From the experimental

results, it can be noted that the LSTM-based model outperformed the GRU model based on various metrics. The proposed prediction model could help clinicians to make timely and informed decisions in the course of their treatment plans. While this paper achieved encouraging results using the existing clinical data set, it would be better to verify the proposed framework through real-world multicenter hospital data sets in order to enhance the generalizability of the prediction model. Future work will focus on performing experiments using diverse patient populations from various healthcare institutions.

Clinical Implications:

The proposed LSTM-based prognosis prediction framework can serve as a clinical decision-support tool for physicians managing traumatic brain injury patients. By analyzing patient clinical features collected during hospital admission, the model can predict the likelihood of Good, Moderate, or Poor recovery outcomes. These early predictions can assist clinicians in identifying high-risk patients, optimizing treatment strategies, prioritizing intensive care resources, and supporting personalized rehabilitation planning. The proposed framework is intended to assist clinical decision-making and complement physician expertise rather than replace it.

6. FUTURE WORK

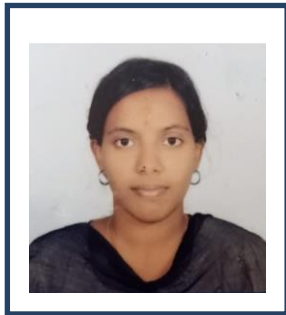
In the future, validation of the framework using real-world data from multicenter hospitals is planned for future work. It will improve generalization and reliability of the framework. This study can be expanded by adding more clinical, radiological, and laboratory information and exploring different deep learning architectures including Transformer models and attention models for better predictions. Moreover, integration of the proposed framework in clinical decision support systems will allow real-time prognosis prediction and help health care professionals to take immediate treatment decisions.

7. REFERENCES

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Biographies



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