A New Epileptic Seizure Prediction Framework Based on Electroencephalography Signals

OLA M. ASSIM, AHLAM F. MAHMOOD
Department of Computer Engineering
University of Mosul
Mosul
IRAQ

Abstract: - This research seeks to evaluate how effectively seizures can be predicted and managed in epilepsy using a specialized deep learning model based on Long Short-Term Memory (LSTM) neural networks. The model leverages non-invasive scalp electroencephalography (EEG) recordings for predicting seizures. To develop and assess the proposed LSTM neural network model, a comprehensive dataset was gathered. The model emphasizes achieving high sensitivity and reducing false alarms to improve its real-time applicability. The evaluation involved various metrics to measure accuracy, sensitivity, and rates of false positives and false negatives. The effectiveness of the proposed LSTM neural network model was outstanding, with accuracy rates ranging from 99.07% to 99.95%. Notably, the sensitivity score of 1 confirmed precise prediction for all seizure cases. The model demonstrated minimal false positive and false negative rates, highlighting its reliability in predicting seizures. This study emphasizes the promising potential of the proposed LSTM neural network model in providing advanced warning for seizures. The high accuracy and sensitivity rates suggest its usefulness in enabling timely preventive measures for patients, ultimately reducing the occurrence of seizures. This innovative approach holds significance in enhancing the overall management and quality of life for individuals dealing with epilepsy.

Key-Words: - Seizure, prediction, Long Short long-term memory, Electroencephalography

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1 Introduction

Epilepsy is a long-term neurological condition that arises unexpectedly in the brain, marked by recurring episodes. The root of this disorder is linked to irregularities in the activity of brain neurons [1]. When someone is affected by this sudden neurological condition, it results in a disturbance of typical brain function, giving rise to diverse abnormal reactions like fainting, loss of physical balance, convulsions, muscle contractions, and a temporary loss of consciousness [2]. Epilepsy patients face significant consequences as seizures can profoundly affect all aspects of their lives, even posing life threatening risks [3]. Therefore, it's crucial to predict epilepsy early on to manage seizures effectively. The importance of detecting epilepsy at an early stage lies in giving patients timely awareness of potential risks. This enables them to take preventive measures to control seizures and avoid potentially life-threatening situations during episodes [4-6]. Early prediction is immensely significant not just for patients and their families but also for healthcare professionals. Various screening techniques for epilepsy, such as Electroencephalography (EEG) [7], are available. EEG allows for continuous monitoring of electrical brain activity, effectively capturing hidden features of neurological disorders. EEG stands out as a convenient and cost-effective option. Understanding seizures involves breaking down the process into four distinct states: the ictal state, preictal state, postictal state, and interictal state, as illustrated in Figure 1. The crucial aspect of creating a seizure prediction system capable of anticipating seizures is distinguishing preictal and interictal periods. The preictal period, which varies in duration across studies, refers to the period preceding a seizure. The interictal period encompasses the segments of the signal that are neither preictal nor ictal [8]. Identifying the pre-ictal state as early and reliably before seizure onset is crucial to improving seizure prediction accuracy.

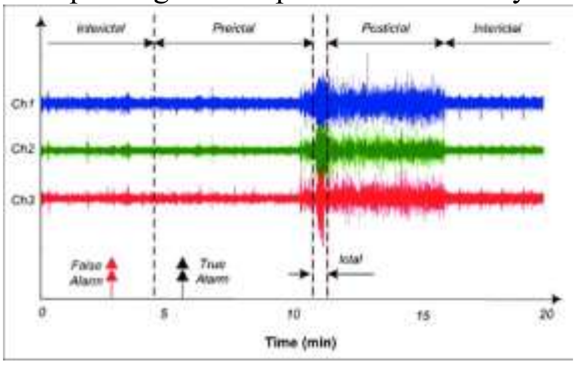


Fig. 1. Brain states for Epileptic patients.

Over the past few decades, there has been a proliferation of algorithms dedicated to predicting seizures. These algorithms aim to anticipate seizures by analyzing preictal changes [9]. Deep learning is One of the subfields of artificial intelligence. In contrast, Deep learning has surpassed traditional machine learning methods by excelling in automatic representation learning, significantly reducing the need for manual feature engineering [10-11]. Despite some research progress in epilepsy prediction, to predict a seizure, one must consider the uniqueness of each person's epilepsy and the significant variability in seizure patterns. What may work effectively for one person may not yield the same results for another [12]. The primary purpose of epilepsy prediction is to allow patients enough time to take preventive measures or prepare for impending seizures to control them or avoid accidents. The main contributions of our research are as follows: • Creating a diverse EEG signal from many datasets enhances the model's flexibility and demonstrates its real-world relevance. • Development of a two-layer LSTM model optimized for time series analysis, particularly in the context of seizure prediction for each patient individually. • Classification of ictal and interictal states was presented, resulting in accurate and early seizure predictions. • Robust performance across different patients makes the model's generalizability and potential for clinical applications.

In this paper, Section 2 presents previous research. Section 3 concludes with the results and insights gained from the experiments presented in Section 4, Section 5 provides a discussion, and Section 6 offers final remarks and prospects.

2 Related works

In seizure prediction, researchers have leveraged well-established classification algorithms and evaluation metrics. Seizure prediction is often approached as a binary classification task, where the objective is to distinguish between pre-seizure and non seizure states. Classification models are trained using input data to predict whether a seizure will occur within a specific time window. Over the past few years, there has been a notable rise in the use and acceptance of deep learning methods, and they have shown great promise in automatically extracting features from time series data. In [13], convolutional neural networks were used to extract spatial features, and recurrent neural networks predicted seizures early in time. [14] presented Long-term recurrent convolutional network (LRCN) is proposed for predicting epileptic seizures. EEG time series are converted into 2D images for multichannel fusion. Deep features were extracted using a convolutional network block, and preictal segments were identified using a block of LSTM. Ref. [15] shows EEG segments of various durations evaluated using Single layer and two-layer LSTM models. The proposed models in [16] are based on the Convolutional Neural Network (CNN) model. In [17], A three-transformer tower model is employed to fuse and classify the extracted features of EEG signals. The study [18] proposes a patient-specific seizure prediction method using a deep residual shrinkage network (DRSN) and gated recurrent unit (GRU). In [19], An end-to-end epileptic seizure prediction approach is proposed based on the long short-term memory network (LSTM). This paper introduces a highly effective method for predicting seizures using EEG recordings for each patient individually. It specifies the period before seizures for each patient to take the necessary to reduce the risks. During the period before seizures, we divided it into different time segments. We used advanced deep learning techniques to analyze and categorize these segments, and this approach proved effective in accurately predicting seizures. Sensitivity is a key metric used to assess the performance of seizure prediction algorithms. It gauges the accuracy of predicting seizures by dividing the number of correctly predicted seizures by the total number of seizures recorded [20]. Other important performance indicators include the warning time, which indicates the proportion of time the system gives advance notice of a potential seizure, and the false positive error rate [21-22].

3 Methodology

Based on previous research, different algorithms have been adapted to predict epileptic seizures, all geetpmetta to obtain higher classification accuracy eagt previous predictions. In the paper, the proposal includes the following:

3.1 Dataset

In this study, a diverse range of patients from two different datasets are used as follows:

1) A neonatal EEG dataset was used. It includes 79 raw EDF files capturing newborn EEG recordings and three annotation files in CSV formats. This comprehensive collection is a valuable resource for studying brain activity and exploring possible neurological conditions in newborns. Some patients diagnosed with epileptic seizures, according to the first specialist, were selected, and the model was applied separately. Patients 1, 15, 19, 25, 38, 41, 50, and 66 with an EEG record length of 6,993, 6,898, 9,006, 6,709, 6,095, 9,684, 9,850 and 11,350 seconds were selected. These lengths provide valuable insights into the duration of EEG recordings for specific patients, which is vital for further analysis and research in neonatal EEG and seizure prediction.

2) The EEG data used in this study is sourced from epilepsy patients at Children's Hospital Boston and the Massachusetts Institute of Technology, collectively referred to as CHB MIT. The dataset comprises recordings from 22 epileptic patients spanning a duration of 20 hours, during which neurologists meticulously documented the occurrences of seizures. The patients in the analysis exhibited more than three seizures in their EEG recordings. Specifically, patients: P.12-R.08 had four seizures, P.12-R.27 experienced six seizures, P.12-R.29 also had six seizures, P.12-R.38 recorded five seizures, P.15 R.54 had five seizures, and P.16-R.17 also experienced five seizures. Each of these patients had an EEG record length of 3600 seconds.

3.2 The proposed model

The proposed prediction model is an LSTM (Long Short-Term Memory) neural network designed specifically for processing sequential data and well-suited for tasks involving time series analysis and other sequential data domains. The proposed architecture comprises three main layers: the first LSTM layer consists of 64 units (neurons), and the second LSTM layer includes 32 units. It processes the output sequences from the first LSTM layer. The final Dense layer has a single unit, representing the model's output. It performs a regression task, predicting a continuous value. This layer contains 33 trainable parameters, Fig 2. shows the model’s architecture with the details about the training process. This LSTM model aims to capture complex patterns and dependencies present in sequential data. It's a relatively small model with a moderate number of parameters.

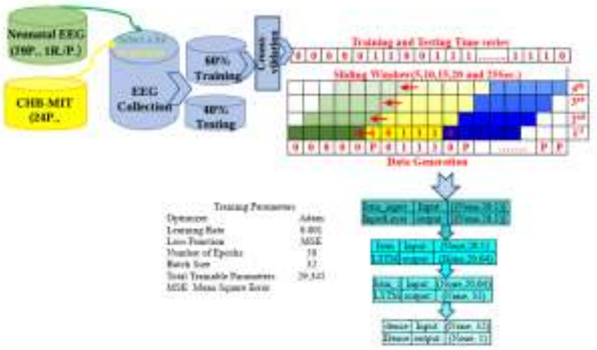


Fig. 2: Architecture of the proposed LSTM model.

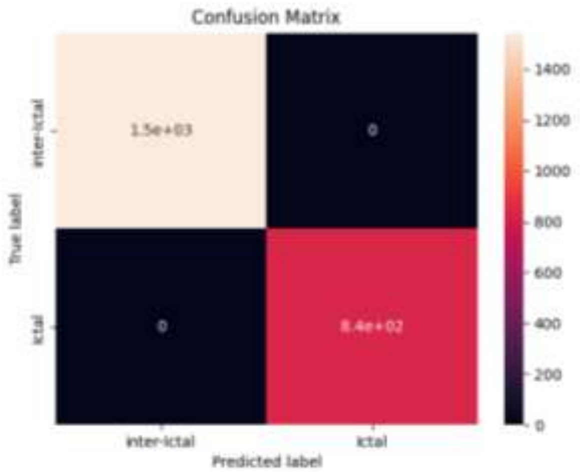
4 Results

The classification results of the proposed model are listed in Table 1. The model's performance is consistently strong, achieving high accuracy and sensitivity for all patients at this time interval. The test scores (RMSE) remain low, indicating accurate predictions close to the actual seizure occurrence.

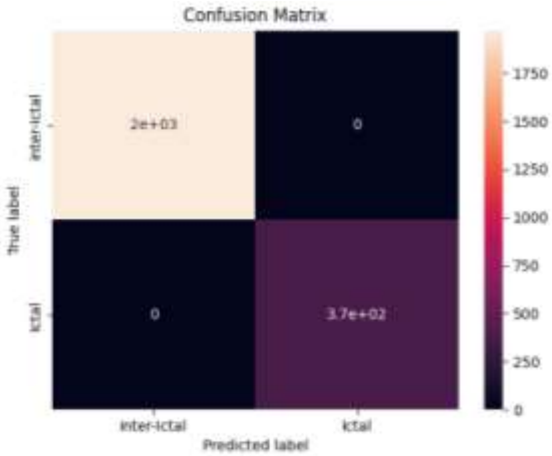
Table 1. The results before 20 seconds of a seizure occurring.

P.No.	Train		Test		Acc		Sen.		fpr		fnr	
	R1	R2	R1	R2	R1	R2	R1	R2	R1	R2	R1	R2
P1	0.08	0.18	0.10	0.12	0.990	0.976	1	0	0	0	0	1
P15	0.08	0.18	0.07	0.12	0.995	0.986	1	0	0	0	0	1
P19	0.05	0.05	0.03	0.03	0.999	0.997	1	0	0	0	0	1
P25	0.07	0.07	0.04	0.05	0.998	0.992	1	0	0	0	0	1
P38	0.08	0.18	0.08	0.12	0.984	0.983	1	0	0	0	0	1
P41	0.10	0.10	0.08	0.09	0.993	0.986	1	0	0	0	0	1
P50	0.05	0.05	0.05	0.05	0.998	0.991	1	0	0	0	0	1
P66	0.02	0.04	0.02	0.03	0.999	0.999	1	0	0	0	0	1

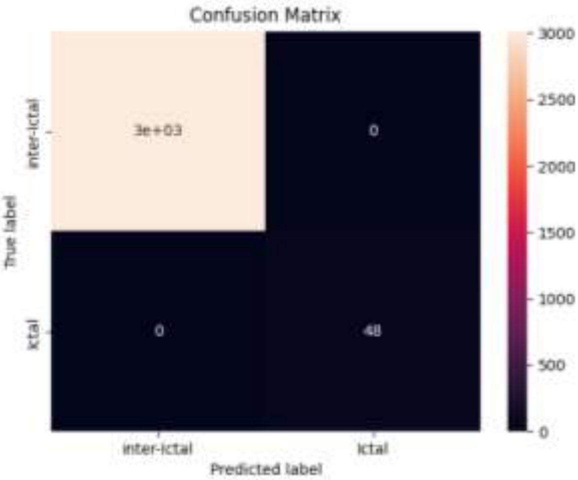
Pre-seizure period, the model shows slightly reduced performance, particularly in sensitivity, as the model is not capturing the pre-seizure patterns effectively. The accuracy remains high, but the sensitivity is 0 for all patients, indicating that the model is not correctly predicting the pre-seizure state. As is evident in the results, the period before the seizure that can be expected differs from one patient to another. For patients (1, 15, 25, 41) it was predicted 28 minutes before the onset. Patient 19 can predict his seizures 27 minutes before their occurrence. Patient 32's seizures can be predicted 23 minutes in advance, while Patient 51 seizures can be predicted 31 minutes in advance.



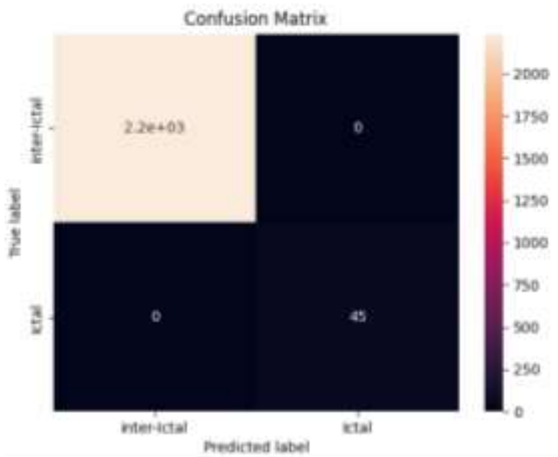
Patient 1



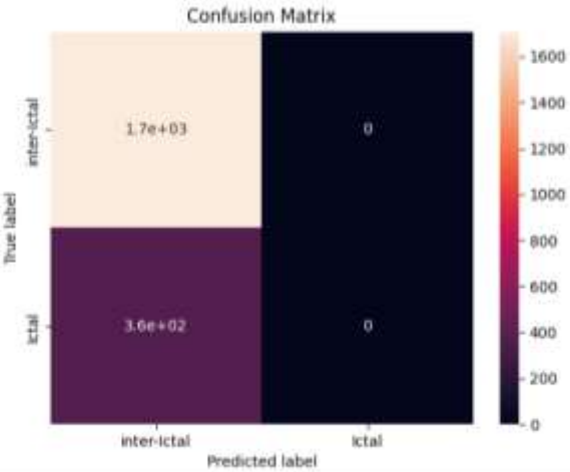
Patient 15



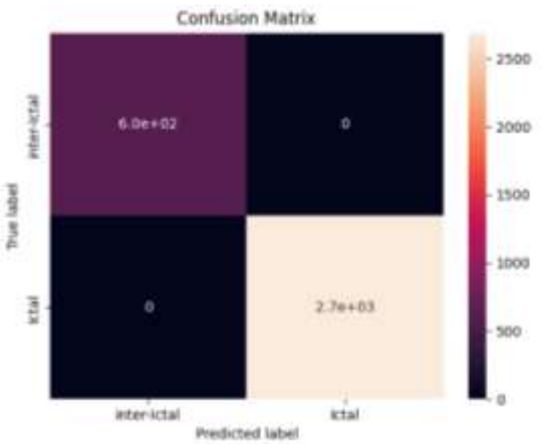
Patient 19



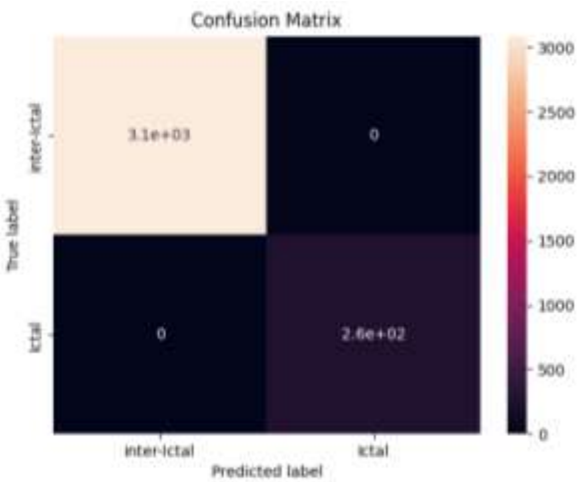
Patient 25



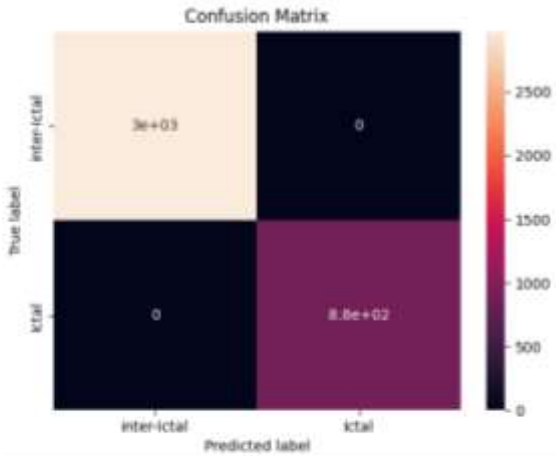
Patient 38



Patient 41



Patient 50



Patient 66

Fig. 3 The confusion matrix of different patients.

The accuracy and loss of the training and validation model for patient 66 are shown in Fig.4.

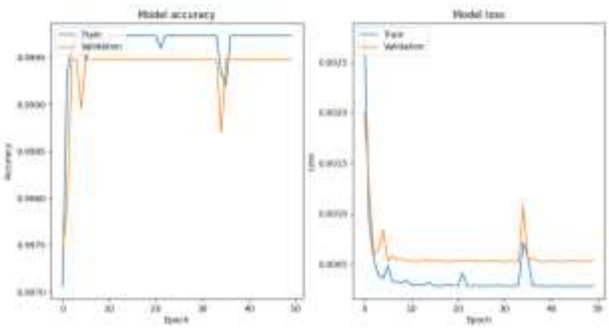


Fig. 4 Accuracy and Loss Curves of Patient 66

5 Discussion

The results from various studies reflect the performance of different seizure prediction and detection methods. [13] achieved a notable accuracy of 99.6% while maintaining a low false alarm rate of 0.004 h-1, and the prediction time for seizures was reported to be around 1 hour. Conversely, Reference [14] demonstrated a balanced accuracy of 93.40%, a sensitivity of 91.88%, and a specificity of 86.13%, with a corresponding false positive rate of 0.04 F P/h. The aggregated outcomes from [15] showcased consistently high performance, with an average accuracy of 98.14%, sensitivity of 98.51%, and specificity of 97.78%. Similarly, Reference [16] reported a solid accuracy rate of 95%. Additionally, [17] exhibited a sensitivity of

92.1%, emphasizing the method's capability to identify positive instances correctly. Furthermore, [18] indicated a sensitivity of 90.54% and an AUC of 0.88, suggesting its effectiveness in distinguishing between positive and negative cases. The corresponding false prediction rate was noted as 0.11/h. Regarding mean sensitivity, Reference [19] reported an average of 91.76%, with an associated false prediction rate of 0.29/h. In the proposed approach, as outlined, the accuracy values demonstrated variability across different patients, ranging from 99.07% to 99.95%. Impressively, a sensitivity of 1 indicated accurate predictions for all ictal states. Equally noteworthy, no false alarms were indicated by a false positive rate of 0 and no missed ictal states as denoted by a false negative rate of 0. The period before seizure occurrences was estimated to be between 23 to 32 seconds. These results underline the advancements in seizure prediction and detection techniques, showcasing substantial accuracy rates and sensitivities across various studies. However, the proposed approach stands out for its personalized accuracy rates and the ability to accurately predict imminent seizures, minimizing false alarms and missed events. Fig. 5 compares previous studies and the proposed model in the performance metrics.

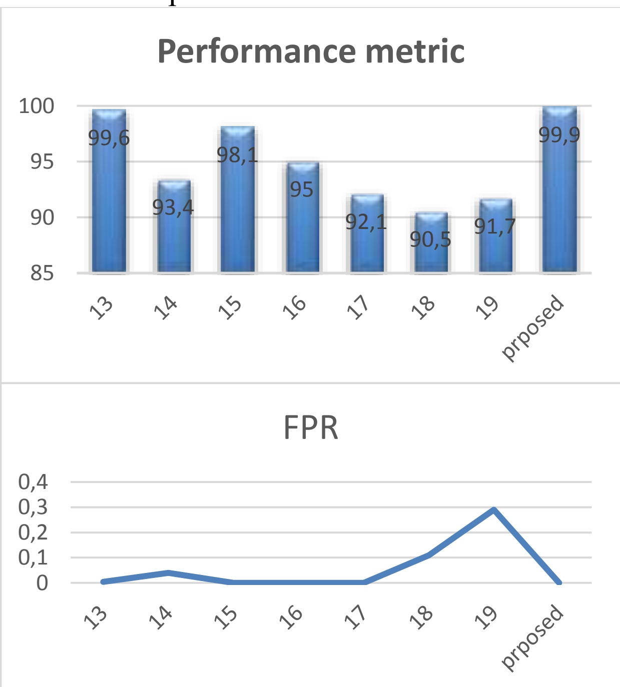


Fig. 5 Comparison of performance metrics in the proposed model and previous studies

6 Conclusion

This study presents a novel Long Short-Term Memory (LSTM) neural network model for seizure prediction using non-invasive scalp EEG recordings. The model has shown remarkable accuracy in distinguishing between ictal and interictal states, allowing for effective seizure prediction.

The LSTM architecture has established its proficiency in the reliable detection of seizure occurrences by demonstrating a notable combination of high accuracy, sensitivity, and low rates of false positives and false negatives. LSTM neural network model demonstrates strong predictive capabilities in seizure detection, offering a reliable and accurate solution for managing epilepsy. Its consistent performance across various patients reaffirms its potential for practical clinical applications, providing valuable insights for timely intervention and improving the quality of life for patients affected by epilepsy. Despite the promising results obtained with the proposed LSTM model, several avenues for further refinement and exploration are identified:

1. Multimodal Data Integration: The incorporation of supplementary data modalities, such as clinical insights or other physiological signals, has the potential to improve the model's precision and provide additional perspectives, thereby advancing the comprehensiveness of seizure prediction.
2. Real-time Deployment: Integrating our model into real-time seizure prediction systems, which allows for continuous monitoring and timely alerts to patients and caregivers, is valuable for optimizing seizure management.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.