Integrated EEG Signal Fusion for Advanced Epileptic Seizure Analysis

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Abstract: Epileptic seizures can result in substantial harm to the brain, which can lead to cognitive decline and memory loss. Reducing the severity of seizures is largely dependent on early identification. Currently, the doctors visually inspect EEG signals in order to diagnose seizure activity, which can be time-consuming and difficult. In order to automatically monitor and detect seizures through the brain's bio-signals, we propose a new method: simplistic convolutional neural network-long short-term memory model (1DCNN-LSTM). First, the unprocessed EEG dataset is pre-treatment and normalized, and we extract the sequence of features by a 1D CNN, and pass them to the LSTM layer. The temporal features are supplied to a few fully connected layers for final seizure recognition. Using data from UCI epileptic seizure detection dataset, the suggested model was assessed. In terms of recognition accuracy, the results are excellent: 82.00% for five-class seizure recognition and 99.39% for binary seizure recognition. The attribution of accuracy is considerably above that of classical machine learning methods and outshines other deep learning models widely recognized as competitors.

1 INTRODUCTION

Millions of individuals worldwide suffer from the neurological condition known as epilepsy. It develops as a result of a confluence of acquired and inherited elements, with the body undergoing abnormal brain activity that results in disorientation, unconsciousness, uncontrollable movements, etc. 5 crore individuals throughout the globe to be troubled by seizure disorder; most of whom are adults, with the rest being children. Abnormal birth oxygen levels, brain injuries that occur in pregnancy, intracranial tumor, and unfamiliar blood sugar are some of the possible causes, however these are mostly unexplained. There were two kinds of seizure: focal seizures and generalized Tonic-Clonic seizures. A generalized seizure attacks the brain as a whole whereas a focal seizure attacks only certain regions of the brain. There are various classes into which generalized seizures have been divided. These include myoclonic, Tonic-Clonic, Atonic, Tonic-Clonic seizures, Absence, and Clonic, among others, that end in convulsive seizures. The rests differentiate epilepsy from a significant condition that may have a devastating impact on the patient's physical as well as mental well-being-even causing death. These people would be much better off if they received adequate and appropriate care at the right time. Electroencephalography can be used to study the brain non-invasively. This technique can yield all the epilepsy-related information that cannot be gathered through other physiological procedures. EEG signals are mostly covered on the scalp but may also be recorded intracranially. EEG signals can be broadly classified into 4 states; these are Interictal, Postictal, Ictal, and Preictal. The Preictal stage has further significance because, minutes before the seizure occurs, it serves as an information source upon when the seizure onset is going to happen. By using the classification of interictal and preictal stages to predict the ictal state, seizures may be avoided and their harmful effects mitigated by taking medication on time. In the past, the primary method used by medical professionals to diagnose epilepsy or determine the origin of seizures was the visual interpretation of EEG signal data. However, new developments in deep learning techniques have made

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it possible to create automated algorithms for identifying seizure activity associated with epilepsy. Deep learning has grown significantly in the last few years and is now applied in many domains, most notably image and natural language processing. CNNs basically use two characteristics in a different way to outperform other neural networks in different tasks. These characteristics include different filters which are applied over a variety of layers-for example: Convolution, pooling, normalization, and fully connected layers. However, the process of learning relevant and representational features active from EEG bio-signals presented as a time series is inherently difficult for CNNs. Hence, CNNs were unable to apply an accurate modeling upscaling of raw EEG signals onto seizure detection outcomes.

2 RELATED WORKS

110 features were then created for each seizure in the time, frequency, and time-frequency domains after preprocessing of the signals by the traditional pipeline. The features were ranked added in order to find the important ones using the method of extreme Gradient Boosting with statistical tests, Abirami S et al, (Abirami, Tikaram, et al. , 2024). With the introduction of machine learning algorithms, automated diagnosis systems can help doctors make rapid and accurate diagnoses, inform the patients, and speed up the classification procedure. It is the presentation of a new multi-path deep learning network for seizure-type classification, H. Albaqami et al, (Albaqami, Hassan, et al. , 2023)

There is a new feature extraction method because of specific bands common spatial pattern, MSBCSP, for multi-class. It applies the joint approximation diagonalization, JAD, to the original CSP algorithm in the case of a multi-classification problem. Energy of Intrinsic Mode Functions is extracted through Complete Ensemble Empirical Mode Decomposition with Adaptive Noise, D. Wu et al, (Wu, Li, et al. , 2023). Whereas self-regulating primitive discovery of seizures from a average EEG has been obtainable, classification of seizure types has not been attempted. Thus, P. Swarubini's and et al, study caters to classify seven types of seizures using non-seizure EEG (Abirami, Swarubini, et al., 2023). From every preictal data segment in 17 EEG channels and 1 ECG channel, the time-domain characteristics were extracted. Various classifiers like k-nearest neighbour, decision tree, random forest, naive Bayes, support vector machines were utilized to access the classification accuracy. Wenjuan Xiong's and et al, research by using random forest on 15-0 min preictal period of EEG and ECG data achieved the best classification accuracy results at 87.83% (Xiong, Nurse, et al. , 2023).

In the case of epileptic patients, accurate identification of the seizure type is of great importance to help design a treatment plan and administer medications. Diagnosis of epileptic seizures is most commonly carried out using the electroencephalography technique, commonly abbreviated as EEG. Signals from the EEG are most often used in epilepsy research, and the signals carry vital information regarding electrical activity in the brain. Among the various deep network architectures that have been broadly applied in learning representations for EEG signals in epilepsy research, CNNs are just one of them. M. Hussain et al, (Alshaya, and, Hussain, 2023). A Nicolet EEG machine samples the EEG data set at 125 Hz. It has been feasible to obtain IEDs, for example spikes, sharps, slow waves, and spike-wave discharges (SWD), by robust preprocessing, feature extraction, and optimal classifiers. Results The results of the developed classifier are tested against clinical impressions provided by experienced epileptologists. R. K. Joshi et al, (Joshi, Kumar, et al. , 2022). Hence, development procedures automatically would support medical professionals with the early identification and diagnosis of epileptic seizures as well as classification. Intelligent diagnostic techniques depend on development that needs for the physiology and pathophysiology of seizure, by using machine learning in classification and identification of symptoms. Adetunji C. O et al, (Adetunji, Olaniyan, et al. , 2023). Design, procedure and strategy Multiple illness patients encounter many problems especially in situations where they have been diagnosed with more than one dysfunction, especially when they use wheelchairs and are sighted. Neelappa R. U. N et al, (Neelappa, and, Harish, 2023).

About thirty percent of epilepsy patients remain unmedicated or unaspirantedly operated upon.The preictal area is the area of the brain showing abnormal activity just before a seizure occurs, often sometime in the minutes leading up to it. Poorani S et al, (Poorani, and, Balasubramanie, 2023).In this respect, this research work presented a novel deep learning methodology for the prediction of successful seizure in iEEG accurately. It used channel increment strategy in conjunction with 1D-CNN. As an initial step, we segmented the iEEG signals using 4-sec sliding windows non-overlap. Wang X et al, (Wang, Zhang, et al. , 2023).

This paper introduces an epilepsy detection algorithm which could reduce the memory requirements of the system by using few characteristics only. This study also introduces a new entropy estimation technique for features extraction so that computation requirement of the algorithm will be reduced using bitwise operations instead of logarithmic ones. Yan X et al, (Yan, Yang, et al. , 2022).This has led to aggressive application of algorithms of machine learning to classify seizure diseases from big data, and thus present neurologists with shortlisted results. According to P. Boonyakitanont et al, (Boonyakitanont, Lek-Uthai, et al. , 2020) many features, data transformations, and classifiers have been researched in order to classify and assess seizures using EEG signals. Raw EEG signals, directly obtained without any preprocessing as input into the system, reduce the amount of computation. Secondly, BNLSTM and CASA retained the time and spatial information of the raw EEG data respectively, M. Ma et al, (Ma, Cheng, et al. , 2021).

This paper introduces a new CNN algorithm along with the common spatial pattern (CSP) algorithm for seizure prediction. According to real signals, Y. Zhang et al, (Zhang, , et al. , 2020)first divide the pre-ictal signals and combine them together to form artificial preictal EEG signals as an approach to the trial imbalance situation between two states.

3 PROPOSED SYSTEM

It includes real-time monitoring, feature extraction, preprocessing, classification, and data acquisition. This research describes a novel method for 1D CNN-LSTM-based epileptic seizure identification .

First, the raw EEG signal data was preprocessed. Next the LSTM and 1D CNN were used in turn. Then 1D CNN combined with the LSTM model identifies epileptic seizures for data processing and getting an accurate outcome as shown below as the result graph.

Now let us see discuss the Dataset Description, 1D CNN, LSTM Structure, and CNN Combined with LSTM Model in 1D which has to be implemented to detect the Seizure after the multichannel signals have been gathered to provide a key improvement in accuracy.

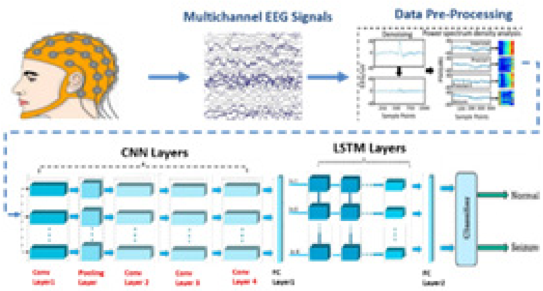

Figure 1 : Block Diagram

3.1 Dataset Description :

This study uses the publicly accessible 500-subject UCI Epileptic Seizure Recognition Data Set. Each of five folders included in the dataset had 100 recordings in total, and every recording sample held 4097 data points that were gathered over a period of 23.5 seconds. UCI preprocesses that dataset and then splits each sample into 23 1-second segments, randomly shuffles the data, and produces 11,500 timeseries EEG's signal datas and samples. There are 5 types of

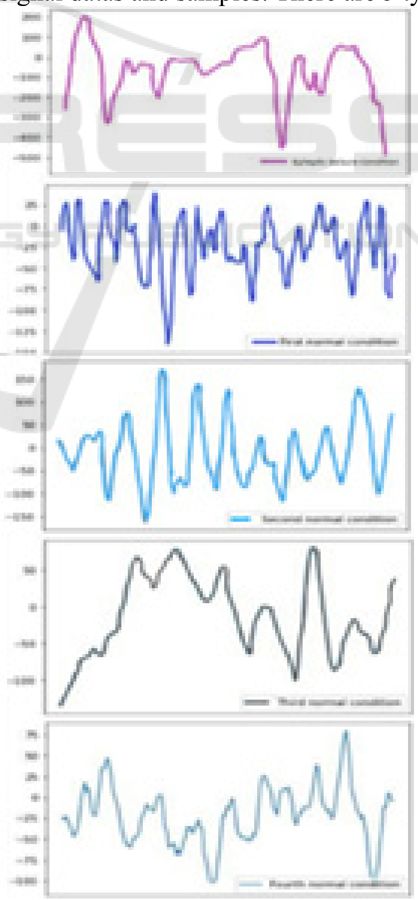

Figure 2: Quartet normal circumstances and the EEG raw signa which is in undulation of one tonic seizure state

medical conditions in the UCI dataset. These include four normal conditions where no seizure takes place and one associated with epileptic seizures. Such conditions include records in which patients undergo seizures, records in which patients are open-eyed during an EEG, records of patients who are closed-eyed during an EEG, healthy brain regions of subjects, and the brain tumor region of the subjects. Despite the fact that the raw EEG signal waveform for the epileptic seizure condition is significantly different compared with normal conditions, many normal situations cannot be differentiated. Hence, both tasks of binary and five-class epileptic seizure recognition are dealt with in this model to estimate the efficiency of the advanced approach appropriately. The dataset is openly accessible to all users.

3.2 1D CNN :

To extract relevant and comprehensive features from 1D time-series data, 1D convolution operations along with multiple filters are applied within the 1D CNN. For this experiment, one dimensional feature maps and convolution filters are utilized that suit the raw EEG properties. The more layers added to the CNN through the incorporation of more convolutional layers, the more progressive the disclosing of sophisticated traits that are reliable and unique in diagnosing epileptic seizures.

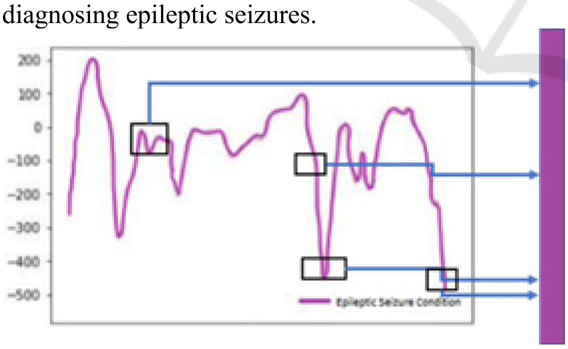

Figure 3: One-dimensional Filtering Process

3.3 LSTM Structure

The LST block consists of four gates: an InputGate-zi controls the information that flows into the cell; a ForgetGate-zf controls the amount of information retained within the cell, the cell state gate z that saves information over time, and the output gate zo, which chooses how much information from the cell will be used for output computation.

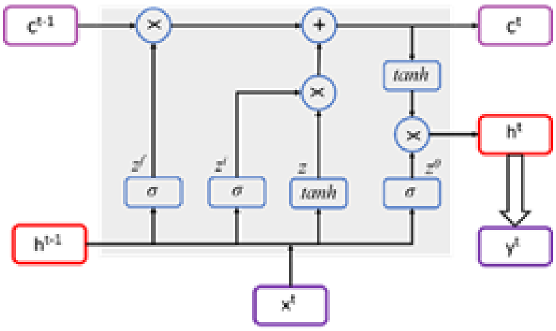

Figure 4 : Layout of the LSTM cell

Every gate consists of an activation function along with a fully connected layer. In addition to this, the LSTM block also contains three outputs: the Current CellState (ct), the Current HiddenState (ht), and the Current Output (yt), whereas there are also three inputs involved, including the PreviousCellState (ct-1), the PreviousHidden State (ht-1), and the CurrentInput (xt). It is the hidden state which produces the current output. The statistical expression is given by

$$z^f = \sigma\left(W^f [x_t, h_{\{t-1\}}]\right)$$

$$z\hat{}i = \backslash sigma(W\hat{}i\ [x\_t, h\_\{t-1\}])$$

$$z = \backslash tanh(W[x\_t, h\_\{t-1\}])$$

$$z^0 = \sigma\left(W^0 [x_t, h_{\{t-1\}}]\right)$$

$$c\hat{}t = z\hat{}f \ \backslash times\ c\hat{}\{t-1\} + z\hat{}i\ \backslash times\ z$$

$$h\hat{}t = z\hat{}0\ \backslash times\ \backslash tanh(c\hat{}t)$$

$$y\hat{}t = \backslash sigma(W\hat{}h\ h\_t)$$

3.4 CNN Combined with LSTM Model in 1D

The advanced approach toward CNN combined with LSTM 1-Dimensional model architecture consists of an InputLayer, followed by four convolutional layers, a PoolingLayer, two LSTM layers, four fully connected layers, and a Softmax OutputLayer. Since 1-Dimensional EEG's indication is in the form of 178x1, it can be supplied directly as the input data to the model. The first convolutional layer, responsible for extraction of features from the raw data, applies 64 1D convolutional kernels sized at 3x1 and strides at 1Convolutional layer followed by a ReLU ActivationLayer helps to begin the Non-Linearity within the reprensentation. Definitions: numerical precision of 1-Dimensional convolution and mathematical definition of ReLU activation:

$$y_j^l = \sigma\left(\sum_{i=1}^{N_{l-1}} conv\,1D\left(w_{i,j}^l, x_i^{l-1}\right) + b_j^l\right)$$

As a result of the 1-Dimensional convolution and ReLU Activation, 64 176 x 1 feature maps are generated. Then the output is passed to a layer called 1D max-pooling. This represents the whole mathematical formula of the process of 1D max-pooling.

4 EXPERIMENTAL RESULTS

Ninety percent of the data available in this experiment was used to train the 1D convolutional LSTM, 1D CNN, and DNN models. Ten percent remained as test data. Dropout prevented overfitting during training for 100 epochs. At random, scrambling happened before feeding these models the data. The accuracy for the final training and test data sets of every epoch was calculated while evaluating the model's generalization capacity and looking out for overfitting. Finally, after 10 training cycles, if generalization no longer increased, checkpoints were created and the learning rate was changed. Major Tasks for the Study This paper considered the development of tasks concerning recognition of seizure, first, in binary and then, as 5-class. While five-class task required the identification of seizures and normal situations, such as both opened eyes and closed eyes, EEG activity from wholesome mental state areas, and EEG's motion from the malignancy affected region, the binary work just required the identification of seizures and normal conditions.

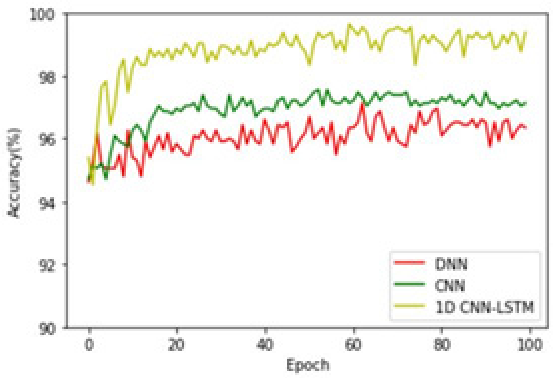

Figure 5 : Assessing each of these output of the models on the Binary Recognition test

4.1 Binary Recognition Task:

Figure 5 of this chapter depicts the 1-Dimensional CNN combined LSTM model's performance on the task of Binary Recognition. This compared the results produced by the proposed model to the yields of two other deep learning models applied in the space of utilization of epileptic seizure, namely DNN and standard CNN. The figure clearly states that though the DNN model converged the fastest, loss parameters for training and testing the suggested model were found to be less, hence increasing the accuracy. The typical CNN performed similarly in training compared with the proposed model, however it performed much worse in testing. Since this model achieved the best accuracy while testing to be done across most of the training period, Figure 6 further shows that the advanced 1-Dimensional CNN combined LSTM Model outperforms the CNN and then DNN Models. However, all three models are compared in Table 1 and it is shown how the suggested model is better in terms of seizure activity validation.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{F1 Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Table 1: The DNN, CNN, and the suggested 1-Dimensional CNN combined with LSTM Model's relative efficiency in handling binary classification problems

Methods	Accuracy	Precision	Recall	F1-score
CNN	94.17%	93.34%	91.25%	0.9319
DNN	97.34%	92.17%	84.70%	0.9227
Proposed Model	99.40%	98.40%	98.37%	0.9754

TN and FN state the number of seizures that arose accurately classed and inaccurately classified, respectively; and non-seizure activities that were not classified as seizure activities are indicated by TN. The count of any other sort of different kind of a seizure task which is mistakenly labeled is given by FP. The proposed LSTM and 1D CNN model outperforms the normal CNN and DNN models since it presents high F1-score, precision, recall, accuracy values at 0.9754, 98.40%, 98.37%, and 99.40%, respectively. Values outperform the regular CNN and DNN models with increases in F1-score as 0.0435 and 0.0527; precision: 5.06% and 6.23%; recall: 7.12% and 13.67%; as well as increases in accuracy: 5.23% and 2.06%

Table 2: The Five-Class classification task variation of CNN, DNN, and the suggested 1-Dimensional CNN combined with LSTM model.

Methods	Accuracy	Precision	Recall	F1-score
CNN	64.40%	65.74%	66.77%	0.6775
DNN	67.74%	69.43%	67.57%	0.6641
Proposed Model	81.00%	81.77%	82.70%	0.8174

4.2 FiveClass Recognition Task:

Figure 7 presents the results of the three models applied to the FiveClass Identification operation, and it is evident that the 1-Dimensional CNN combined LSTM model exhibits the efficient identification of variation compared to the DNN and CNN models. This conclusion is further supported by Table 2, which shows that the advanced approach outshines the several two models in Accuracy, Precision, Recall, and F1-score.

5 RESULT

Capturing the 1D Convolution Operation from the raw EEG data tends to identify the seizure and non-seizure circumstances by considering their temporal characteristics. Normal conditions are represented by four classes, where the waveform pattern of the EEG is smoother and more periodic. The case of the epileptic seizure condition is introduced as containing strong spikes and anomalies. Long-term dependencies in the time series data are followed by making use of the LSTM block structure. Models such as CNN, LSTM, and CNN-LSTM showed high testing accuracies for the binary recognition challenge of seizure versus non-seizure. CNN-LSTM generally outperforms the others. On the other hand, model performances were varied for the five-class recognition challenge. In this case, 1D CNN-LSTM seems to offer superior cross-class generalization. The average accuracies for DT, DNN, CNN, CNN-LSTM, and SVM, k-NN, and SVM, among others, indicated that deep learning models—especially CNN and CNN-LSTM—were drastically better than a more traditional model such as k-NN and SVM.

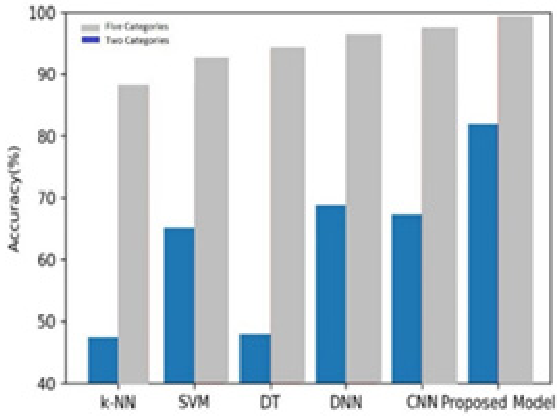

Figure 6: The mean precisions of 1-Dimensional CNN combined with LSTM, k-NN and DNN approaches

6 CONCLUSION

From this, the suggested model made use of an LSTM network combined with a CNN for the analysis of Epileptic Seizures by using the EEG's indications. The LSTM approach would classify the sequential EEG signals that were recognized after the 1D CNN had gotten the features out from the EEG data, thus completing the whole end-to-end network. So, the model was tested on the two different recognition tasks, which include binary and five-class recognition along with the UCI epileptic seizure recognition dataset. It depicted excellent performances for both five-class and binary recognition, where the five-class recognition was showing an accuracy of 82.00%, whereas binary recognition resulted in 99.39%. The proposed model showed a key improvement in accuracy compared to some other techniques including DT, CNN, SVM, DNN and k-NN with the help of 3.04%, 2.26%, 7.09%, 5.43%, and 5.35% above the accuracy of the binary recognition challenge, respectively.

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