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The Deep Learning Based Epileptic Seizure Detection Using 2-layer Convolutional Network with Long Short-Term Memory

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Abstract: Epilepsy is a pervasive chronic neurological disorder characterized through irregular electrical discharges in the brain which causes seizures. Epilepsy seizure is a disorder that affects the brain cells with an influence on an effectiveness of central nervous system. Electroencephalography (EEG) is a majorly utilized method for epileptic seizure detection and diagnosis. In this research, Deep Learning (DL) methods of 2-layer Convolutional Neural Network (CNN) with Long Short-Term Memory (LSTM) are proposed for an automatic detection and diagnosis of an epileptic seizure. In the pre-processing phase, a Butterworth filter method of order 2 is used to remove noise in the EEG signal. The 2-layer CNN is used for the process of feature extraction. In 2-layer LSTM, one layer is utilized to perform short-term dependencies, while another layer is utilized to perform long term dependencies. In the end, the proposed method classifies seizures into epileptic and non-epileptic. The results demonsrates that the proposed method delivers performance metrics of better accuracy of 99.90% and sensitivity of 90.06% using CHB-MIT and Bonn datasets which contains EEG signals as compared to the existing methods like CNN and Epilepsy-Net.

Keywords: Butterworth filter, Convolutional neural network, Deep learning, Electroencephalography, Epileptic seizure, Long short-term memory.

1. Introduction

Epilepsy seizures are sudden bursts of electrical activity in the brain that disrupt its normal functioning [1]. Epilepsy is considered through recurrent, unprovoked seizures, affecting individuals of all ages with a substantial effect on the quality of life. It modifies the natural electrical activity among the brain's neurons which leads to different clinical manifestations based on the affected region of the brain [2, 3]. The harshness of Epilepsy is based on the total amount of neurons affected in the regions of the brain. Worldwide, millions of people are diagnosed with epilepsy with the greatest impact on infants as well as adults between the age of 65 to 70 [4]. Therefore, identifying an effective diagnosis tool for epileptic seizure detection is examined as a significant problem. An epileptic seizure is categorized into two groups of focal and generalized epilepsy [5]. Generalized epilepsy begins in one region of the brain and spreads to other areas through an extensive neuronal network. Conversely, focal epilepsy is constrained to a particular area of the brain, with seizures limited to that area. Symptoms vary based on the affected region and do not initially spread across the entire brain [6, 7].

Electroencephalography (EEG) is a non-invasive manner developed for the effective detection of epileptic seizures [8]. Recording brain activities through EEG signals often contain a crucial amount of random noise, which impacts accuracy of the model [9]. But the manual seizure diagnosing is time consuming and expensive due to the stochastic and nonstationary nature of EEG signals [10]. Hence, it is important to develop an automated seizure diagnosing system to help experts in examining the EEG signals [11]. The EEG signals generally involve a number of channels and artefacts which arises to challenges and difficulties for specialists during the process of diagnosis. To overcome these problems, an automatic diagnosis based on Deep Learning (DL) can support to enhance the performance of the epileptic seizure diagnosis [12, 13]. The DL based algorithms are employed for feature extraction and fusion approaches for epileptic seizure diagnosis. An aim of this paper is to design and implement an efficient approach for epileptic seizure detection using DL techniques approaches [14, 15].

The significant highlights of this research are discussed as follows:

- This research proposes a model that utilizes Neural Network classification algorithms and Deep Learning for seizure detection.
- 2-layer CNN-LSTM is proposed in which one layer is utilized to perform short-term dependencies and another layer is used to perform long term dependencies. A Butterworth filter is utilized to remove noise in EEG signals in the pre-processing step.
- The 2-layer CNN is used to extract the relevant features from epileptic seizure. At the end of classification, the result of the 2-layer LSTM is classified into epileptic and non-epileptic.

This paper is arranged as follows: Section 2 provides the literature review, Section 3 illustrates the proposed methodology of this research, while Section 4 demonstrates the results and discussion, and Section 5 demonstrates the conclusion of this research.

2. Literature survey

The related works of epilepsy classification are given in this section along with its merits and limitations.

Hassan [16] introduced an automatic feature extraction approach based on an integration of CNN and Machine Learning (ML) approaches. A Butterworth filter approach and Discrete Wavelet Transform (DWT) were used in pre-processing for classifying the EEG into multiclass, multichannel and multisubject. The introduced method was selected to minimize a dimensionality of a data through a utilization of correlative data for the identification of relevant features. The selected features were fed to the ML for classifying the signals. This method enhanced the capability of generalization of the classifier. However, the introduced approach faced challenges in generalizing over various subjects due to variations in EEG patterns, results in poor performance.

Malekzadeh [17] developed a Computer Aided Diagnosis (CAD) for an automatic diagnosis of epileptic seizures. Initially, this approach utilized the band-pass filter with 0.5-40HZ cut-off frequency to eliminate objects of EEG data, while Tunable-Q Wavelet Transform (TQWT) was deployed to decomposition. Then, linear and non-linear features were extracted according to fractal dimensions. The CNN-RNN through number of layers were utilized for the classification process. CNN-RNN achieved a greater level of accuracy than all methods. However, the performance of TQWT heavily depends on parameters selection and redundancy, which required careful tuning. Inappropriate parameter settings affecting the quality of the extracted features.

Lebal [18] presented Epilepsy-Net based on the DL in EEG signal to detect epileptic seizures with non-epileptic seizures without handcraft feature extraction. In Epilepsy-Net approach, the 1D CNN, Recurrent Neural Network (RNN), and Attention Mechanism were combined and depicted by ResNet and the Inception architectures of the CNN. The convolutional attention block had an efficient impact on EGG signal classification. A deep Transformer model was generated by a minimum number of epileptic patients. However, Epilepsy-Net does not rely on handcrafted features, it was still sensitive to the preprocessing steps applied to the EEG data.

Shoka [19] developed an effective encrypted EEG data classification and identification approach utilizing Chaotic Baker Map and Arnold Transform method by CNN. The time series of the EEG was modified into 2D spectrogram image and encrypted by Chaotic Baker Map and Arnold Transform approaches. The obtained outcome was then provided for the CNN-based transfer learning approaches. The proposed method was accurate and helpful to health professionals handling epileptic patients. However, the process of encrypting EEG data potentially loses important features which are complex for accurate classification. This negatively impacts the CNN's ability to learn and identify patterns.

Duan [20] introduced an automatic approach to epileptic seizure according to deep Metric learning. Two 1D convolutional embedding approaches were developed as deep feature extractors for both single and multi-channel EEG signals. These approaches utilized a deep metric to map inputs into an embedding space, performing a stage-wise training scheme that incorporated an extended classification layer. The vote strategy method was used to enhance the efficiency of the embedding approaches. However, an effectiveness of the 1D convolutional embedding approaches vary across different EEG datasets.

Usman [21] developed a prediction of epileptic seizure approach, which predicted the preictal state before the onset of seizure using EEG. The empirical model decomposition approach was utilized to eliminate the noise. The Generative Adversarial Networks (GAN) were used to develop preictal data for performing the class imbalance issues. The CNN with three layers were utilized for the extraction of features and LSTM was utilized for classification among preictal and interictal conditions. However, the model's dependence on synthetic data generated by GAN affected its capability to generalize to unseen data.

Singh and Malhotra [22] implemented a cloud-fog integrated neuro-care method, which performed temporal analysis of raw EEG with DL algorithms to detect epileptic seizures. This approach was performed with a greater variance-based channel selection process to select raw EEG signals, pursued through filtering and segmentation into various limited-time temporal segments. The CNN, RNN, and stacked autoencoder DL classifiers were used for the classification process. However, the performance of proposed method was extremely sensitive to the quality of EEG data. Noise in the signals adversely affected the embeddings, results in poor reduced seizure detection accuracy.

3. Proposed methodology

In this research, epileptic seizure detection is developed by using the 2-layer CNN-LSTM. The proposed method involves two different datasets namely, CHB-MIT and BONN are collected. The pre-processing was carried out using Butterworth filter with 2 orders, while classification was done using 2-layer CNN-LSTM. Fig. 1 depicts the epileptic seizure detection using 2-layer CNN-LSTM.

3.1 Dataset acquisition

The developed research is analysed using two EEG signal datasets of CHB-MIT [23] and BONN [24]. A detailed description of these datasets is given as follows.

3.1.1. CHB-MIT dataset

The CHB-MIT is an open-source EEG data developed by Children's Hospital Bostan and the Massachusetts Institute of Technology (MIT). It involves non-invasive recordings from 23 paediatric patients of male and female. EEG recordings are recorded utilizing a 10 to 20 system at the sampling range of 256Hz with 16-bit resolution. A binary classification approach is examined in a total of 1600 and 800 cases for each category. Each case has a length of 5.0s, consisting of 1280 sampling points per channel. Fig. 2 illustrates the EEG signal of CHB-MIT dataset.

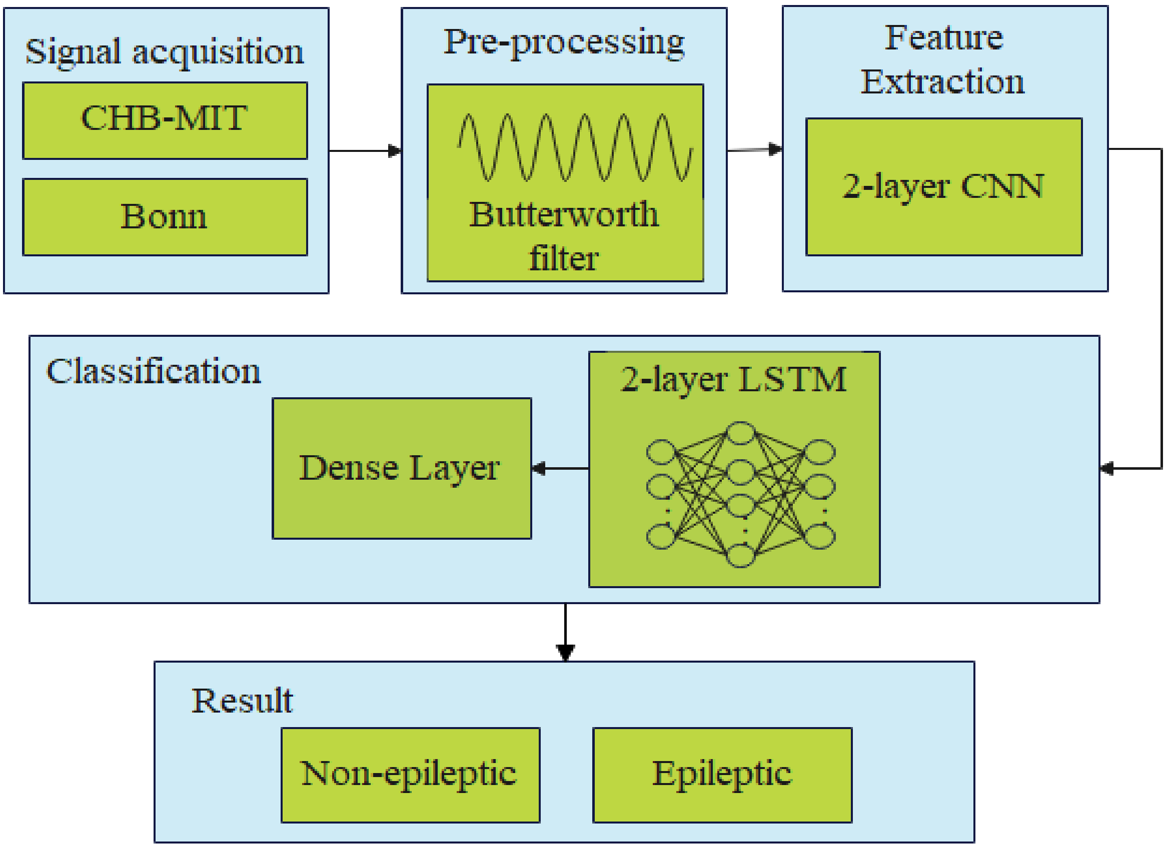

Figure. 1 Block diagram of the proposed method

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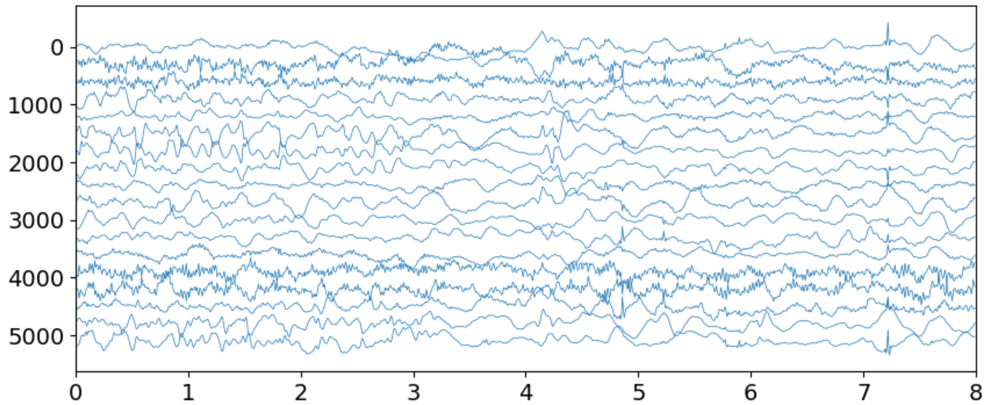

Figure. 2 EEG signal of CHB-MIT dataset

3.1.2. Bonn dataset

The Bonn dataset is recorded from Bonn University and is majorly utilized in the region of epileptic seizure determination and detection. It is a publicly obtainable data with 500-EEG single-channel data and is sampled with 173.6 Hz by 23.6 duration. This dataset considers 5 classes of S, F, N, O and Z by 100 channel recordings in every class. Intercranial electrodes are utilized with 5 patients, endured from epilepsy to obtain the data of S, F and N classes. A relaxed and awaked state is offered to the class of O and Z EEG region. Fig. 3 depicts the EEG signal of Bonn dataset.

3.2 Pre-processing

Original EEG signals are acquired from a database with noise, which controls EEG signals with low-frequency spectrum and leads to the loss of some helpful data. The frequency range of this dataset is 0-86.8 Hz and if the frequencies are greater than 50Hz, it is considered as noise. Hence, pre-processing of signals is essential to eliminate an unnecessary frequency. In this, 5 sets of EEG signals acquired from the collected dataset are transmitted by zero-phase of band-pass filter with the 2nd order. The EEG recordings from datasets are transmitted through the Butterworth filter, which filters out a slower and higher frequency noise characteristic, and restricts a frequency signal data to a range of [0.5, 50] Hz. Finally, the pre-processed EEG signals are categorized three DNN models one after another.

3.3 Feature extraction

To achieve an FE step, a pre-processed signal is provided for feature extraction to extract the features in the dataset. The extraction of the feature is an actual device for extracting significant relevant features for dimension reduction. The feature extraction is utilized to minimize the problems of time complexity, over-fitting, decreases the number of required resources to handle large datasets for enhancing the accuracy of the model. In this phase, the network layers are utilized to extract the features and these are given to the classification process.

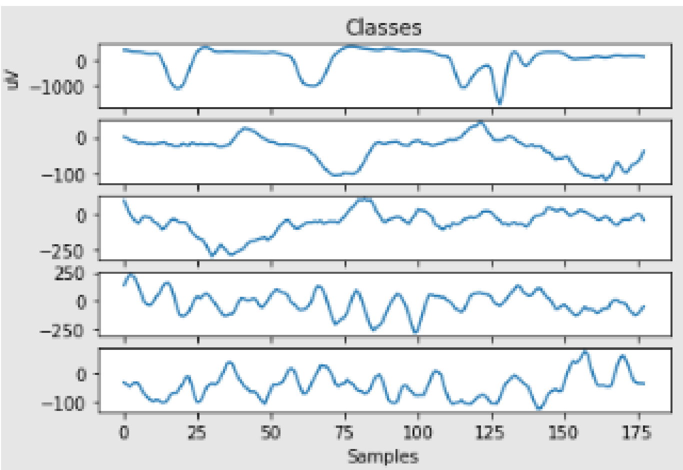

Figure. 3 EEG signal of Bonn dataset

3.3.1. 2-layer convolutional neural network

In DL, CNN [25] is a successful classification approach in Seep Neural Network (DNN) structures in a number of fields like image classification, Computer Vision (CV), and speech analysis. The significant aim of CNN is employed for developing a deeper network through smaller number of parameters. CNN is a positive method in numerous applications and the final output of CNN is entrenched in bias as well as weights of earlier layers, which are expressed in the following Eqs. (1) and (2).

$$\Delta W_l(t+1) = -\frac{x\lambda}{n} W_l - \frac{x}{n}\frac{\partial C}{\partial W} + m\Delta W_l(t) \quad (1)$$

$$\Delta B_l(t+1) = -\frac{x}{n}\frac{\partial C}{\partial B_l} + m\Delta W_l(t) \quad (2)$$

Where, C, m, λ, x, B, t, n, l and W represent the function of cost, momentum, parameter of the regularization, leaning rate, bias, updating step, number of training samples, number of layers and weight.

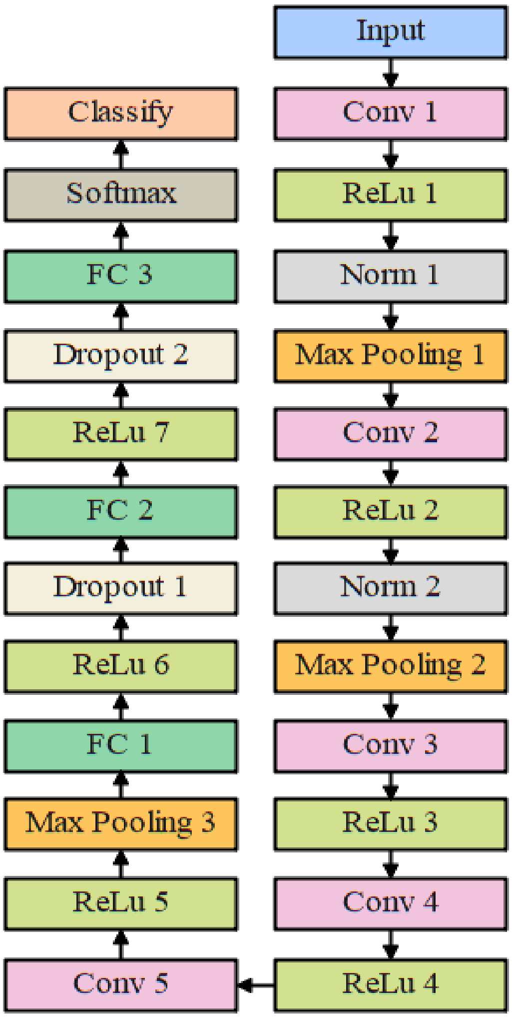

Figure. 4 CNN Architecture

$\Delta W_l(t+1)$ demonstrates the change in the weight for the lth layer at the next time step $(t+1)$. $\frac{\partial C}{\partial W}$ demonstrates a gradient of the cost function C with respect to the weights W. $\Delta B_l(t+1)$ demonstrates the change in the bias for the lth layer at the next time step $(t+1)$. $\frac{\partial C}{\partial B}$ demonstrates the gradient of the cost function C with respect to the bias B respectively.

The CNN contains multiple layers of input, convolutional, pooling layer, Fully Connected (FC) and output layer, these are associated through the learned weights and biases. This layer plays an important function in CNN work through utilizing the kernels as per size, padding, and number. Fig. 4 demonstrates the basic architecture of CNN.

- **Convolutional layer:** The convolutional layers are the elementary units utilized in CNN which is called filters. A recurrent form of these filters to an input data through the sliding window results in a feature map. The outcome of this is expressed in Eq. (3).

$$O_c = \sum_{i=0}^{N-1} x_i h_{c-i} \quad (3)$$

Where x demonstrates the signal, h denotes a filter, N is a number of essentials in x. O_c demonstrates the Convolution operation at index C. x_i - ith element of input signal x; h_{c-i} demonstrates the Convolution kernel applied at index $c-i$.

- **Pooling layer:** An outcome of the convolutional layer is fed to the pooling layer. These establish various feature maps for small signals in the feature locations. This problem is overcome by signal processing using down sampling. By performing this approach, the lower-resolution data version discards the fine details of the data.
- **Fully Connected (FC) layer:** A pooling layer outcome is fed to the FC layer. A convolution with pooling is a beginning procedure for CNN. The outcome of this procedure is consumed into the FC neural network architecture, which controls the output of classification. A variation of several neurons occurs in a last layer of FC layer are epileptic and non-epileptic. The extracted feature from CNN is then provided to the LSTM approach.

3.4 Classification

The output of the extracted feature from the 2-layer CNN is provided as input to the classification process. In this phase, the different epileptic seizures are classified utilizing 2-layer Long Short-Term

Memory architecture. A detailed description of this method is discussed as follows.

3.4.1. 2-layer long short-term memory

The LSTM is utilized for time series forecasting. A model that learns long-term temporal dependencies is an important feature to be estimated in time series data. The 2-layer LSTM is introduced in this method. One layer is used for short-term dependencies while the other is used for long-term dependencies. The LSTM has various memory cells in the hidden layers for read, write and delete operations, which are permitted by three gates of input, output and forget gate. The data transfers from one to another state through the cell states. The cell state and hidden state are utilized in obtaining data for processing in the following state. Control what data is moved to be stored in a cell state (c_t). An output gate (o_t) identifies what data from the cell state is utilized as output (o_t), whereas the forget gate (f_t) examines what data will be passed away from the cell state (c_t). With the utilization of these gates, both long and short-term time series are collected from the LSTM cells. Fig. 5 illustrates the general architecture of LSTM.

- **Input Gate:** It becomes a significant part in the cell state's changes and updates. A current input as well as prior hidden state are obtained by sigmoid function and $tanh$ function. The sigmoid function compresses the values among 0 and 1, where, 0 and 1 represent completely deprived and holding values. The $tanh$ function helps in allocating a network through the flattened values among -1 and 1. The output of $tanh$ and sigmoid function is accumulated, providing the desired outcome as expressed in Eqs. (4) and (5).

$$i_t = \sigma\,(W_i h_t - 1 + b_i) \tag{4}$$

$$g_t = tanh\,(W_g h_t - 1 + b_g) \tag{5}$$

- **Forgot Gate:** The significance of the sigmoid layer lies among 0 and 1, an indicator of the amount of data permitted to be moved to the other layer, called forgot gate. This layer is managed by data maintenance or loss. The forgot gate can be expressed in Eq. (6).

$$f_t = \sigma\,(W_f h_t - 1 + W_f h_t) \tag{6}$$

- **Cell State:** The cell state is significant to LSTM, represented by C. It is passed to the whole construction through less direct inter relation. These effects design a data pass while keeping it unmodified. However, a data flow is changed from one to another, discretely handled through a surround known as gates. Initially, an outcome of forgot gate is in a state of vectors that obtain pointwise multiplication through prior cell state, providing an intermediate cell state. At the same time, the extension of pointwise addition occurs between an output of input gate as well as an intermediate cell state. The cell state is expressed in Eq. (7).

$$C_t = f_t * C_{t-1} + i_t * g_t \tag{7}$$

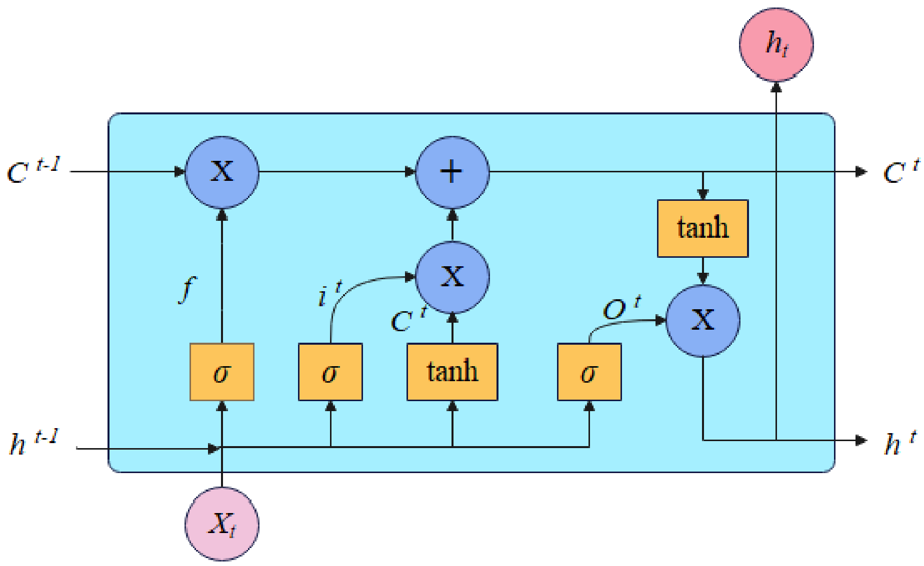

Figure. 5 LSTM Architecture

- **Output Gate:** It becomes a significant part in examining the following hidden state. A data about an input of the model is embraced in the hidden state. It is significant for prediction and classification. An outcome of output gate is developed during a current input as well as prior hidden state are moved by sigmoid function. A present hidden state contains two inputs: outcome of output gate and another one is developed during the present cell state is forwarded by $tanh$ activation. The multiplication is followed between the inputs, results to the present hidden state. The output gate is expressed in Eqs. (8) and (9).

$$O_t = \sigma\,(W_o h_t - 1 + W_o h_t) \tag{8}$$

$$h_t = O_t * \tanh\,(C_t) \tag{9}$$

Where, σ is logistic sigmoidal function, W_i, W_f, W_o are network weights matrices, and h_t, $h_t - 1$ are the hidden states. The outcome of these layers is provided to the dense layer to effectively classify the EEG signal.

3.4.2. Dense layer

The 2-layer CNN-LSTM contains CNN for feature extraction and LSTM for the classification. An initial layer is the convolutional layer used for short-term dependencies and another layer is used for long-term dependencies. An input data is 23×1 and the number of filters utilized are 14, while the kernel size is 6. The max-pooling layer is subsequent by LSTM layer with 100 cells and dropout layer which supports in enhancing the effectiveness. These are succeeded by a flattened layer and 5 dense layers. A Rectified Linear Unit (ReLU) is used in the first 4 dense layers, as well as a sigmoid activation function that is utilized in a final dense layer.

4. Experimental results

The proposed method is executed on Anaconda Navigator 3.5.2.0 (64-bit). Python 3.10.12 software tools and system specification with Windows 10 (64-bit) operating system, Intel core i7 processor, and 16GB RAM. The proposed epileptic seizure classification method utilizes several performance metrics to estimate the system performance. The assessment metrices of accuracy, precision, sensitivity/Recall, and F1-score are utilized for estimating the proposed method. The mathematical expression for each metric is described as the following Eqs. (10) to (13).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{10}$$

$$Sensitivity/Recall = \frac{TP}{TP+FN} \tag{11}$$

$$Precision = \frac{TP}{TP+FP} \tag{12}$$

$$F1 - score = \frac{2TP}{2TP+FP+FN} \tag{13}$$

Where, TP demonstrates the True Positive, TN illustrates the True Negative, FP is the False positive, FN refers to the False Negative;

4.1 Performance analysis

This section verifies the dependability of proposed 2-layer CNN-LSTM approach using Bonn and CHB-MIT dataset and evaluates its performance based on accuracy and loss function in terms of the number of epochs. Fig. 6 illustrates the proposed method’s accuracy and loss function on the CHB-MIT dataset. Fig. 7 illustrates the proposed method’s accuracy and loss function of the Bonn dataset.

Fig. 6(a) represents the exponential curve for accuracy with the CHB-MIT dataset, which obtains flat return after an initial rise. Fig. 6(b) represents the exponentially decreasing curve for loss function on the CHB-MIT dataset in terms of the number of epochs (100) obtained at time of validation of the proposed method. The loss function from this dataset obtains minimum loss value with enhancements in epochs. Hence, this representation of accuracy and the proposed 2-layer CNN-LSTM model are provided with temporal EEG segments of minimum time to obtain accurate epileptic seizure detection.

In Fig. 6(c) illustrates the performance of the proposed method of CHB-MIT, as shown in the form of a confusion matrix. In the first class, 1831 samples are correctly predicted and 15 samples are not correctly predicted. In the second class, 437 samples are correctly predicted while 17 samples are not correctly predicted. Hence, the misclassification rates of 15% and 17% are obtained for the non-epileptic and epileptic classification classes, respectively. Therefore, the accuracy plot and the confusion matrix act as evidence of better performance of the Transformer model.

Fig. 7(a) represents the exponential curve for accuracy with the Bonn dataset, which obtains the flat return after an initial rise. Fig. 7(b) represents the exponentially decreasing loss function with Bonn dataset with respect to number of epochs (100) taken at the time of validation of a proposed method.

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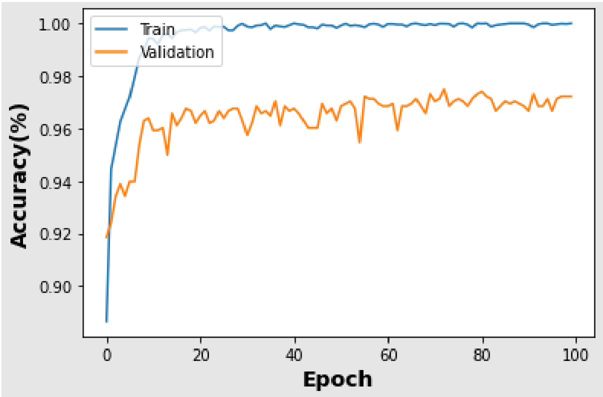
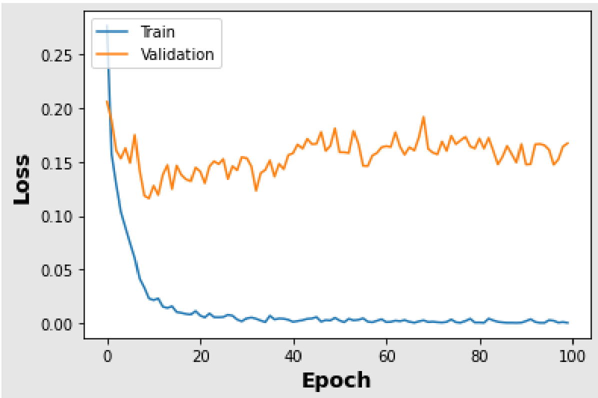


(a)



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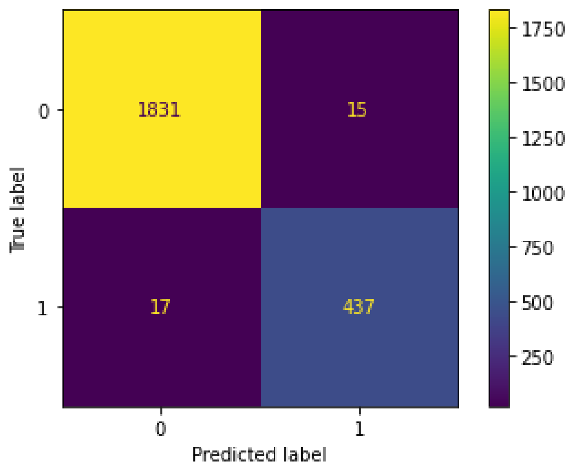
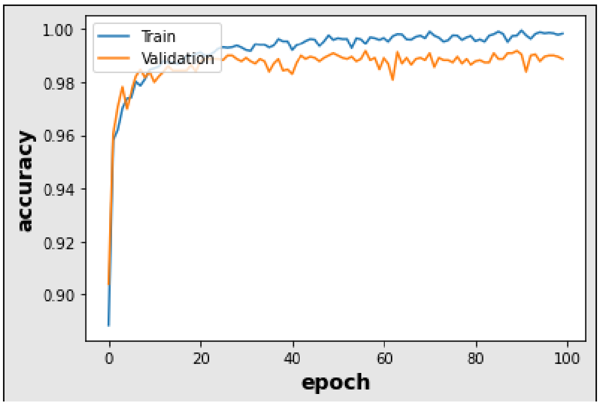
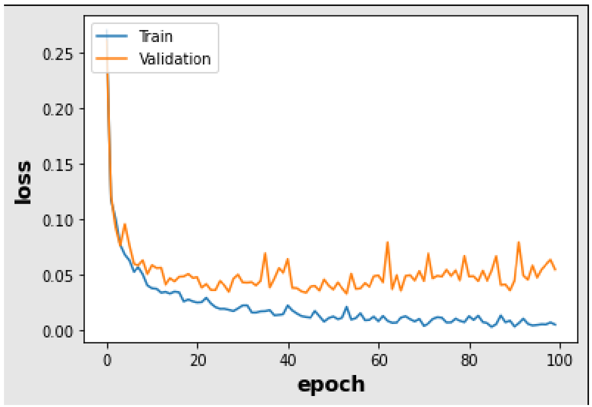


(c)

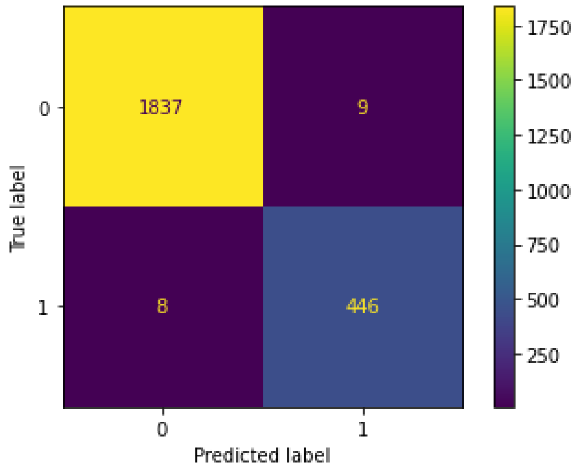
Figure. 6 Performance of proposed method in terms of accuracy, loss function and confusion matrix of CHB-MIT dataset



(a)



(b)



(c)

Figure. 7 Performance of proposed method in terms of accuracy, loss function and confusion matrix of Bonn dataset

The loss function from this dataset obtains minimum loss value with enhancements in epochs. Hence, this illustration of accuracy and the proposed 2-layer CNN-LSTM model are provided with temporal EEG segments of minimum time to obtain an accurate epileptic seizure detection.

In Fig. 7(c) illustrates the effectiveness of the proposed method of Bonn dataset, shown in the form of a confusion matrix. In the first class, 1837 samples are correctly predicted and 9 samples are not correctly predicted. In the second class, 446 samples are correctly predicted and 8 samples are not correctly predicted. Hence, the misclassification rates of 9% and 8% are obtained for the non-epileptic and epileptic classification classes. Therefore, the accuracy plot and confusion matrix evidence a superior effectiveness of Transformer model.

Table 1. Comparative Analysis using CHB-MIT dataset

Author	Method	Accuracy (%)	Sensitivity/Recall (%)	Specificity (%)	Precision (%)	F1-score (%)
Hassan [16]	CNN	97.1	N/A	N/A	N/A	N/A
Lebal [18]	Epilepsy-Net	98.22	93.92	N/A	89.78	91.80
Duan [20]	Deep Learning	86.68	79.64	93.71	N/A	N/A
Proposed	2-layer CNN-LSTM	99.90	98.06	98.89	98.72	98.66

Table 2. Comparative Analysis using Bonn dataset

Author	Method	Accuracy (%)	Sensitivity/Recall (%)	Specificity (%)	Precision (%)	F1-score (%)
Hassan [16]	CNN	94.00	90.20	N/A	N/A	N/A
Lebal [18]	Epilepsy-Net	97.00	97.57	N/A	97.71	97.43
Duan [20]	Deep Learning	98.60	97.20	100	N/A	N/A
Proposed	2-layer CNN-LSTM	99.90	98.06	100	98.72	98.66

4.2 Comparative analysis

This section demonstrates the comparison of the proposed 2-layer CNN-LSTM in terms of number of performance metrics. Table 1 displays the comparative analysis using CHB-MIT dataset. Table 2 presents the comparative analysis on the Bonn dataset. The outcomes of the proposed method are seen to be commendable, as opposed to the existing methods.

4.3 Discussion

This section explains the limitations of existing methods over the proposed method's strengths. The limitations of the existing methods: CNN [16] faced challenges in generalizing over various subjects due to variations in EEG patterns, results in poor performance. The Epilepsy-Net [18] does not rely on handcrafted features, it was still sensitive to the preprocessing steps applied to the EEG data. In Deep learning [20], the effectiveness of the 1D convolutional embedding approaches vary across different EEG datasets. To overcome these challenges, this research aims to proposes the 2-layer CNN-LSTM approach for the epileptic seizure utilizing the EEG signals. This approach significantly integrates the advantages of CNN and LSTM networks, allowing it to surpass in feature extraction process. The CNN layers are proficient at capturing spatial features from the EEG signals, while the LSTM layers are accomplished at modelling the temporal dependencies, which are important for accurately identifying seizure patterns over time. The proposed 2-layer CNN-LSTM approach achieves a commendable outcome. It outclasses the pre-existing methods with an accuracy of 99.90%, and sensitivity/recall of 98.06%, using CHB-MIT and Bonn datasets. The proposed 2-layer CNN-LSTM approach illustrates the better performance compared to existing models, achieving higher accuracy, sensitivity, precision, and F1-scores across CHB-MIT and Bonn datasets. This enhanced performance indicates a more reliable and robust detection of epileptic seizures, even in challenging conditions such as class imbalance or limited data availability.

5. Conclusion

In this research, Deep Learning (DL) methods of 2-layer CNN with LSTM called 2-layer CNN-LSTM is proposed for an automatic detection and diagnosis of an epileptic seizure. In the pre-processing step, the Butterworth filter method with order 2 is used to remove the noise in the EEG signal. In 2-layer LSTM, one layer is used for short-term dependencies while the other is utilized for long-term dependencies. The outcome of the 2-layer CNN-LSTM is fed to the dense layer for an effective classification. In the end, the outcomes of the proposed method are classified as epileptic or non-epileptic. The results demonstrates that the proposed delivers

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commendable performance on metrics of accuracy, sensitivity, precision and F1-score, with respective values of about 99.90%, 90.06%, 98.72%, and 98.66%, ensuring superior results in comparison to the existing methods: CNN, LSTM and CNN-RNN. In the future, the proposed attention approach will be employed with other neurological pathologies utilizing EEG signals.

Notation:

Variables	Description
C	Cost function
m	Momentum
λ	Parameter of the regularization
x	Leaning rate
B	Bias
t	Updating step
n	Number of training samples
l	Number of layers
W	Weight
$\Delta W_l(t+1)$	Change in the weight for the lth layer at the next time step $(t+1)$
$\frac{\partial C}{\partial W}$	Gradient of the cost function C with respect to the weights W
$\Delta B_l(t+1)$	Change in the bias for the lth layer at the next time step $(t+1)$
$\frac{\partial C}{\partial B}$	Gradient of the cost function C with respect to the bias B respectively
O_c	Convolution operation at index C
x_i	ith element of input signal x
h	Filter
N	Number of elements in x
h_{c-i}	Convolution kernel applied at index $c-i$
i_t , f_t , and O_t	Input, forgot and output gate; C_t represents the cell state
g_t	Candidate cell state
b_i and b_g	Bias term associated with the input gate and candidate cell state
σ	Logistic sigmoidal function
W_i, W_f, W_o	Network weights matrices of input, forgot and output gate
$h_t, h_t - 1$	Hidden states
$*$	Element-wise multiplication
tanh (C_t)	Hyperbolic tangent of the C_t

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, have been done by 1st author. The supervision and project administration, have been done by 2nd author.

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