Automatic Identification of Epilepsy Seizures from EEG Signals Using a Hybrid CNN and LSTM Model

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***Abstract*—The neurological illness known as epilepsy is characterized by a disruption in the normal functioning of the brain and can be found in severe cases. It is estimated that more than 10 percent of the whole population across the entire planet is affected by this ailment Every single day. When acquiring information on the brain's electrical activity, electroencephalograms, often known as EEGs, are utilized rather frequently by researchers. In this paper, an end-to-end system is proposed that utilises a combination of two deep learning models, namely Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTM), to classify electroencephalogram (EEG) data of epilepsy disordered people into three distinct categories: preictal, normal, and seizure. The findings of the experiment were obtained by making use of a dataset that is well-known and easily available, which Bonn International University provided. Within this CNN-LSTM classification model, the tasks of feature extraction, selection, and classification are all carried out in an automated fashion. Because of this, there is no longer a requirement for a manually devised methodology for feature extraction. In this study, the performance of the CNN-LSTM model is studied and assessed with relation to specificity, sensitivity, and accuracy. This is accomplished through the usage of the 10-fold cross-validation approach. The accuracy is 99.33%, the sensitivity is 99.33%, and the specificity is 99.66% concurrently, as indicated by the findings that were gathered while the trials were being carried out and the data that were collected. The results of our research indicate that deep learning approaches are the most appropriate choices for categorization when compared to other methods that are currently deemed to be state-of-the-art.**

***Keywords*—** Epilepsy, LSTM, Machine learning, deep learning, classification.

Introduction

EEG signals are not continuous, they display nonlinearity, and they are very complicated. They are likewise nonlinear in their behavior. This trait makes it more challenging to visually examine and grasp the EEG data. This is because of the nature of the signals. The researchers and academics have carried out activities such as feature extraction, statistical analysis, ranking of features, and classification by contrasting the results and performances of a large number of different classifiers. This is about the reviews [1] that have been carried out by professionals in the field of research and academia. Standardized, well-organized, and structured stages make up the totality of the process. These phases each have their own unique characteristics. Furthermore, to solve the problems that are related to the diagnosis of epilepsy, several different deep-learning algorithms have been created and implemented. The classification of seizures has been improved, which has allowed for this to be performed. In the field of electroencephalogram (EEG) prediction and classification, deep learning has recently been utilized. Deep learning is an improved form of artificial neural networks (ANN), which has been introduced in recent years. An accurate identification of normal, seizure, and the preictal class was accomplished by Acharya et al. [2] through the utilization of a Deep Convolutional Neural Network consisting of thirteen layers. In this particular network, there were three fully connected layers, five convolutional layers, and five max-pooling layers. A specialist computer-aided design (CAD) technology is utilized in their work to accurately classify electroencephalogram (EEG) data. Additionally, Jaafar et al. [3] have employed Deep Neural Networks, which can aid in learning from the data itself without the requirement for any extraction of the feature set beforehand. For the purpose of training a long-term short-term memory (LSTM) network, which in turn assists in distinguishing seizures from the background, this network is trained with segments that are each four seconds in length. A 5-fold cross-validation analysis was performed on the research that was published in their article. It was determined that the Freiburg EEG dataset would be the most suitable database to use for the purpose of categorization. Hussein et al. [4] have showed that it is capable of learning the discriminative EEG features in connection to epileptic episodes on its own. This was accomplished via the use of a technology that is based on deep learning. After the time-series EEG dataset has been segmented into epochs that do not overlap, the data is then fed into an LSTM network at the end of the process. After that, the output from the LSTM network is fed into the Soft-max function for the purpose of classification. This is done to achieve better results. Within the framework of [5], Yao et al. have focused their efforts on acquiring the major seizure patterns. To acquire full information from the spatial and temporal discriminating qualities, a unique attention method and a bi-directional LSTM (Bi-LSTM) network are utilized. This is done to get the desired outcome. The purpose of cross validation is to test the performance of the model and to overcome any sort of seizure fluctuations. Cross-validation is something that is done. Within the scope of their research, Yuvaraj et al. have made an effort to eliminate the need for a visual evaluation of EEG data [6]. To work on a framework for unsupervised feature learning that has the potential to aid in the automatic detection of seizure onset, the research study makes use of a deep convolutional neural network (CNN). This is done to work on the framework. The total amount of time that the recordings were made is 526 hours, and the dataset that was used there include 181 seizures that were suffered by 23 paediatric patients. The model is able to generate a result that is not just optimal but also accurate since it makes use of a technique known as 4-fold nested cross-validation. When it comes to ternary examples, such as ictal, normal, and interictal, Ullah et al. [6] have made an effort to solve the challenge that occurs in the process of EEG categorization. The design of the technique that they have proposed has been accomplished by the use of a collection of pyramidal one-dimensional CNN models. The CNN model that has been proposed makes use of a refinement method, which enables the model to run with 61% fewer parameters than it would have otherwise. In their research, they make use of a well-known dataset from the University of Bonn, which is a benchmark dataset. This dataset is used for the aim of detecting epilepsy. In the research project that is referred to as [7], Yao and his colleagues have focused their efforts on removing variances and determining underlying seizure patterns. To get the varied seizure patterns, a Bi-LSTM network in conjunction with an attention mechanism has been utilized with the goal of obtaining the information. There has been a use of both sorts of features, specifically spatial and temporal features. To remove noise from electroencephalogram (EEG) data and break them down into sub-bands, several filters and frequency domain analysis methods, including discrete wavelet transform (DWT), are utilized [8]. In light of this, the computation of the wavelet energy distribution in each sub-band is regarded as a feature set for the purpose of classification. When it comes to the categorization of epilepsy, this is the fundamental tradition that the vast majority of researchers subscribe to. Using the line length characteristic that is dependent on waveform changes is something that is done in. The detection of fluctuations in the amplitude and frequency of the signal is the means by which this objective is accomplished. Furthermore, the concept of wavelet transform is employed in the procedure that is being described here. Statistical variables such as Sample Entropy (SampEn), Approximate Entropy (ApEn), Phase Entropy-1 (S1), Phase Entropy-2 (S2), higher-order statistics (HOS), and power spectrum are employed as characteristics for the aim of epilepsy categorization in a majority of the research that have been conducted [105]. The Gaussian mixture model (GMM) and the Support Vector Machine (SVM) are two examples of classification systems that have been claimed to employ these qualities [9]. Other classification methods could possibly use these properties. The purpose of this study is to provide an effective approach for the identification of epileptic seizures. This method enables quick detection and classification, and it does not require any filtering or signal decomposition techniques to be utilized. During the course of the research that is being proposed, raw EEG waves are utilized directly. As a computer-aided diagnostic (CAD) system, a unique CNN-LSTM model was proposed for the classification of electroencephalogram (EEG) signals into three separate classes, namely preictal, normal, and seizure[10]. These classes were determined by the categorization of the signals. This action was taken in consideration of the relevance of seizure detection as well as the contemporary trend of using deep learning to the very same concept. The EEG database that is accessible to the general public and is maintained by Bonn University is also employed for the purpose of studying and monitoring the performance of the CNN-LSTM model. The fact that this model is capable of performing end-to-end classification without making use of any feature extraction strategies is what distinguishes it as a novel and forward-thinking methodology. One of the practical applications of the computer-aided diagnostic (CAD) system that has been developed is the detection of epilepsy seizures for patients who are unknown to the system with a significant degree of accuracy. Additionally, this study has the potential to assist the supply of valuable inputs to undertake additional experiments on the detection of epileptic seizures and expand the research knowledge in this specific sector. This is because the study can support the provision of useful inputs[11].

Material and Methods

The proposed approach and the database that was used are both described in this section. Within the context of EEG-based seizure classification, a deep CNN-LSTM-based classification model is utilized to classify seizures into three distinct categories: normal, preictal, and seizure.

A. Description of the Dataset

This research makes use of the Bonn EEG database, which is accessible to the general public and is maintained by the University of Freiburg (http://epilepsy.uni-freiburg.de/db). With the use of visual examination and evaluation owing to muscular activity and eye movements, all of the EEG segments were initially and first selected from continuous multichannel ECG recordings. Artifacts were eliminated by using use of visual examination and assessment. The normal (set-Z) class, the pre-ictal (set-N) class, and the seizure (set-S) class are the three categories that make up the dataset. Every subset is made up of one hundred single-channel instances of the EEG fragments. A record of 23.6 seconds is contained inside each fragment, and the sampling rate is 173.6 hertz [12]. The normal dataset may be broken down into five healthy individuals, each of whom has one hundred instances. In addition, the preictal class contains one hundred data samples from five epileptic patients who were not experiencing seizures at the time that the data was taken. The third and final class, which is known as the seizure class, is comprised of one hundred instances that include the same individuals at the time of the epileptic episode [13].

B. Normalization

In this particular investigation, the database is made up of data samples that have both a significant and a little amount of volatility. When the data are considered and thought of as random variables, normalization is one of the approaches that is traditionally taken. Transformation to the normal distribution is what is meant by the term "normalizing." First and foremost, the application of z-score normalization is carried out as a preprocessing step by means of equation (1) [14].

$$Z = \frac{(x - \mu)}{\sigma} \tag{1}$$

Z is the z-score, x is the random variable, μ is the mean, and σ is the standard deviation. These are the variables that are represented in the formula that was shown before.

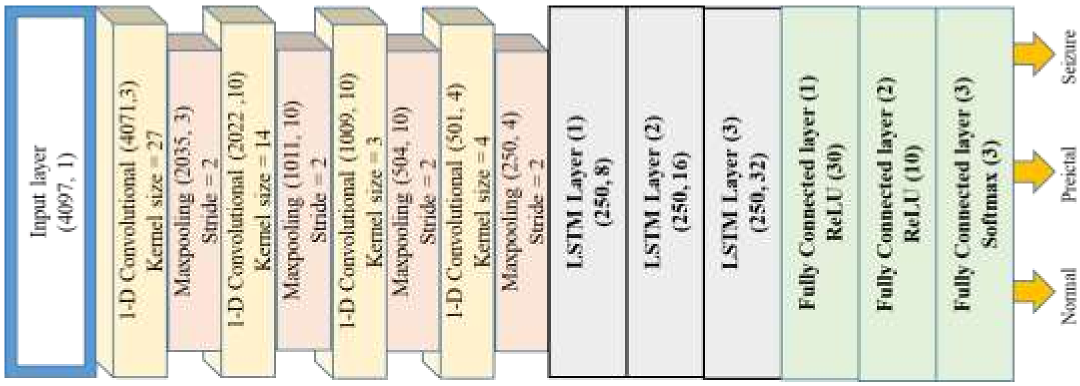

Fig.1. Proposed architecture of CNN-LSTM model for EEG signal classification

To automatically identify three distinct categories of EEG signals, the model that has been presented is a novel hybrid deep learning model that is a combination of CNN and LSTM that has been developed. The architecture of the CNN-LSTM model that has been presented is shown in Figure 2. As shown in Figure 2, the convolution layer is comprised of layers 1, 3, 5, and 7, while the max pooling layer is comprised of layers 2, 4, 6, and 8. There are LSTM layers at the 9, 10, and 11 levels. In the last level of the architecture, there is a further sequence of three layers that are all connected. Convolutional layers are used to extract the spatial characteristics of the maps, while the LSTM layer is used to aid the model in acquiring the temporal dynamics that are intrinsically present in the feature maps. After that, the EEG segments are graded according to the outcomes of the most recent LSTM cell, which is accomplished through the linked layers [15]. The hybrid CNN-LSTM model that was built may be broken down into four convolution layers, each of which has a stride of 1. The kernel is moved across the input vector one sample at a time for every convolution operation. At the same time, the matrices that are overlaid are multiplied and added together [16]. It is necessary to train the model to get spatial information that is both relevant and informative, and the kernel weights are continuously modified throughout this process. The shorter segments are padded with zeroes, which allows for full convolution to take place in this particular instance. During this convolution procedure, bias is not introduced into the data. After each convolutional layer, a max-pooling filter of size 2 with a non-overlapping stride is applied. This is done to achieve a decrease in the size of the input representation that is equal to half[17]. LSTM layers are utilized in subsequent phases to facilitate the extraction of valuable temporal data from the feature maps. The LSTM units that are used repeatedly are given the characteristics that have been extracted. The CNN-LSTM model described here has a total of fifteen layers. There are a total of 4097 inputs, and it includes four convolutional layers, four max-pooling layers, three LSTM layers, and three fully connected layers. We specify the needed filter/kernel size for every layer using this method.

The CNN LSTM model starts with the convolution layer, which accepts an input of 4071 data with 27 kernel sizes once it has been constructed. After that, the max-pooling layer accepts 2022 inputs with 14 kernel sizes and takes half of the number, which is 2035, from the convolutional layer that came before it. In the subsequent step, the convolutional layer receives maximum pooling inputs of 1011 with a kernel size of 4, and the max-pooling layer receives inputs of 504 respectively. Similarly, the final convolutional layer incorporates a maximum pooling value of 250 and an input value of 501. Additionally, each of the three layers of the LSTM is comprised of 8, 16, and 32 cells. The flattened layer receives the output of the layers that make up the LSTM. It is possible to connect the completely connected layer with the ReLU activation function by using the flatten function [18]. Following this, the Soft-max activation function is utilized for multiclass classification in the next three layers, which are fully coupled to one another.

C. Experimental Results

The Hybrid CNN and LSTM model is programmed in Win-Python 3.6.6 using the Keras library as the implementation language. The Dell workstation that was used for all of the trials has a dual Intel Xeon E5-2600 CPU, 2.4 GHz, and 64 GB of random access memory (RAM). To evaluate the effectiveness of the suggested strategy, several simulations were carried out, with the learning rate and the number of epochs being varied. Several different train-test ratios that may be used for training and testing have been considered. The first experiment utilized ninety percent of the data for training purposes, while the remaining ten percent was utilized for testing purposes. An additional method that was utilized was a 10-fold cross validation strategy. After the EEG data has been first segmented into ten equal pieces, nine of the ten signal segments have been utilized for training purposes. The one-tenth portion of the signals that was left over was utilized for testing purposes. The technique described above was repeated ten times, with the test and training datasets being made different each time. With a batch size of 34, the technique was performed in a manner that was comparable to convolutional backpropagation (BP). The studies that were addressed in the introductory part and following discussion sections utilized 10-fold cross validation; hence, in order to retain similarity, the proposed CNN-LSTM model is likewise tested through the use of 10-fold cross validation. Immediately after this, the gradient of the loss function about the weight was computed using the backpropagation approach. Because of this, the erroneous signals in the network experienced feedback in the other direction. The weights in a network were updated at the time that training was taking place. In this CNN-LSTM model, the training parameters were specified as follows: the input batch size was 34, the learning rate was 1e-3, the regularisation was 0.01, and the total number of training epochs was 100. In Figure 3, a visual representation of the training and validation process is presented. Following the completion of each training cycle, validation with test data was carried out. It is the categorical cross-entropy that is utilized for the purpose of loss evaluation of the CNN-LSTM model. During the training procedure, the Adam optimizer is utilized.

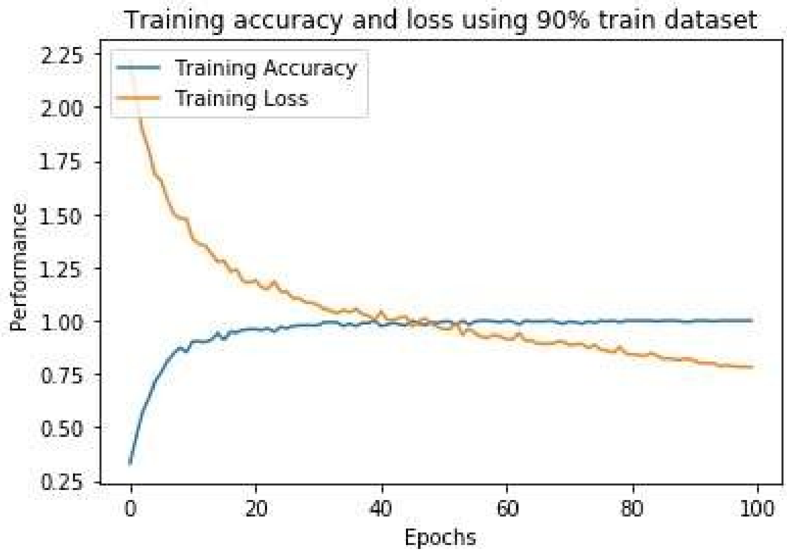

Fig. 2. Accuracy and loss plots of the training process

Four primary performance indicators are used to evaluate the overall performance of the model. These measurements are the accuracy, specificity, sensitivity, and positive predictivity (PPV) of the classification. All of these measurements are computed using the confusion matrix by use of equations (2) through (5). [19] Where TP stands for true positive, FP stands for false positive, FN stands for false negative, and TN is for true negative and FN stands for false negative.

$$\text{Accuracy}=\frac{(TP+TN)}{(TP+TN+FP+FN)}\ , \quad (2)$$

$$\text{Sensitivity} = \frac{TP}{(TP+TN)}, \quad (3)$$

$$\text{Specificity} = \frac{TN}{(FPTN)}, \quad (4)$$

$$\text{PPV} = \frac{TP}{(TP+FP)}. \quad (5)$$

Both the confusion matrix and the average of all 10-fold cross-validation performance of the proposed model are presented in Table 1(a) and Table 1(b), respectively from Table 1. According to the findings of the performance evaluation, the average accuracy of the 10-fold cross-validation is 99.33%, the average positive predictivity level is 99.33%, the average sensitivity level is 99.33%, and the average specificity level is 99.67%.

Table 1: Classification performance for train-test ratio 90:10 across all 10-folds (a) confusion matrix, (b) performance measure

(a)				
Classes		Predicted		
		Normal	**Pre-ictal**	**Seizure**
Actual	**Pre-ictal**	0.0	100.0	0.0
	Seizure	1.0	0.0	99.0
	Normal	99.0	0.0	1.0

Classes	(b)			
	Accuracy (%)	**PPV (%)**	**Sensitivity (%)**	**Specificity (%)**
Seizure	99.00	99.00	99.00	99.50
Normal	99.00	99.00	99.00	99.50
Pre-ictal	99.00	99.00	99.00	90.00

The CNN-LSTM model has been trained and evaluated on a variety of train-test ratios, including 80:20, 70:30, and 60:40, in the second, third, and fourth experiments, respectively. A similar evaluation of the CNN-LSTM model's potential is carried out as described above, and the results are presented in Tables 2 through 4.

Table.2. Classification performance for train-test ratio 80:20 across all 10-folds (a) confusion matrix, (b) performance measure

(a)				
Classes		**Predicted**		
		Normal	**Pre-ictal**	**Seizure**
Actual	**Pre-ictal**	0	100	0
	Seizure	5	3	92
	Normal	95	2	3

Classes	**(b)**			
	Accuracy (%)	**PPV (%)**	**Sensitivity (%)**	**Specificity (%)**
Pre-ictal	95.23	95.23	100.00	97.50
Seizure	96.84	96.84	92.00	98.50
Normal	95.00	95.00	95.00	96.00

Table 3. Classification performance for train-test ratio 70:30 across all 10-folds (a) confusion matrix, (b) performance measure

(a)				
Classes		**Predicted**		
		Normal	**Pre-ictal**	**Seizure**
Actual	**Pre-ictal**	7	93	0
	Seizure	2	0	98
	Normal	99	0	1

Classes	(b)			
	Accuracy (%)	**PPV (%)**	**Sensitivity (%)**	**Specificity (%)**
Pre-ictal	100.00	100.00	93.00	100.00
Seizure	98.99	98.98	98.00	99.50
Normal	91.66	91.66	99.00	95.50

Table 4. Classification performance for train-test ratio 60:40 across all 10-folds (a) confusion matrix, (b) performance measure.

(a)				
Classes		**Predicted**		
		Normal	**Pre-ictal**	**Seizure**
Actual	**Pre-ictal**	4.0	96.0	0.0
	Seizure	0.0	0.0	100.0
	Normal	99.0	0.0	1.0

Classes	(b)			
	Accuracy (%)	PPV (%)	Sensitivity (%)	Specificity (%)
Pre-ictal	100.00	100.00	96.00	100.00
Seizure	99.01	99.00	100.00	99.50
Normal	96.11	87.61	99.00	98.00

The confusion matrix for the 80:20 ratio, along with other characteristics, is presented in Tables 2(a) and 2(b). In this case, 95% of the samples are accurately categorized as normal EEG signals, whereas the other 5% are classifications that are wrong. When it comes to the Pre-ictal class, one hundred percent of the EEG signals are correctly identified, while zero percent are classified wrongly. In the instance of the Seizure class, 92% of the cases are correctly classified, while just 8% of the cases are incorrectly classified. The confusion matrix for the 70:30 ratios is presented in Table 3(a), and the remaining performance measures are reported in Table 3(b). 99% of the samples have been successfully categorized as normal EEG signals in our model, whereas 1% of the samples have been wrongly classified. Ninety-three percent of the EEG signals that belong to the Pre-ictal class are correctly categorized, whereas seven percent are diagnosed wrongly. In addition, when it comes to the Seizure class, 98% of the occurrences are correctly identified, whereas 2% are classified wrongly. Additionally, the 60:40 ratio confusion matrix is shown in Table 4(a), and Table 4(b) has a listing of additional performance indicators. One percent of the samples have been wrongly labeled as abnormal EEG signals, whereas the remaining 99% have been accurately classified as normal EEG signals. Ninety-six percent of EEG signals are properly categorized while the patient is in the Pre-ictal class, whereas four percent are diagnosed wrongly. Within the Seizure class, one hundred percent of the samples are correctly categorized, while zero percent of the samples are wrongly classified.

Discussion

The deep learning models are well-known for the end-to-end classification and prediction outputs that they provide. This implies that they did not require any hand-crafted features or dimension reduction approaches. Table 5 is developed in order to demonstrate that the suggested model performs better in comparison to other approaches that are considered to be state-of-the-art. A compilation of the computations and performance evaluations of several additional research studies is shown in Table 5. Before submitting the EEG signals to a 1-D CNN model for classification, Chowdhury et al. [20] utilized a butter worth filter to make sure that the noise was removed from the signals. While their method was able to obtain an accuracy of 99.4 percent for the Bonn (A-E) binary classification issue, the suggested system was able to achieve an almost same accuracy of 99.4 percent without filtering for the Bonn (AB-CD-E) multiclass classification problem. The short-time Fourier transform (STFT) is a non-stationary signal processing approach that has been developed by Mandhouj et al. [21] as a means of extracting useful information from electroencephalogram (EEG) data. After that, the STFT is transformed into a spectrogram picture, which is subsequently utilized as an input in the classification model. Based on EEG spectrogram data, they developed a deep convolutional neural network (CNN) model that is capable of identifying and categorizing epileptic episodes effectively. The discrete wavelet transform (DWT) was utilized for feature extraction by Wani et al[22]. Following the decomposition of the input EEG Signal into sub-bands, the sub-band was then used as an input to an artificial neural network for classification. The level of accuracy that they are achieving is 95%. The feature extraction strategy that Srinivasan et al. [23] utilized was based on the concept of approximation entropy. The current amplitude values of a signal can be predicted by the approximative entropy method by using the signal's prior values as a basis. The categorization of epilepsy class was accomplished by the use of the artificial neural network model. For the purpose of feature extraction, Guo, Ling, and colleagues [24] utilised wavelet transformations that were developed from multi-wavelet transforms. For classification, they utilized artificial neural networks (ANN). In their study [25], Song and colleagues developed a unique technique for the automated identification of epileptic seizures. For feature extraction, they focused on developing an optimized sample entropy method. To determine whether the EEG signal that was captured was normal or seizure-related, the extreme learning machine was utilized. In their study [26], Acharya and colleagues developed a system that could be used to automatically identify normal, pre-ictal, and ictal situations based on EEG signal recordings [25]. Entropy characteristics such as approximation entropy, phase entropy 1, and phase entropy 2 were taken into consideration. After that, the data that had been extracted from the features was input into seven distinct types of classifiers. These classifiers were as follows: support vector machine (SVM), Naive Bayes classifier, K-Nearest Neighbor, Gaussian mixture model, Decision tree, PNN, and Fuzzy Sugeno entropy [26]. Among the seven classifiers that were discussed before, the fuzzy classifier was the one that was able to differentiate between the three classes with the best level of accuracy and efficiency [27]. An automated feature extraction and classification process is carried out from EEG data using a deep CNN-LSTM model, which has been utilized in the model that has been conceptualized [28]. Given that it is a sequential model, the CNN-LSTM model has fared very well in comparison to previous research [29]. This is because the deep CNN model is utilized to extract superior features, while the LSTM model is utilized for correct classification [30].

Table 5. Performance comparison from literature for detection of epileptic and normal classes.

Method	Extracted Feature	Accuracy (%)	Year/Author
Extreme learning machine	Sample entropy	95.67	2010/ Song et al. [19]
Butterworth filter and CNN structure	Nonlinear pre processing filter	99.40	2019/ Chowdhury et al. [20]
STFT Spectrogram with deep CNN	time–frequency transformations	98.22	2021/ Mandhouj et al. [21]
Artificial Neural Network	DWT	95.00	2019/ Wani et al. [22]
Multiple-Layer Perceptron Neural Network (MLPNN)	DWT	95.20	2010/ Guo et al.[23]
Fuzzy logic	Entropy measures	98.10	2012/ Acharya et al. [24]
Gaussian classifier	HOS and power spectral density	93.11	2011/ Chua et al. [25]
SVM	Weighted Permutation Entropy	97.25	2016/ Tawfik et al. [26]
13-layer CNN Model	NA	88.70	2018/ Acharya et al. [27]
Hybrid CNN-LSTM	NA	99.33	Proposed Model

Conclusion

The fact that this model can carry out an end-to-end classification without making use of any feature extraction approaches is what makes it so innovative. After the database has been normalized, the input is then handed over to the model in its entirety. EEG data are used in the suggested model, which is a CNN-LSTM model with 15 layers. The model is designed to identify seizures automatically. This model is equipped with the power to learn more effectively and accurately differentiate between seizure, pre-ictal, and normal EEG signals. This capability is achieved by taking into consideration the most recent technological advancements and the most cutting-edge approaches. To evaluate the suggested model, performance measures such as accuracy, sensitivity, specificity, and precision are utilized at various points. When analyzing the overall effectiveness and performance of the model, sensitivity is essential because it indicates whether or not the model is accurately predicting the existence of a disease. On the other hand, accuracy is essential for determining whether or not the model is accurate. An automated multiclass classification has been carried out, and the results have been attained with an average accuracy of 99.33%, a specificity of 99.66%, and a sensitivity of 99.33%. The proposed model has been validated by applying it to the Bonn University EEG dataset, which is accessible to the general public and is extensively utilized. The outcome demonstrates that the suggested model is superior in terms of functionality, accuracy, and efficacy when it comes to gathering all of the information and identifying epileptic seizures. The absence of any feature extraction and selection procedures is one of the benefits that comes with using this paradigm. Another restriction of the article is that the size of the database that was utilised is rather modest. This is the bare minimal constraint. In the subsequent research, we will be able to put the suggested model and approach to the test by utilizing more EEG datasets. Additionally, the categorization of EEG signals may also be accomplished by the use of a variety of deep learning models, such as the Restricted Boltzmann Machine (RBM) and the Auto-encoder methods.

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