Journal of Physical Chemistry and Functional Materials

Home Page of Journal: https://dergipark.org.tr/jphcfum

Epileptic Seizure Detection from EEG Signals with Recurrent Neural Networks Based Classification Model

Serpil Aslan[a]* and Harun Bingöl[a]

[a]*Malatya Turgut Ozal University, Department of Software Engineering, Malatya, Türkiye*

** Corresponding author: E-mail: serpil.aslan@ozal.edu.tr*

ABSTRACT

Epileptic seizures are a neurological disorder that occurs as a result of sudden and uncontrolled electrical activities of the non-contagious brain. This condition may cause the person to lose normal activities temporarily. Epileptic seizures are a severe disease that affects approximately 60 million people in the world, usually manifested by symptoms such as loss of consciousness, muscle twitching, sudden sensory changes, or behavioural changes. Genetics, brain injury, hormonal fluctuations, infections, or metabolic problems are some of the possible causes of epileptic seizures. Although the severity and duration of the seizure varies from person to person, it is usually very short and rarely reaches a point where it endangers human life. However, such seizures need to be recognized as soon as possible in order to improve the quality of life of individuals and reduce the frequency of seizures. Epileptic seizures are a manageable disease with early diagnosis and appropriate treatment. Recognizing epileptic seizures begins with understanding a person's symptoms and triggering factors. These symptoms may include loss of consciousness, muscle twitches, sudden sensory changes, and behavioural changes. The symptoms of seizures, past medical history, and neurological examinations are essential in the diagnosis process. From past to present, many methods have been developed for the early diagnosis and detection of epileptic seizures. One of these is analyzing the brain's neural activities using electroencephalography (EEG), which helps experts make a diagnosis. Although EEG signals are used as a powerful tool in epileptic seizure recognition, distinguishing the signals within them is both costly and requires highly expert experience. Therefore, this study proposed an automatic classification model for pre-processed EEG signals using Dual-Tree Complex Wavelet Transform (DT-CWT) based on deep learning-based Recurrent Neural Networks (RNN) architecture to assist experts. Compared to classical machine learning methods, deep learning-based models require less manual feature engineering because they perform data automatically thanks to deep networks instead of manually selecting and transforming the data features. These advantages make the model more general and flexible. The proposed model aims to classify EEG signals and detect epileptic seizures effectively and quickly in the early stages.

ARTICLE INFO

***Keywords*:**

Deep Learning
Epilepstic Seizure
RNN
BiLSTM
CNN

Received: 2024-06-13
Accepted: 2024-07-03
ISSN: 2651-3080
DOI: 10.54565/jphcfum.1500546

1. Introduction

Epilepsy is a widespread neurological disorder worldwide. Epilepsy is a condition characterized by recurrent seizures and can affect any age group. It is estimated that approximately 60 million people worldwide live with epilepsy [1]. However, it is thought that this number may be higher because some people may experience their symptoms and seizures without medical attention and go unreported. Additionally, new cases of epilepsy emerge every year. Epilepsy may have different prevalences in different geographic regions around the world. This condition can be affected by genetics, lifestyle, and environmental factors. It can occur at any age and tends to begin in childhood. Epilepsy is recognized as a standard, chronic neurological condition that affects a large number of people worldwide and frequently causes seizures because it affects so many people. The brain's electrical activity can be recorded using an EEG, which measures potentials in a specific brain region. EEG and graphically displayed measures of brain cell electrical activity. From past to present, many methods have been developed for the early diagnosis and detection of epileptic seizures [2]. EEG data can be used to identify a wide range of neurological conditions, including autism, Parkinson's disease, and epilepsy. Since distinct changes in brain electrical activity occur during epileptic seizures, electroencephalogram (EEG) signals are often used in the diagnosis and treatment of epilepsy [3]. Nevertheless, skilled neurologists' visual inspection and analysis of EEG data are laborious and time-consuming. Modern equipment and quick decision-making are also required, as evidenced by consistent and complete data, poor staff training, and misinterpretations in pathology [4].

Researchers have proposed many approaches to automate epilepsy diagnoses from EEG signals [5,6]. The suggested methods emphasize feature extraction techniques, particularly in the time and frequency domains, based on machine learning and deep learning. Features are extracted from EEG signals using statistical computations in machine learning-based methods. Some statistical parameters that are examples of these include the average of the coefficients' absolute values, the coefficients' maximum and minimum absolute values, the average of the coefficients' powers, standard deviation, variance, and skewness [7]. Ravi et al. [8] aimed to detect epilepsy from EEG signals using the Random Forest (RF) classifier, one of the classic machine learning classifiers. Discrete wavelet transforms (DWT), and fuzzy relations extract features and reduce their dimensionality through a novel method described by Kocadağlı et al. [9]. This makes it possible to categorize EEG signals and accurately identify epileptic seizures early on. In this process, other hybridized tools include feature extraction, gradient-based algorithms, artificial neural networks, and genetic algorithms. Recent developments in deep learning have suggested numerous novel, cutting-edge methods for the diagnosis and detection of epileptic seizures. A deep learning-based ensemble approach for epileptic seizure prediction was presented by Usman et al. [10]. The suggested method automatically extracts features from EEG signals using a three-layer custom convolutional neural network. These features are combined with manually created features to create an extensive feature set. Combining the SVM, CNN, and LSTM outputs trained an ensemble classifier using the feature set. Rashed-Al-Mahefuz et al. [11] presented a novel method utilizing a convolutional neural network model based on deep learning. The suggested method of converting time-domain signals to frequency domain has produced encouraging results. Upon reviewing the literature, it can be observed that deep learning-based approaches offer automatic feature extraction without the need for manual feature extraction, in contrast to machine learning-based approaches. The deep learning approach provides a faster and free system from computational errors compared to the classical machine learning approach.

The 1DCNN-BiLSTM model was presented in this study to capitalize on the popularity of deep learning-based methods for the detection of epileptic seizures as well as the strength of deep networks' capacity for representation in learning abstract features. The suggested model uses DT-CWT to analyze the dataset, which is mainly made up of EEG signals in both time and frequency, to produce features that contain the relevant data. By the acquired conversion signals, a new data set is generated. A hybrid model that combines the benefits of recurrent and convolutional neural networks is fed the generated data set. In the 1DCNN stage of the proposed model, sufficiently meaningful local information was extracted by taking advantage of the feature extraction power of CNNs. In the BiLSTM phase, the BiLSTM sequential learning layer was used to avoid ignoring the temporal features in the features obtained from the 1DCNN phase. The success of the proposed model was compared with CNN, LSTM, and BiLSTM classification models.

2. Material and Method

Dataset

The dataset used in this study was taken from Kaggle [12], one of the online data-sharing platforms in data science and machine learning. The reconstructed EEG time series dataset of the University of Bonn contains five target classes: A, B, C, D, E, 179 features, and 11500 samples. Each series consists of 100 single-channel EEG signal recordings for 23.6 seconds. EEG recordings are free from any noise caused by muscle movements. Five healthy individuals with their eyes open provided Set A. The five healthy individuals in Set B had their eyes closed. Five epileptic patients' records are included in sets C, D, and E. Set C includes recordings from the opposite hemisphere's hippocampal hemisphere in epilepsy patients who were not yet experiencing seizures. The recordings from the pre-seizure epileptic region pertain to a patient with epilepsy, identified as Set D. The records that were collected from epileptic patients during their epileptic seizures are located in Set E.

Electroencephalogram (EEG)

An electroencephalogram (EEG), which measures potentials in the brain region, is a medical test or technique used to record brain activity [13]. EEG measures electrical activity in the brain and converts this activity into a graph. Brain cells use electrical signals to communicate. The frequency of these signals is primarily divided into five categories with frequency distributions between 0-100, known as frequency bands. These are delta (0.5-4Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and Hama (30 Hz). EEG evaluates brain activity by measuring and recording these signals. EEG is usually done through an EEG device with electrodes (usually placed on the scalp). These electrodes are used to measure electrical activity in the brain. Medical professionals widely use EEG technology to analyze brain behavior. It is a diagnostic tool for diagnosing and monitoring epilepsy, sleep disorders, brain damage, brain tumors, and other neurological disorders. EEG results are examined and interpreted to identify abnormalities or pathology in brain activity.

DT-CWT

DT-CWT, introduced by Kingsbury [14], is a transformation technique used in image and signal processing fields. DT-CWT is a process based on wavelet transform and expands traditional Wavelet Transform (WT). Compared with DWT, the advanced features of DT-CWT have approximate shift invariance and preferred anti-aliasing ability. The primary purpose of DT-CWT is to provide a more detailed analysis of a signal or image in both time and frequency space. However, unlike traditional wavelet transforms, DT-CWT works with complex numbers and preserves both amplitude and phase information. DT-CWT is called a "double tree" because it combines two separate wavelet transform trees (real-tree and imaginary-tree). Each is created using different filter sampling strategies. This enables DT-CWT to exhibit better directional and scalar behavior. DT-CWT can be used wherever one wants to extend the capabilities of traditional wavelet transformation and enable the analysis of more complex signals. It is frequently used in image, video, medical, and signal-processing applications. DT-CWT can be used in many areas, such as feature extraction, compression, filtering, and pattern recognition.

CNN

CNN is one of the deep learning methods initially developed for image recognition and later successfully applied in text classification studies. CNN architectures, which have a multi-layered structure, have a forward propagation neural network structure [14]. It mainly consists of convolution, pooling, and complete connection components. The convolution layer is the basic building block to extract features from image and text data. The output from the convolution layer is given as input to the pooling layer. Unlike manual feature extraction in traditional Machine Learning methods, convolutional neural networks learn and recognize features automatically [15]. The pooling layer reduces and summarizes the feature map produced by the convolution layers. In this way, since essential features of the feature vectors are selected, computational complexity is reduced, and resistance to overfitting is provided. Finally, the resulting output is input to the entire link layer. In the fully connected layer, feature maps from the convolution and pooling layer are flattened and then processed through a series of hidden layers and an output layer, which are used for classification and prediction tasks. The basic structure of the basic CNN architecture is seen in Figure 1.

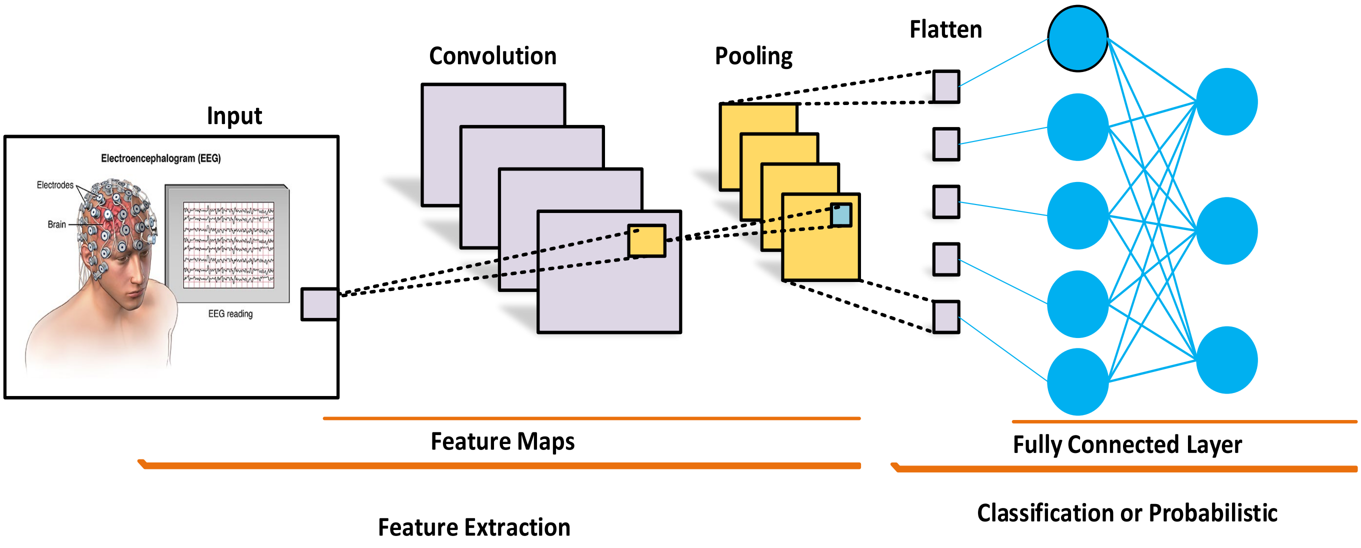

Figure 1. Basic CNN Architecture

LSTM and BiLSTM

In deep neural network modeling, a specific recurrent neural network (RNN) model called long short-term memory (LSTM) can learn long-term dependencies in sequential data. LSTM can capture sequential data by considering prior data [16]. It also has feedback connections, which set it apart from regular RNNs. Three layers comprise the LSTM architecture: "Forget," "Input," and "Output." These blocks are sequential and repeating, responsible for determining the flow. Figure 2 shows the general configuration of the LSTM and BiLSTM models. The LSTM model is a valuable method for sequence modeling since each hidden layer's input is determined by the cell's computation from the previous time instant [80]. However, the state of a time t depends only on the information prior to time t because, in the LSTM model, information can only be propagated prospectively. Data loss could result from this. Figure 2 depicts that the BiLSTM model has a bidirectional information flow, unlike LSTM. This model treats every input equally. Two LSTM networks train the sequence in this model. Forward training is carried out by one LSTM network, and another carries out backward training.

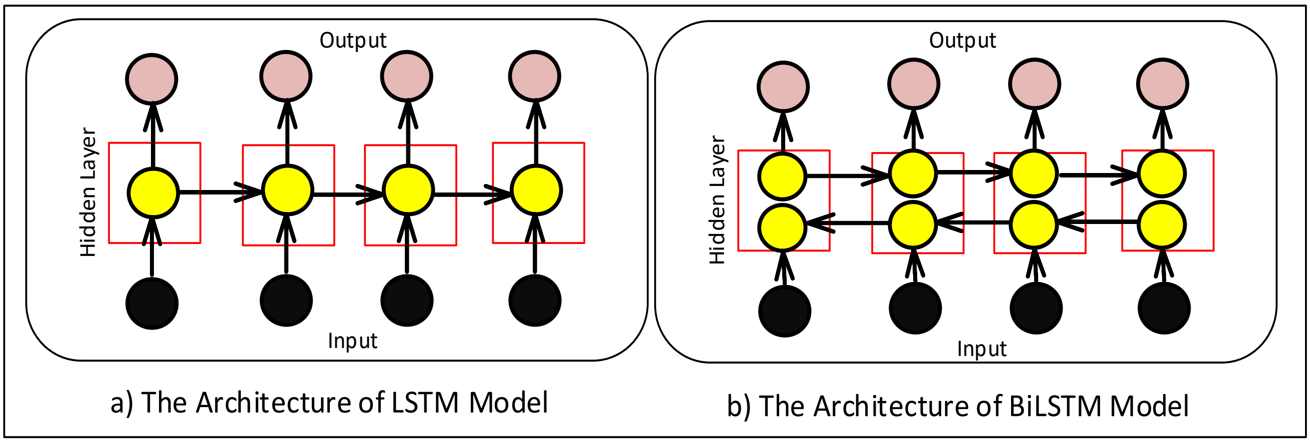

Figure 2. The Architecture of LSTM and BiLSTM Model [14]

Proposed Model

The general flow diagram of the model proposed in this study for the early diagnosis and treatment of epilepsy is shown in Figure 3. The proposed model uses 1DCNN-BiLSTM models to benefit from the success of deep learning-based approaches for epileptic seizure detection and the power of representation ability that enables deep networks to learn abstract features. In the proposed model, features containing meaningful information are obtained by first analyzing the dataset of EEG signals, both time and frequencies, using DT-CWT. A new data set is created according to the obtained conversion signals. The generated dataset is fed to a hybrid model that combines the strengths of both convolutional and recurrent neural networks. In the proposed model, at the 1DCNN stage, sufficiently meaningful local information was extracted by taking advantage of the feature extraction power of CNNs. In the BiLSTM stage, the BiLSTM sequential learning layer was used to avoid ignoring the temporal features in the features obtained from the 1DCNN stage. The success of the proposed model was compared with CNN, LSTM, and BiLSTM classification models.

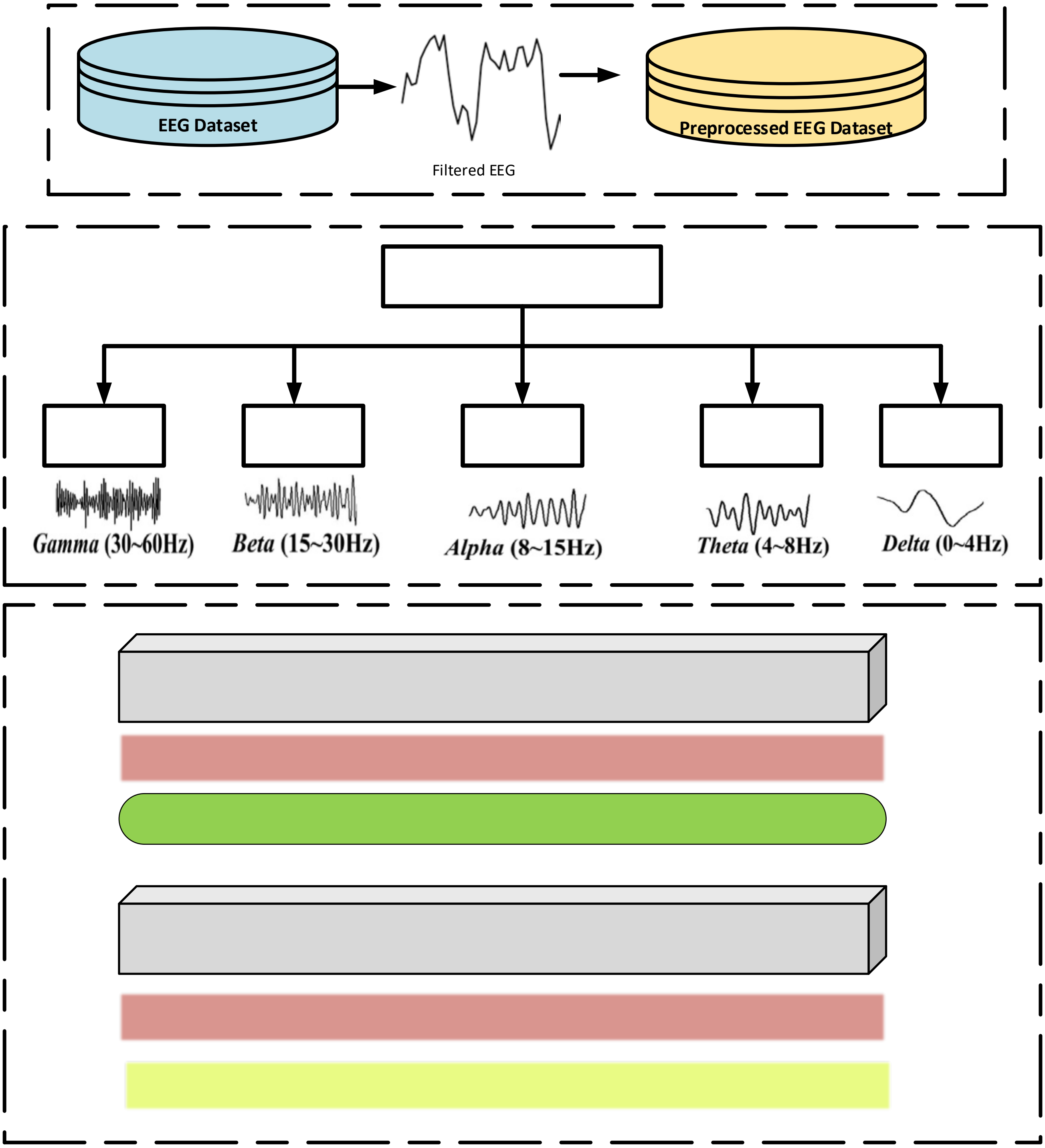

Figure 3. The Basic Architecture of the Proposed Model

3. Results and Discussions

In this study, a dataset downloaded from Kaggle, an open-access site that data scientists widely use and where datasets can be shared and downloaded, was used in experimental applications. The model successfully classified sets A, B, C, and D as the state with no epileptic seizure and set E as epileptic seizure activity. To evaluate the performance of the proposed model in the study, we used four different performance scales. In this study, "Accuracy, Precision, Recall, and F1-score" are among the commonly used evaluation criteria [14]. DT-CWT technique was used for the model's CNN input. The model is critical in obtaining acceptable results by combining two deep learning structures, CNN and LSTM. Figure 4 presents the complexity matrices of the proposed model and the CNN and BiLSTM deep learning models that form the proposed model. Obtaining a confusion matrix for models is essential to evaluate the model's performance. The confusion matrix shows the relationship between the actual labels and the labels predicted by the model. In this way, it helps understand which classes the model predicts correctly or incorrectly and provides insights that can be used to improve model performance.

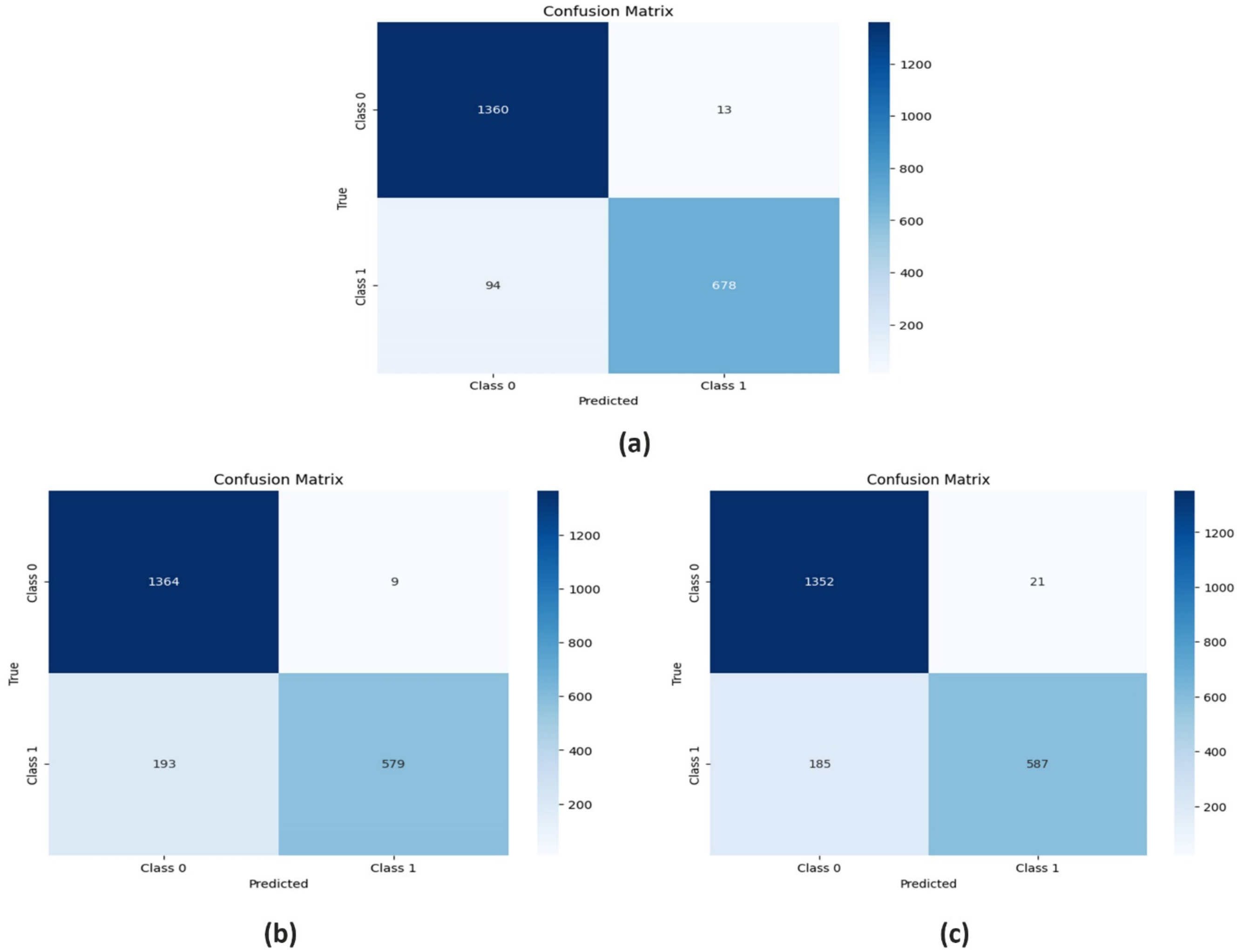

Figure 4. Confusion Matrix of (a) The Proposed Model, (b) BiLSTM and (c) CNN.

Table 1 provides evaluation results for the suggested model. It compares the performance of deep learning-based methods and the suggested model for epileptic seizure detection. Table 1 illustrates that the optimal DT-CWT-1DCNN-BiLSTM yielded the best results, with 96.12%. The second-highest accuracy performance was obtained with the BiLSTM classifier, with 91.48%. The successful performance of the model proposed in the study stems from the strong ability to capture local features provided by the CNN architecture and the combined use of BiLSTM's ability to capture and remember long-term dependencies. This combination is especially powerful when working with sequence data or time series data.

Table 1. The Performance Comparisons of the Classification Models

Classification Model	Accuracy	Precision	Recall	F1-Score
DT-CWT-1DCNN-BiLSTM	**0.9612**	**0.9705**	**0.9561**	**0.9687**
LSTM	0.8975	0.9044	0.8984	0.8956
BiLSTM	0.9148	0.9342	0.8805	0.9084
CNN	0.8987	0.9274	0.8515	0.8705

4. Conclusion

Epilepsy seizure activity was detected with a high accuracy rate using the methods employed in this study. The suggested method leveraged the success of deep learning-based techniques for epileptic seizure detection and the potency of representation ability that enables deep networks to learn abstract features by utilizing the 1DCNN-BiLSTM model. The model developed using the publicly available Bonn data set has outperformed other studies in the literature regarding experimental results. In the proposed model, the dataset consisting primarily of EEG signals is analyzed in both time and frequencies using DT-CWT to obtain features containing necessary information. A new data set is created according to the obtained conversion signals. The generated dataset is fed to a hybrid model that combines the strengths of both convolutional and recurrent neural networks. In the proposed model, at the 1DCNN stage, sufficiently meaningful local information was extracted by taking advantage of the feature extraction power of CNNs. In the BiLSTM stage, the BiLSTM sequential learning layer was used to avoid ignoring the temporal features in the features obtained from the 1DCNN stage. The success of the proposed model was compared with CNN, LSTM, and BiLSTM classification models. Our study is essential regarding the approach it brings to the literature and the high scores it receives. Future studies will determine the model's performance on different data sets.

Acknowledgement: The acknowledgments come at the end of an article after the conclusions and before the notes and references.

Competing interests

The authors declare that they have no competing interests.

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