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Research Article

Deep Convolution Auto Encoder based classification and detection of Epileptic Seizure using EEG signals

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Abstract:

Electroencephalogram (EEG) has become one of the most vital tools used by physicians to diagnose several neurological disorders of the human brain and, in particular, to detect Epileptic seizures. Because of its peculiar nature, the consequent impact of epileptic seizures on the quality of life of patients made the precise diagnosis of epilepsy extremely essential. Therefore, this article proposes a novel deep-learning approach for detecting seizures in patients based on the classification of raw multichannel EEG signal recordings that are minimally pre-processed. The new approach takes advantage of the automatic feature learning capabilities of a two-dimensional deep convolution auto encoder (2D-DCAE) linked to a neural network-based classifier to form a unified system that is trained in a supervised way to achieve the best classification accuracy between the ictal and interictal brain state signals. For testing and evaluating the approach, models were designed and assessed using three different EEG data segment lengths and a 10-fold cross-validation scheme. Based on five evaluation metrics, the best performing model was a supervised deep convolutional auto encoder (SDCAE) model that uses a bidirectional long short-term memory (Bi-LSTM) – based classifier, and EEG segment length of 4 s. Using the public dataset collected from the Children's Hospital Boston (CHB) and the Massachusetts Institute of Technology (MIT), this model has obtained 98.79 ± 0.53% accuracy, 98.72 ± 0.77% sensitivity, 98.86 ± 0.53% specificity, 98.86 ± 0.53% precision, and an F1-score of 98.79 ± 0.53%, respectively.
Keywords: Innovative seizure detection**,** Epilepsy, machine learning, EEG, signal, Deep learning, 2D-DCAE, Bi-LSTM.

1. Introduction

Epilepsy is inevitably recognized to be one of the most critical and persistent neurological disorders affecting the human brain. It has spread to more than 50 million patients of various ages worldwide (1) with approximately 450,000 patients under the age of 17 in the United States out of nearly 3 million American patients diagnosed with this disease (2) Epilepsy can be characterized apparently by its recurrent unprovoked seizures.

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A seizure is a period of anomalous, synchronous innervations of a population of neurons that may last from seconds to a few minutes. Epileptic seizures are ephemeral instances of partial or complete abnormal unintentional movements of the body that may also be combined with a loss of consciousness. While epileptic seizures rarely occur in each patient, their ensuing effects on the patients' emotions, social interactions, and physical communications make diagnosis and treatment of epileptic seizures of ultimate significance.

Electroencephalograms (3) which have been around for a long time, are commonly used among neurologists to diagnose several brain disorders and in particular, epilepsy attributable to workable reasons, such as its availability, effortlessness, and low cost. EEG operates by positioning several electrodes along the surface of the human scalp and then recording and measuring the voltage oscillations emanating from the ion current flowing through the brain. These voltage oscillations, which correspond to the neuronal activity of the brain, are then transformed into multiple time series called signals. EEG is a very powerful non-invasive diagnostic tool since we can use it precisely to capture and denote epileptic signals that are characterized by spikes, sharp waves, or spike-and-wave complexities. As a result, EEG signals have been the most widely used in the clinical examination of various epileptic brain states, for both the detection and prediction of epileptic seizures.

By interpreting the recorded EEG signals visually, neurologists can substantially distinguish between epileptic brain activities during a seizure (ictal) state and normal brain activities between seizures (interictal) state. Over the last two decades, however, an abundance of automated EEG-based epilepsy diagnostic studies has been established. This was motivated by the exhausting and time-consuming nature of the human visual evaluation process that depends mainly on the doctors' expertise. Besides that, the need for objective, rapid, and effective systems for the processing of vast amounts of EEG recordings has become unavoidable to be able to diminish the possibility of misinterpretations. The availability of such systems would greatly enhance the quality of life of epileptic patients.

Following the acquisition and pre-processing of EEG raw signals, most of the automated seizure detection techniques consist of two key successive stages. The first stage concerns the extraction and selection of certain features of the EEG signals. In the second step, a classification system is then built and trained to utilize these extracted features for the detection of epileptic activities. The feature extraction step has a direct effect on the precision and sophistication of the developed automatic seizure detection technique. Due to the non-stationary property of the EEG signals, the feature extraction stage typically involves considerable work and significant domain-knowledge to study and analyze the signals either in the time domain, the frequency domain, or in the time-frequency domain (4) Predicated on this research, it has become the mission of the system designer to devise the extraction of the best-representing features that can precisely discriminate between the epileptic brain states from the EEG signals of different subjects.

In the literature, several EEG signal features extracted by various methods have been proposed for seizure detection. For example (5), used approximate entropy and sample entropy as EEG features, and integrated them with an extreme learning machine (ELM) for the automated detection of epileptic seizures. (6) used non-subsampled wavelet–Fourier features for seizure detection. (7) proposed an algorithm that combines wavelet decomposition and the directed transfer function (DTF) for feature extraction. (8) proposed using matrix determinant as a feature for the analysis of epileptic EEG signals. Certainly, even with the achievement of great results, it is not inherently guaranteed that the features derived through the intricate, and error-prone manual feature extraction methodology would yield the maximum possible classification accuracy. As such, it would be very fitting to work out how to build substantial systems that can automatically learn the best representative features from minimally pre-processed EEG signals while at the same time realize optimum classification performance(9).

The recent advances in machine learning science and particularly the deep learning techniques breakthroughs have shown its superiority for automatically learning very robust features that outperformed the human-engineered features in many fields such as speech recognition, natural language processing, and computer vision as well as medical diagnosis (10) Multiple seizure detection systems that used artificial neural networks (ANNs) as classifiers, after traditional feature extraction, were reported in previous work. For instance (11), used multilayer perceptron (MLP) for classification after using discrete wavelet transform (DWT) and K-means algorithm for feature extraction (12) also used MLP as a classifier after using discrete short-time Fourier transform (DSTFT) for feature extraction. In (13) ANNs were evaluated for classification after using the local neighbour descriptive pattern (LNDP) and one-dimensional local gradient pattern (1D-LGP) techniques for feature extraction. (14) Performed cepstral analysis utilizing generalized regression neural network for EEG signals classification. On the other hand, convolutional neural networks (CNNs) were adopted for both automatic feature learning and classification. As reported, most of the deep learning algorithms that involved automatic feature learning have targeted single-channel epileptic EEG signals. It is therefore still important to research more data-driven algorithms that can handle more complex multichannel epileptic EEG signals.

Therefore, in this work, to address the limitation of the classification schemes alluded to above, a novel deep learning-based system that uses a two-dimensional supervised deep convolutional auto encoder (2D-SDCAE) is proposed for the detection of epileptic seizures in multichannel EEG signals recordings. The innovative approach in the proposed system is that the AE is trained only once in a supervised way to perform two tasks at the same time. The first task is to automatically learn the best features from the EEG signals and to summarize them in a succinct, low-dimensional, latent space representation while performing the classification task efficiently. The method of consolidating the simultaneous learning to perform both tasks in a single model, which is trained only once in a supervised way, has proven to have a good impact on improving the learning capabilities of the model and thus achieving better classification accuracy.

SDCAE models is designed to test the novel approach, and their performance for seizure detection in children is evaluated. Both models are used to classify EEG data segments to distinguish between ictal and interictal brain states. 2D-DCAE in this system, the convolutional layers of the encoder network are attached to one Bi-LSTM recurrent neural network layer to do the classification task. The model is trained in a supervised manner to only do the classification task. By quantitatively evaluating the performance of the proposed models using different EEG segment lengths, new approach of using SDCAE will prove to be a very good candidate for producing one of the most accurate seizure detection systems.

2. Materials and Methods

2.1 Dataset

Patients' data obtained from the online Children's Hospital Boston–Massachusetts Institute of Technology (CHB–MIT) Database were used to assess and measure the efficacy of the proposed models. The dataset is recorded at Boston Children's Hospital and consists of long-term EEG scalp recordings of 23patients with intractable seizures (15) 23 channels EEG signals recordings are collected using 21 electrodes whose names are specified by the International 10–20 electrode positioning system using the modified combinatorial nomenclature as shown in Figure 1. The signals are then sampled at 256 Hz and the band-pass filtered between 0 and 128 Hz.

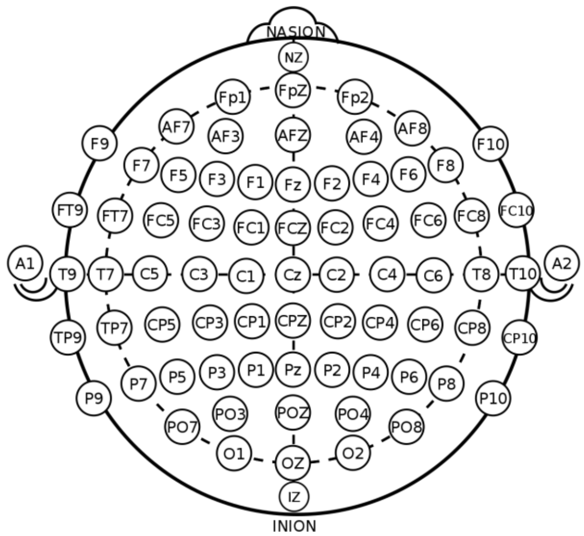

Figure 1. 21 EEG electrode positions based on the 10–20 system

In this study, 16 out of the 23 patients are selected for the assessment of the classification models. More details about the selected patients are listed in Table 1. Seizures less than 10 s are too short so, all Chb16's seizures were not considered for testing (16).

2.2 Dataset Preprocessing

To prepare the EEG dataset before the training phase, all segments combined are pre-processed by applying z-score normalization for all channels at one to ensure that all values are standardized by having a zero mean (μ) and unit standard deviation (σ) using the Eq. (1)

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

Next, as a batch, the whole dataset values are scaled to the [0, 1] range using Min–Max normalization to ensure that the original and the reconstructed segments have the same range of values. Finally, the channel's dimension of the segments is extended by one column to be more suitable for the AE to be used.

Table 1. Seizure duration patients from the CHB-MIT database

Patient	Gender	No. of Seizure	Duration
Chb01	F	7	442
Chb02	M	2	172
Chb03	F	7	402

Chb05	F	5	558
Chb06	F	10	153
Chb07	F	3	325
Chb08	M	5	919
Chb09	F	4	276
Chb10	M	7	447

3. Proposed Method Architecture

The objective of the article is to build accurate and reliable deep learning models for epileptic seizure detection based on differentiating between two classes of epileptic brain states, interictal and ictal.

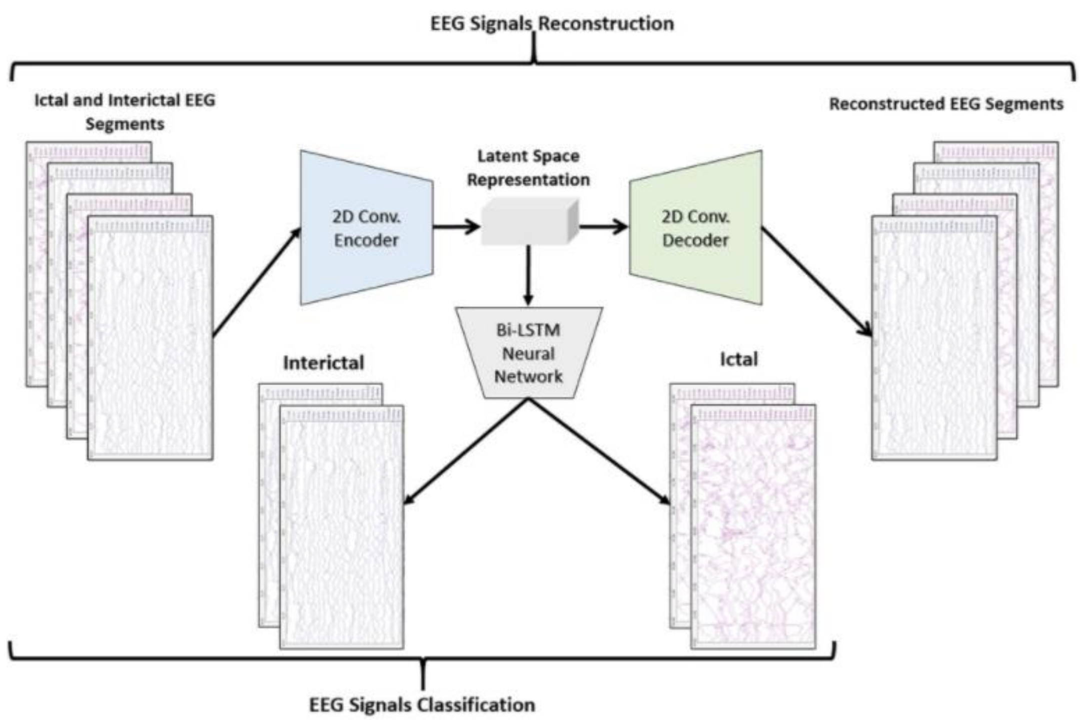

Figure 2. Block diagram of 2D-DCAE + Bi-LSTM model for seizure detection.

The proposed models automatically learn powerful features that help to achieve a high classification accuracy of minimally pre-processed EEG signals. training a network to reconstruct its input while trying to minimize a loss function between The target is to eliminate the overhead induced by the exhausting manual feature extraction process and also replacing complex systems that require long training times with a much simpler, faster, and more efficient system that benefits from the structure and functionality of AEs. An AE neural network consists of two sub networks: an encoder and a decoder. The encoder network is used for compressing (encoding) the input information (EEG signals in our case) into a lower-dimensional representation and the decoder is used in a reverse way to decompress or reconstruct the original signal. AE-based compression is accomplished by continually the original input and the reconstructed one.

2D-DCAE-based models are proposed for automatically learning inherent signal features from labeled EEG segments while being trained in a supervised way. Figure 2 shows the block diagram of the second proposed model which consists of a 2D-DCAE but in this case, the encoder output which is the latent space representation is feed into a Bi-LSTM recurrent neural network to perform the classification task.

4. 2D- Deep Convolutional Auto encoder

Convolutional neural networks are a special class of feed forward neural networks that are very well-suited for processing multidimensional data like images or multi-channel EEG signals. Applications of CNNs in a variety of disciplines, such as computer vision and pattern recognition, have recorded very impressive outcomes (17). This is due to its great ability to hierarchically learn excellent spatial features for the representation of data of different types. The parameter sharing and sparse connections properties of CNNs make them much more memory-savers compared to MLPs networks that consist of fully connected layers. As a result of these advantages, a two-dimensional convolution auto encoder stacked with convolution and pooling layers is proposed in this work rather than a standard AE that uses only fully connected layers.

The encoder sub network of the AE is a CNN consists of four convolutional layers and four max-pooling layers stacked interchangeably. The convolutional layers are responsible for learning the spatial and temporal features in the input EEG signals segments while the max-pooling layers are used for dimensionality reduction by down sampling. A single convolutional layer is made up of filters (kernels) consisting of trainable parameters (weights) that slide over and convolve with the input to generate feature maps where the number of feature maps equals the number of the applied filters. A configurable parameter (stride) controls how much the filter window is sliding over the input. The pooling layer performs down-sampling by lowering the dimension of the feature maps to reduce computational complexity. The low dimensional output of the encoding network is called latent space representation or bottleneck. On the other side, the decoder subnetwork consists of four convolutional layers and four upsampling layers which are also deployed interchangeably and are used to reconstruct the original input.

In all models, in the encoder network, the convolutional layers are configured with 32, 32, 64, and 64 filters, respectively. In the decoder network, the first three convolutional layers are configured with 64, 32, and 32 filters while the last layer has only one filter. All convolutional layers have a kernel size of 3 × 2, and a default stride value equals one. To keep the height and width of the feature maps at the same values, all convolutional layers are configured using the same padding technique. The activation function used in all convolutional layers, except the last layer, is the rectified linear unit (ReLU) defined in Eq. (2) because of its sparsity, computational simplicity, and sturdiness against noise in the input signals (18).

$$f(x) = \max\{o, x\} \qquad (2)$$

where x is the weighted sum of the inputs and f(x) is the ReLU activation function.

The final convolutional layer of the 2D-DCAE uses the sigmoid activation function defined in Eq. (3) to generate an output in the range [0, 1].

$$y = \frac{1}{1+e^{-z}} \qquad (3)$$

where x is the weighted sum of the inputs and y is the output of the activation function.

All max-pooling layers are configured to perform input down sampling by taking the maximum value over windows of sizes (2, 2) except the last layer that uses a window of size (2, 3). The first upsampling layer does its job by interpolating the rows and columns of the input data using a size (2, 3) while the last three upsampling layers use (2, 2) sizes.

Our models apply the Batch Normalization (batch norm) technique for speeding up and stabilizing the training process and to ensure high performance. The batch norm transform (19) is defined as:

$$BN\gamma, \beta(xi) = \frac{xi - \mu B}{\sqrt{\sigma_B^2 \quad + \epsilon}} + \beta \qquad (4)$$

where an input vector xi is normalized within a mini-batch B = {x1,x2…xm} having a mean μB and variance σ_B^2. β and γ are two parameters that are learned jointly and used to scale and shift the normalized value while ∈ is a constant added for numerical stability. Four batch normalization layers are deployed between the four convolutional and max-pooling layers of the encoder subnetwork.

5. Long short-term memory (LSTM)

Long short-term memory (LSTM) is a architecture of recurrent neural networks. It was developed to solve numerous problems that vanilla RNNs suffer during training using back propagation over Time (BPTT) such as information morphing and exploding and vanishing gradients (20). By proposing the concept of memory cells (units) with three controlling gates, LSTMs are capable of maintaining gradients values calculated by back propagation during network training while preserving long-term temporal dependencies between inputs. Figure 3 shows the structure of a single LSTM cell

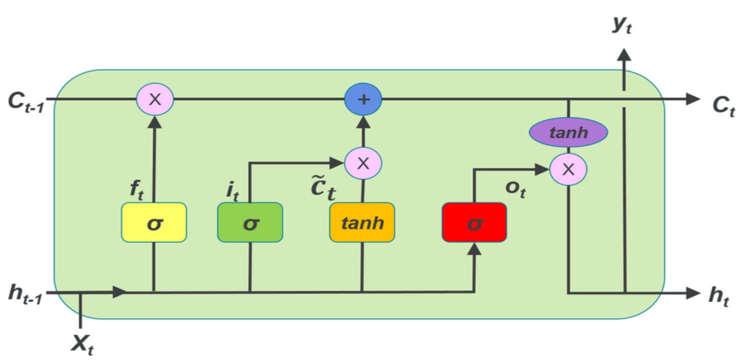

Figure 3. Long short-term memory cell structure.

6. Performance Evaluation

Various statistical metrics commonly used in the literature such as accuracy, sensitivity (recall), specificity, precision, and F1-score (22) have been calculated to assess the classification efficiency of the models against the testing set, in each of the ten iterations of the 10-fold cross-validation. These evaluation metrics are defined as follows from equation 5 to equation 9.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \text{ x } 100\% \qquad (5)$$

$$Sensitivity = \frac{TP}{TP+FN} \text{ x } 100\% \qquad (6)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \text{ x } 100\% \qquad (7)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \text{ x } 100\% \qquad (8)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \text{ x } 100\% \qquad (9)$$

Where P denotes the number of positive (ictal) EEG segments while N denotes the number of negative (interictal) EEG segments). TP and TN are the numbers of true positives and true negatives while FP and FN are the numbers of false positives and false negatives, respectively. In this study, accuracy is defined as the percentage of the correctly classified EEG segments belonging to any state (ictal or interictal), sensitivity is the percentage of correctly classified ictal state EEG segments, specificity is the percentage of correctly classified interictal state EEG segments, while precision determines how many of the EEG segments classified as belonging to the ictal state are originally ictal state EEG segments. Finally, the F1-score combines the values of precision and recall in a single metric.

7. Results

Figure 4 shows the ranges of values of performance metrics calculated based on the 10-Fold cross validation classification results of the EEG segments of lengths 1, 2, and 4 s.

Table 2. Classification results using different EEG segment lengths.

EEG Segment Length	Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)
1s	DCAE+Bi-LSTM	98.07±0.31	97.83±0.52	98.32±0.43	98.31±0.42	98.07±0.32
2s	DCAE+Bi-LSTM	97.27±0.65	97.27±1.34	97.27±1.09	97.28±0.50	98.32±0.64
4s	DCAE+Bi-LSTM	98.79±0.53	98.72±0.77	98.86±0.53	98.86±0.53	98.79±0.53

The mean and standard deviation of all metrics over the 10-folds are then calculated and summarized in Table 2. Figure 5 shows the visualization of the classification results of the models using different EEG segment lengths.

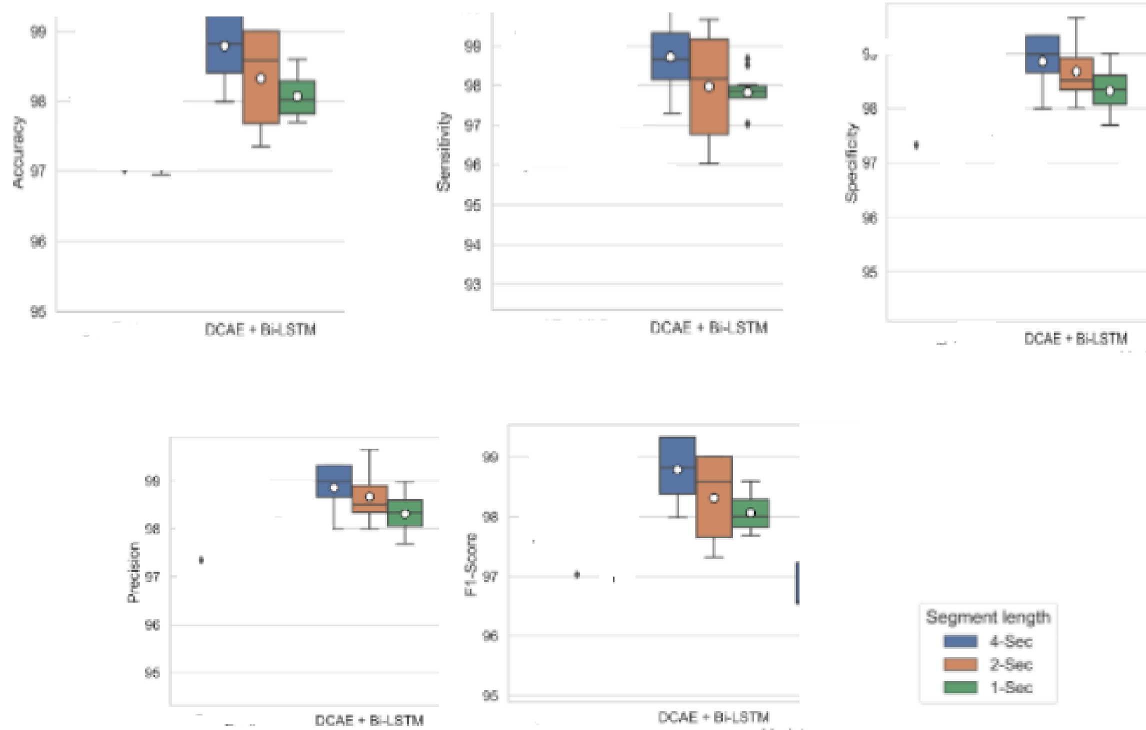

Figure 4. Boxplots showing ranges of performance metrics percentages calculated based on the 10-fold cross-validation results.

8. Discussion

As seen from the results, for all EEG segment lengths and evaluation metrics, Furthermore, as highlighted in Table 2, using a segment length of 4 s, the DCAE + Bi-LSTM model has achieved the highest performance in terms of all evaluation metrics.

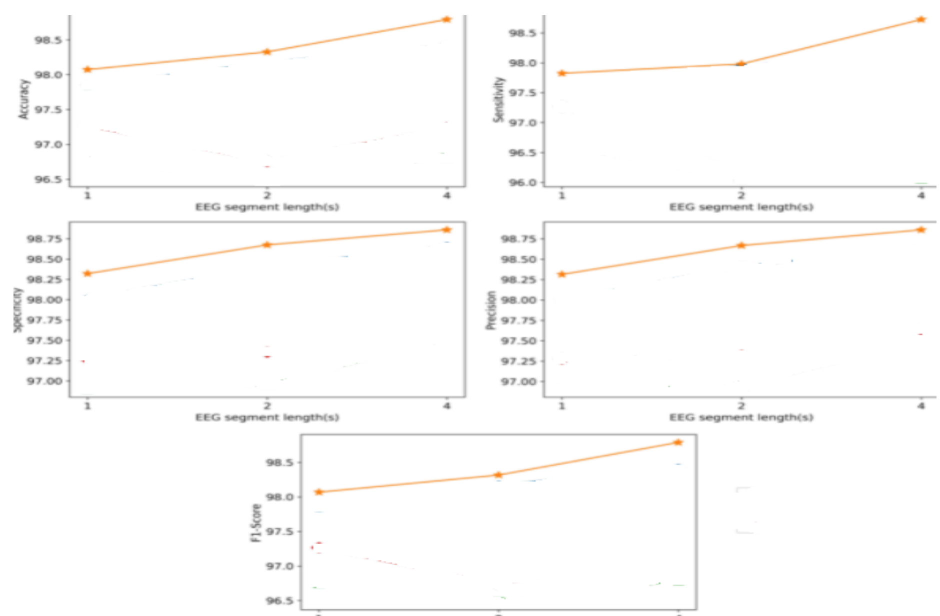

Figure 5. Visualization of the classification results of the models using different EEG segment lengths.

SDCAE model, a 4-s EEG segment length is the best choice to get the best classification performance. Generally, it can be noticed that all models that utilized a Bi-LSTM for classification have accomplished better results compared to their counterpart models that use MLP-based classifiers using the same EEG segment lengths. That can be explained as Bi-LSTM networks are more capable to learn better temporal patterns from the generated latent space sequence better than MLP networks.

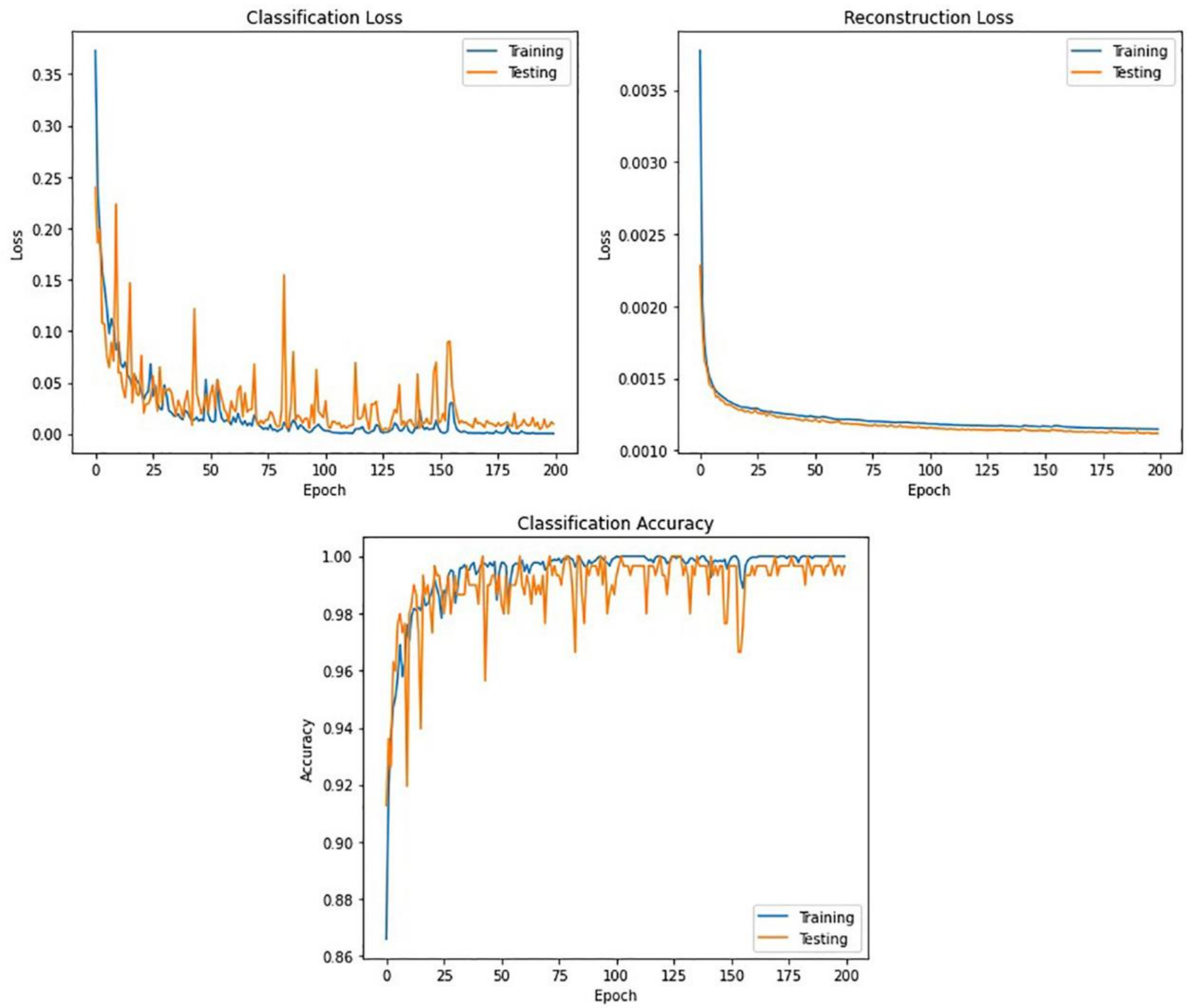

Figure 6. Accuracy and loss curves against the number of epochs obtained while training the DCAE + Bi-LSTM model.

Finally, by comparing the standard deviations in the evaluation metrics values for all models, it is clear that the results of the SDCAE models mostly have less dispersion compared to the other models, which means that the SDCAE models' performance is more consistent across all cross-validation iterations. Figure 6 shows the classification accuracy, CL, and RL curves for the training and testing datasets obtained while training the winning model (DCAE + Bi-LSTM) in one of the iterations of the 10-fold cross-validation.

9. Conclusion

A novel deep-learning approach for the detection of seizures is proposed. The approach uses a 2D-SDCAE for the detection of epileptic seizures based on classifying minimally pre-processed raw multichannel EEG signal recordings. In this approach, an AE is trained in a supervised way to classify between the ictal and interictal brain state EEG signals to exploit its capabilities of performing both automatic feature learning and classification simultaneously with high efficiency. SDCAE models that use Bi-LSTM networks-based classifiers is designed and tested using three EEG data segment lengths.. The twelve models are trained and assessed using a 10-fold cross-validation scheme and based on five evaluation metrics, the best performing model was the SDCAE model that uses a Bi-LSTM and 4 s EEG segments. This model has achieved an average of 98.79% accuracy, 98.72% sensitivity, 98.86% specificity, 98.86% precision, and finally an F1-score of 98.79.

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