ISSN: 2583-9292 (ONLINE)
DOI: 10.21917/ijdsml.2026.0187

NEURAL NETWORK-DRIVEN CLASSIFICATION OF EPILEPSY EEG DATA

Harshita, Pinkee and Kuldeep Tomar
Department of Computer Science and Engineering, NGF College of Engineering and Technology, India

Abstract

Epilepsy is a chronic, non-communicable brain disease and one of the most common neurological disorders worldwide. Epileptic seizures can progress from brief loss of attention and muscle twitching to severe and prolonged convulsions, and the frequency of seizures can also increase from once a year to multiple times a day, making epilepsy prediction very difficult. Moreover, due to the uncertainty, suddenness, and recurrence of epilepsy, patients often lose control of their bodies and lose consciousness, resulting in injuries and threat to life. Effective analysis and accurate classification of epilepsy can procure these episode's and situation's. Therefore, in this paper using deep learning models namely BiLSTM, DenseNet, and EfficientNetV2 vide epilepsy EEG dataset provided by University of Bonn's which is based on time series subsequently, transformed into 2D dataset by using Gradient-weighted Class Activation Mapping (Grad-CAM) for seizure detection. Consequently, all three models are able to classfy Epileptic seizures whereas results show that the EfficientNetV2 model achieves the best classification accuracy for two-dimensional EEG images of epilepsy, reaching 98.69%, thus confirming the feasibility of the EfficientNetV2 model in epilepsy seizure detection.

Keywords:

Epilepsy, Electrophysiological Signals, Deep Learning, Long Short Memory, Convolutional Neural Networks

1. INTRODUCTION

The processing of electrophysiological signals for diagnostic purposes has seen significant advances in the field of medicine, and currently, the incorporation of artificial intelligence (AI), and particularly deep learning (DL), is producing important developments in the treatment of neurological disorders [1][2]. In general, the signals are captured by sensors that translate electrophysiological phenomena into weak electrical potentials, which, after appropriate analog processing, are converted into digital signals compatible with computer analysis.

The electroencephalogram (EEG) is the recording of the electrophysiological action signals of brain cells, known as neurons. This activity results from the superposition of multiple electrical impulses (action potentials) [3][4], generated in neurons, a product of ionic exchange across the cell membrane (the process of ionic diffusion). The EEG is obtained by positioning a set of electrodes on the skull, over the scalp. The International Electrode Placement System [5] generates a map of points separated by 10 or 20% of the total area under recording, with a nomenclature associated with the name of the cranial region covered.

The correct interpretation of the EEG by the expert allows for the recognition and analysis of different neuropathologies or neurological states, such as sleep disorders, epilepsy, level of anesthesia, presence of brain activity, or even death. Epilepsy is a very common neuropathy that manifests as unexpected explode of uninhibited electrical activity in certain regions of the cerebral cortex. Epileptic patients suffer from recurrent seizures, with manifestations that range from mild abnormal sensations to unpredictable changes that can lead to immediate loss of consciousness and convulsions [6]-[8]. This neuropathology affects approximately 1% of the world's population. Figures 1a and 1b, generated with the EEGLAB electroencephalographic signal processing software [9], correspond to signal segments from the EEG channels for a control patient (without the neuropathy) and an epileptic patient, respectively.

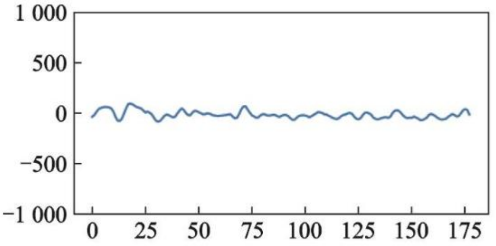


Fig.1(a). EEG channels for a controlled patient

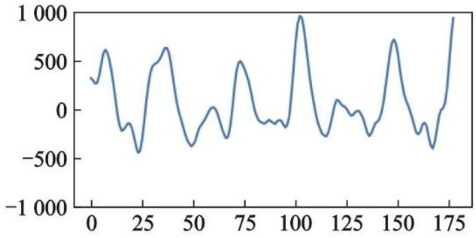


Fig.1(b). EEG channels for an epileptic patient

EEG signals can reflect the discharge activity of neurons in the brain and have the recompense of elevated sequential motion and non-invasiveness. They are extensively used to observe epilepsy, sleep disorders, Parkinson's and Alzheimer's disease, emotional state, and cognitive load [6]-[8]. Because the EEG signals during an epileptic seizure are more chaotic than normal EEG signals, they exhibit rapid and dramatic changes, including sharp waves, spikes, and spike-and-slow-wave complexes [6]-[8]. This is quite different from the signals during the non-seizure period. Therefore, epileptic seizures can be detected by analyzing EEG signals. Seizure detection is essentially a binary or multi-class classification problem of EEG signals. Seizure detection is achieved by determining the state of the signal at each moment. The classification study of epileptic EEG signals mainly consists of two parts: feature extraction and classification.

Commonly used feature extraction methods include autoregressive (AR) models, common spatial patterns (CSP), wavelet transform (WT), power spectral density (PSD) estimation, nonlinear dynamics, etc. [7].

2. BACKGROUND

Numerous interesting studies have reported on DL applications in EEG. Below are some works on the subject of this article: Zendehbad et al. [2] and Seijas et al. [11] reviewed the literature on DL applications in EEG classification. Their search located and analyzed 90+ publications in specialized databases such as Web of Science, Scopus, IEEE and PubMed. For each document studied, they presented key aspects such as the network architecture (CNN, recurrent networks, etc.), the type of task addressed by the network (neuropathy detection, emotion classification, seizure prediction, among other possible tasks), and concluded by presenting the achievements and results obtained in each publication.

Raghavendra et al. [12], also present a comprehensive review, specifically focused on AI-driven automated diagnosis applied to electrophysiological signals and images of five selected neurological disorders. The review covers the last two decades. The neuropathies considered are epilepsy, Parkinson's disease, Alzheimer's disease, multiple sclerosis, and ischemic stroke. In the study, the authors analyze and compare the different methods of feature extraction and selection, the dimensionality reduction techniques used, and the classification techniques.

Golmohammadi et al. [13] describe the development of a high-performance, computerized EEG examination structure based on machine learning (ML) values and big data handling. The developed system is a hybrid architecture that integrate temporal and spatial context, integrating hidden Markov models (HMM) for the sequential decoding of EEG events and spatial post-processing based on linear programming (CNN). The system's models were trained and evaluated using the Temple University Hospital (TUH) EEG database. The authors report that the system records and classifies clinically relevant patterns of brain activity, such as spikes and sharp waves, generalized periodic epileptiform discharges, and lateralized periodic epileptiform discharges; it also detects eye movements, artifacts, and background activity [2, 6]. According to the results presented in the article, the system exhibits a sensitivity above 90% while maintaining a specificity below 5%.

Agrawal et al. [14] proposed a CCNs to categorize signals as epileptic or non-epileptic. The novelty of this work is that the network is based on transfer learning, and for this purpose they experiment with three well-known pre-trained convolutional networks: googlenet [15], resnet101 [16] and vgg19 [17]. The database used is that of the University of Bonn [18], each signal is segmented into 23 onesecond segments (178 samples). 1-second signals are converted to 224 RGB images×224 pixels using the following algorithm: Set E (epileptic class), from the 2300 signals of 1 second duration, it takes 2292 signals and forms a matrix of 2292×178, then this matrix is converted into a vector of 407976 elements. This vector is resized into 8 matrices of 224×224 elements, discarding the rest of the vector elements. Then convert this matrix to RGB image using a special MATLAB function [19]. The same process was applied to non-epileptic signals (not specified in the article), but generating only 8 RGB images of the non-epileptic class. The number of images used to train the network was sixteen, of which 11 (70%) were used for training and 5 (30%) for testing. The authors replaced the last layer with one of two classes and substituted the densely connected layers. Their results show that the best accuracy was achieved with vgg19 (99.8%), but the shortest training time was achieved by the network pre-trained with googlenet (98.55% accuracy) at 41 seconds, much less than the 10.45 minutes it took to train the network based on vgg19.

Hussein et al. [20] propose a fourlayer network. The first layer is a Long Short-Term Memory (LSTM) layer, the second is a densely connected layer. These two layers extract the most relevant features [20] representing the EEG signal classes, which are the inputs for the third, one-dimensional average pooling layer. The final output softmax layer estimates the class of the input signal. The database they used in this work is from the University of Boon [18], which they expanded (enhanced) by adding white noise and artifacts such as artificial muscle and eye movements, obtained through models. They proposed four classifier models: a) Two binary models with the normal and epileptic classes (A vs E and ABCD vs E); b) One three-class model with the normal (A), interictal (C), and epileptic (E) classes; and c) Five-class models: A vs B vs C vs D vs E. The authors proposed two training strategies: 1) They divided the Data in two sets, one for training and one for testing, with various split percentages, and 2) Cross-validation with three, five, and ten sets. Each of the signals from sets A to E (4097) were resized to 2048×2. For both evaluation strategies, for all problems (two, three, and five classes), and with no added noise or artifacts, accuracy, sensitivity, and specificity were all 100%. For classifiers with muscle and eye-movement artifacts, and white noise, accuracy is affected by the signal-to-noise ratio (SNR), but for certain SNR levels, the accuracy of all classifiers was 100%.

Türk and Özerdem [21] use the University of Bonn database [18] and propose four classifiers: a) Binary (AB); b) Three-class (ABE); c) Four-class (ACDE); and d) Five-class (ABCDE). The training signal corresponds to the complete signal (4097 samples) of the set selected for each classifier, without preprocessing. The scheme proposed by the authors consists of a block that performs the continuous wavelet transform of the signal, which outputs an image (scalogram) of the 662-bit signal.×536 pixels. Then, this image goes through a block that resizes it to 32×32 pixels, using a cubic interpolation method [21].Finally, the resized image is passed to a classifier based on the convolutional network. The parent wavelet function they used was the continuous Morlet. The architecture of the convolutional network consisted of two sequences of convolution and maxpooling layers (4 layers), a dense layer, and an output softmax layer with a number of output nodes depending on the number of classes [21]. The data were divided into 90% (180, 270, 360, 450 signals for each classifier) for training, and 10% (20, 30, 40, 50 signals for each classifier) for testing. The training set was divided into 80% (144, 216, 288, 360 signals) to train the network and 20% (36, 54, 72, 90 signals) to measure the validation error at each epoch during training.Each classifier was trained using cross-validation of 10 sets The overall average accuracy, sensitivity, and specificity were 98.01, 96.92, and 98.59, for the classifiers A versus C versus E, A versus D versus E, B versus C versus E, and B versus D versus E, respectively.

The work of Gegein et al. [22], also corresponds to a hybrid platform (like [13]), but in this case used as a classifier to discriminate between pathological and non-pathological EEG. The platform uses a Temporal Convolutional Network (TCN) to extract sequential features and a CNN for spatial features; the database used, similar to [13], is also TUH. The TCN uses, as a feature vector, the calculations derived from applying the following operations: Discrete Fourier Transform, Continuous and Discrete Wavelet Transforms, and connectivity features between electrodes based on Hilbert Transform; these operations were applied to segments of a selected EEG channel. The authors state that the reported results place the proposed feature-based decoding framework at the same level as next-generation deep neural networks. The accuracy range between the two is 81% to 86%.

Zhao et al. [23] propose a one-dimensional convolutional network composed of three convolutional blocks and three blocks with densely connected layers for the detection of epileptic signals using the University of Bonn database [18]. The three convolutional blocks (for feature extraction) consisted of the following layers: Convolution, Normalization, ReLu, Dropout, and Maxpooling [23]. The first two densely connected blocks consisted of a densely connected layer, a ReLu layer, and a Dropout layer [23]. The last block consisted of a densely connected layer and a softmax output layer, with as many output nodes as there were classes (2, 3, or 5). The authors propose three models: a) A binary classifier of the normal and epileptic classes; b) A three-class classifier: normal, interictal, and ictal; c) A five-class classifier: A, B, C, D, and E.The authors propose eight different convolutional neural network architectures, from which they selected model M7 [23] (by crossvalidation), which yielded the best performance in accuracy, sensitivity, and specificity for the fiveclass case. Each signal in the dataset was divided into 23 non-overlapping 1-second segments (178 samples) to increase the number of signals from 500 (100 per type) to 11,500 (2,300 per type). The authors designed 14 binary classification models where they combined signals A, B, C, and D, designating them as the normal class versus the ictal class represented by signals E.For the three-class case, they designed five classifiers, where four of the classifiers took two of the classes from sets A, B, C, and D, and the third class corresponded to set E. The fifth threeclass classifier corresponded to the combination of sets AB as the first class, sets CD as the second class, and set E as the third class. For the five-class classifier, each Sets A, B, C, D, and E represent a class. All convolutional networks were trained with crossvalidation on 10 datasets. For the case of training three classes with the combination of sets AB, CD, and E, the average accuracy of the crossvalidation training was 96.97% [23].

Yean et al. [24] studied the non-Gaussianity in the emotional EEG signal (joy, displeasure, or neutral) of stroke patients and control patients. Non-Gaussianity was determined by calculating the statistical metrics [9]: skewness and kurtosis. The estimated distribution function of the emotional EEG was symmetrically non-Gaussian for both the stroke and control groups. In particular, the non-Gaussian EEG distribution was found to be more frequent in control patients than in those with stroke.

Acharya et al. [25] first used a 13 layered DCNN to detect three categories: ordinary, preic, and ictal. The accuracy, specificity, and sensitivity of this model were 88.67%, 90.00%, and 95.00%, respectively. George et al. [26] converted one-dimensional EEG data into twodimensional EEG images and used the ResNET-50 model, a subclass of convolutional neural networks, to classify scalp EEG data from Boston Children's Hospital into three categories: ictal, non-ictal, and preictal. The model achieved an accuracy of 94.98%.

Thara et al. [26] used a BiLSTM model to achieve binary classification of epileptic seizures and non-seizures on the University of Bonn dataset. Shekokar et al. [27] proposed unidirectional and bidirectional 3-layer LSTM networks for detecting epileptic seizures, and the bidirectional LSTM network model was found to be superior.

The above research results show that the accuracy of deep learning-based epilepsy EEG classification is improved compared with traditional methods. However, it requires a large number of network layers and combinations of different deep learning algorithms, which increases the complexity of the detection system. At the same time, according to the literature [28], in addition to processing one-dimensional EEG data, one-dimensional EEG data can also be converted into two-dimensional EEG images for classification of epilepsy and nonepilepsy. In the current deep learning algorithms for image classification, traditional convolutional neural networks are expanded by adjusting the depth, width and image resolution of the input network individually, while the EfficientNetV2 model [29] uses a composite coefficient to expand the network, so the EfficientNetV2 model is significantly better than other networks overall. In order to further improve the accuracy of epilepsy EEG classification, this paper uses BiLSTM, DenseNet and EfficientNetV2 models to classify two different EEG signal data types and compares and analyzes them. At the same time, the gradient-weighted class activation mapping (Grad-CAM) method is used to visualize and analyze the classification results.

3. EXPERIMENTAL DATA AND METHODS

3.1 DATASET

The investigational preprocessed dataset is by the University of Bern, Germany. The original dataset consisted of five different subsets, A to E, with 100 files in every compartment. Each file enclosed 4,097 Electrophysiological Signals data which collected over the time frame of 23.6 seconds of brain motion, with a fixed frequency of 173.61 Hz. Amongst them, subsets A and B were EEG signals collected from normal individuals without epilepsy in open and closed eye states, respectively; subset C was EEG signals collected from the contralateral region of the lesion in epileptic patients during the interictal period; subset D was signals collected from the lesion area in epileptic patients during the interictal period; and subset E was EEG signals [28] . Since this paper performs binary classification of epileptic EEG signals, the dataset for the ictal period only contains subset E, which has a small amount of data. Therefore, the preprocessed version of this dataset was selected.

3.2 PREPARING THE DATASET

This section involves preprocessing and reconstructing the raw EEG data. The preprocessing of the dataset mainly involves filtering using a bandpass filter of 0.53–40 Hz and removing artifacts using visual detection techniques. Data reconstruction involves dividing the 4,097 time series data from the original dataset into 23 data blocks and arranging them randomly. Each data block contains 178 signal sequences, with a total duration of 1 second. Therefore, the original dataset is split into 11,500 data entries, each consisting of 178 signal sequences. The last column of data is labeled {1, 2, 3, 4, 5}. Data labeled 1 represents data from the epileptic seizure period, while data labeled 2–5 represent data from the non-seizure state.

This paper uses two data types for processing: one-dimensional time series and two-dimensional images. In the two-dimensional images, the waveform differences between the two states increase due to the adjustment of the voltage value range. To maintain data balance, 2,300 records were randomly selected from the data labeled 2-5 as data on non-seizure epilepsy. These records were then uniformly labeled 0 and recombined with the data labeled 1 to form 4,600 records. Therefore, the ratio of seizure-prone to non-seizure data was 1:1. The recombined dataset was then randomly divided into training, validation, and test sets in an 8:1:1 ratio.

3.3 EXPERIMENTAL MODEL

3.3.1 Processing Model for One-Dimensional Time Series

Long short-term memory (LSTM) network models improve upon the gradient vanishing and exploding problems of recurrent neural networks (RNNs), making them more suitable for handling long-term sequence problems. The BiLSTM model, composed of forward and backward LSTM, can better process epileptic EEG data from two directions. As shown in references [26] [27], bidirectional LSTM networks are more advantageous in processing EEG sequences; therefore, this paper selects the BiLSTM model to process one-dimensional sequence signals . The algorithm flow is shown in Fig.2. The input to the BiLSTM model in this paper first passes through a linear layer activated by ReLU; then through a bidirectional recurrent layer, with the recurrent units designated as LSTM units, totaling 128; then through two more linear layers, each preceded by a Dropout and BN layer; finally, Softmax is used as the activation function to achieve binary classification of epileptic seizures and non-seizures.

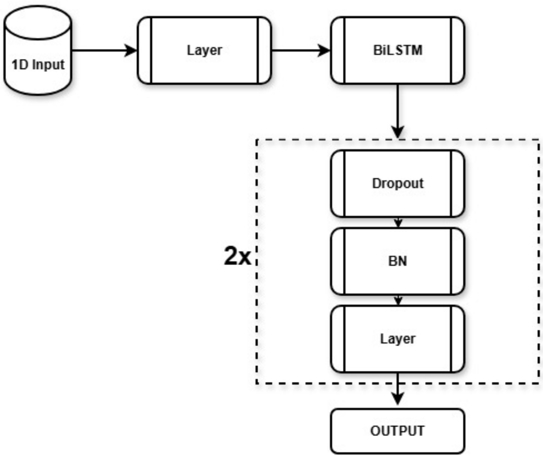


Fig.2. Flowchart based on BiLSTM algorithm

3.3.2 Processing Model of Two-Dimensional Electroencephalogram Images:

For two-dimensional EEG images of epilepsy, the EfficientNetV2 model was used, with DenseNet as the experimental control group . The algorithm flowchart is shown in Fig.3. The EfficientNetV2 network model is an improvement on EfficientNetV1, optimizing training speed and the number of parameters. It also introduces an improved progressive learning method that dynamically adjusts the regularization method based on the size of the training images. The EfficientNetV2 model consists of convolutional, Fused-MBConv, and MBConv modules. Two-dimensional EEG images are first processed through a 3×3 convolutional layer to extract feature values; then, they are processed through the Fused-MBConv and MBConv modules, with the kernel size k uniformly set to 3×3; finally, binary classification is achieved through a 1×1 convolutional layer, a pooling layer, and a fully connected layer. DenseNet, based on deep residual networks, employs a dense connection mechanism, interconnecting all layers. Each layer is connected to all preceding layers to achieve feature reuse and serves as input for the next layer. In the DenseNet network structure shown in Fig.3, except for the first Conv7×7, each Conv has BN and ReLU layers before it. The Conv1×1 and Conv3×3 modules are set with the number of layers according to the numbers on the left. Each layer adopts a dense connection mechanism. Finally, linear classification is achieved and output through the average pooling layer and the fully connected layer.

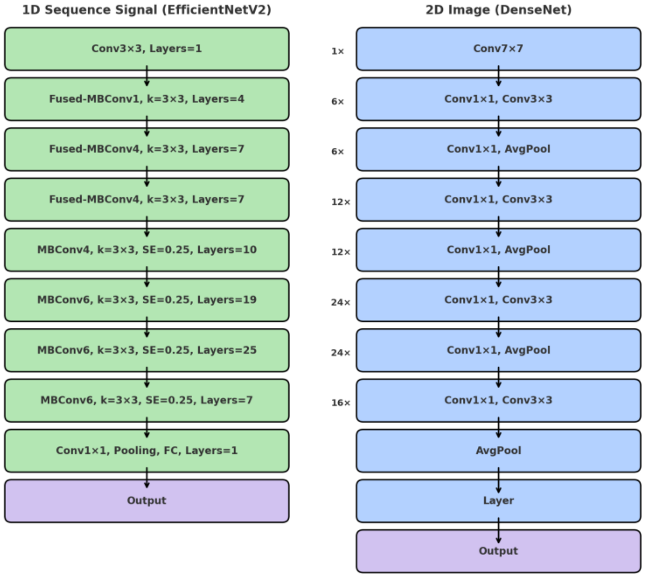


Fig.3. Workflow of EfficientNetV2 algorithm and DenseNet algorithm

3.3.3 Grad-CAM:

How a trained deep learning algorithm classifies images is often unknown, leading many to consider it a black box lacking interpretability. Grad-CAM [19], however, was developed for visual interpretation of convolutional neural network models, serving as the foundation for visual model judgment. Grad-CAM generates a rough localization map corresponding to the classification category, highlighting the important regions of interest to the network model. Furthermore, for image classification, visualization can not only capture important regions but also provide reasonable explanations for seemingly unreasonable classifications. Grad-CAM calculates weights by weighting and summing the feature layers of different categories using activation functions without altering the original network structure, and then uses global gradient averaging to calculate the weights.

$$L^{c}_{Grad\text{-}CAM} = ReLU\left(\sum_{k}\alpha^{c}_{k}A^{k}\right) \tag{1}$$

where, A represents the feature layer output by the last convolutional layer. k - feature layer A - Middle k One channel; c represents the category to which it is classified; A^k representative feature layer A Central Channel k Data; α^{c}_{k} representatives targeting A^k. The weight of is calculated using the following formula:

$$\alpha^{c}_{k} = \frac{1}{Z}\sum_{i}\sum_{j}\frac{\partial y^{c}}{\partial A^{k}_{ij}} \tag{2}$$

where, ∂y^c represents the category not activated by Softmax c Predicted score; A^{k}_{ij} representative feature layer A. In the passage k, the median coordinate is i_j Data at the location Z; it is the width × height of the feature layer.

3.4 EVALUATION INDICATORS

For ease of comparison, Accuracy, Sensitivity, Specificity and Precision are used as evaluation metrics, depicted as under:

$$Sensitivity = \frac{TP}{TP+FN} \tag{3}$$

$$Specificity = \frac{TN}{TN+FP} \tag{4}$$

$$Precision = \frac{TP}{TP+FP} \tag{5}$$

$$Accuracy = \frac{TN+TP}{TN+TP+FN+FP} \tag{6}$$

where, TP represents true positive; TN represents true negative; FP represents false positive; and FN represents false negative. Meanwhile, ROC curves and AUC are used to evaluate model performance: the ROC curve evaluates the classification model's performance using two metrics: the true positive rate and the false positive rate; and AUC is the area under the ROC curve, with a value closer to 1 indicating a better model.

4. EXPERIMENT AND RESULTS ANALYSIS

4.1 EXPERIMENTAL SETUP

This paper uses three models to process two types of EEG data: the BiLSTM model is used for one-dimensional sequences, and the DenseNet and EfficientNetV2 models are used for two-dimensional EEG images, with DenseNet serving as the experimental control group. The experimental setup is shown in Table.1.

Table.1. Experimental settings

Data Types	Model	DL framework
One-dimensional sequence	BiLSTM	Pytorch
Two-dimensional image	DenseNet	
	EfficientNetV2	

4.2 EXPERIMENTAL SETUP AND PARAMETER CONFIGURATION

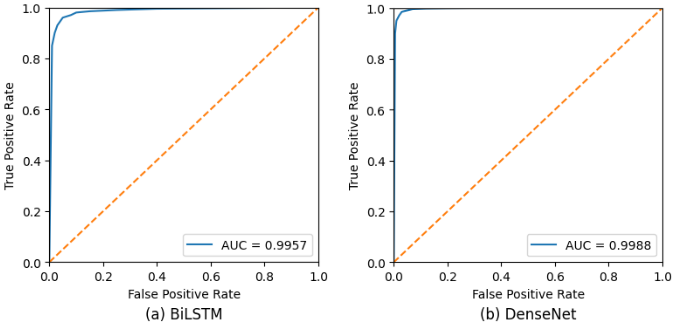
This experiment was carried out on a Linux environment using the deep learning framework namely PyTorch, trained on a Tesla V100 machine with 32 GB of GPU memory. For the three models, the hyper-parameter namely learning rate is initialized to 0.001, the loss function pinned as binary cross-entropy, the optimization method is fixed as adam, and the batch size for the networks training is set to 64. Through multiple parameter tunings, the iteration period for the BiLSTM model was set to 100, while that for DenseNet and EfficientNetV2 was set to 20.

4.3 CLASSIFICATION RESULTS AND ANALYSIS

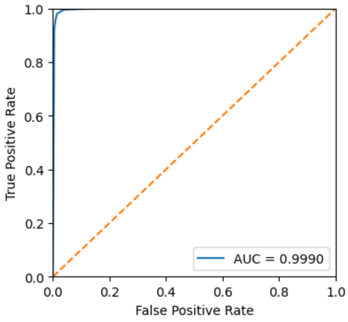
This study used three classification models to compare two data types: BiLSTM, DenseNet, and EfficientNetV2. The evaluation metrics used in the results analysis were accuracy, sensitivity, specificity, precision, and ROC curve. The training results are shown in Table.2, and the ROC curve is shown in Fig.4.

Table.2. Results by Models

Model	Accuracy	Sensitivity	Specificity	Precision	AUC
BiLSTM	97.39	96.66	98.18	98.3	99.57
DenseNet	98.04	97.08	99.09	99.14	99.88
Efficient NetV2	**98.69**	**98.33**	**99.09**	**99.15**	**99.9**



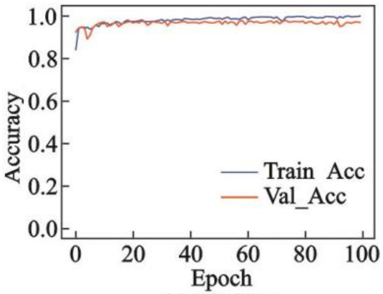
(a) BiLSTM (b) DenseNet



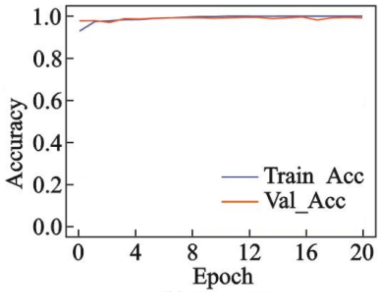
(c) EfficientNetV2

Fig.4. ROC curves of the three models

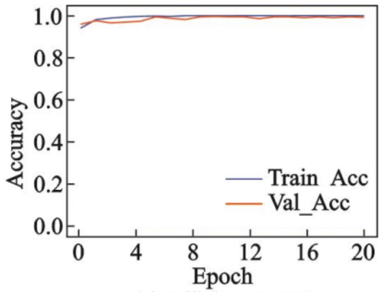
As exposed in Table.2, all three models performed well in terms of accuracy. Compared to the BiLSTM model for processing one-dimensional sequences, the DenseNet and EfficientNetV2 models for processing two-dimensional images showed better results, with EfficientNetV2 achieving the highest accuracy of 98.69%. Similarly, in terms of sensitivity, specificity, and precision, the two models for processing two-dimensional images outperformed the BiLSTM model, with EfficientNetV2 achieving the highest values in all three categories, reaching 98.33%, 99.09%, and 99.15%, respectively. The ROC curves in Fig.4 shows that the AUC values of all three models were above 99%, with EfficientNetV2 reaching the highest at 99.90%. By comparing the various evaluation metrics of these three models, it can be found that all three models performed well in recognizing epileptic EEG signals, with the EfficientNetV2 model showing the best performance.



(a) BiLSTM



(b) DenseNet



(c) EfficientNetV2

Fig.5. Training and validation accuracy magnitude variation curves for the three models

The Fig.5 shows the curves of the BiLSTM, DenseNet, and EfficientNetV2 models during training and validation sets, respectively, while Train_Acc and Val_Acc represent the accuracy values during training on the training and validation sets. After 20 iterations, the accuracy and loss function curves of the BiLSTM model gradually converge and remains stable within a certain range. Ultimately, the recognition accuracy on the training set stabilizes at around 100%, the accuracy on the validation set stabilizes at around 97%, and the highest accuracy on the final test set is 97.39%. After 4 iterations, the accuracy and loss function curves of the DenseNet model gradually converge, with the highest accuracy on the final test set reaching 98.04%. After five iterations, the accuracy curve and loss function curve of the EfficientNetV2 model gradually converged. The recognition accuracy of the training set stabilized at around 100%, the accuracy of the validation set stabilized at around 99%, and the highest accuracy of the final test set was 98.69%.

Outcome shows that the EfficientNetV2 model achieves the best classification accuracy for two-dimensional EEG images of epilepsy, reaching 98.69%, thus confirming the feasibility of the EfficientNetV2 model in epilepsy seizure detection. Furthermore, Grad-CAM is introduced for visualization analysis of the two-dimensional images, improving the interpretability of the classification results.

5. CONCLUSIONS

This paper focuses on two data types of epilepsy EEG data: one-dimensional time series and two-dimensional EEG images. Using BiLSTM, DenseNet, and EfficientNetV2 models, respectively, the paper implements seizure detection on the University of Bonn's epilepsy EEG dataset. Results show that the EfficientNetV2 model achieves the best classification accuracy for two-dimensional EEG images of epilepsy, reaching 98.69%, thus confirming the feasibility of the EfficientNetV2 model in epilepsy seizure detection. Further, Grad-CAM is introduced for visualization analysis of the two-dimensional images, improving the interpretability of the classification results. In clinical practice, epilepsy seizures are typically detected by observing clinical symptoms and EEG. However, manual interpretation of EEG data is not only inefficient due to the large amount of data involved, but also prone to misjudgment based solely on past experience. Therefore, this paper proposes a binary classification system for epileptic seizures and non-seizure states, which is beneficial for monitoring and clinical diagnosis of patients in the later stages of their condition. To further facilitate daily home monitoring of patients, it is necessary to classify the pre-seizure and interacted periods; the method presented in this paper is also applicable to this, and this is a direction for further research.

REFERENCES

[1] A.V. Perez-Sanchez, "Artificial Intelligence-based Epileptic Seizure Prediction from Bioelectrical Signals: A Review", *Signals*, Vol. 6, No. 10, pp. 1-10, 2025.

[2] S.A. Zendehbad, A.S. Razavi, N. Tabrizi and Z. Sedaghat, "A Systematic Review of Artificial Intelligence Techniques based on Electroencephalography Analysis in the Diagnosis of Epilepsy Disorders: A Clinical Perspective", *Epilepsy Research*, Vol. 215, pp. 1-7, 2025.

[3] S. Beniczky and D.L. Schomer, "Electroencephalography: Basic Biophysical and Technological Aspects Important for Clinical Applications", *Epileptic Disorders*, Vol. 22, No. 6, pp. 697-715, 2020.

[4] A. Biasiucci, "Electroencephalography (EEG)", *Current Biology*, Vol. 29, No. 3, pp. 85-90, 2019.

[5] M. Teplan, "Fundamentals of EEG Measurement", *Measurement Science Review*, Vol. 2, pp. 1-11, 2002.

[6] Y. Sun, C. Wei, V. Cui, M. Xiu and A. Wu, "Electroencephalography: Clinical Applications during the Perioperative Period", *Frontiers in Medicine*, Vol. 7, pp. 1-7, 2021.

[7] W. Haiyu, H. Jianfeng and W. Yinglong, "A Review of EEG Signal Processing Methods", *Computer Era*, No. 1, pp. 13-15, 2018.

[8] M.N.P. Liman and A. Al Sawaf, "Epilepsy EEG", *StatPearls*, pp. 1-7, 2026.

[9] A. Delorme and S. Makeig, "EEGLAB: An Open Source Toolbox for Analysis of Single-Trial EEG Dynamics Including Independent Component Analysis", *Journal of Neuroscience Methods*, Vol. 134, No. 1, pp. 9-21, 2004.

[10] R.R. Selvaraju, M. Cogswell and A. Das, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization", *Computer Vision and Pattern Recognition*, pp. 1-7, 2016.

[11] C. Seijas, A. Caralli and S. Villazana, "Neuropathology Classifier Based on Higher Order Spectra", *Journal of Computer and Communications*, Vol. 1, pp. 28-32, 2013.

[12] U. Raghavendra, U.R. Acharya and H. Adeli, "Artificial Intelligence Techniques for Automated Diagnosis of Neurological Disorders", *European Neurology*, Vol. 82, No. 1, pp. 41-64, 2019.

[13] M. Golmohammadi, A. Hossein, H. Nejad, S. Lopez de Diego, I. Obeid and J. Picone, "Automatic Analysis of EEGs using Big Data and Hybrid Deep Learning Architectures", *Frontiers in Human Neuroscience*, Vol. 13, pp. 1-8, 2019.

[14] A. Agrawal, C. Gupta and P. Garg, "A Deep Transfer Learning Approach for Seizure Detection using RGB Features of Epileptic Electroencephalogram Signals", *Proceedings of International Conference on Cloud Computing Technology and Science*, pp. 367-373, 2019.

[15] A. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke and A. Rabinovich, "Going Deeper with Convolutions", *Proceedings of International Conference on Computer Vision and Pattern Recognition*, pp. 1-9, 2015.

[16] K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition", *Proceedings of International Conference on Computer Vision and Pattern Recognition*, pp. 770-778, 2016.

[17] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition", *Proceedings of International Conference on Computer Vision and Pattern Recognition*, pp. 1-7, 2014.

[18] R. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David and C. Elger, "Indications of Nonlinear Deterministic and Finite-Dimensional Structures in Time Series of Brain Electrical Activity: Dependence on Recording Region and Brain State", *Physical Review E*, Vol. 64, No. 6, pp. 1-6, 2001.

[19] J. Agg, "What's New in Simulink", Available at https://la.mathworks.com/content/dam/mathworks/mathworks-dot-com/images/events/matlabexpo/uk/2019/whats-new-in-simulink-r2019a-and-r2019b.pdf, Accessed in 2019.

[20] R. Hussein, H. Palangi, R.K. Ward and Z.J. Wang, "Optimized Deep Neural Network Architecture for Robust Detection of Epileptic Seizures using EEG Signals", *Clinical Neurophysiology*, Vol. 130, pp. 25-37, 2019.

[21] O. Turk and M. Ozerdem, "Epilepsy Detection by using Scalogram based Convolutional Neural Network from EEG Signals", *Brain Sciences*, Vol. 9, No. 5, pp. 1-8, 2019.

[22] L. Gemein, R. Schirrmeister, P. Chrabąszcz, D. Wilson, J. Boedecker, A. Schulze-Bonhage, F. Hutter and T. Ball, "Machine-Learning-based Diagnostics of EEG Pathology", *NeuroImage*, Vol. 220, pp. 1-8, 2020.

[23] W. Zhao, "A Novel Deep Neural Network for Robust Detection of Seizures using EEG Signals", *Computational and Mathematical Methods in Medicine*, Vol. 2020, pp. 1-9, 2020.

[24] Wen-Yean, M. Murugappan, M. Iqbal, W. Khairunizam, B. Siao-Zheng, A. Joseph and Z. Ibrahim, "A Study of Non-Gaussian Properties in Emotional EEG in Stroke using Higher-Order Statistics", *Proceedings of International Conference on Electrical and Computer Technologies*, Vol. 672, pp. 635-645, 2020.

[25] U.R. Acharya, S.L. Oh, Y. Hagiwara, J.H. Tan and H. Adeli, "Deep Convolutional Neural Network for the Automated Detection and Diagnosis of Seizure using EEG Signals", *Computers in Biology and Medicine*, Vol. 100, pp. 270-278, 2018.

[26] F. George, A. Joseph and B. Bibin, "Epileptic Seizure Prediction using EEG Images", *Proceedings of International Conference on Communication and Signal Processing*, pp. 1595-1598, 2020.

[27] K. Thara, B.G. PremaSudha and X. Fan, "Epileptic Seizure Detection and Prediction using Stacked Bidirectional Long Short-Term Memory", *Pattern Recognition Letters*, Vol. 128, pp. 529-535, 2019.

[28] M. Tan and Q.V. Le, "EfficientNetV2: Smaller Models and Faster Training", *Proceedings of International Conference on Computer Vision and Pattern Recognition*, pp. 1-7, 2021.

[29] R.G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David and C.E. Elger, "Indications of Nonlinear Deterministic and Finite-Dimensional Structures in Time Series of Brain Electrical Activity: Dependence on Recording Region and Brain State", *Physical Review E*, Vol. 64, No. 6, pp. 1-7, 2001.