STM JOURNALS

Trends in
Opto-electro & Optical Communication

ISSN: 2231-0401 (Online)
ISSN: 2347-9957 (Print)
Volume 14, Issue 3, 2024
September–December
DOI (Journal): 10.37591/TOEOC

https://journals.stmjournals.com/toeoc

Research TOEOC

Advancing EEG Technology for Affordable and Effective Epilepsy Detection

Jaya Jeswani[1], Sarthak Patil[2], Rushikesh Redij[2], Bhargavi Marathe[2,*]

Abstract

For a proper diagnosis and prompt treatment, epilepsy, a neurological condition marked by recurring seizures, needs to be continuously monitored. Manual interpretation is frequently used in traditional approaches for identifying epileptic seizures from electroencephalogram (EEG) signals, which can be laborious and error-prone. In this research, a novel method for automatically detecting epilepsy from EEG data using deep learning algorithms is presented. According to centers for disease control and prevention (CDC) research, over 3 million Americans suffer from epilepsy. This study investigated the use of deep learning techniques for both EEG data analysis and seizure diagnosis. Here, a method known as 1D CNN-Long Short-Term Memory Networks (LSTM) is used, which combines long short-term memory with a dimensional convolution neural network. Whereas the lengthy short-term memory component concentrates on extracting temporal details, CNN mainly pulls spatial features from the standardized EEG sequence analysis. The CHB-MIT dataset is used in the study, with 80% of it being randomly divided into training and 20% into testing. Accuracy rates of up to 98% have been attained with the use of the CNN architecture, with CNN-LSTM achieving an average accuracy of 85%. A very effective and reasonably priced EEG identification tool designed for epilepsy has been developed because of advances in electroencephalogram (EEG) technology.

Keywords: Epilepsy, convolutional neural network, convolutional neural network-long short-term memory, signal analysis, epileptic seizure recognition

INTRODUCTION

The World Health Organization indicates that epilepsy seizures are the second most widespread neurological condition after stroke. Approximately 1% of the world's population is affected by this condition. Individuals with epilepsy are required to take long-term medication due to the unpredictability of seizures, which can cause significant damage to their physical and mental well-being. The detection and analysis of epilepsy symptoms can significantly aid the early identification of epileptic seizures. This helps to ensure the well-being of patients and prompts them to consider emergency antiepileptic medications when necessary. Advancements in electroencephalogram (EEG) technology have resulted in the creation of a cost-efficient and highly effective EEG identification tool specifically intended for epilepsy.

An electroencephalogram (EEG) is commonly used for diagnosis. Medical experts still rely on visual examinations to detect epileptiform irregularities. However, this method is prone to mistakes and time-consuming. The EEG characteristics of patients with epilepsy differ from those of healthy individuals. Individuals with epilepsy typically exhibit two phases of EEG

***Author for Correspondence**
Bhargavi Marathe
E-mail: 02003007.bhargaveemba@student.xavier.ac.in

[1]Professor, Department of Information Technology, Xavier Institute of Engineering, Mumbai, Maharashtra, India
[2]Student, Department of Information Technology, Xavier Institute of Engineering Mumbai, Maharashtra, India

Received Date: August 02, 2024
Accepted Date: October 16, 2024
Published Date: October 30, 2024

Citation: Jaya Jeswani, Sarthak Patil, Rushikesh Redij, Bhargavi Marathe. Advancing EEG Technology for Affordable and Effective Epilepsy Detection. Trends in Opto-electro & Optical Communication. 2024; 14(3): 11–18p.

activity, inter-ictal and ictal, each with distinct characteristics. Interpreting EEG signals by neurosurgeons to diagnose epilepsy is a standard procedure in the medical field. The detection and recognition of these signals, however, is a laborious and thorough process that requires substantial resources of both material and personnel, along with a significant risk associated with diagnosis. Consequently, the automated detection of EEG signals for epilepsy diagnosis is crucial.

Moreover, the expertise required is highly limited. Misdiagnosis of this nature can potentially lead to fatalities. Consequently, the creation of a computerized automated human assistance system for rapid and precise disease diagnosis is imperative. Professionals traditionally examine and assess complete EEG using conventional methods. Because the reports were lengthy, this could take a lot of time.

Simultaneously, it is susceptible to inaccuracies because human error cannot be eliminated from the analysis. Consequently, an automated diagnostic system for detecting and treating epilepsy has been developed over the years. This assists in alleviating the burden on healthcare professionals. Additionally, this approach is more precise and efficient than the older methods.

RELATED WORK

This study explored some of the advanced approaches employed in identifying epilepsy. Gupta et al. [1] used a CNN architecture with four convolutional layers.

Zubair et al. [2] applied a discrete wavelet transform to extract features from the time–frequency domain. These dimensions were then reduced using techniques such as subpattern-based principal component analysis (PCA) and cross-subpattern correlation-based PCA. By combining Sparse principal component analysis (SPPCA) and SUBXPCA with Catboost and Random Forest, an accuracy level of 97% was achieved.

An image with three channels was created using a short-time Fourier transform. This constructed image is then subjected to pre-trained models such as Alex Net, DenseNet201, and Efficient Net. Additionally, a CNN is employed to extract both low- and high-frequency signals from an image [3].

Liu et al. [4] implemented an innovative method called the updated Tunable Q-Factor Wavelet Transform (RTQWT) for detecting features. By utilizing energy ratio distributions, this technique identifies distinct and shared feature spaces, which are subsequently utilized for signal reconstruction. These reconstructed signals are classified in the context of epilepsy detection. Different classifiers were utilized to evaluate the performance and consistency of RTQWT in recognizing these signals.

A deep learning approach naïve proposed here by Rowan Naïvehab Halawa [5]. The paper incorporates wavelet-based EGG signals into the developed model, enabling the integration of pre-ictal and inter-ictal signal prediction. Cherukuvada and R. Alvizhi utilized a belief network in conjunction with oppositional Aquila-optimizer-based Feature Selection for feature selection [6].

Hassan introduced a CNN machine learning technique in conjunction with various other deep learning algorithms such as random forest, support vector machine, and logistic regression [7].

Xiong [8] introduced an enhanced multilayer network through genetic algorithm optimization for seizure detection. Feature extraction involves utilizing the Pearson correlation coefficient, information, and permutation disalignment index. Seizure detection was performed using the random forest method, achieving an accuracy rate of 98.88%.

Mathur et al. [9] developed a method using the Ramanujan Periodic Subspace (RPS) to detect epileptic EEG signals efficiently. Their approach is not only accurate and reliable but also performs well even with noise and artifacts, matching the results of more complex techniques.

Table 1. CHB-MIT dataset.

Type	Scalp EEG
Subjects	22
Male Subjects	5
Female Subjects	7
Channels	23
Sampling Rate	256
Seizures	198
Recording	644 hr.

Seizure detection employs a machine learning methodology that encompasses both black-box and non-black-box techniques. To enhance this process, a deep learning approach utilizing convolutional neural networks was employed for feature extraction and classification. This was complemented by the vector machine proposed by Usman et al. [10].

MATERIALS AND METHODS

The dataset description is shown in Table 1.

This research utilized the CHB-MIT dataset, which included electroencephalogram (EEG) recordings from 23 young patients. These individuals consisted of boys ranging from 3 to 22 years old and girls ranging from 1.5 to 19 years old, all receiving care at the Children's Hospital Boston.

This dataset is accessible to the public via PhysioNet.org with open access. The data were collected at a frequency of 256 Hz and then organized into separate files, each containing one hour of recordings per subject. Table 1 provides a detailed description of the dataset [11].

Convolution Neural Network Model

An algorithm for identifying patterns in a dataset is called a convolution neural network. The convolutional neural network is widely recognized as the most prominent algorithm for image recognition and classification. A convolutional neural network learns from image-like and image-derived data using a special type of layer called a convolutional layer. Convolutional, pooling, and numerous hidden or dense layers constitute the layers that makeup CNN architecture.

Let's examine each layer that makes up CNN: The convolutional layer in a convolutional neural network, where the convolutional layer is the foundational layer. Through kernels (weights) that differentiate various images from one another, feature extraction is sometimes referred to as classification. Therefore, a link representing a distinct kernel exists between the convolution and preceding layers.

Consequently, each distinct kernel is employed for convolution operations to generate the output or activation map of the current convolutional neuron. The kernel acts as a matrix to communicate with the input EEG signal. Moreover, it includes a stride that is initially set to one and determines how the filter convolves over the input signal. The stride indicates the number of pixels that the kernel should shift at a time.

Pooling layer: One of the key purposes of pooling in convolutional neural networks is to perform downsampling. This procedure ensures that the fundamental features are preserved by reducing the size of the feature map. Max pooling is a widely used type of pooling for this purpose, which requires the selection of a kernel size and stride length during the design of the architecture.

Flatten layer: In this step, the initial three-dimensional layer is transformed into a one-dimensional array. The processed data are then utilized as an input for the fully connected layer for classification.

Dense layer: The resulting output of the LSTM layer is transformed into a one-dimensional array, which is an essential process before passing it to the fully connected layers. After flattening, the data were sent through a dense layer with a specific number of neurons.

The intermediate layer facilitates the understanding of the intricate connections between different attributes. Ultimately, the result of the network is produced by the last dense layer, which incorporates the SoftMax activation function specifically designed for the given classification task.

CNN-LSTM Model

The CNN-LSTM architecture comprises two components: CNN and LSTM. The first part, that is, the CNN, comprises convolution layers, normalization layers, and a max pooling layer. A Conv3D layer was introduced, indicating that the data were in 3D format. Following the Conv3D layer, A batch normalization layer was included to enhance stability and speed up the training procedure by standardizing the input for the next layer.

Another Conv3D layer was applied, potentially capturing higher-level spatiotemporal features in the data. Similar to the previous batch normalization layer, this layer normalizes the input to the next layer, promoting stable and efficient training. Another Conv3D operation captures additional features in the reduced spatial dimensions. The utilization of an A-Max Pooling layer results in an additional reduction in the spatial dimensions of the data.

A new batch normalization layer was utilized to standardize the input before proceeding to the next layer. The output from the preceding layers is then restructured and inputted into an LSTM layer. The LSTM proved beneficial for capturing extended relationships and sequential patterns within the dataset.

The output of the LSTM layer is transformed into a one-dimensional array by flattening it, which is a necessary step before feeding the data into fully connected layers. The flattened data were passed through a dense layer with a certain number of neurons. This layer helps learn the complex relationships between features.

An additional dense layer is included, potentially decreasing the dataset's dimensionality further.

Ultimately, the outcome of the network is determined by the last dense layer, which utilizes the SoftMax activation function specifically designed for classification purposes.

According to the formula below, accuracy is calculated as the number of correct predictions divided by the total number of forecasts:

$$Accuracy = \frac{TP+TN}{(TP+FP+FN+TN)}$$

In terms of accuracy, TP stands for true positive forecasts and TN for true negative predictions.

Conversely, false positive (FP) and false negative (FN) indicate false-positive and false negative results, respectively, where positive labels are misclassified and negative labels are incorrectly identified [12].

Precision is a measure of the accuracy of a model in correctly identifying positive labels. The number of true positives was divided by the total number of true positives and true negatives.

This measure provides valuable information regarding the model's certainty in correctly classifying positive examples. A higher precision value indicates a greater level of confidence in the model predictions [12].

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive+ False Positive}}$$

The importance of sensitivity lies in its ability to evaluate how accurately a model can detect real seizures. In the field of epileptic seizure detection, achieving a high level of sensitivity is crucial to minimize the risk of missing seizures, which can greatly impact patients. 1. Sensitivity, sometimes known as recall or true positive rate, assesses how well the model can recognize positive occurrences, such as actual seizures.

It is defined as:

$$Sensitivity = \frac{\text{True Positive}}{\text{True Positive+ True Negative}}$$

The false-positive rate can be calculated by dividing the number of FP by the total number of false positives and true negatives (TN) [12]:

$$False\ Postive\ Rate\ = \frac{False\ Positive}{False\ Positve + True\ Negative}$$

Implementation

Exploratory data analysis (EDA) encompasses the initial phases of data exploration and comprehension. This involves examining the data distribution, identifying patterns, and addressing any missing or outlier values in the dataset.

Evaluation Metrics

The performance of the model was assessed by utilizing evaluation metrics that involve the calculation of accuracy. Once the data have been prepared, they are transformed into a NumPy array, which is a widely used numerical array in Python. For Model Creation - A novel architecture known as CNN-LSTM was created, merging convolutional layers to extract features and long short-term memory layers to capture extended dependencies within sequential data. The architecture of this model consists of these two components, which work together to process and understand sequential information effectively. A deep learning framework such as TensorFlow is used to implement the model. This framework allows the specification of the model's architecture, activation functions, and other pertinent parameters.

The NumPy array representing the data is subsequently split into training and testing sets, and a critical step in the process is to assess the model's performance on new data. A typical approach involves allocating 80% of the data for training and reserving 20% for testing. However, this percentage may vary depending on the size of the information and requirements. Subsequently, the model was trained using the provided training data. Throughout this process, the model learns to map the input data to their corresponding output labels through forward and backward propagation.

The testing dataset was used to assess the performance of the model at the conclusion of the training phase. This procedure is crucial for assessing the ability of the model to apply its lessons to fresh confidential data. Various evaluation metrics, such as accuracy, precision, recall, sensitivity, and false-positive rate, can be utilized to assess the efficiency of the model, as shown in Figures 1 to 4.

RESULT

The results demonstrate the accuracies of different features associated with the detection of epilepsy using the CNN and CNN-LSTM architecture. The datasets were randomly divided into training and test sets. Eighty% of the data were assigned for training purposes, while the remaining 20% were set aside for testing. Replicating the outcomes obtained using the CHB-MIT dataset is the main goal. Studying the dataset shown in Tables 2 and 3, we found several inconsistencies in the calculation of the inter-ictal hours described in the detention of pre-ictal or inter-ictal signals. Therefore, we decided to focus on patients in whom these problems were reduced (or almost absent). Ultimately, we selected patients 1, 2, 21, and 23.

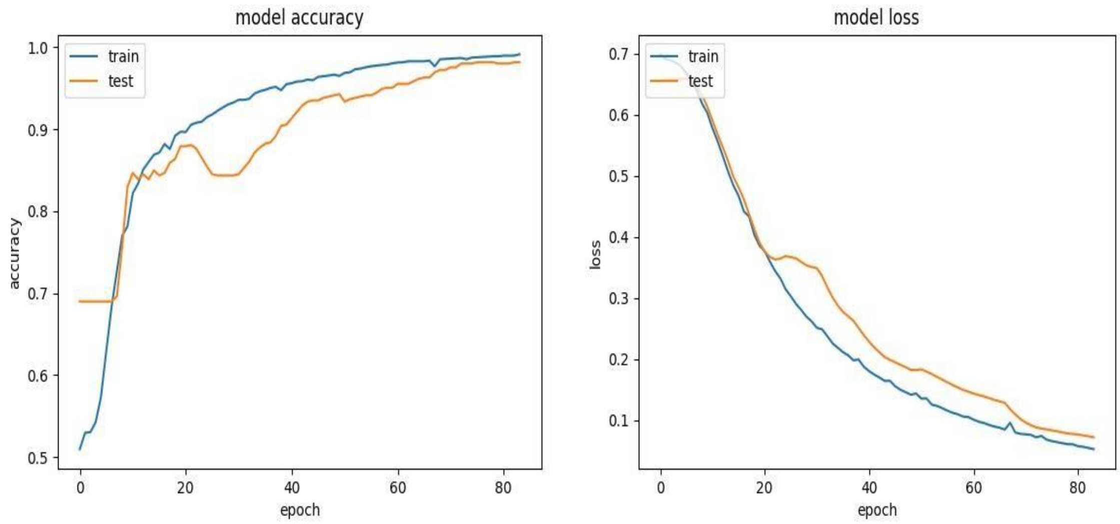

Figure 1. CNN training and validation accuracy.

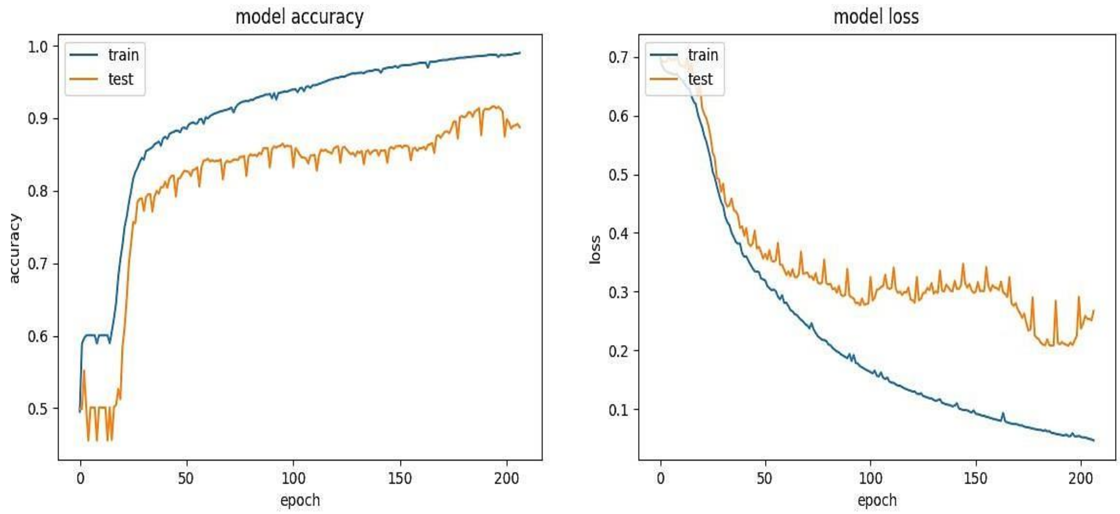

Figure 2. Patient 02 accuracy and loss.

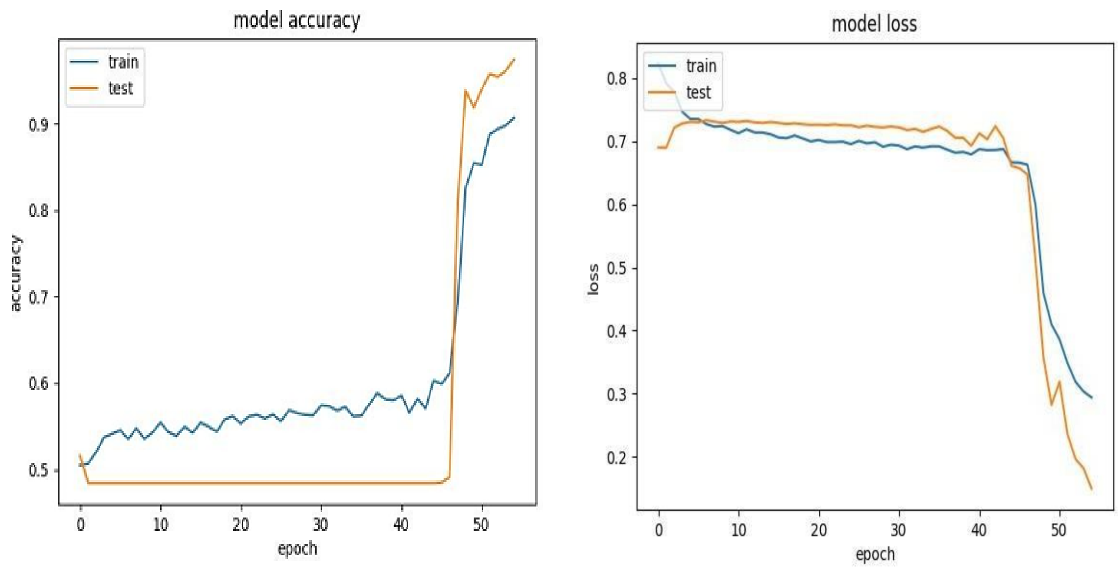

Figure 3. Patient 21 accuracy and loss.

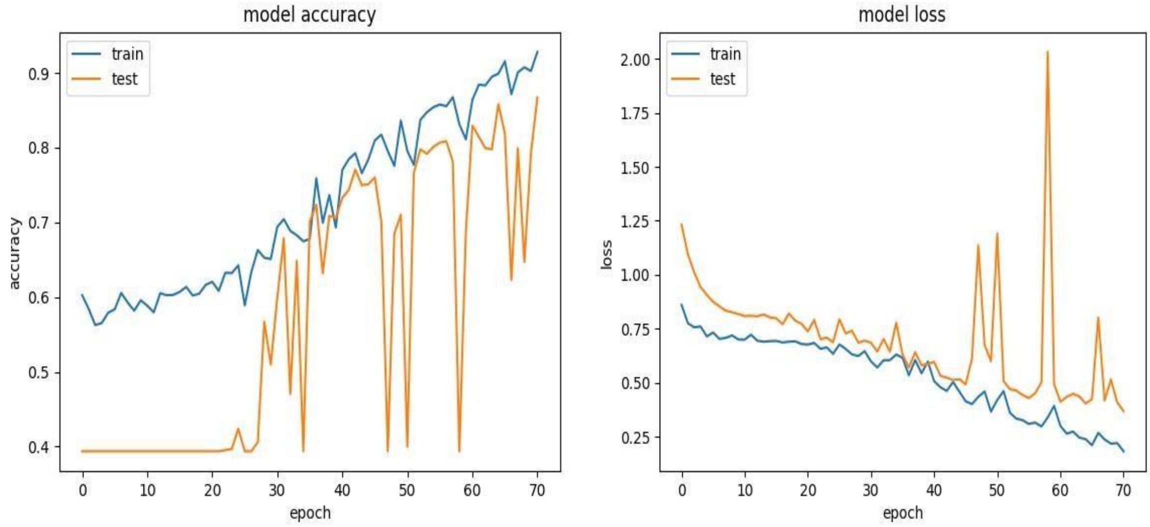

Figure 4. Patient 23 accuracy and loss.

Table 2. CNN results.

Patient	Accuracy	Sensitivity	FPR
01	0.99	0.91	0.0
02	0.99	1.0	0.01
21	0.95	0.46	0.01
23	1.0	1.0	0.0

Table 3. CNN-LSTM result.

Patient	Accuracy	Sensitivity	FPR
01	1.0	1.0	0.0
02	1.0	1.0	0.0
21	0.72	0.0	0.0
23	1.0	1.0	0.0

CONCLUSION

This study focused on the problem of automatic seizure detection using EEG signals. This study presents a novel deep-learning-based automatic epilepsy detection approach based on EEG data. According to CDC data, more than 3 million Americans have epilepsy. The article concludes that researchers have developed a simple and affordable way to detect epilepsy by analyzing brainwaves. They used advanced technology to accurately identify the seizures. This makes it easier and faster for doctors to diagnose epilepsy, helping patients to receive proper treatment without expensive or difficult tests.

REFERENCES

1. Gupta S, Sameer M, Mohan N. Detection of epileptic seizures using convolutional neural network. In: International Conference on Emerging Smart Computing and Informatics (ESCI); 2021. IEEE. p. 786–90. DOI: 10.1109/ESCI50559.2021.9396983.
2. Zubair M, Belykh MV, Naik MUK, Gouher MF, Vishwakarma S, Ahamed SR, Kongara R. Detection of epileptic seizures from EEG signals by combining dimensionality reduction algorithms with machine learning models. IEEE Sensors J. 2021;21:16861–9. DOI: 10.1109/JSEN.2021.3077578.
3. Chen W, Wang Y, Ren Y, Jiang H, Du G, Zhang J, Li J. An automated detection of epileptic seizures EEG using CNN classifier based on feature fusion with high accuracy. BMC Med Inform Decis Mak. 2023;23:96. DOI: 10.1186/s12911-023-02180-w. PubMed: 37217878.

4. Liu Z, Zhu B, Hu M, Deng Z, Zhang J. Revised tunable Q-factor wavelet transform for EEG-based epileptic seizure detection. IEEE Trans Neural Syst Rehabil Eng. 2023;1707–20. DOI: 10.1109/TNSRE.2023.3257306. PubMed: 37028382.
5. Halawa RI, Youssef SM, Elagamy MN. An efficient hybrid model for patient-independent seizure prediction using deep learning. Appl Sci. 2022;12:5516. DOI: 10.3390/app12115516.
6. Cherukuvada S, Kayalvizhi R. Feature selection with deep belief network for epileptic seizure detection on EEG signals. Comput Mater Continua. 2023;75:4101–18. DOI: 10.32604/cmc.2023.036207.
7. Hassan F, Hussain SF, Qaisar SM. Epileptic seizure detection using a hybrid 1D CNN-machine learning approach from EEG data. J Healthc Eng. 2022;2022:9579422. DOI: 10.1155/2022/9579422. PubMed: 36483658.
8. Xiong Y, Dong F, Wu D, Jiang L, Liu J, Li B. Seizure detection based on improved genetic algorithm optimized multilayer network. IEEE Access. 2022;10:81343–54. DOI: 10.1109/ACCESS.2022.3196004.
9. Mathur P, Chakka VK, Shah SB. Ramanujan periodic subspace based epileptic EEG signals classification. IEEE Sens Lett. 2021;5:1–4. DOI: 10.1109/LSENS.2021.3086755.
10. Usman SM, Usman M, Fong S. Epileptic seizures prediction using machine learning methods. Comput Math Methods Med. 2017;2017:9074759. DOI: 10.1155/2017/9074759. PubMed: 29410700.
11. Siddiqui MK, Morales-Menendez R, Huang X, Hussain N. A review of epileptic seizure detection using machine learning classifiers. Brain Informat. 2020;7:5. DOI: 10.1186/s40708-020-00105-1. PubMed: 32451639.
12. Mardini W, Bani Yassein MM, Al-Rawashdeh R, Aljawarneh S, Khamayseh Y, Meqdadi O. Enhanced detection of epileptic seizure using EEG signals in combination with machine learning classifiers. IEEE Access. 2020;8:24046–55. DOI: 10.1109/ACCESS.2020.2970012.

