Mathematical Modelling of Engineering Problems
Vol. 10, No. 1, February, 2023, pp. 84-92
Journal homepage: http://iieta.org/journals/mmep

Ensemble Machine Learning Based Identification of Adult Epilepsy

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https://doi.org/10.18280/mmep.100110

Received: 30 May 2022
Accepted: 12 October 2022

Keywords:
artificial intelligence, ensemble learning, epilepsy, machine learning, neuroscience

ABSTRACT

Epilepsy is a chronic non-communicable illness that affects brain individuals and impacts more than 50 million people globally. To predict epileptic seizures, we proposed machine learning-based ensemble learning technique in this study. In the pre-processed stage, we applied some important techniques such as Power line noise reduction and dividing the record into windows of 5 seconds. The project is created by the help of ensemble machine learning technique, which employs several machine learning algorithms, we used the following algorithms: decision tree, support vector machine, artificial neural networks, and convolutional neural networks. We used a dataset from PhysioNet website that contains adult EEG signals. Several convolutional layers were used to extract features from the EEG signals, after that, the feature set is utilized to train a classifier model, which combines the results. Our approach successfully reached 91% accuracy while 91% sensitivity and 91% specificity, respectively.

1. INTRODUCTION

Epilepsy affects approximately 65 million people worldwide [1] is a result of brain dysfunction complicated by genetic abnormalities or acquired aetiology [2]. The neurologist and intensive care unit can identify seizure activity by changes in electroencephalogram (EEG) signals; these signals represent different brain regions. Below Figure 1 shows the brain channels and EEG signals.

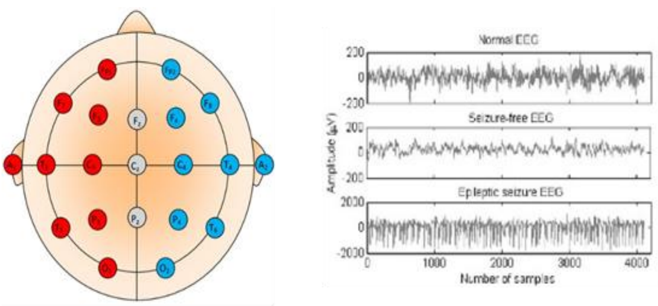

Figure 1. Brain channels and different EEG signals

During an epileptic seizure, abnormal signals are recorded. Because of the critical situation of these patients and the necessity for immediate interpretation of the recorded EEG, we proposed a simple and highly accurate tool that helps the treating team identify an ongoing seizure activity. The first step of our idea that we applied is creating a system that analyses EEG data and predicts epileptic activity via analysing EEG raw data as input, then applying multiple machine learning and deep learning algorithms to identify and notify the caring team. This is believed to improve epilepsy [3]. Predicting epileptic seizures entails detecting preictal conditions to regulate the first or future seizures. Seizures are brief bursts of electrical activity in the brain that impair normal functioning. They may appear in several ways, depending on which part of the brain is affected. The capture of scalp or intracranial EEG recordings, pre-processing, feature set extraction, and classification are all common epileptic seizure prediction methods. An alert is issued when a preictal condition is successfully detected, allowing an oncoming seizure to be managed before it happens. Although we are focusing in this work on epilepsy, the dataset will comprise EEG signals from adult epilepsy patients.

We obtained the dataset through the PhysioNet browser; it contains EEG brain waves from 14 epileptic adults (8 men and 6 females), each with a varied number of records and channels. Reducing noise, separating single records into epochs, balancing the data, and partitioning the data for training, testing, and validation are all strategies that must be used to eliminate undesirable signals. The ensemble approach we used is maximum voting, the maximum voting works as follows: Each of the models, Decision Tree (DT), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Convolutional Neural Network (CNN) will forecast for a single data point, and each prediction will be given a vote. Finally, the final projection will be based on the majority of the models' predictions. The implementation can be represented in four parts: data overview, data pre-processing, feature extraction, and model implementation.

2. RELATED WORK

Per the "International League against Epilepsy" (ILAE) in 2014, epilepsy definition is "a transient occurrence of signs and/or symptoms due to abnormal, excessive or synchronous neuronal activity in the brain" [4]. Epilepsy can be diagnosed by three main symptoms: at least two seizures having occurred over 24 hours, reflex seizures having occurred twice or more over 10 years, or/and epilepsy syndrome [4].

The most common symptom is called "epileptic seizure" [5], which is a seizure caused by a disrupting episode with the brain's activities, and not all epileptic patients have seizures [6]. Approximately 50 million people over the world have epilepsy [7], or 1% of the population. According to the Saudi Epilepsy Society, 0.654% of people in Saudi Arabia suffer from this disease. Epilepsy affects all ages; the symptoms and signs differ by age group. For example, in new-borns, the symptoms involve a lack of oxygen during delivery and/or abnormal brain development, in which the symptoms in infants are brain tumours and/or genetic disorders [8].

Therefore, an accurate diagnosis is important. As childhood is the stage of brain formation, epilepsy occurs within a more dynamic nervous system and might thus be interfering with brain development that could affect the individual in several ways, such as the failure to develop skills, a slower rate of development, and the possibility of losing previously developed skills [8]. Every 4.8/1000 children worldwide have epilepsy. In the US, 0.94/1000 children under 18 have epilepsy [9, 10]. In recent years, epilepsy diagnosis in infants and children has improved, and new methods to identify epilepsy have become hot topics for researchers. Electroencephalogram (EEG) signals can reflect the state of brain activities with time. It is a complex and nonlinear interconnection between a billion neurons [11]. In addition, it is frequently the way to diagnose epilepsy by analysing the EEG data; in this regard, several studies have focused on aiding epileptic patients to find suitable treatments.

Alotaibi et al. [12] proposed an ensemble machine learning approach to identify paediatric epilepsy. The dataset was obtained from the children's hospital Boston Massachusetts institute of technology (CHB-MIT) that was comprised of scalp EEG database of epileptic paediatric signals. After due pre-processing they applied ensemble learning model along with a group of classifiers comprising of Naïve Bayes (NB), Support vector machine (SVM), Logistic regression (LR), k-nearest neighbour (KNN), Linear discernment (LD), Decision tree (DT). It was claimed that the Ensemble learning model outperformed by achieving 100% for all parameters in contrast to state-of-the-art studies in the literature. The study does not cover the adult epilepsy patient data. The EEG signals can be classified as seizure and non-seizure by using a key point computation-based "local binary pattern" (LBP) [13]. Processing of the EEG signals is divided into three phases, the first phase called "key point localization", the second called "key point-based local binary pattern computation", and the third called histogram feature. Afterward, the "support vector machine" classifier categorizes the signals into (seizure/non-seizure). These methodologies were easy to use and simple to implement, it was achieved good performance compared with existing methods in other studies.

In Tharayil et al. [14], the authors developed a method to predict epileptic seizures in adult and child patients together. This method called linear mixed model; they applied these techniques to more than 1.2 million seizures recorded. The primary discovery was that all developed models achieved higher accuracy in adults than in children. The authors stated the reasons for this, such as that seizure patterns of children and adults are different, or that undercounted seizures in children not being available. The early discover of epileptic seizures can help the patient to avoid any side effects in the brain. In Usman et al. [15], data pre-processing converted 23 EEG signals channels into a single signal channel to improve the "signal-to-noise ratio" (SNR) and then applied "empirical mode decomposition" (EMD) to increase the SNR. The authors selected SVM as a classifier, and the result revealed that the model predicted the seizure prior to its occurrence by 23.6 minutes, up to a maximum prediction time of 33 minutes. Kabir and Zhang [16], the proposed approach is performed by dividing the EEG signals into groups based on time period and then drawing a sample from each group of the class via optimum-allocated techniques (OTA) before combining all the samples; afterward, the features are extracted from OTA set.

Several other machine learning, deep learning and AI based techniques have been applied for disease predictions in the literature and it is among the hottest areas of research in healthcare and several other disciplines [17-30].

The rest of the paper is organized as follows: Section 3 presents dataset and its pre-processing steps. Section 4 present the feature extraction. Section 5 implements the model. Section 6 presents the results and discussion while section 7 concludes the paper.

3. DATA PRE-PROCESSING

We obtained the dataset through the PhysioNet browser [31]; it contains EEG brain waves from 14 epileptic adults (8 males and 6 females), each with a varied number of records and channels. With an average age of 43.5 years old, most patients fall between 41 and 62 years old. In addition, the dataset has 3 seizures as an average per patient, while the record time average per patient is 550.2 minutes (9.17 hours).

3.1 Dimensions reduction

The extremely large size of data leads to multidimensional datasets. Having multidimensional data in the dataset makes the job of analysing or searching for any patterns in the dataset difficult. This challenge led scientists to look for a good solution. Finally, they came up with the dimensionality reduction technique, which reduces the number of dimensions in the dataset based on the task requirement.

In the dataset, we found a variation in the number of channels in most of the records, and after searching for the names of the channels, we found that all records have the same number of EEG channels, and the other channels are not brain channels. We proposed to use the Dimensional Reduction techniques to reduce the number of channels for each record to 29 channels, which is only the EEG channels in all records. This helps us to reduce the amount of data that will be processed, which also helps in reducing pre-processing time, training model time, and saving resources.

Figure 2 is a screenshot of the data before reducing the dimensions and Figure 3 after using the dimensions reduction technique.

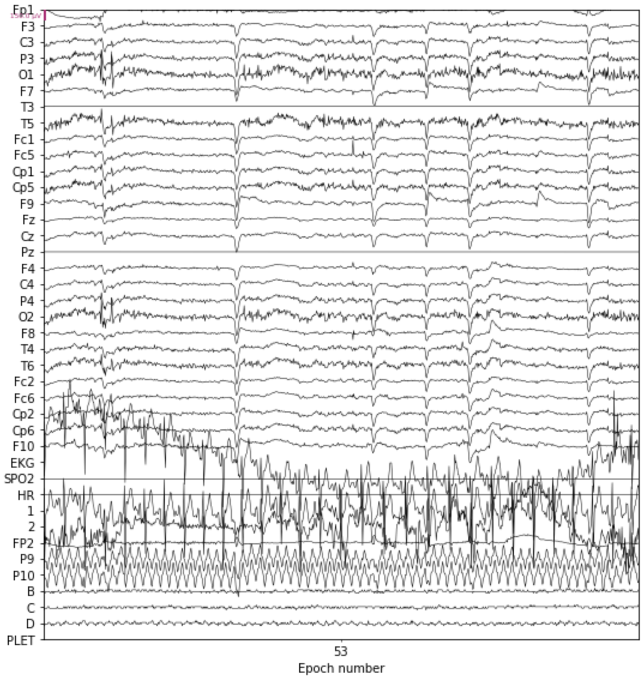

Figure 2. Dataset before reducing the dimensions

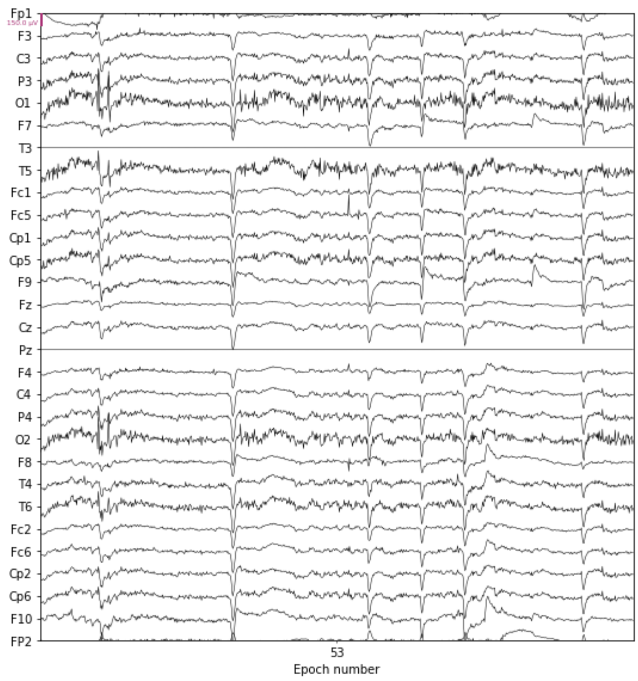

Figure 3. Dataset after reducing the dimensions

3.2 Noise reduction

Unwanted data objects, features, or records that do not assist in explaining the feature or the link between the feature and the target are referred to as noise. The algorithms often ignore patterns in data due to noise. "Noisy data" has been used interchangeably with the term "corrupt data." However, any data that cannot be read and processed accurately by computers, such as unstructured text, is included in its definition. Noisy data is any data that's been collected, stored, or modified in such a way that it cannot be read or utilized by the application. Humans make errors and equipment is inherently incorrect while collecting data, so the information gathered has some inaccuracy [32].

The electrical network generates noise, which is referred to as power-line noise. Its intensity may vary from region to region based on the type of power line being used. It's made up of 50Hz strong peaks (or 60Hz depending on your geographical location). At harmonic frequencies, there may be some peaks as well [33].

Figure 4 depicts a noisy data before noise reduction and Figure 5 after using the power-line noise reduction filter. Noise free data provides a better classification and prediction of the disease.

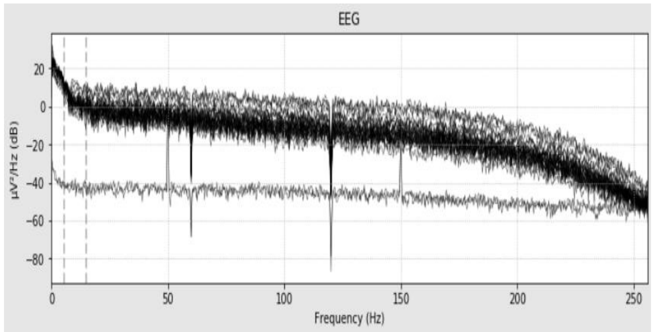

Figure 4. Dataset before power-line noise reduction filter

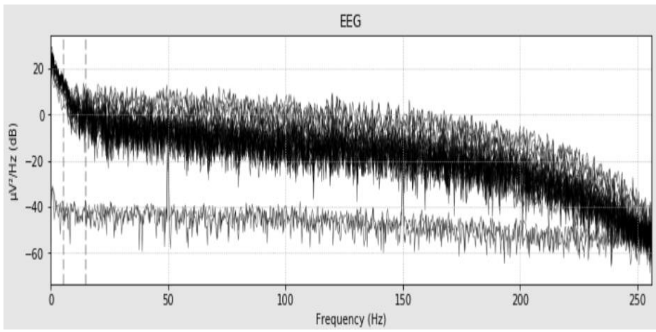

Figure 5. Dataset after power-line noise reduction filter

As described in the figures, data is consisted of EEG signals duly processed by means of the PhysioNet browser [34]. Once taken, same signals dataset was chosen for the further processing and analyses. It is worth mentioning that the said browser inherently conducts the wavelet transformations to bring the signals in the form that can be further processes and analysed. The characteristics and behaviour of the EEG signals are explained in the Figures 2 to 5 with and without filtering, respectively.

3.3 Data epoching

Epoching data is the process of dividing records into small windows, which helps the algorithms to train and reduces the pre-processing time. In this study, we divided each record into epochs of 5 seconds with a 1 second overlap. We ended up with many epochs. The Figures 2 to 5 are the statistical representation of the result of this step. It is also specified on the x-axis of each figure.

3.4 Data labelling

The process of identifying raw data (image, text, signal, etc.) and adding one or more relevant and informative labels to give context so that a machine learning model can learn from it is known as data labelling in machine learning. The result of the project depends on this step. If the labelling is incorrect, the result will be incorrect. In current study, we label non-seizure epochs as 0 and seizure epochs as 1.

3.5 Data balancing

The importance of data balance is that it can help the model learn the examples equally for each class target in the dataset. So, the learning across the targets will be fair. In current study, we found that the data is completely imbalanced among the targets; the number of non-seizure epochs is larger than the seizure epochs. Statistically, our data is divided into 90% non-seizure epochs and 10% seizure epochs. We proposed reducing the number of non-seizure epochs to be close to the number of seizure epochs, in order to balance the dataset. Other techniques like increasing the other side may not be effective and good in case of seizer dataset. However, in case of imaging dataset such techniques are more viable where one image can produce several images by means of mutation operations.

4. FEATURE EXTRACTION

The process of transforming raw data into numerical features that can be processed while maintaining the information in the original dataset is referred to as feature extraction. It provides better outcomes than simply applying machine learning to raw data.

There are two approaches to extracting features. The first approach is by applying the classical mathematical equations such as Max, Min, Standard Deviation, etc. The second approach is by taking data as input to the convolutional layers and letting the model predict the features. Based on the nature of data second approach is used. Sequentially all the steps employed to achieve better and better features. Though this task was pretty tedious but consequently, it helped the proposed models in achieving commendable results.

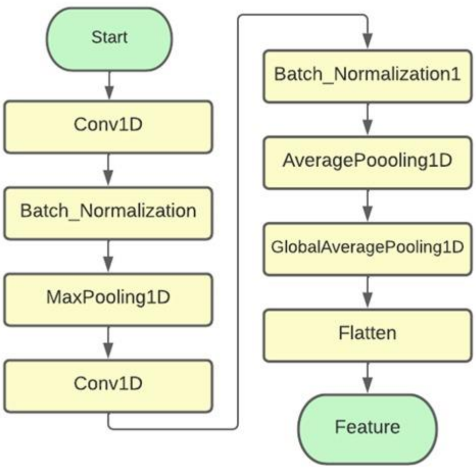

Figure 6. Deep learning layers

In current study, we used the data as input, then we fed it into different conventional layers. At this stage, the layers will take on the job of extracting the features. In the end, we stop flattening to convert the features into a 1-dimension array. This process allows the developer to take advantage of extracting features from conventional layers. Otherwise, the developer will move to the classical approach. Figure 6 shows precisely how this step is done.

5. MODEL IMPLEMENTATION

5.1 Convolutional Neural Network (CNN)

In current study, we built a CNN model with the following settings: Binary Cross Entropy is the loss function, and 0.001 is the Adam Learning Rate. It can be used in a variety of real-world problems, such as image analysis, health risk assessment, and recommender systems. Moreover, it works for both classification and regression problems [34]. Figure 7 shows the structure of the proposed CNN model.

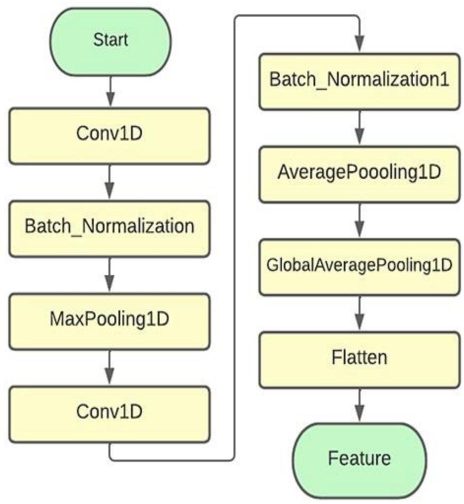

Figure 7. Structure of CNN model

5.2 Support Vector Machine (SVM)

A classical machine learning algorithm is SVM, which can handle classification and regression problems both from discrete and numerical data, respectively. In the SVM algorithm, each data object is plotted as a point in an n-dimensional space, with the value of each feature being the value of a particular coordinate [35].

We classify the data by locating the hyper-plane that clearly distinguishes the two groups. In current study, we used the extracted features as input to our SVM model. We applied hyperparameter optimization techniques to find the best settings for our dataset and applied grid search techniques with the settings in the following Table 1.

Table 1. Grid search SVM settings

Hyperparameter	Range
C	[0.1, 1, 3, 7, 9, 10, 100, 1000]
Gamma	[1, 0.1, 0.01, 0.001, 0.0001]
Kernel	[linear, rbf]

After several experiments and trial over the dataset we found the best setting for the dataset that is represented in following Table 2. As described it was based on the experts' opinion and hit and trial method to find the best settings for the current environment. As enlisted, the best results were found at the parameters values 1, 1, and radial basis function (RBF) against the parameters C, Gamma and Kernel type, respectively.

Table 2. SVM best settings

Hyperparameter	Best setting
C	1
Gamma	1
Kernel	RBF

5.3 Decision Tree (DT)

A decision tree is a type of machine learning that has a built-in form of tree structure. In addition, the data will be processed and divided into a form of a graphical tree using an algorithm. There are two essential units in a decision tree, which are node and leaf [36]. In current study, we took the extracted features as input to the proposed DT model. We then applied hyperparameter optimization techniques to find the best setting for our dataset. We applied grid search techniques with the settings in the following Table 3.

Table 3. Grid search DT settings

Hyperparameter	Range
Criterion	[entropy, Gini]
Max Depth	range (1,10)
Min Samples Split	range (2,10)
Min Samples Leaf	range (1,5)

After that, we found the best setting for the data, and it's represented in Table 4. The criterion was Gini index, maximum depth was 2, minimum samples split was chosen as 2 while minimum sample leaf was taken as 1, in the Weka tool environment.

Table 4. Grid search DT settings

Hyperparameter	Best settings
Criterion	Gini
Max Depth	2
Min Samples Split	2
Min Samples Leaf	1

6. RESULTS AND ANALYSIS

After collecting the dataset and pre-processing it, the pre-processed dataset will be split into three parts: training data of 70%, validation of 20%, and testing data of 10%. and using the convectional layer for feature extraction. After extracting the features, the dataset will be fed to the classifiers to classify them into seizures and non-seizures. The empirical experimental comparison is made between the three classifiers: Support Vector Machine (SVM), Decision Tree (DT), Convectional Neural Network (CNN), and Ensemble Model. The data set will be fed to the three classifiers: Support Vector Machine (SVM), Decision Tree (DT), Convectional Neural Network (CNN), and Ensemble Model. Table 5 below illustrates each classifier's prediction results in a micro-average based on their model evaluation. The Support Vector Machine (SVM) classifier achieved the highest accuracy at 93%, precision at 93%, recall at 94%, and F1-score at 93%, respectively.

Other algorithms such as DT, CNN and Ensemble learning algorithms managed to obtain the highest accuracy as 91%. Similar, results were obtained for the precision as well. In term of recall, SVM dominates with 94%, DT and Ensemble algorithm achieved 91% each. CNN was however, on the lower side with 87%.

In terms of F1-score, SVM outperformed all the other approaches. DT and Ensemble learning algorithms achieved 91% each while CNN exhibits a relatively poor F1-score as 89%.

Table 5. Classifiers results

Classifier	Accuracy	Precision	Recall	F1-score
SVM	93%	93%	94%	93%
DT	91%	91%	91%	91%
CNN	91%	91%	87%	89%
Ensemble	91%	91%	91%	91%

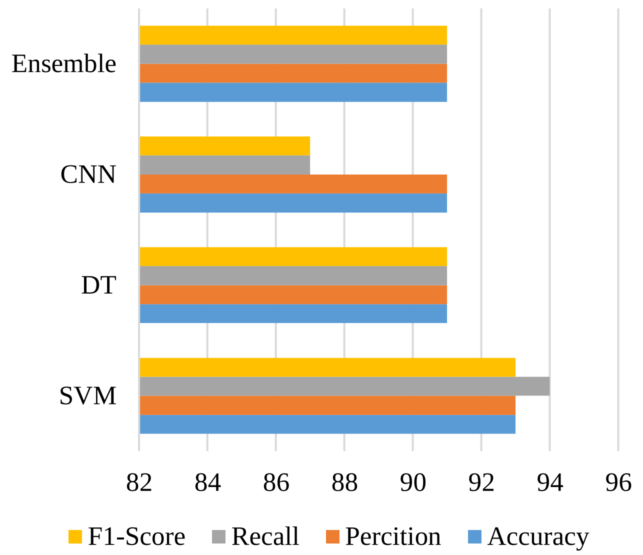

Figure 8. Classifiers comparison

Figure 8 is a visualization and representation of the classifier result, and we can see that is not always ensembles increase the accuracy of the model, but it is always give us a stable accuracy and the most accurate one.

7. CONCLUSION

To sum up, the dataset is divided into 3 chunks 70% training data, validation 20% and testing data 10%. The SVM classifier has the greatest accuracy, with a performance measure of 93% precision, 94% recall, and 93% F1-score of all the classifiers. Although, we observed that the ensemble model always improves the model's accuracy, and provide the most exact stable accuracy. Because of time constraints, we employed the Grid search strategy, which is the most basic hyperparameter optimization technique. We also discovered that boosting accuracy using the ensemble approach is not guaranteed; we obtained 93% accuracy with SVM but only 91% with the ensemble.

The advantage of the ensemble learning algorithms is that it assures that the outcome is accurate. This will aid medical workers in developing new treatment plans, saving time and efforts [37]. This concept may be used to create an embedded device that the patient can use at home, the gadget will send the data to the hospital's cloud server executing the proposed model with optimized machine learning algorithms, which after due analysis identify the seizures and alert the hospital in case of emergency. It can also predict future seizures and alert the user. In future, further machine learning, deep learning models as well as the extreme learning machines with cloud computing models may be investigated to further fine-tune the results [38-78].

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