

# FORECASTING OF EPILEPSY SEIZURES USING BRAIN HEART INTERACTION SCHEME WITH MACHINE LEARNING MODELS

Kamal kumar<sup>1</sup>, Gagandeep<sup>2</sup>

<sup>1</sup>Research Scholar, IKGPTU University Kapurthala

<sup>2</sup>CGC Landran, IKGPTU University Kapurthala

Corresponding Author email id: kamalkumar1987366@gmail.com

## Abstract:

**Introduction:** A severe and chronic neurological disorder called epilepsy can be identified by analysing the signals sent by neurons in the brain. Electroencephalogram (EEG) and electrocardiography (ECG) methods are commonly used to monitor these brain and heart signals. These signals are well-known for producing large amounts of data as well as for being complicated, noisy, nonlinear, and non-stationary. Epilepsy is estimated to contribute 1% of the world's overall illness burden, with a 0.5% to 1% prevalence rate. The frequent occurrence of seizures in those with epilepsy is one of the main signs of the condition. Abrupt disruptions or aberrant brain activity are the outcome of seizures.

**Method:** In order to detect seizure activity early on, this study employs an ensemble machine learning model that incorporates latest machine learning model. PhysioNet datasets are collected and used in this way to train machine learning algorithms and generate model files. In this research, to reduce complexity and improved efficiency, a novel approach based on the brain-heart interaction (BHI) is used for identifying the brain's firing region at the time of seizure start. The nonlinear coupling and fluctuation of phase-synchronization between brain areas and heart activity, which are useful in differentiating between seizures, may be studied with BHI. To lower the computational complexity, we transfer the EEG channels into two surrogate channels in our technique. Additionally, in order to preserve system power, the firing location detector only activates after a seizure is identified.

**Results:** combining data from heart and brain signals, this research hopes to increase the effectiveness of seizure prediction and ultimately enhance patient treatment and outcomes. The model achieved a diagnostic accuracy of 95%, indicative of its robust performance in distinguishing epileptic seizure signals from non-seizure states. This high accuracy underscores the efficacy of the employed machine learning algorithms and the effectiveness of integrating brain and heart signals for early epilepsy detection.

**Discussion:** This study developed a new approach by combining brain and heart signals which outperform up to date approaches, the outcome of this novel strategy it can be applied in clinical practice also.

**Keywords:** Random Forest, SVM, Ensemble model, Electroencephalogram, and Electrocardiography.

## 1. Background of the Study

Epilepsy is a neurological illness affecting millions of individuals worldwide. It is characterized by frequent, unpredictable seizures that manifest as abnormal brain electrical activity [1]. Epilepsy is a neurological illness that affects millions of individuals worldwide. It is characterized by frequent, irregular seizures that manifest as abnormal brain electrical activity. Seizures can have a significant negative influence on an epileptic's quality of life and lead to a number of medical and psychological issues. Reliability in seizure prediction is

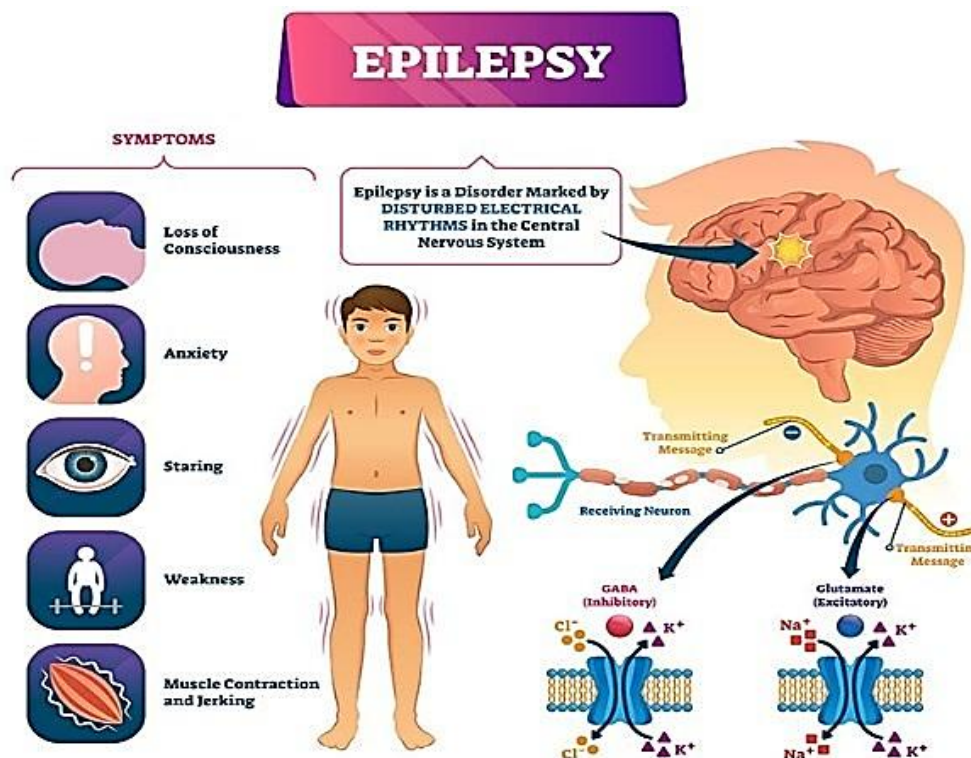


Figure 1. Schematic diagram of Epilepsy

essential for both prompt intervention and improved quality of life for individuals with this illness [2]. Figure 1 represent the schematic diagram of Epilepsy.

A crucial topic of study in the fields of neurology and medical technology is epilepsy prediction. Two main diagnostic instruments stand out among the variety of methods used:

electroencephalography (EEG) and electrocardiography [3]. The EEG records electrical impulses in the brain, whereas the ECG measures electrical signals in the heart. These diverse physiological data sources provide insightful information about the intricate interactions between the heart and brain, offering a comprehensive viewpoint for epilepsy prediction [4]. More precise and dependable prediction models are made possible by the multimodal approach to the detection of pre-seizure patterns provided by the synchronized monitoring of EEG and ECG data. The comparison of data from two sources may reveal minute relationships between heart and brain activity that would go unnoticed if the data from each source were used separately [5].

Abnormal electrical brain activity and heart rate changes are among the physiological phenomena that epileptic seizures frequently entail in a cascade fashion. Combining EEG and ECG data makes it possible to identify particular biomarkers and patterns that occur prior to seizures [6]. Often called "ictal" or "preictal" markers, these biomarkers function as early warning indicators that provide a window of opportunity for prompt intervention. The goal of research is to create prediction models that can foresee upcoming seizures by analyzing abundant EEG and ECG data using machine learning and sophisticated signal processing techniques. Novel strategies for seizure prediction have been sparked by recent developments in data analysis and medical technology [7]. Particularly in the field of epilepsy research, machine learning has demonstrated promise as a method that might revolutionize understanding and care for this illness. By examining the effectiveness of ensemble approaches and Support Vector Machines (SVM) in forecasting epileptic seizures, this research adds to the expanding body of knowledge. Epileptic seizure prediction is a difficult task because of the intrinsic complexity of brain electrical activity, the variety in seizure morphologies, and the heterogeneity of patient data. Conventional prediction techniques have frequently failed to deliver the precision and dependability required for therapeutic applications [8]. However, machine learning makes it possible to identify complex links and patterns within enormous datasets, which opens the door to the possibility of developing better prediction models. It explores the difficulties currently associated with predicting epileptic seizures, the role that machine learning approaches play in resolving these difficulties, and how ensemble methods and SVM in particular might be useful tools in achieving our research goals. Both ensemble techniques and SVM are attractive options for this crucial task because they use the advantages of numerous models to improve prediction accuracy and data classification efficiency, respectively [9]. The other portions of the study will be organized as follows: a detailed overview of the

dataset, a presentation of the research methods, a more extensive analysis of the literature on machine learning-based seizure prediction, and the provision of empirical results and insights. The Support Vector Machine (SVM), Random Forest, and Logistic Regression algorithms have been selected for seizure prediction based on their unique characteristics and task fit [10-11]. SVM excels in organizing high-dimensional data by identifying the most appropriate hyperplanes, which makes it ideal for identifying complex patterns in EEG and ECG signals that are indicative of seizures [12]. Random Forest, as an ensemble approach, reduces noise and overfitting, improving the model's ability to identify a variety of seizure-related factors. Logistic regression is faster and easier to read even if it is simpler. This helps to make the relationship between seizure occurrence and input feature likelihood clearer. These algorithms' benefits are compounded by integrating them to create a robust and reliable prediction model that ensures exact early epileptic seizure detection [13-14]

## **2. Literature survey/ Related Work of this Study**

Power spectrum analysis is a useful method for classifying epileptic patterns using electroencephalography (EEG) recordings, according to Shan Liu et al. [1]. However, the coexistence of periodic and aperiodic components in the EEG may provide challenges in detecting or predicting epilepsy. The paper looked at the significance of the periodic and aperiodic components of the EEG power spectrum for the diagnosis and prognosis of epilepsy, respectively. utilizing two public ally accessible datasets, we analyze the roles played by the periodic and aperiodic components of the signals in epilepsy diagnosis and prediction by utilizing a power spectrum density parameterization technique. The average classification accuracy of the periodic and aperiodic components for 10 clinical tasks on the Bonn EEG database was 96.68% and 73.9%, respectively.

Nabil Sabor et al. [2] reported that Integrating ECG data alongside EEG can enhance seizure detection. However, existing methods either combine the derived characteristics or categorization results of EEG and ECG separately, ignoring possible synergy, leading to small gains in detection rates. Furthermore, these approaches often take a complex approach, considering all EEG channels simultaneously. Additionally, the crucial aspect of pinpointing the location of epilepsy firing, essential for diagnosis, has often been overlooked. As a result, a brand-new technique is developed to pinpoint the precise firing region of a seizure within the brain, based on the idea of brain-heart interaction (BHI).

According to Yongte Zheng et al. [3], when it comes to brain modulation therapy for Closed-loop electrical stimulation is becoming more and more popular for treating refractory epilepsy. However, the precise mechanism governing seizure control remains unclear, and the effectiveness of electrical stimulation is still not optimal. It evaluates the immediate seizure control efficacy of multi-site closed-loop stimulation (MSCLS) in a mouse model using a specifically designed closed-loop neuro stimulator.

Damián Pascual et al. [4] asserts that in addition to decreasing the patients' quality of life, the unexpected nature of these seizures may endanger their lives. In order to minimize the impact on patients' health and to notify caretakers of epileptic seizures, contemporary electroencephalography (EEG) monitoring technologies are being created. These seizure detection systems use contemporary machine learning techniques; however, their learning procedure usually requires a significant amount of provided personal data.

According to Siyuan Chang et al. [5], a model forecasting technique is used in a closed-loop brain stimulation method to reduce epileptic episodes. To mimic various forms of epileptic seizures, a neural mass model (NMM) with physiologically relevant characteristics that may be adjusted is used as a black-box brain model. An auto-regressive moving-average Volterra model that demonstrates the complex relationship between brain responses and stimulation has been developed using system identification.

According to Kei Hata, Koichi Fujiwara et al. [6], individuals with refractory epilepsy may be able to do their regular daily activities with the use of wearable or implanted brain-cooling technology. The unique technique cools the epileptic center by means of a cooling device that is inserted in the hollow of the skull and administers cold saline. The effluent is then cooled and circulated using a Peltier device. In this paper, the architecture of the system and the simulation method used to assess its viability were described. They used mathematical models based on fluid dynamics equations as well as data from a cat model. The main objective of a seizure prediction system, according to Theekshana Dissanayake et al. [7], is to accurately determine the preictal brain stage, which happens before to a seizure episode. Advantageous solutions to the seizure prediction problem were offered as patient-independent seizure prediction models have been tuned to function well over a wide range of participants in a dataset. To develop models that can manage the significant subject-to-subject variability found in EEG data, however, not much research has been done [8]

In past, various strategy adopted for investigation of epilepsy seizures using individual

EEG, ECG data or combined of them as shown in Table 1. Table 1 containing three types of signals one is EEG recording, second is ECG recording and third one is combination of both. In literature, mostly researchers focus on the time and frequency domain signal which are not capable to capture the randomness behavior of signal which present during the onset time and the developed model not detect seizures effectively due to limited dataset. Moreover, in the literature channel-based allocation is not available so; that proposed system is not capable to recognize the firing location. Brain is an overall in charge of the epilepsy problem which generate a signal transferred to the heart nervous system and affect the heart rate variability of epilepsy person. So, combination of ECG and EEG reduce the error of EEG and increase detection rate. In the previous work, researchers used standalone ECG or EEG signal and not suggesting any correlation between ECG and EEG signal. So, that detection rate is not exceeding 8% as shown in [9].

These shortcomings in the literature motivate us to develop a new methodology in this research is developed for early recognition of seizures and firing location which is possible using brain heart interaction. The significant thing in the BHI is to study the nonlinear bonding and changes in the phase synchronization between brain and heart which help to make a differentiation between seizures and non-seizures events [10]. To reduce the complexity, the EEG sphere is converted into two hemisphere which is known as left and right hemisphere and make an interaction with ECG which reduce complexity and increase detection rate.

Table 1. Literature review of existing techniques

| Ref. No. | Signal | Data Used    | Characteristics                 | Model Used                              | Evaluation Metrics |
|----------|--------|--------------|---------------------------------|-----------------------------------------|--------------------|
| [25]     | EEG    | Bonn dataset | Image based features            | Support vector Machine                  | Accuracy = 98.7%   |
| [26]     |        |              | spectral domain-based features  | K-Nearest Neighbor                      | Accuracy = 98%     |
| [27]     |        |              | Spectral moment-based features  | SVM Model                               | Accuracy = 98.6%   |
| [28]     |        |              | Wavelet based features          | Feedforward Neural Network Architecture | Accuracy = 91%     |
| [29]     |        |              | Frequency domain-based features | Random Forest Model                     | Accuracy = 92.4%   |

|      |            |                                                                                |                                                  |                                                   |                                                  |
|------|------------|--------------------------------------------------------------------------------|--------------------------------------------------|---------------------------------------------------|--------------------------------------------------|
| [30] | Signal     |                                                                                | Time domain-based features                       | BPNN Network Architecture                         | Accuracy = 92.6%                                 |
| [31] |            |                                                                                | TQWT features                                    | Random Forest                                     | SN=97%, SP=93%, Accuracy=98.4%                   |
| [32] |            | CHB-MIT, 22 subjects, 2 seizure type, 198 seizure occurrence/2.8 h, accessible | Time domain-based characteristics                | Genetic Algorithm                                 | False Alarm rate = 0.41/23h                      |
| [33] |            |                                                                                | Power based characteristics                      | Random Forest                                     | Accuracy = 98.3%                                 |
| [34] |            |                                                                                | Time and frequency-based features                | Boost decision tree                               | Sensitivity = 86%, specificity = 98.7%           |
| [35] |            | Freiburg (intracranial EEG), 21, 87 seizures occur, accessible                 | Time and frequency based Wireless power transfer | Weighted Extreme learning machine                 | False Alarm Rate = 0.36/h Sensitivity = 96.3%    |
| [36] |            |                                                                                | discrete wavelet transfer                        | Support vector Machine                            | Sensitivity = 94%                                |
| [37] |            |                                                                                | Dual frequency-based feature                     | Two Support vector machine classifiers            | Accuracy = 95.8%, Specificity = 95.6%            |
| [38] |            | TUSZ (Scalp EEG), 312 subjects, 6 seizure types, 1790 seizure occurs           | Differential energy-based features domain        | Convolution Neural Network/Long Short-term Memory | Sensitivity = 29.83%, False Alarm rate = 6/24 h  |
| [39] |            |                                                                                | DWT features                                     | Convolution Neural Network                        | Specificity = 88.70%, False Alarm rate = 10/24 h |
| [40] | ECG Signal | Bonn + CHB-MIT (single channel)                                                | Frequency and time domain features using TQWT    | Least square-support vector machine               | Accuracy = 96.5 %, Sensitivity = 68.5%           |
| [41] |            | Wistar Albino Glaxo Rijswijk recorded                                          | Bi-frequency domain features                     | Support Vector Machine                            | Accuracy = 89.5%, sensitivity = 70.2%            |
| [42] |            | Physio net dataset                                                             | Bi-frequency domain features                     | Threshold approach                                | Accuracy = 93.1%,                                |

|      |                  |                                                                             |                                                                    |                              |                                                                               |
|------|------------------|-----------------------------------------------------------------------------|--------------------------------------------------------------------|------------------------------|-------------------------------------------------------------------------------|
|      |                  |                                                                             |                                                                    |                              | sensitivity = 83.2%                                                           |
| [43] |                  | 12 subjects/38 seizure                                                      | Maximal heart rate gradient                                        | Hybrid approach              | False Alarm rate = 1.84/12h, sensitivity = 76.5%                              |
| [44] | ECG & EEG Signal | Kilifi County Hospital Dataset, scalp EEG, 2 seizure type, 660 seizure/48 h | Time and frequency domain features based six features              | Convolutional Neural Network | Accuracy = 70.52%, sensitivity = 89.5%, specificity = 70.43%                  |
| [45] |                  |                                                                             | Statistical characteristics                                        | K-Nearest Neighbor           | False Alarm Rate = 2.35/24h                                                   |
| [46] |                  | Epilepsia (scalp EEG, non-seizure EEG, 180 seizure occurrences, not free    | Time and frequency domain features with discrete wavelet transform | Support Vector Machine       | Detection latency rate = 15.2, 11, 10.8s<br>False Alarm rate = 0.9, 2.4, 1.5s |

### The main contribution/Novelty of this research as listed as below:

1. Existing literature related to Epilepsy seizures is studied.
2. A novel approach is identified known as Brain Heart Interaction for identifying the brain firing region at the time of seizure start.
3. The physio net dataset is employed to gather data.
4. Th most trendy machine learning algorithms are used to forecast seizures.

The paper is structured as follows: Part 2 discuss about the literature review of this research, Part- 3 discussed about the existing system while Section 4 describe the proposed methodology and data collection. Section 5 discussed about the training with ensemble machine learning models and Section 6 describe the comparative analysis and result section discussed in part 7. Section 8 conclude the results.

### 3. Proposed System

Random Forest is used into the Machine Learning Ensemble Model. Next, Support Vector Machine (SVM) and Logistic Regression are used to predict seizures. The aim is to determine whether seizures are happening early on. Figure 2 represent the architecture of Proposed System

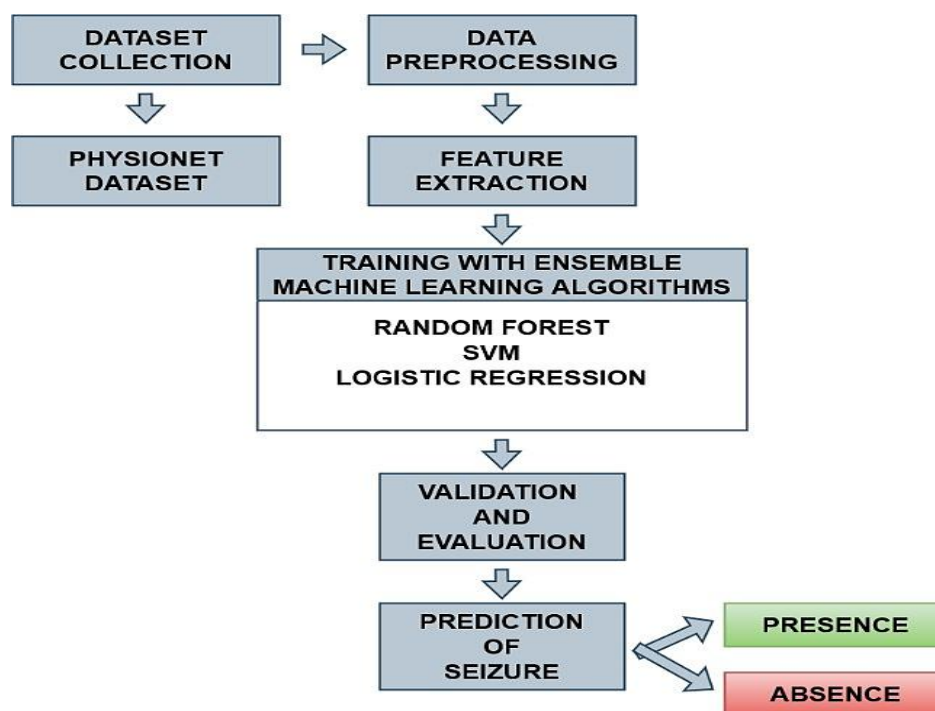


Figure 2. Architecture of the Proposed Methodology

The physio net dataset will be the source of the necessary datasets. To clean up and arrange the gathered datasets, a preprocessing method is used. Preprocessing is an essential step in getting the datasets ready for additional analysis [17-18]. The datasets are preprocessed and then used to extract relevant characteristics that are used to create the model file. The next step is to apply machine learning algorithms designed to identify seizure activity. When data is entered to forecast seizures, the system successfully identifies the presence of epilepsy episodes. The prediction process involves preprocessing brain and heart signals, extracting relevant features, and then inputting these features into the SVM classifier, which distinguishes between seizure and non-seizure states based on the trained model. This talent plays a crucial role in enabling timely and precise diagnosis, which in turn promotes efficient therapy. As a result, by merging brain and cardiac information, this research greatly improves the diagnostic procedure for seizure identification, reaching a degree of accuracy [19-20]

### 3.1 Dataset Collection

The PhysioNet dataset is employed to gather data. PhysioNet, formally the Research Resource for Complex Physiologic Signals, was founded in 1999 and is housed under the auspices of the National Institutes of Health (NIH) [21-22]. Supporting and advancing biomedical research and education are at the center of its main and continuing goals. This is partially accomplished by making large sets of clinical and physiological data, as well as the related open-source software, freely accessible. Moreover, PhysioNet organizes an annual series of challenges in association with the Computing in Cardiology conference. Figure 3 shows the waveform of physio net dataset.

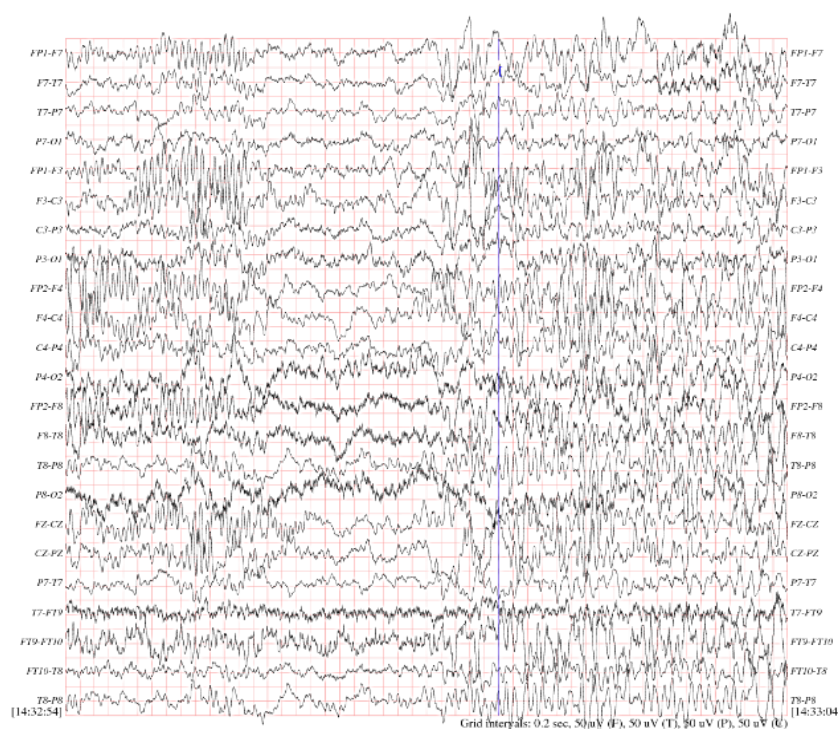


Figure 3. Waveform of Physio dataset

These challenges aim to focus research efforts on open problems in fundamental and clinical science. The PhysioNet team also actively works on cutting edge projects involving the study of physiologic data, using a foundational and translational approach to this endeavor. The EEG and ECG recordings in the carefully selected PhysioNet dataset are essential for seizure prediction research [23]. To ensure openness and reproducibility in this study method, the dataset's particular characteristics—including sample size, duration of recording, and patient demographics—will be described accurately. Moreover, the preprocessing techniques used to improve the PhysioNet dataset's suitability for machine learning analysis will be discussed.

### 3.2 Data Preparation:

Raw data frequently has a variety of flaws, including noises, missing values, and formats that are inappropriate for deep learning models to utilize directly. In order to make the data suitable for deep learning models, it is important to do data preparation. This procedure increases these models' efficiency as well as their accuracy [24-25]. Data preprocessing, which converts raw input into a format that the neural network can readily interpret, is a common first step in the deep learning process. Preprocessing is essentially applying a number of operations to the data in order to change or alter it. To make sure the data is in an acceptable state for additional analysis, these transformations are performed prior to the data being entered into the algorithm.

### 3.2.1 Feature Extraction:

The process of keeping the crucial components of the original dataset while transforming unprocessed data into numerical attributes that can be managed efficiently is known as feature extraction. The preprocessed signals are then used to extract domain-specific information, such as statistical measurements, spectral characteristics, time-frequency representations, and nonlinear dynamics. Using data-driven approaches and domain expertise, these variables are chosen to differentiate between seizure and non-seizure states. The results are usually better when this approach is used instead of just applying machine learning to the complete set of data [47]. Feature extraction is an essential technique for reducing the amount of redundant or superfluous data in a dataset. This decrease in data size speeds up the machine learning process's learning and generalization stages while simultaneously lessening the computing load. It is anticipated that the features chosen in this manner would capture the relevant information from the input data. Consequently, this improves machine learning models' effectiveness and capacity for generalization from the data.

|    | ALGORITHM                              |
|----|----------------------------------------|
| 1  | import warnings                        |
| 2  | warnings. Filter warnings("ignore")    |
| 3  | train_feature_data = [] for train data |
| 4  | in train_balance_df.values:            |
| 5  | print(train_data.shape)                |
| 6  | Hurst_Coefficient =                    |
| 7  | pyeeg.hurst(train_data[:-1])           |
| 8  | Mean = np.mean(train_data[:-1])        |
| 9  | Standrd_Deviation =                    |
| 10 | np.std(train_data[:-1])                |
| 11 | Petrosian_Fractal_Dimension =          |
|    | pyeeg.pfd(train_data[:-1])             |

|    |                                                                                                                                                                                                                                                 |
|----|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 12 | Hjorth_Mobility, Hjorth_complexcity                                                                                                                                                                                                             |
|    | = pyeeg.hjorth(train_data[:-1])                                                                                                                                                                                                                 |
| 13 | Correlation_Dimension =                                                                                                                                                                                                                         |
|    | nolds.corr_dim(train_data[:-1],1)                                                                                                                                                                                                               |
| 14 | kurtosis_feature =                                                                                                                                                                                                                              |
|    | kurtosis(train_data[:-1])                                                                                                                                                                                                                       |
| 15 | skew_feature = skew(train_data[:-1])<br>train_feature_data.append([Hurst_Coefficient,Mean,Standrd_Deviation,Petrosian_Fractal_Dimension,Hjorth_Mobility,Hjorth_complexcity,Correlation_Dimension,kurtosis_feature,skewfeature,train_data[:-1]]) |

#### 4. Training with Ensemble Machine Learning Algorithms:

Following the feature extraction phase, Random Forest is given the parameters. Next, in order to determine Support Vector Machines (SVM) are used to treat epileptic episodes. The Support Vector Machine (SVM) classifier plays a critical role in the proposed method for early detection of epilepsy seizures by combining brain (EEG) and heart (ECG) signals. Specifically, the SVM is used to classify the extracted features from both EEG and ECG signals into seizure and non-seizure states. This involves training the SVM with a labeled dataset where the combined features from both signal types are used as input, allowing the classifier to learn the distinguishing characteristics of seizure events. The SVM's ability to handle high-dimensional data and its effectiveness in binary classification tasks make it an ideal choice for this application, aiming to improve detection accuracy and reduce false positives through optimized parameter settings and robust training procedures. Then, the logistic regression approach is applied. To learn from the data and make predictions, these algorithms will go through a training phase when they will use the characteristics that have been retrieved. The objective is to determine the accuracy of each of these machine learning techniques. You may determine which algorithm works best for a given task by comparing the accuracies of each one. Upon identification of the most precise method, an input picture may be analyzed to reliably forecast the occurrence of a seizure. Because SVM is good at handling high- dimensional data and differentiating between classes with non-linear boundaries, it is used. Using patterns and information from the input data in this example, an image this method makes predictions by utilizing machine learning. You may increase the usability of the machine learning model for this specific application by employing

the most accurate algorithm to generate more accurate forecasting results.

|    | ALGORITHM                                                                                                   |
|----|-------------------------------------------------------------------------------------------------------------|
| 1  | from sklearn. tree import                                                                                   |
| 2  | Decision Tree Classifier                                                                                    |
| 3  | from sklearn.ensemble import                                                                                |
| 4  | RandomForestClassifier,                                                                                     |
| 5  | VotingClassifier                                                                                            |
| 6  | from sklearn.linear_model import                                                                            |
| 7  | Logistic Regression                                                                                         |
| 8  | from sklearn.svm import SVC                                                                                 |
| 9  | rfClf = Random Forest Classifier ()                                                                         |
| 10 | svmClf = SVC (probability = True)                                                                           |
| 11 | logClf = Logistic<br>Regression(max_iter<br>=500)                                                           |
| 12 | clf = Voting Classifier (estimators =<br>[('rf',rfClf), ('svm',svmClf), ('log',<br>logClf)], voting='soft') |
| 13 | clf.fit(train_feature_data.iloc[:, :-<br>1], train_feature_data.iloc[:, :-1]) #                             |
|    | pickle.dump(clf,open('"/content/gdr<br>1                                                                    |
|    | ve/MyDrive/seizure<br>project/ensemble                                                                      |
|    | e_weight. p","wb"))                                                                                         |

### 5.1 Validation and Evaluation

The datasets must be validated and assessed after training with ensemble machine learning methods. Validation and assessment are essential steps in machine learning that determine how well-trained models operate and are reliable. Validation in machine learning is akin to endorsing or confirming the predictions generated by a trained model. It seeks to confirm that the model is producing accurate and trustworthy predictions and that its predictions correspond with predicted results. On the other hand, machine learning assessment deals with the comprehensive analysis and testing of the machine learning model in its whole as well as its applicability in various scenarios. This technique includes analyzing the model's training process and estimating the model's prediction accuracy across various situations and datasets.

### 5.2 Prediction of Seizure

The ensemble machine learning model that has been developed is utilized to forecast seizures; it ascertains the likelihood of seizures by evaluating the input data by analyzing the features

obtained from the EEG and ECG data. The main objective is to improve prediction efficiency, which will eventually help seizure sufferers by lowering the proportion of incorrect predictions. Since the illness can usually be treated with the appropriate therapies in its early stages, improving patient outcomes, early detection is crucial. The aim of this research project is to identify the best prediction model, which involves utilizing the most effective machine learning techniques to distinguish between individuals with seizures and healthy individuals. The chosen model is improved through validation and assessment in order to guarantee its dependability and correctness. Once developed and validated, the model can reliably identify the presence of epileptic seizures when given information. This capacity allow the timely detection of seizures and permits the administration of efficient therapy. Therefore, by identifying seizures more precisely than current models could, combining data from the heart and brain signals improves patient treatment and outcomes.

|    | ALGORITHM                                 |
|----|-------------------------------------------|
| 1  | import data                               |
| 2  | warnings.filter warnings("ignore")        |
| 3  | import matplotlib.pyplot as plt           |
| 4  | input_value =                             |
| 4  | test_data.sample(n=1).values.tolist()[0]  |
| 5  | ]                                         |
| 6  | Print ("Input Signal:", input_value)      |
|    | Hurst_Coefficient =                       |
| 7  | pyeeg.hurst(input_value)                  |
| 8  | plt.title("Signal")                       |
| 9  | plt.plot(input_value)                     |
| 10 | Mean = np.mean(input_value)               |
| 11 | Standrd_Deviation =                       |
|    | np.std(input_value)                       |
| 12 | Petrosian_Fractal_Dimension =             |
|    | pyeeg.pfd(input_value)                    |
| 13 | Hjorth_Mobility, Hjorth_complexcity       |
|    | = pyeeg.hjorth(input_value)               |
| 14 | Correlation_Dimension =                   |
|    | nolds.corr_dim(input_value,1)             |
| 15 | kurtosis_feature = kurtosis (input value) |
|    | kurtosis(input_value)                     |
| 16 | skew_feature = skew(input_value)          |
| 17 | feature_data =                            |
|    | [Hurst_Coefficient,Mean,Standrd_Dev       |
|    | iation,Petrosian_Fractal_Dimension,Hj     |
|    | orth_Mobility,Hjorth_complexcity,Cor      |
|    | relation_Dimension,kurtosis_feature,s     |
|    | kew_feature]                              |
| 18 | input_data =                              |
|    | np.array(feature_data).reshape(1,-1)      |

|    |                                      |
|----|--------------------------------------|
| 19 | ensemble_weight =                    |
|    | pickle.load(open("/content/gdrive/My |
|    | Drive/seizure_project/ensemble_weigh |
|    | t.p", "rb"))                         |
| 20 | labels = ['seizure', 'non seizure']  |
|    | prediction =                         |
| 21 | ensemble_weight.predict(input_data)  |
|    | print ("predicted class              |
|    | is:", labels[int(prediction[0])])    |

## 5. Comparative Analysis:

In contrast to the existing system, which relies on CNN, MLP, and SVM algorithms and struggles with accuracy, detection rates, and false alarms due to data variability and overfitting risks, the proposed system introduces an Ensemble Model comprising Random Forest, SVM, and Logistic Regression. Addressing these challenges, the proposed approach emphasizes robust optimization of EEG signals and transparent feature extraction, while integrating diverse measures across time and frequency domains to enhance performance evaluation for more reliable seizure prediction in clinical settings. Furthermore, the proposed system demonstrates superiority over existing methods by utilizing Ensemble Machine Learning Algorithms and the Physio net dataset, leading to improved accuracy and reliability in seizure detection. By incorporating EEG and ECG signals and employing time domain feature extraction methods, the proposed model provides a comprehensive understanding of preictal states and cardiac irregularities, essential for accurate diagnosis and effective treatment planning. Moreover, rigorous validation and evaluation procedures ensure the model's robustness, establishing it as a dependable tool for predicting epilepsy seizures and enabling timely interventions.

## 6. Results:

We used the PhysioNet dataset in this work, which is an invaluable biomedical research resource that includes EEG and ECG recordings that are essential for seizure prediction studies. The dataset was cleaned and normalized using preprocessing approaches to make it compatible with deep learning models. The comparison of metrics shown in Figure 4.

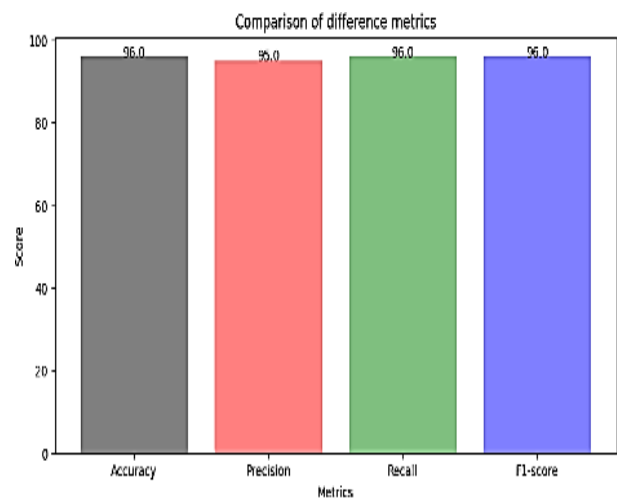


Figure 4. Evaluation metrics comparison

Then, using the preprocessed signals, feature extraction techniques were used to identify domain-specific properties that made it easier to distinguish between seizure and non-seizure states. The collected characteristics were then used to train ensemble machine learning algorithms. Figure 5 represent the metrics of seizure and non-seizure class

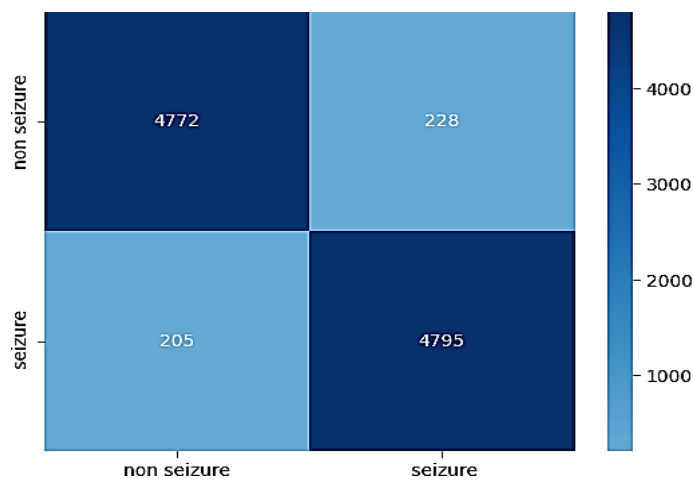


Figure 5. Metrics of Seizure and non-seizure class

Because SVM is so good at handling high- dimensional data, it has become the most accurate algorithm. In order to confirm the dependability and effectiveness of the trained models and show their capacity to precisely identify epileptic episodes, validation and assessment procedures were carried out. By combining data from heart and brain signals, this research hopes to increase the effectiveness of seizure prediction and ultimately enhance patient treatment and outcomes. The model achieved a diagnostic accuracy of

95%, indicative of its robust performance in distinguishing epileptic seizure signals from non-seizure states. This high accuracy underscores the efficacy of the employed machine predictive algorithms and the effectiveness of integrating brain and heart signals for early epilepsy detection. Figure 6 shows the accuracy score of seizure and non-seizure class while Figure 7 represent the ROC Curve.

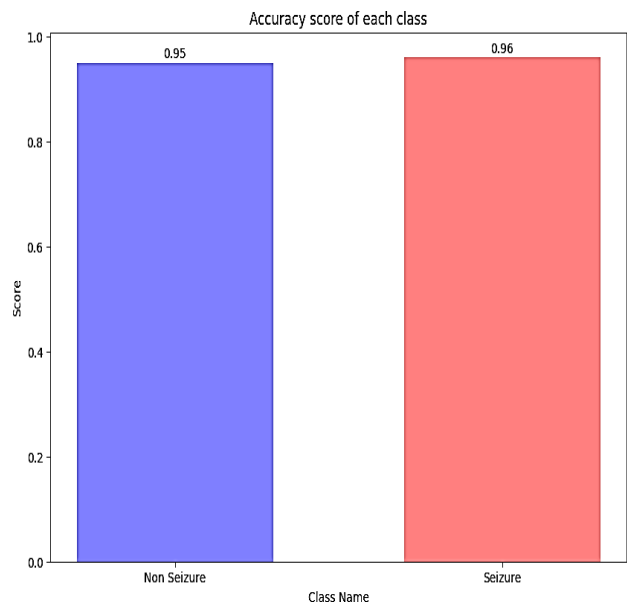


Figure 6. Accuracy comparison

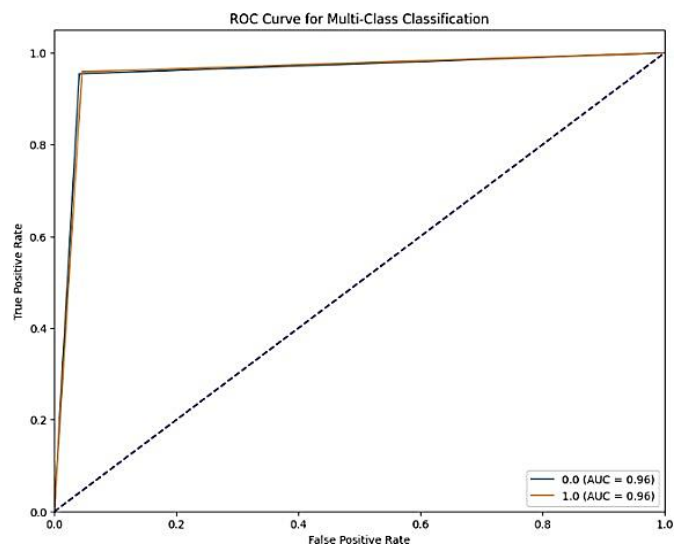


Figure 7. ROC Curve

7. Conclusion:

To sum up, this framework offers a promising direction for the development of early methods

for the identification of epileptic seizures. To improve performance, optimize feature extraction techniques, utilize advanced machine learning algorithms like deep learning, and employ data augmentation to enhance the training dataset's diversity and robustness. High accuracy is achieved through the integration of advanced signal processing techniques, optimized feature selection, and the application of effective predictive models particularly Support Vector Machines (SVM), which effectively differentiate between seizure and non-seizure states. Reliability is achieved by validating the method on diverse datasets, performing cross-validation, and ensuring consistent results across different patient profiles, which enhances the robustness and generalizability of the seizure detection system. This system seeks to meet the important requirement for accurate and prompt seizure prediction by ensemble literature methods in feature extraction, ensemble learning, and data preparation. The suggested methodology's efficacy and dependability may be further demonstrated by extensive validation and evaluation, opening the door to better patient outcomes and quality of life. Going forward, more study and cooperation in this area might have a big influence on the field of managing epilepsy, which would eventually help those who are afflicted with it.

## 8. Future Perspective

In the quest for continuous improvement, several avenues for future enhancement of this framework emerge. Firstly, exploring advanced feature extraction techniques, such as deep learning-based methods, could unlock deeper insights from physiological signals, potentially enhancing the discriminatory power of the model. Finally, ongoing validation and refinement of the framework through clinical trials and real-world deployment will be essential to validate its efficacy and facilitate its integration into clinical practice. By embracing these avenues for future enhancement, the framework has the potential to continually evolve and deliver ever-improving outcomes for individuals with epilepsy.

## REFERENCES

- [1] Shan Liu, Jiang Wang, Member, IEEE, Shanshan Li, and Lihui Cai (2023). Epileptic Seizure Detection and Prediction in EEGs Using Power Spectra Density Parameterization, vol 31, 3884-3894.
- [2] Nabil Sabor, Hazem Mohammed, ZheLi, Guoxing Wang. (2022). BHI-Net: Brain-Heart Interaction-Based Deep Architectures for Epileptic Seizures and Firing Location Detection. *ieee transactions on neural systems and rehabilitation engineering*, vol. 30, Digital Object Identifier 10.1109/TNSRE.2022.3181151.

- [3] Zheng, Y., Jiang, Z., Ping, A., Zhang, F., Zhu, J., Wang, Y., ... Xu, K. (2019). Acute Seizure Control Efficacy of Multi-site Closed-loop Stimulation in a Temporal Lobe Seizure Model. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, doi:10.1109/tnsre.2019.2894746.
- [4] Pascual, D., Amirshahi, A., Aminifar, A., Atienza, D., Rylvlin, P., & Wattenhofer, R. (2021). EpilepsyGAN: Synthetic Epileptic Brain Activities with Privacy Preservation. *IEEE Transactions on Biomedical Engineering*, 68(8), 2435–2446. doi:10.1109/tbme.2020.3042574.
- [5] Chang, S., Wei, X., Su, F., Liu, C., Yi, G., Wang, J., ... Che, Y. (2020). Model Predictive Control for Seizure Suppression Based on Nonlinear Auto- Regressive Moving-Average Volterra Model. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 1– 1. doi:10.1109/tnsre.2020.3014927.
- [6] Hata, K., Fujiwara, K., Inoue, T., Abe, T., Kubo, T., Yamakawa, T., ... Kano, M. (2019). Epileptic Seizure Suppression by Focal Brain Cooling With Recirculating Coolant Cooling System: Modeling and Simulation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 27(2), 162– 171. doi:10.1109/tnsre.2019.2891090.
- [7] Dissanayake, T., Fernando, T., Denman, S., Sridharan, S., & Fookes, C. (2021). Deep Learning for Patient-Independent Epileptic Seizure Prediction Using Scalp EEG Signals. *IEEE Sensors Journal*, 21(7), 9377– 9388. doi:10.1109/jsen.2021.3057076.
- [8] Tamanna, Tasmi, et al. "Predicting seizure onset based on timefrequency analysis of EEG signals." *Chaos, Solitons& Fractals* 145 (2021): 110796.2.
- [9] Emara, Heba M., et al. "Hilbert Transform and Statistical Analysis for Channel Selection and Epileptic Seizure Prediction." *Wireless Personal Communications*, 116, 4 (2021): 3371-3395.
- [10] Ma, Debiao, JuntengZheng, and LizhiPeng. "Performance Evaluation of Epileptic Seizure Prediction Using Time, Frequency, and Time– Frequency Domain Measures." *Processes* 9.4(2021):682.
- [11] Banupriya, C. V., and D. Devi Aruna. "Robust Optimization of electroencephalography Signals for Epilepsy Seizure Prediction by utilizing VSPO Genetic Algorithms with SVM and Machine Learning Methods." *Indian Journal of Science and Technology* 14.16 (2021): 1250- 1260.
- [12] Rahman, R., Varnosfaderani, S. M., Makke, O., Sarhan, N. J., Asano, E., Luat, A., & Alhawari, "Comprehensive analysis of EEG datasets for epileptic seizure prediction." 2021 IEEE International Symposium on Circuits and Systems (ISCAS). IEEE, 2021.
- [13] Usman, Syed Muhammad, Shehzad Khalid, and Sadaf Bashir. "A deep learning based ensemble learning method for epileptic seizure prediction." *Computers in Biology and Medicine* 136 (2021): 104710.
- [14] Hussein, R., Lee, S., Ward, R., & McKeown, M. J. "Semi-dilated convolutional neural networks for epileptic seizure prediction." *Neural Networks* 139 (2021): 212-222.
- [15] Jana, Ranjan, and Imon Mukherjee. "Deep learning based efficient epileptic seizure prediction with EEG channel optimization." *Biomedical Signal Processing and Control* 68 (2021): 102767.
- [16] Savadkoohi, Marzieh, Timothy Oladunni, and Lara Thompson. "A machine learning approach to epileptic seizure prediction using Electroencephalography (EEG) Signal." *Biocybernetics and Biomedical Engineering* 40.3 (2020):1328-1341.
- [17] Prathaban, BanuPriya, and Ramachandran Balasubramanian. "Dynamic learning framework for

epileptic seizure prediction using sparsity based EEG Reconstruction with Optimized CNN classifier." *Expert Systems with Applications* 170 (2021): 114533.

[18] Alshebeili et.al., "Inspection of EEG signals for efficient seizure prediction." *Applied Acoustics* 166 (2020): 107327.

[19] Zhang, Yuan, et al. "Epilepsy seizure prediction on EEG using common spatial pattern and convolutional neural network." *IEEE Journal of Biomedical and Health Informatics* 24.2 (2019): 465-474.

[20] Wang, Gang, et al. "Seizure prediction using directed transfer function and convolution neural network on intracranial EEG." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 28.12 (2020): 2711-2720.

[21] Baghdadi, Asma, et al. "Robust feature learning method for epileptic seizures prediction based on long-term EEG signals." 2020 International Joint Conference on Neural Networks (IJCNN). IEEE, 2020.

[22] Liu, Xuefei, Jinbao Li, and MingleiShu. "Epileptic Seizure Prediction Based on Region Correlation of EEG Signal." 2020 IEEE 33rd International Symposium on Computer-Based Medical Systems (CBMS). IEEE, 2020.

[23] Carvalho, Vinícius R., et al. "Evaluating five different adaptive decomposition methods for EEG signal seizure detection and classification." *Biomedical Signal Processing and Control* 62 (2020):

[24] Guedes, Beatriz, et al. "Prognostic significance of specific EEG patterns after cardiac arrest in aLisbon cohort." *Clinical Neurophysiology Practice* 5 (2020): 147-151.

[25] L. Boubchir, S. Al-Maadeed, A. Bouridane, and A. A. Chérif, "Time- frequency image descriptors-based features for EEG epileptic seizure activities detection and classification," presented at the IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP), South Brisbane, QLD, Australia, 2015.

[26] E. Tessy, P. P. M. Shanir, and S. Manafuddin, "Time domain analysis of epileptic EEG for seizure detection," in *Proc. Int. Conf. Next Gener. Intell. Syst. (ICNGIS)*, Sep. 2016.

[27] F. Riaz, A. Hassan, S. Rehman, I. K. Niazi, and K. Dremstrup, "EMD- based temporal and spectral features for the classification of EEG signals using supervised learning," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 1, pp. 28–35, Jan. 2015.

[28] O. Kocadagli and R. Langari, "Classification of EEG signals for epileptic seizures using hybrid artificial neural networks-based wavelet trans- forms and fuzzy relations," *Expert Syst. Appl.*, vol. 88, pp. 419–434, Dec. 2017.

[29] M. Mursalin, Y. Zhang, Y. Chen, and N. V. Chawla, "Automated epileptic seizure detection using improved correlation-based feature selection with random forest classifier," *Neurocomputing*, vol. 241, pp. 204–214, Jun. 2017.

[30] T. Zhang and W. Z. Chen, "LMD based features for the automatic seizure detection of EEG signals using SVM," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 8, pp. 1100–1108, Aug. 2017.

[31] A. I. Sharaf, M. A. El-Soud, and I. M. El-Henawy, "An automated approach for epilepsy detection based on tunable Q-wavelet and firefly feature selection algorithm," *Int. J. Biomed. Imag.*, vol. 2018, pp. 1–12, Sep. 2018.

- [32] A. Baldominos and C. Ramon-Lozano, "Optimizing EEG energy-based seizure detection using genetic algorithms," in Proc. IEEE Congr. Evol. Comput. (CEC), Jun. 2017, pp. 2338–2345.
- [33] D. Wu et al., "Automatic epileptic seizures joint detection algorithm based on improved multi-domain feature of cEEG and spike feature of aEEG," IEEE Access, vol. 7, pp. 41551–41564, 2019.
- [34] M. S. J. Solaija, S. Saleem, K. Khurshid, S. A. Hassan, and A. M. Kamboh, "Dynamic mode decomposition based epileptic seizure detection from scalp EEG," IEEE Access, vol. 6, pp. 38683–38692, 2018.
- [35] Q. Yuan et al., "Epileptic seizure detection based on imbalanced classification and wavelet packet transform," Seizure, vol. 50, pp. 99–108, Aug. 2017.
- [36] K. D. Tzimourta, A. T. Tzallas, N. Giannakeas, L. G. Astrakas, D. G. Tsalikakis, and M. G. Tsipouras, "Epileptic seizures classification based on long-term EEG signal wavelet analysis," presented at the Precis. Med. Powered by pHealth and Connected Health, Singapore, 2018.
- [37] N. Mahmoodian, A. Boese, M. Friebe, and J. Haddadnia, "Epileptic seizure detection using cross-bispectrum of electroencephalogram signal," Seizure, vol. 66, pp. 4–11, Mar. 2019.
- [38] M. Golmohammadi, S. Ziyabari, V. Shah, I. Obeid, and J. Picone, "Deep architectures for spatio-temporal modeling: Automated seizure detection in scalp EEGs," in Proc. 17th IEEE Int. Conf. Mach. Learn. Appl. (ICMLA), Dec. 2018, pp. 745–750.
- [39] Z. Zhang et al., "DWT-Net: Seizure detection system with structured EEG montage and multiple feature extractor in convolution neural network," J. Sensors, vol. 2020, pp. 1–13, Aug. 2020.
- [40] Y. Lu, Y. Ma, C. Chen, and Y. Wang, "Classification of single-channel EEG signals for epileptic seizures detection based on hybrid features," Technol. Health Care, vol. 26, no. S1, pp. 337–346, Jan. 2018.
- [41] L. S. Vidyaratne and K. M. Iftikharuddin, "Real-time epileptic seizure detection using EEG," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 25, no. 11, pp. 2146–2156, Nov. 2017.
- [42] F. Es haggi, J. Frounchi, P. Shahabi, and M. Sadighi, "Absence epilepsy seizure onsets detection based on ECG signal analysis," presented at the 20th Iranian Conf. Biomed. Eng. (ICBME), Dec. 2013, pp. 219–222.
- [43] G. Shamim, Y. U. Khan, M. Sarfraz, and O. Farooq, "Epileptic seizure detection using heart rate variability," in Proc. Int. Conf. Signal Process. Commun. (ICSC), Dec. 2016.
- [44] T. De Cooman et al., "Adaptive nocturnal seizure detection using heart rate and low-complexity novelty detection," Seizure, vol. 59, pp. 48–53, Jul. 2018.
- [45] B. R. Greene, G. B. Boylan, R. B. Reilly, P. de Chazal, and S. Connolly, "Combination of EEG and ECG for improved automatic neonatal seizure detection," Clin. Neurophysiol., vol. 118, no. 6, pp. 1348–1359, Jun. 2007.
- [46] S. Nasehi and H. Pourghassem, "Real-time seizure detection based on EEG and ECG fused features using Gabor functions," presented at the Int. Conf. Intell. Comput. Bio-Med. Instrum., Wuhan, China, 2011.

[47] M. Qaraqe, M. Ismail, E. Serpedin, and H. Zulfi, "Epileptic seizure onset detection based on EEG and ECG data fusion," *Epilepsy Behav.*, vol. 58, pp. 48–60, May 2016.