



## Development of an Epileptic Seizure Monitoring Information System Based on Intelligent Algorithms

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**Abstract:** Epilepsy is a common neurological disorder that needs a direct interference to control the seizures properly. However, the detection of seizure often requires the presence of experienced neurologists, which is not always accessible. This challenge highlights the need to develop an automated system for seizure detection. In response, the main aims and objectives of this article are to propose and develop an algorithm for efficiently detecting instant notifications based on machine learning algorithms using EEG signals. Filtering technique is applied to the captured data to eliminate noise from the data before doing feature extraction, power spectral density (PSD) and spectral entropy. These features are then computed to train several classifiers like support vector machines (SVM), K-nearest neighbors (KNN), multi-layer perceptron (MLP), random forest (RF), and gradient boosting (GB). KNN turns out to be the most successful classifiers of all. In this model, precision was shown to be at 0.94, recall of 0.93, and F1-score of 0.93 percentage accuracy for seizure identification which, in turn, gives a total of 95% for total accuracy. The contribution and novelty of this article is that it can classify the situations of epileptic seizure

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monitoring into three classes (pre-seizure), (seizure), and (non-seizure), the alert messages are sent through the GSM using an Arduino microcontroller that connects to a SIM900 module to send alert message during the seizure event.

**Keywords:** Seizure detection, information system, machine learning algorithms, GSM, EEG signals.

## 1. Introduction

Epilepsy is a disorder of the nervous system that is characterized by recurrent and unprovoked seizures. It affects over 50 million people worldwide, about 80% of epilepsy patients live in poor countries, and many of them do not receive the necessary therapy (WHO, 2023). These seizures are typically caused by abnormal, excessive neuronal activity in the brain that leads to a great variety of symptoms from minor absent seizures to convulsions. Effective management and monitoring of epilepsy are key to improving the lives of those living with this disorder (Stafstrom & Carmant, 2015). Current monitoring techniques mostly include in-hospital electroencephalography (EEG), which, while effective in a controlled environment, presents limitations in continuous, long-term monitoring essential for accurate diagnosis and management (Duun-Henriksen et al., 2020). Traditional EEG systems are often bulky, expensive, and impractical for everyday use, additionally the intermittent nature of seizures requires a monitoring system capable of continuous observation, a requirement not achieved by conventional methodologies. Recent advances in machine learning (ML) and the Internet of Things (IoT) combine two advanced technologies that can be a good solution for a portable, efficient monitoring for epilepsy. That's required needed to develop portable, efficient, real-time epilepsy monitoring systems. These would enable continuous monitoring for days, weeks or years, as well as early detection intervention to help reduce risks from seizures that can occur undetected.

A real-time epileptic monitoring system based on a machine learning approach and IoT techniques is developed and evaluated in this work. We then applied a variety of preprocessing filters in the development of an EEG-ML-based seizure detection system for the CHB-MIT dataset.

The aim of this work is to demonstrate the feasibility and effectiveness of an ML and IoT-based epilepsy monitoring system. By leveraging advanced signal processing

techniques and robust classifiers, this system aspires to bridge the gap between hospital-based monitoring and real-time, everyday seizure detection, as shown in Figure1.

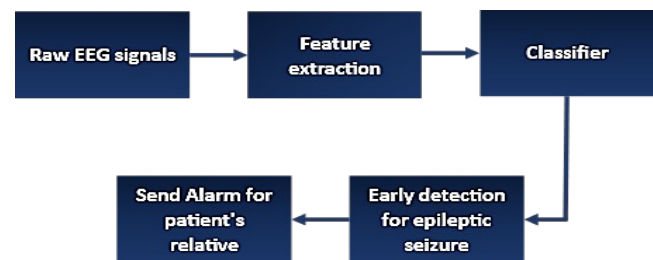


Figure 1. EEG-based seizure detection and alert system.

EEG can be considered as the main standard for seizure detection according to its ability to capture the electrical signal activity of the brain. Many studies have focused on leveraging EEG signals to improve the detection systems of seizure. The early methods for seizure detection were based on the traditional signal processing techniques, such as frequency-domain analysis, time-domain analysis, and time-frequency domain analysis. (Siddiqui et al., 2020) improved an algorithm that used amplitude and frequency attributes to detect seizures in EEG records, also the researchers have explored various feature extraction techniques to improve the accuracy of seizure detection as shown in Table 1. Ibrahim et al. (2017) presented KNN-based classifier to detect epilepsy. In this model feature extraction was achieved by applying Shannon entropy. The distribution and the complexity of the EEG signals may reveal information about the brain's features and condition. With the KNN method, this seizure predictor compares the entropy of every iteration throughout the moving window to analyze the pre-seizure and normal baselines. Zhang et al. (2018) presented a new method by combining the singular value decomposition (SVD), generalized Stockwell transform (GST), and random forest

classifier. The unprocessed EEG was converted into a matrix (frequency-time) using GST, and the singular values were retrieved using SVD. After those steps, classification operation took place using random forest. The time complexity of this method was not specified. RF typically takes longer to generate the tree.

This method can understand high-level EEG differentiations between seizure and normal EEG. An LSTM-based epilepsy detection method was proposed by (Abbasi et al., 2019), employing a long short-term memory (LSTM) classifier. The research obtained an accuracy of up to 95% for classifying pre-ictal, inter-ictal, and ictal signals, and for a binary classification (inter-ictal versus ictal) reached an accuracy of 98%. The EEG signals were considered wide-sense non-stationary random signals and attributes like a Hurst exponent and ARMA were produced, while a novel epileptic EEG detection approach was proposed by (Wei et al., 2019), by using a 12-layer convolutional neural network (CNN) with two key enhancements, the Merger of Increasing and decreasing sequences (MIDS) to highlight waveform features, and data boosting using Wasserstein generative adversarial networks (WGANs). The CHB-MIT Scalp EEG database was applied for patient-cross validation, obtaining a 74.08% sensitivity and 95.89% singularity with the developed CNN, and the method also obtained a 90.57% seizure event detection with a 4.68-second mean latency, displaying its power to assist in clinical diagnosis.

Another approach called a non-patient-specific and non-seizure specific was introduced by (Mansouri et al., 2019) with automatic seizure detection employing EEG signals. This approach applies a network model of the brain and a distance metric based on EEG spectral profiles. This approach gave an average latency of 8 seconds, a sensitivity of 83%, and a false alarm rate of 2.9%. Its efficiency and low cost make it convenient for use in portable EEG devices for epilepsy control.

For the grouping of generalized ES types that used a feed-forward multi-layer neural network architecture (MLP ANN), (Sarić et al., 2020) presented a field programmable gate array (FPGA) based solution. The developed FPGA systems based on MLP ANN are very suitable for real-time ES diagnosis in both biomedical and non-clinical settings. 822 recorded signals from the Temple University Hospital Seizure Detection Corpus (TUH EEG Corpus) dataset were used to train, verify, and test the ANN algorithm.

The system applied five attributes as inputs, which were extracted from EEG signals using a time-frequency

assessment called continuous wavelet transform (CWT) and statistical methods. 583, which means that 70% of the whole sample, were used for improving the system in MATLAB and TensorFlow, and 30% of the samples which were 239 samples were also used for final testing on the FPGA. After that, k-fold cross-validation was used to get the appropriate parameters for the ANN system. Finally, the high-performance ANN model for real-time seizure classification was achieved on the FPGA system in terms of median validation accuracy obtained within the cross-validation.

## 2. Literature Survey

Many researchers have made great efforts in this research field, with the most prominent being the following (Table 1):

(Hu et al., 2020) presented a Bi-LSTM network to find seizures employing the local mean decomposition method to minimize the computations. In this method, two LSTM networks with opposite directions are combined, and the advantage of this approach is that it may get the benefits of both the two stages, the after and before.

(Alhussein et al., 2019) proposed a controlled EEG pathology diagnosis approach based on a deep learning algorithm. This technique converts the raw EEG data into a spatio-temporal form and is then fed into a CNN. Two CNN approaches were applied both learning low and deep, as well as a combined technique based on a multi-layer perceptron. The deep CNN approach with combined features exceeded prior results when examined on the Temple University Hospital EEG Abnormal Corpus, producing an accuracy of 87.96%.

(Hosseini et al., 2017) presented a deep learning and cloud computing enabled seizure detection scheme producing an accuracy of 96% with an optimized CNN, and an accuracy of 94% with an optimized stacked auto-encoder (SAE). Their brain computer interface (BCI) targets medically refractory epilepsy patients producing a deep learning approach getting optimized results with principal component analysis (PCA), differential search algorithm (DSA), and independent component analysis (ICA). By integrating cloud computing and the Internet of Things (IoT), the BCI gives real-time processing of EEG and ECoG data. The system illustrated its effectiveness on ECoG datasets from 11 patients, showing a patient-specific solution for seizure detection and localization.

Table 1. Summary of previous research works on algorithms.

Author	Year	Dataset	Features	Classifier Algorithm	Result
(Ibrahim et al., 2017)	2017	CHB-MIT	Shannon entropy	KNN	76.4 ACC
(Zhang et al., 2018)	2018	Bonn	GST, SVD	Random forest	99.63% ACC
(Abbasi et al., 2019)	2019	Bonn	Hurst Exponent , (ARMA)	LSTM	95% (trinary classification) 98% (binary classification) ACC
(Wei et al., 2019)	2019	CHB-MIT	–	CNN	90% Sen
(Mansouri et al., 2019)	2019	CHB-MIT	Power in band of interest	Adaptive threshold Distance network	83% Sen
(Sarić et al., 2020)	2020	TUH	CWT,statistical value	MLP ANN	95.14% ACC
(Hu et al., 2020)	2020	CHB-MIT	LDM,statistical	Deep BI_ LSTM	93.61% Sen
(Alhussein et al., 2019)	2019	TUH	FFT	CNN, SVM	89.13% ACC
(Hosseini et al., 2017)	2017	Self-made dataset (11 volunteers participated)	PCA, ICA, DSA	CNN, SAE	96% (optimized CNN) 94% (optimized SAE)

### 3. Methodology

The proposed research work includes several steps that can be summarized as follows:

#### 3.1 Data Collection

Using the open-source CHB-MIT dataset [14] from PhysioNet (<https://physionet.org/>). This dataset was created by researchers from the Massachusetts Institute of Technology and Children’s Hospital Boston and is currently available on the PhysioNet data repository. Figure 2 illustrate signals for one patient. Access to the PhysioNet server is facilitated through Cygwin software, making data retrieval straightforward. For each patient in the CHB dataset, the number of seizure and non-seizure EEG recording files is specified.

The dataset comprises 23 patients: 5 males (aged 3-22 years) and 17 females (aged 1.5-19 years). The European Data Format (.edf) files for each patient’s seizures and non-seizures clearly show the spikes with the start and end times of seizures when viewed using (EDF Browser). Due to the international 10-20 system, the EEG signals were recorded from multiple channels positioned on the scalp, although the primary datasets are provided in a 1-dimensional format. All signals in this dataset were recorded at a frequency of 256 Hz with 16-bit resolution. This database was collected at the Boston Children’s

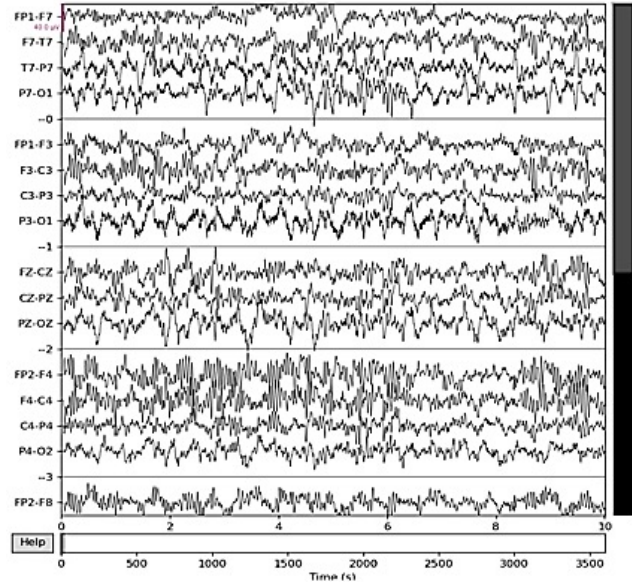


Figure 2. EEG signals for one patient (cb15\_6).

Hospital, consists of EEG recordings from pediatric subjects with severe seizures. Subjects were monitored for up to several days following withdrawal of anti-seizure medication in order to characterize their seizures and assess their candidacy for surgical intervention.

Recordings, grouped into 23 cases, were collected from 22 subjects (5 males, ages 3 to 22; and 17 females,

ages 1.5 to 19). (Case chb21 was obtained 1.5 years after case chb01 from the same female subject). The file SUBJECT-INFO contains the gender and age of each subject.

All signals were sampled at 256 samples per second with 16-bit resolution. Most files contain 23 EEG signals (24 or 26 in a few cases). The International 10-20 system of EEG electrode positions and nomenclature was used for these recordings (Ali, 2009). Depending on the info file, we will extract EEG signal from start time of seizure and end time and label it as seizure. Before seizure time in 60 second we extract this sample and labeled as pre-seizure and other sample will be normal. Figure 2 shows the EEG signals for one patient.

### 3.2 Preprocessing

In biomedical signal processing, it is difficult to identify noise in raw signals so that their impact on feature extraction may be reduced. EEG recordings contain a wide range of artifacts, some of which are technological in nature, while others are physiological. The preprocessing stage attempts to eliminate these artifacts without losing relevant information. Noise of technical origin depends on the acquisition settings, which are related to the type of EEG (scalp or intracranial), including gain (vertical resolution), cut-off frequencies of high-pass and low-pass filters, characteristics of the notch filter, and sampling rate (Orosco et al., 2013).

#### 3.2.1. Bandpass Filtering

EEG signals tend to have a variety of frequency components, some of which might be meaningless or simply noise. To isolate the frequency range that was relevant for seizure activity, a bandpass filter with a range of 0.5-45 Hz was applied to the patients' EEG. This range includes the delta, theta, alpha, beta, and gamma waves, which are regarded as of prime importance for the proposed analysis, and excludes higher-frequency noise and low-frequency drifts.

#### 3.2.2 Notch Filtering

A typical source of noise in EEG readings is power line interference (60 Hz). To eliminate this, a notch filter centered at 60 Hz was applied. This step effectively removed the power line noise.

### 3.3 Channel Selection

For each subject's recorded data, 17 channels were chosen from all the available channels present, as shown in Figure 3. These channels are a mixture of frontal, temporal, central, parietal, and occipital electroencephalographic

leads and are able to provide a holistic view of the brain's electrical activity. The chosen channels are: ['FP1-F7', 'F7-T7', 'T7-P7', 'P7-O1', 'FP1-F3', 'F3-C3', 'C3-P3', 'P3-O1', 'FP2-F4', 'F4-C4', 'C4-P4', 'P4-O2', 'FP2-F8', 'F8-T8', 'P8-O2', 'FZ-CZ', 'CZ-PZ']. These channels can be considered as common channels for all subjects, taking under consideration all the possibilities that a pixel could be in an edge position, and then, these possibilities are collected into a single prototype, as stated in Figure 3.

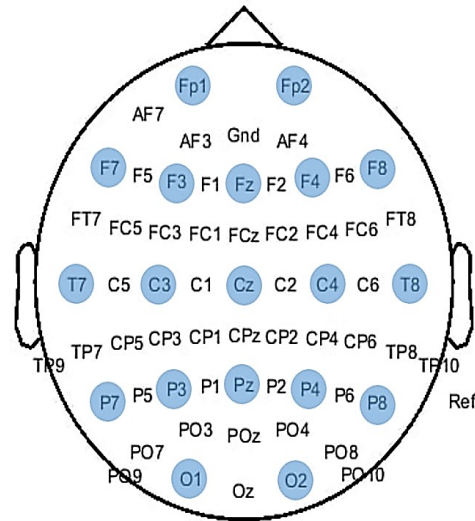


Figure 3. Electrode location.

### 3.4 Seizure Segmentation

There is a need for precise and accurate labelling of the seizure events in order to better evaluate the detection effect when training classifiers. We adopted the start and end times of each seizure event according to the provided annotations in the CHB-MIT dataset. According to the annotated seizure onsets and endings provided in the CHB-MIT dataset, for each seized we cropped out the corresponding EEG segment, along with a 60-second segment from before the seizure onset (pre\_seizure) for the duration of the seizure. In addition to seizure data, a separate pool of non-seizures was randomly selected from the recordings as a control. These data points were then stored in separate variables to undergo necessary feature extraction and subsequent classification.

### 3.5 Features Extraction

The proposed feature extraction method was based on entropy calculations. Spectral entropy, based on Shannon entropy, quantifies the regularity over randomness of the power spectrum during a given period of time, The

retention period for each trial was extracted to calculate PSD  $Psd(f)$  via Welch’s method. The PSD of a time series was defined as the distribution of power as a function of frequency. The normalized PSD was defined as  $Psd(f)$  divided by the total power to obtain a probability density function.

$$Psd(f) = \frac{Psd(f)}{\sum_{f=0.5}^{f=45} Psd(f)} \quad (1)$$

where  $\wedge Psd(f)$  was the normalized PSD of  $Psd(f)$ . We estimated spectral entropy based on the PSD within 0.5–100 Hz. The entropy of  $\wedge Psd(f)$  was generated by using the following equation:

$$SE = -k \sum_{f=0.5}^{f=45} Psd(f) \log(Psd(f)) \quad (2)$$

In effect, spectral entropy reflected the uniformity of the power spectrum distribution. The greater the spectral entropy was, the more uniform the power spectral distribution was. (Tian et al., 2017).

### 3.6 Classification

This article applies different ML classifiers to assess collected EEG data in trying to detect epileptic seizures. These classifiers are support vector machine (SVM), k-nearest neighbors (KNN), multi-layer perceptron (MLP), random forest (RF), and gradient boosting (GB).

#### 3.6.1 Support Vector Machine (SVM)

The SVM classifier is particularly applied to large area space, making it an excellent choice for EEG data. SVM aims to find the hyperplane that maximizes the margin between two classes. For a binary classification problem, the decision boundary is defined as:

$$f(x) = w^T x + b \quad (3)$$

Where  $w$  is the weight vector,  $x$  is the input feature vector, and  $b$  is the bias term. The optimization problem for SVM is to minimize the following objective function:

$$\min_{w,b} \frac{1}{2} \|w\|^2 \text{subject to } y_i(w^T x_i + b) \geq 1 \forall i \quad (4)$$

To handle non-linearly separable data, the soft margin SVM introduces slack variables  $\xi$  and the optimization problem becomes:

$$\min_{w,b,\xi} \frac{1}{2} \|w\|^2 + c \sum_{i=1}^n \xi_i \text{subject to } y_i(w^T x_i + b) \geq 1 - \xi_i, \xi_i \geq 0 \forall i \quad (5)$$

where  $C$  is the regularization parameter that controls the trade-off between maximizing the margin and minimizing

classification error (Vapnik, 2013). The kernel trick is used to handle non-linear decision boundaries by mapping the input data into a higher-dimensional space, commonly using the Radial Basis Function (RBF) kernel:

$$K(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right) \quad (6)$$

where  $\gamma$  is a kernel parameter that determines the width of the Gaussian kernel (Schölkopf & Smola, 2001).

#### 3.6.2 k-Nearest Neighbors (KNN)

KNN is a simple yet effective algorithm that classifies a data point based on the majority vote of its k-nearest neighbors. The Euclidean distance is the distance metric commonly used, defined as:

$$d(x_i, x_j) = \sqrt{\sum_{l=1}^p (x_{il} - x_{jl})^2} \quad (7)$$

where  $p$  is the number of features (Abbasifard et al., 2014). An optimal value of  $k$  can be determined through cross-validation, balancing between bias and variance.

#### 2.6.3 Multi-Layer Perceptron (MLP)

MLP is a type of feedforward neural network that is used to learn complex non-linear relationships. The mathematical structure of MLP can consist of an input layer with one or more hidden layers and an output layer. Each neuron in the MLP performs a weighted sum of its inputs, followed by a non-linear activation function, typically the rectified linear unit (ReLU):

$$f(z) = \max(0, z) \quad 8$$

where  $z = w^T x + b$  is the weighted input. The network is trained using backpropagation to minimize a loss function, such as cross-entropy for classification tasks:

$$L(y, \hat{y}) = - \sum_{i=1}^n y_i \log(\hat{y}_i) \quad (9)$$

where  $y$  is the true label and  $\hat{y}$  is the predicted label (Rumelhart et al., 1986).

#### 3.6.4 Random Forest

Random forest is a learning method that builds multiple decision trees during training and outputs the mode of the classes or mean prediction (regression) of the individual trees. Each tree in the forest is trained on a bootstrapped subset of the data, and features are randomly selected for splitting at each node (Breiman, 2001). The Gini impurity is usually used as a standard for selecting the best split:

$$G = 1 - \sum_{k=1}^k p_k^2 \quad (10)$$

where  $p_k$  is the proportion of samples belonging to class  $k$  (Breiman, 2001).

### 3.6.5 Gradient Boosting

The gradient boosting (GB) is an ensemble technique that builds models sequentially; for each new model, the errors can be corrected by using the previous ones. The loss function can be minimized using gradient origin. The key parameters tuned include the learning rate  $\eta$ , the number of boosting stages (MMM), and the maximum depth of individual trees (Friedman, 2001). The objective function for (GB) is given by:

$$F_m(\mathbf{x}) = F_{m-1}(\mathbf{x}) + \eta \sum_{i=1}^n g_i \quad (11)$$

where  $g_i$  is the negative gradient of the loss function with respect to the current model prediction (Friedman, 2001).

## 4. Hyperparameter Tuning

The hyperparameters such as the maximum depth of each tree (`max_depth`) and the minimum number of samples required to split an internal node (`min_samples_split`) were tuned using techniques such as grid search or random search to optimize model performance. Different values of estimators and max depth were tested to find best accuracy. The chosen hyperparameters for each algorithm can also affect training and inference times. As the number of estimators reaches to 100, the model achieves its best accuracy. A `max_depth` of 10 consistently exhibits higher accuracy compared to higher values. This parameter turning was performed using grid search, a systematic method to evaluate a range of its combinations. The optimal configuration for each model ensures the highest accuracy, specificity, and sensitivity (Bergstra & Bengio, 2012)

## 5. Performance Evaluations

The performance of each classifier can be calculated by using the below metrics:

Accuracy is the proportion of correctly classified samples among the total samples.

F1-Score represents the harmonic mean of Precision (Pre) and Recall, giving a single measure of a model's performance.

Recall represents the proportion of True Positive (TP) samples among all actual positive predictions.

Precision represents the proportion of True Positive (TP) samples among all positive predictions.

## 6. System Implementation

The classified outputs from the ML models were smoothly integrated into an epilepsy monitoring system. The implementation involved transmitting the classifier results to an Arduino microcontroller using the pySerial library, which assists in serial communication between Python and external hardware (Chris, 2020), as shown in Figure 4.

Depending on the output of the classifier, a message would be sent to the recipient's phone number. When class 1 (seizure) is received, the module would send (URGENT: The patient has experienced a seizure stat. Please provide immediate assistance). If the class is 0 (pre-seizure) would send (ATTENTION: The patient is showing signs of entering a pre-seizure state through a message state. Please be on standby), as show in Figure 5.

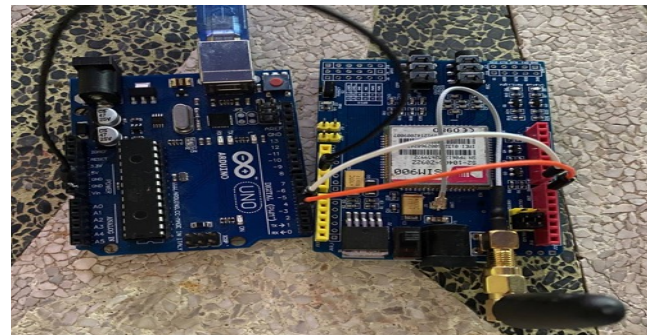


Figure 4. Hardware connection between Arduino and SIM900.

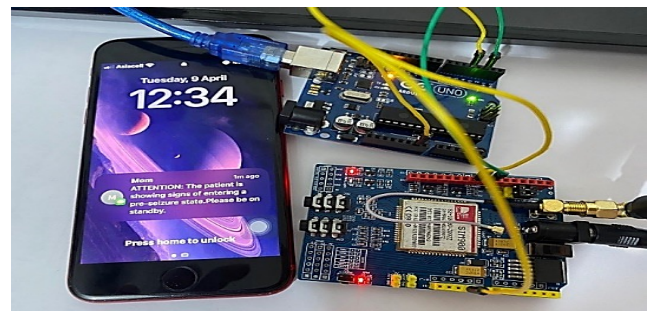


Figure 5. Patient's phone with a message stating "Please be on standby".

## 7. Results

In evaluating the performance of classifiers for EEG signal classification, we considered several performance metrics to assess their effectiveness. These metrics include Accuracy, F1-score, Precision, and Recall as reflected in the metrics presented in Table 2.

Table 2. Implementation results.

Classifier	Classes	Precision	Recall	F1-score	Accuracy
SVM	Pre- seizure	0.85	0.89	0.87	0.78
	Seizure	0.91	0.76	0.83	
	Non- seizure	0.90	0.94	0.92	
KNN	Pre-seizure	0.95	0.94	0.94	0.95
	seizure	0.94	0.93	0.93	
	Non- seizure	0.96	0.98	0.97	
MLP	Pre- seizure	0.87	0.88	0.88	0.89
	Seizure	0.87	0.83	0.85	
	Non- seizure	0.92	0.94	0.93	
Random forest	Pre- seizure	0.85	0.89	0.87	0.88
	Seizure	0.91	0.76	0.83	
	Non- seizure	0.90	0.94	0.92	
Gradient boosting	Pre- seizure	0.85	0.88	0.87	0.88
	Seizure	0.89	0.78	0.83	
	Non- seizure	0.90	0.94	0.92	

The SVM classifier showed strong performance for Pre-seizure and Non-seizure classes, providing high Precision and Recall. However, it had lower performance in detecting Seizure instances, resulting in an overall accuracy of 0.78.

The performance of the KNN classifier is plotted versus the number of neighbors used in the algorithm. As the number of neighbors increases from 3 to 11, there is a noticeable decline in the test accuracy. The best performance is achieved with 3 neighbors, where the test accuracy is highest at 0.95, and it gradually decreases as more neighbors are considered. This behavior suggests that the KNN model is most effective when using a smaller number of neighbors, as shown in Figure 6.

In the random forest algorithm, hyperparameter tuning, specifically modifying the number of estimators and maximum depth, there is a noticeable fluctuation in performance when varying the number of layers and the number of neurons in each layer. Based on these observations, the optimal network configuration comprises four

layers, with the first layer containing 1,000 neurons, the second 500 neurons, the third 200 neurons, and the final layer containing 100 neurons. This configuration gives the best results, as shown in Figure 7.

The figure describes the relationship between test accuracy and the number of estimators across different maximum depths. When the number of estimators increases from 10 to 50, there is a development in an test accuracy for all depths. Also, deeper trees (with maximum depths of 20, 25, 30, 35, and 40) can achieve higher accuracy than trees (with maximum depths of 5, 10, and 15). The highest levels of accuracy are achieved with the deepest trees (maximum depths of 25 and larger), where the accuracy is about 0.90.

In multi-layer perceptron (MLP), when the number of layers and the number of neurons were changed, there was a fluctuation; therefore, it was better to change the

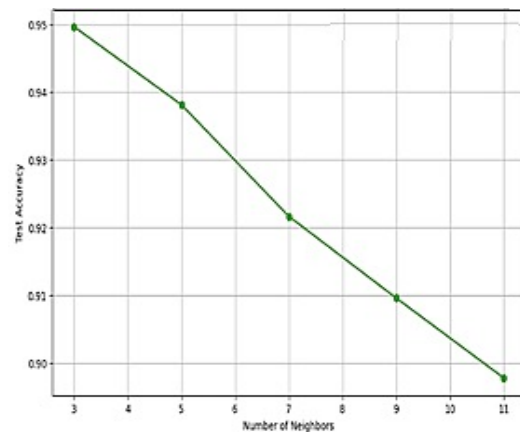


Figure 6. Accuracy vs. number of neighbors for KNN classifier.

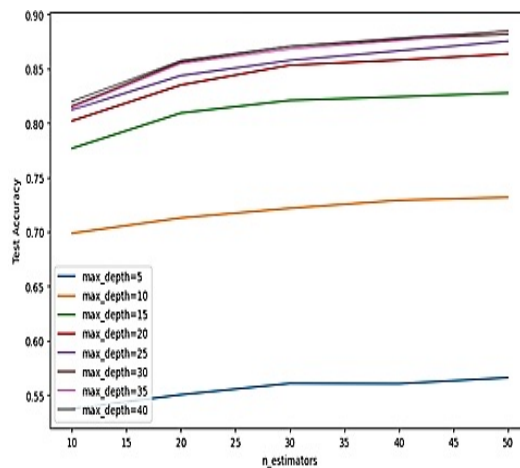


Figure 7. Accuracy vs. n\_estimators for different max. depth.

shape of the hidden layer in order to achieve the best test accuracy, as shown in Figure 8.

In the gradient boosting (GB) algorithm, hyperparameter tuning modifies the number of estimators and maximum depth, as shown in Figure 9. The figure describes the relationship between test accuracy and the number of estimators across various maximum depths. Higher accuracy is obtained when the number of estimators ranges is between 60 to 100. Additionally, a maximum depth of 10 consistently leads to higher accuracy compared to deeper configurations.

According to the obtained results, the max depth and n-estimators are chosen as 10, and 100, respectively.

The results indicate that the KNN and random forest (RF) classifiers achieved robust performance across all classes, with the KNN method slightly outperforming the others in terms of accuracy. Also, the KNN model depends on the number of neighbors, indicating that fewer neighbors help maintain accuracy, while random forest (RF) benefits from a larger number of estimators and greater depth, although it requires careful tuning to avoid overfitting.

It can also be mentioned that the SVM and gradient boosting algorithms, while still effective, had lower Recall for the Seizure class, indicating that they were less effective at detecting seizures compared to other classifiers. The MLP method, although strong, also showed a lower Recall in the Seizure class, suggesting some constraints in its ability to generalize across all classes. The chosen hyperparameters for each algorithm can also affect training and inference times.

Keep in mind that these are general expectations and can vary based on the specific dataset and setup. The execution of the obtained results gives the following variation in latency time, as shown in Table 3.

- SVM: Can have relatively longer training times, especially for large datasets, due to the complexity of finding the optimal hyperplane. Inference time is generally fast.
- KNN: Training is often very fast (it essentially just stores the data), but inference time can be slower, especially with large datasets, as it needs to calculate distances to all neighbors.
- MLP: Training time can vary greatly depending on the network architecture (number of layers, neurons) and the training process (epochs, optimization algorithm). Inference time is usually relatively fast after training.
- Random Forest: Training time is typically moderate as it builds multiple decision trees. Inference time is

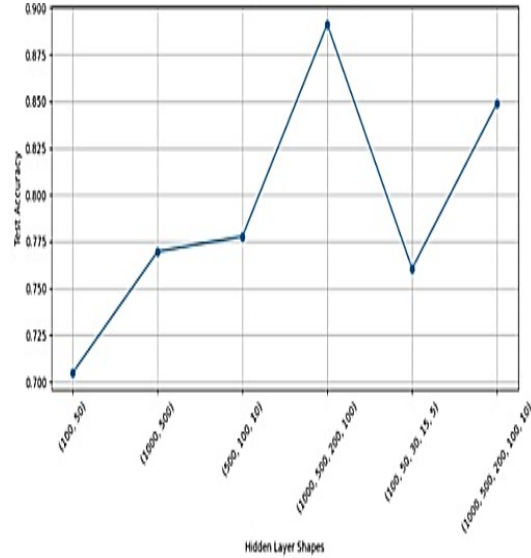


Figure 8. Accuracy vs. n estimators for different max. depth.

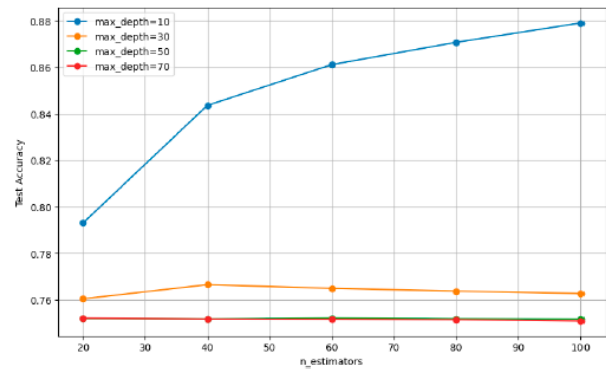


Figure 9. Accuracy vs. n\_estimators for different max. depth.

generally fast as it averages the predictions of the trees.

- Gradient Boosting: Training can be quite time-consuming as it builds trees sequentially, with each tree trying to correct the errors of the previous ones. Inference time is usually relatively fast.

Table 3. Latency time analysis.

Algorithm	Training Time (seconds)	Inference Time (milliseconds per prediction)
SVM	120	2.5
KNN	5	1.1
MLP	90	1.8
Random Forest	45	3.1
Gradient Boosting	180	4.5

## Conclusions

This article applies a developed method for detecting seizures by using machine learning algorithms, as well as creates an alert system that sends warnings via SMS based on an Arduino microcontroller. The developed method begins with preprocessing an open-source dataset, where a series of filters for removing noise and improving signal quality are adopted. Signal features were extracted by calculating the power spectral density (PSD) and spectral entropy (SP), which can be used as inputs for different classifiers like support vector machine (SVM), K-nearest neighbors (KNN), multi-layer perceptron (MLP), random forest (RF), and gradient boosting (GB).

After finishing many trials of hyperparameter tuning, the KNN classifier delivered the best consistent results for all applications. The (PySerial) library then communicated the selected classifier's output to an Arduino microcontroller, which was sent notifications through a (SIM900) shield. Furthermore, the proposed method increases the classifier's accuracy by enabling the extraction of additional more useful features that boost classification performance. As future work, the collection of globalized datasets can be applied, which allows the model to be trained and tested more appropriately across populations.

This strategy addresses the potential limitations of depending primarily on data from Boston-based institutions, ensuring that the classifier is both reliable and usable in the known environment. To establish this proposed method into an applicable model, the EEG sensors for data collection are used, specifically sensors such as the Emotive sensor which would speed up data gathering.

Such developments are important for improving the proposed model into a usable tool for epilepsy monitoring and seizure alarm systems. Finally, it must be mentioned that all the ideas and intelligent algorithms that were proposed in references [23-32], which employed deep and machine learning, were taken into consideration, and the most suitable ones were selected based on accuracy and performance.

## Conflict of Interest

The authors do not have any type of conflict of interest to declare.

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