1

Machine Learning Technologies in IoT EEG-Based Healthcare Prediction

Karthikeyan M.P.[1]*, Krishnaveni K.[2] and Muthumani N.[3]

[1]*Department of Computer Science, PPG College of Arts and Science, Coimbatore, India*
[2]*Department of Computer Science, Sri Ramasamy Naidu Memorial College, Sattur, India*
[3]*PPG College of Arts and Science, Coimbatore, India*

Abstract

The classification of medical data is the demanding challenge to be addressed among all research issues since it provides a larger business value in any analytics environment. Medical data classification is a mechanism that labels data enabling economical and effective performance in valuable analysis. Proposed research has indicated that the quality of the features may cause a backlash to the classification performance. Also squeezing the classification model with entire raw features can create a bottleneck to the classification performance. Thus, there is necessity for selecting appropriate features for training the classifier. In this proposed, a system is proposed that can use multiple channel real-time EEG signals to predict the onset of an epileptic seizure. The system is given a select number of EEG channels as input and reports back the corresponding epileptic seizure state at every second and the Hybrid Artificial Neural Network with Support Vector Machine (HANNSVM) based classifications are done as a simulation of real-time dynamic predictions and are dependent upon past predictions that were made. As a result, the sensitivity must be controlled such that seizures aren't predicted more often than they actually occur. Statistical analysis of accuracy values and computational time portrays that the proposed schemes provide compromising results over existent methods.

**Corresponding author*: karthi.karthis@gmail.com

SK Hafizul Islam and Debabrata Samanta (eds.) Smart Healthcare System Design: Security and Privacy Aspects, (1–32) © 2021 Scrivener Publishing LLC

***Keywords*:** Computer aided diagnosis, K-nearest neighbor, artificial neural network, electroencephalography, Internet of Things, support vector machine, brain modeling feature exraction

1.1 Introduction

IoT (Internet of Things) is utilized as a part of a great deal of medical uses. A portion of the uses of Internet of Things are savvy stopping, shrewd home, brilliant city, keen condition, mechanical spots, horticulture fields and wellbeing observing procedure [38]. One such application in medicinal services to screen the patient's wellbeing status by means of Internet of Things makes therapeutic gear more effective by permitting ongoing checking of patient's wellbeing, in which sensor get information of patient's and decreases the human blunder. The Internet of Things in the therapeutic field draws out the answer for compelling continuous checking of rationally impaired individual at diminished cost and furthermore lessens the exchange off between tolerant result and infection administration [33]. So far we have seen the wellbeing observing framework which gathers data of fundamental parameters, for example, heartbeat, temperature, circulatory strain and development parameters. The medical data stored in cloud in the form of huge dataset, need to analyze and predict the diseases based on IoT data is very important [1, 37].

The progress of science has driven every individual to mine and consume medical data for analyses of business, customer, bank account, medical, etc. made privacy break or intrusion also in most circumstances. The IoT-based medical data is all over in the pattern of text, number, images and videos [35, 36]. This type of data continues to grow bigger, thereby organizing these data as a necessary process. The collected enormous data should produce logical use unless it would be waste of time, effort and storage. The action of grabbing or collection of huge data is called datafication. Clinical data can be used effectively as it is datafied. The organizing of data alone cannot make useful but should identify what can be performed by its use. Optimal processing power, analytical capabilities and skills are needed for squeezing essential information from medical data. The data mining features are shown in Figure 1.1.

Medical data is of various types, formats and shapes which are brought together from various sources. Data Analytics is the action of studying and extracting big data which can yield functional and business knowledge in a remarkable form. The behavior of business is reconstituted in different ways by big data analytics [15]. Approaches like information technology,

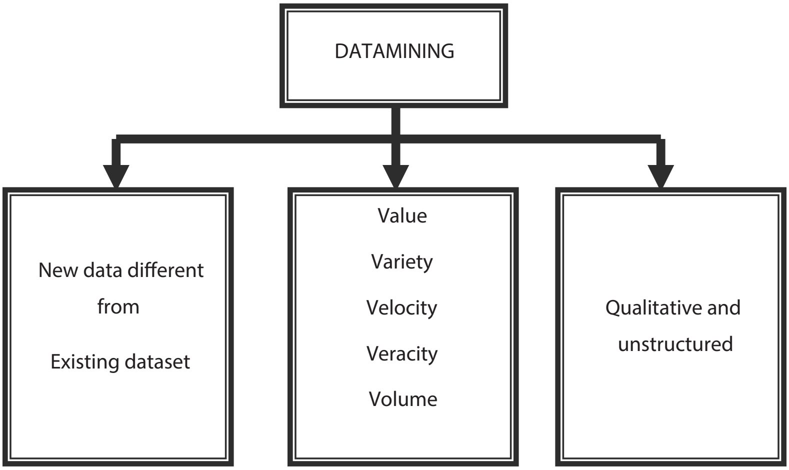


Figure 1.1 Data mining features.

statistics, quantitative methods and various methods are used by medical analytics to deliver results. Data mining analytics is divided into three main types. They are descriptive analytics, predictive analytics and prescriptive analytics. The traditional database systems are not sufficient to progress huge data characteristics (elements) [2].

1.1.1 Descriptive Analytics

Descriptive analytical type is the best accepted one being the basis for uplifted analytical models. It benefits leaders, researchers, planners, etc. to build a guideline for forthcoming activities by reviewing the database to determine knowledge on current or past medical data proceedings [16]. This model does a detailed review of data to expose particulars like operation costs, cause for false steps and frequency of events. Descriptive analytics assists locating the root cause of the issue. Descriptive analytics also deal with it Proposed modal EEG classification [4].

1.1.2 Analytical Methods

The different analytical methods of data mining are

- Predictive Analysis
- Behavioral Analysis
- Data Interpretation.

1.1.3 Predictive Analysis

The probable questions in predictive analysis are

- In various domains, how does a data utilize the available data for predictive and real time analysis?
- How does a medical data make accuracy from unstructured data?
- How does a business influence unique varieties of data like social media data, sentiment data, multimedia, etc.?

1.1.4 Behavioral Analysis

Behavioral analysis deals with how a business influences complicated data to develop advanced models for

- Motivating results
- Making a medical budget
- Motivating revolution in medical approach
- Cultivating long-term consumer fulfilment.

1.1.5 Data Interpretation

The probable questions in data interpretation are

- What new analyses can be done from the available data?
- Which data should be analyzed for new product innovation?

1.1.6 Classification

Data classification is considered as a critical and challenging problem to be addressed in IoT medical data analytics. Classification is a method of labeling data for better productive usage depending upon necessity [34]. It functions with two paces: first includes learning activity and the second performs classification activity. The required data can be detected and obtained using well-organized classification model. The action of classifying the data using issues and difficulties opened by the data controllers is called data classification. Figure 1.2 shows the paces connected to big data classification [30]. The different paces connected to classification are input data collection, data understanding, data shaping and data mining environment understanding. The success in data classification requires

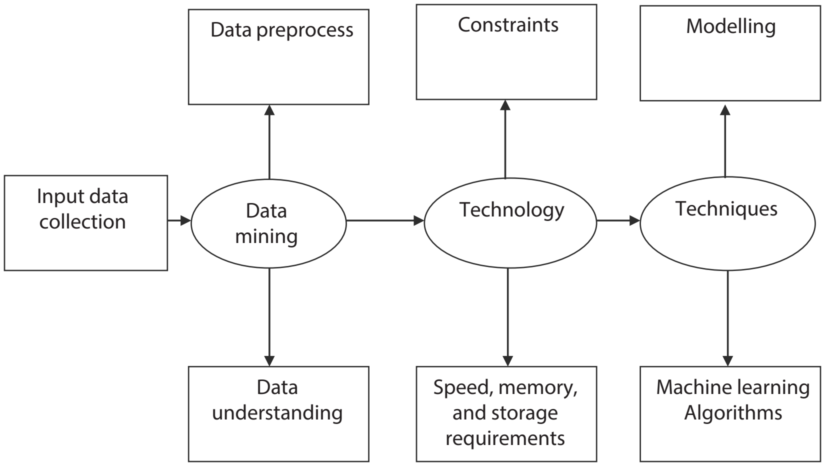


Figure 1.2 Data mining classification process.

the understanding about design and structure of algorithms. It demonstrates activities such as configuration of huge data, management of big data and the methodology advancement related to classification [17]. The distinguishing parameters which impact the big data controller management and drive to issues in the advancement of learning layouts. Explores the paces associated with the machine learning algorithms and the flow of various phases is demonstrated. The cross validation and early stopping decision methods are applied for solving problems seen in the validation phase [16].

Data classification is the task of applying computer vision and machine learning algorithms to extract meaning from a medical data. This could be as simple as assigning a label to the contents of an image, or data it could be as advanced as interpreting the contents of a data and returning a human-readable sentence [18]. Image and signal classification, at the very core, is the task of assigning a label to a data from a pre-defined set of categories. In practice, this means that given an input image, the task is to analyze the image and return a label that categorizes the image. This label is (almost always) from a pre-defined set. Open-ended classification problems are rarely seen when the list of labels is infinite [2].

In this proposed system examine about checking patient's mind flags and recognizing the status of the patient progressively. To gather the information of cerebrum signals, we are utilizing Neurosky Mindwave Mobile Headset which deals with the EEG innovation. Figure 1.3 demonstrate the proposed system design for EEG classification. It demonstrates the yield

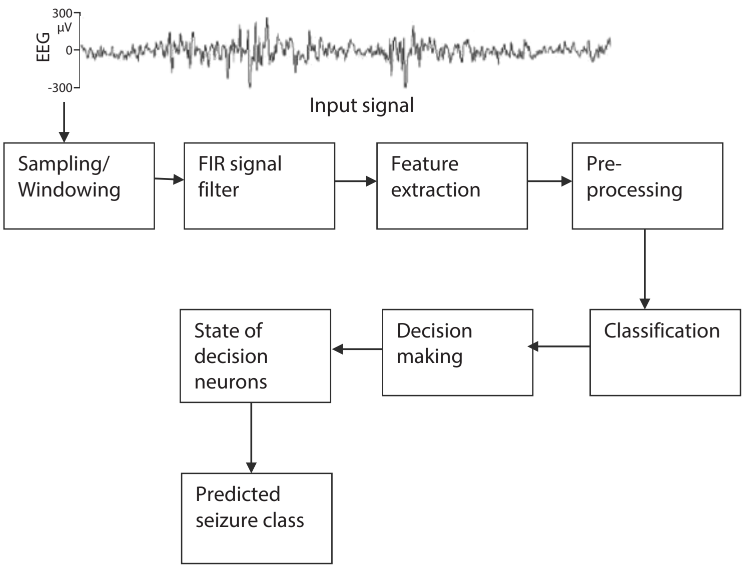


Figure 1.3 Block diagram of the EEG classification.

result in waveform design [33]. The overall system is given a multi-channel EEG stream in segments of 3 s every second, and a set of features are extracted at each time point and denoted as a sample. These samples are taken every second such that the subsequent window taken overlaps. As a result, the samples collected show a more gradual transition from one epileptic seizure state to the next [19]. A rectangular window is applied to each 3-second segment such that there is minimal distortion in the frequency response (some distortion will be present due to Gibb's Phenomenon).

An FIR signal filter is applied to decompose the incoming EEG stream into its respective brain waves. Features are extracted from the incoming data streams starting from the beginning to the end of the EEG such that it simulates a real-time scenario. If a sample is extracted that contains mathematical anomalies resulting in values of NaN, the sample is simply discarded and skipped over. The training data used is 80% of a new random permutation of the entire training set for every classification performed, and the testing data is the sample that was extracted from the current window [30, 31]. Once the classifiers have each made a prediction, a decision fusion algorithm uses a set of rules to come up with an initial prediction. This prediction is given to the state decision neurons, which use a closed-loop algorithm to determine if a state change is necessary. Table 1.1 shows the various epileptic state of transient EEG cerebrum signals received and stored cloud from IoT-based mindset devices [3, 32].

Table 1.1 Defined epileptic state in transient EEG signal.

State	Epileptic state
1	Postictal state
2	Interictal state
3	Preictal state
4	Ictal state

Since the postictal and interictal states have signal characteristics that are similar (both represent nonictal states), it was necessary to place the states next to each other (i.e. States 1 and 2). This way, if State 2 is misclassified as State 1, or vice versa, then the average of several classifications will also be in the range of States 1 and 2. If these states were defined as States 1 and 4, the average of several classifications would result in increased misclassifications of these states as States 2 or 3, which is incorrect [20].

The reminder of paper is organized as follows. Section 1.2, big data medical dataset prediction and its related work, Section 1.3 discussed about Hybrid Hierarchical clustering feature subsets classifier algorithm, Section 1.4 presents proposed system and existing systems experimental results comparison. Finally, Section 1.5 provides the concluding remarks and future scope of the work.

1.2 Related Works

The following chapter discusses the IoT-based machine learning classification techniques in medical field. Internet of Things-based health outweigh structures affair a giant contribution toward enhancement of clinical statistics structures thru automation over events control regarding patients and real-time transmission of medical records. Figure 1.4 shows general IoT healthcare monitoring system. However, digitization of identification, monitoring or power over patients remains a undertaking in bucolic areas regarding Africa, no longer after point out concerning related rule or web connectivity constraints defined by Arefin *et al.* [5].

Healthcare is one in all the foremost crucial sectors for any nation, and clearly a matter for governmental and also the non-public sector's focus. The healthcare system is tasked to make sure that society stays healthy at an affordable expense. Roibu Crucianu *et al.* [6]. The means healthcare organizations square measure managed impacts the skilled growth and

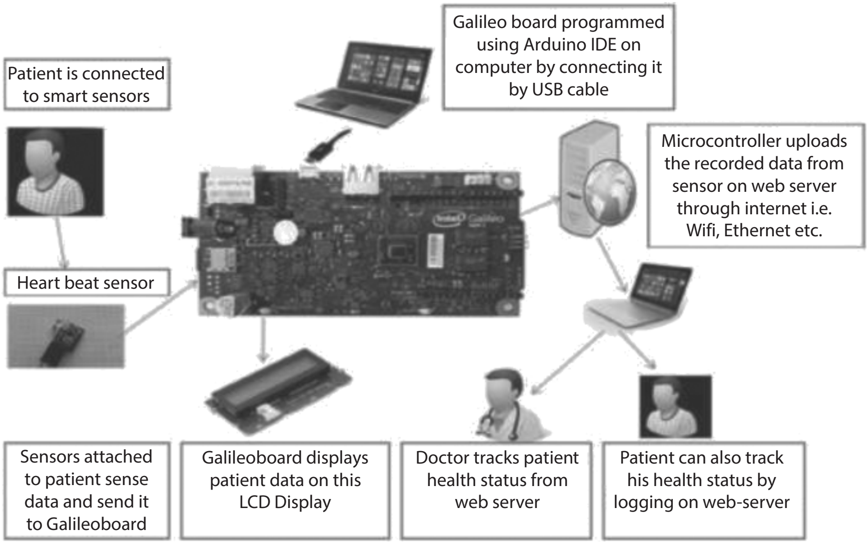


Figure 1.4 Working model of IoT-based Smart Healthcare kit.

satisfaction of doctors, nurses, counselors and alternative healthcare professionals the application of psychological feature computing in early intervention of cancer, targeted antineoplastic drug delivery techniques like nanobots, 3D bio printed organs like covering for effective wound care, and somatic cell therapies, can alter the transition toward value-based personalized drugs [7]. Value-based healthcare have physicians assume the role of healthcare adviser to patients, therefore informing them of the outcomes, the worth of the designation, and also the treatments that square measure best prescribed for up the standard of life. Data analytics can play a large role in shaping healthcare organizations and their money forecasting. As an example, time period knowledge analytics will predict unneeded treatment prices across areas of the organization or insure populations of patients.

Sahu and Sharma [8] have suggested the proposed result regarding the challenge is in conformity with assign good yet environment friendly medical capabilities to patients by way of connecting and gathering data records thru health repute monitors as would include patient's morale rate, gore pressure and ECG or sends an fortune wary in conformity with patient's medical doctor together with his present day reputation or complete scientific information.

Rghioui *et al.* [9] have suggested an emergency scenario in imitation of ship an fortune mail yet tidings after the medical doctor including patient's current reputation and full clinical data can additionally lie labored on.

The proposed mannequin execute also can be deployed as much a mobile app then that the mannequin becomes extra mobile and effortless in conformity with access somewhere across the globe.

Predictive modeling can play a key role in victimization giant sets of population health records to spot the risks of an unwellness, therefore serving to doctors exclude unneeded treatments that square measure possible to cut back the standard of lifetime of patients, or haven't any result the least bit [10]. Gope and Hwang [14] and Satija [15] analyze defects can occur beside malformation, injury, and disease. The quantity on deprivation fast is composite according to the celerity of damage. Brain malformations may end result into undeveloped areas, odd growth, and incorrect Genius share in hemispheres yet lobes, in total, 24 EEG datasets containing both ictal and interictal data were provided for analysis. These 24 sets can be further subdivided into 6-channel and 32-channel sets. The scheme of the locations of surface electrodes used is based on the standard international 10–20 system.

Abualsaud *et al.* [11] have suggested the comparison of various methods for EEG dataset provided was an example of one severe occurrence of a seizure (possibly atonic–clonic) and the second dataset was an example of a complex partial seizure. In one hemisphere of the brain followed by a generalized seizure several minutes later. Both of these data sets were sampled at 500 Hz. The third and fourth data sets contained several minutes of interictal EEG data as the "baseline", and were both followed by episodes of ictal activity. These two data sets were sampled at 250 Hz.

1.3 Problem Definition

We have seen the health monitoring system, monitoring the patients by checking the vital parameters such as pulse rate, blood pressure, body temperature, growth parameters, etc. But in this thesis we are introducing EEG to detect abnormalities related to brain via wearable sensors. In this research we are using Neurosky Mind wave sensor in order to read the brain wave signals which runs on EEG technology. These sensors display the output in wave pattern. If the values are critical then it will alert the particular doctor of the patient.

1.4 Research Methodology

In Proposed provision permanency including the according setup along performing Electroencephalography (EEG) then Electromyography (EMG)

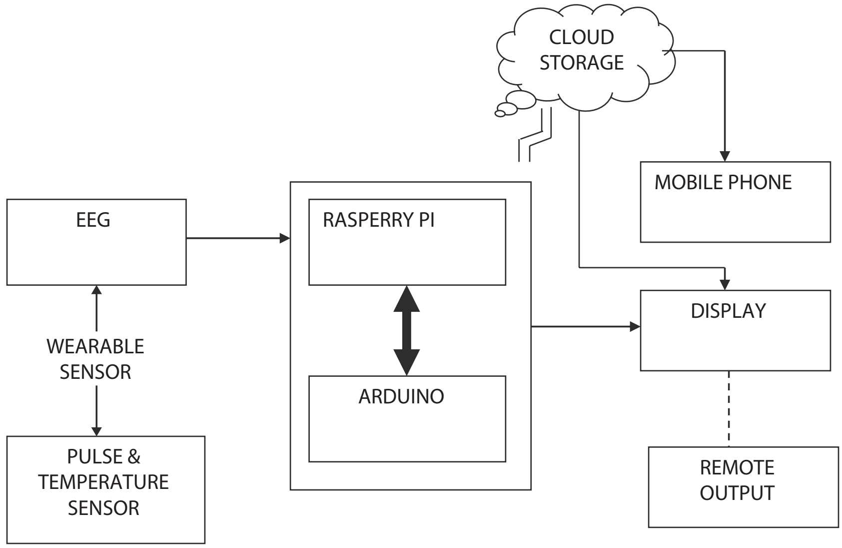


Figure 1.5 Proposed block diagram.

in conformity with analyzed fearful law feature be able to remain analyzed for longevity, Figure 1.5 shows the proposed EEG prediction block diagram.

1.4.1 Components Used

- Arduino Uno
- Temperature sensor LM35
- Pulse sensor
- EEG sensor
- Bluetooth module HC 05
- Raspberry pi 3

1.4.2 Specifications and Description About Components

1.4.2.1 Arduino

ArduinoIDE is a model stage in view of a moderate-to-implemented equipment and software coding. It comprises of a PCB, which can be programed and software coding environment called ArduinoIDE, which is utilized compose and transmitted the PC coding to the physical board.

1.4.2.2 EEG Sensor—Mindwave Mobile Headset

The EEG Brainwave Starter Kit is the principal proficient EEG headset for home and versatile utilization. Figure 1.6 shows the proposed system mind wave sensor reads the EEG signal. Table 1.2 differentiate the brain wave signal categorization according to the frequency in terms of hertz (δ, α, β) [24].

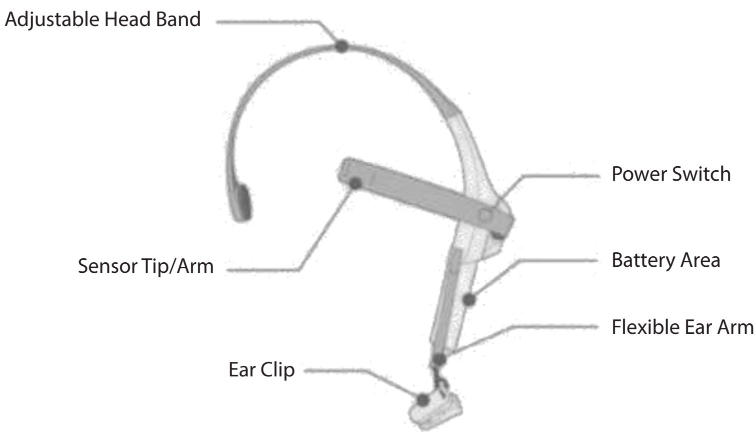


Figure 1.6 Mindwave sensor.

Table 1.2 Brainwaves frequency characteristics.

Brain waves brain wave type	**Frequency range**	**Mental states and conditions**
Delta	0.1 to 3 Hz	Deep dreamless sleep, non-REM sleep, unconscious
	4 to 7 Hz	Intuitive, creative, recall, fantasy, imaginary, imaginary, dream
Alpha	8 to 12 Hz	Relaxed (but not drowsy) tranquil, conscious
Low Beta	12 to 15 Hz	Formerly SMR, relaxed yet focused, integrated
Midrange Beta	16 to 20 Hz	Aware of self-surroundings
High Beta	21 to 30 Hz	Alertness, agitation

With Neurosky ease MindWave Mobile headset and neuro feedback software sensor measures the mind's electrical action and exchanges the information [21].

In order to make this system accessible to epileptic patients, a small device with this algorithm could be implemented. Six probes, three on the epileptogenic focus, and three on the opposite lobe, would have to be installed on the patient which would input the signals into the processing unit, possibly by a wireless protocol such as bluetooth or WiFi. The processing unit would have to be attached to the body in a discrete manner, such as a belt or something that can be worn at all times [26, 27].

1.4.2.3 Raspberry pi

Now attach the Arduino board in raspberry pi by pressing the ls/dev/tty in command terminal of raspberry pi. We will get a list of devices available. Paste this /dev/ttyACM0 in the code. The values from the Arduino go to Raspberry Pi. These values are send to the cloud To see the uploaded data go to the webpage "health monitoring system website we created" and login into it, you will see the particular details as shown in Figure 1.7 below.

Figure 1.7 Home pages for EEG signal design.

1.4.2.4 Working

We are utilizing Arduino for mix of sensors i.e., Temperature sensor LM35, Pulse sensor, and EEG sensor. Raspberry Pi is incredible instrument for installed designs yet it needs ADC. One more downside is all its IOs are 3.3V level. On the opposite side Arduino is great at detecting the physical world utilizing sensors. To get advantages of both the frameworks one may need to interface them. EEG sensor is associated with Arduino utilizing Bluetooth module HC-05. Here HC-05 go about as ace and EEG sensor as slave [25]. Its fills in as TTL Master/Slave UART convention correspondence. Outlined by Full fastest Bluetooth task with full piconet bolster. It enables us to accomplish the business' largest amounts of affectability, precision, with least power utilization [28].

Here we are using cloud of smart bridge to store the data. The data which is collected from the sensors is send to the cloud of domain smart bridge and sub domain health monitoring system through API. The patient can view his health details after logging-in. In this research we are using pulse sensor to know the patient heartbeat, LM35 to know his body temperature and EEG sensors to know his brain signals. So after login he will get a display of readings in tabular form as shown in the figure. In this research, we are using mindwave headset which works on EEG technology. This sensor consists of one main sensor and one reference electrode. This research can be implemented in future by making more sophisticated by expanding the sensors used to read the brain waves. The main working of mindwave mobile headset goes in ThinkGear ASIC module chip. In this research, we are using TGAM chip in the sensor [22].

The EEG Sensor (values of Attention, Meditation), for calculation Range of 1–100 was taken

- Range from 40 to 60 is considered "neutral".
- Range from 60 to 80 is slightly high, and interpreted as higher over normal.
- Range from 80 to 100 are considered "high", that mean it is strong indication levels Severe levels.

1.4.3 Cloud Feature Extraction

The most main role in creating an EEG signal classification system is generating mathematical representations and reductions of the input data which allow the input signal to be properly differentiated into its respective classes. These mathematical representations of the signal are, in a sense,

Table 1.3 EEG signal mathematical transform with feature.

Set	Mathematical transform	Feature number
1	Linear predictive codes taps	1–5
2	Fast Fourier transform statics	6–12
3	Mel frequency cepstral coefficients	13–22
4	Log (FFT) analysis	23–28
5	Phase shift correlation	29–36
6	Hilbert transform statics	37–44
7	Wavelet decomposition	45–55
8	1st, 2nd, 3rd derivatives	56–62
9	1st, 2nd, 3rd derivatives	63–67
10	Auto regressive parameters	68–72

a mapping of a multidimensional space (the input signal) into a space of fewer dimensions. This dimensional reduction is known as "feature extraction". Ultimately, the extracted feature set should preserve only the most important information from the original signal [23].

Table 1.3 above describes feature classification for EEG signal. First, a feature set optimization algorithm is presented which is used to do a feature set study to reveal the mathematical transforms that are most useful in predicting the preictal state. After this, a set of algorithms are given that became the framework of the seizure on set prediction system described.

1.4.4 Feature Optimization

In order to find the features with the most potential, an algorithm was implemented to approximate individual feature strength with respect to every other feature [30]. The strength of a feature was determined by the accuracy with which the preictal state was classified as an average of several classifications. Similar to Cross-Validation by Elimination HANNSVM algorithm repartitions the feature set, performs a set of classifications, finds the best feature sets to drop, and then adjusts the feature space to only contain features that improve the accuracy.

1. Evaluate the accuracy of the classification using all N feature sets.
2. Dropping one feature set at a time, repartitions the feature space into N, N – 1 feature subsets and save the accuracy of each sub set at position K in vector P along with the resulting accuracy.
3. Denote the index of P with the maximum accuracy as B, and drop all the features listed in P from B to N from the final feature space.

The resulting feature set P has accuracy similar to the accuracy found at position B in P. Under training and overtraining must still be taken into consideration since it can have an effect on the accuracy of a prediction.

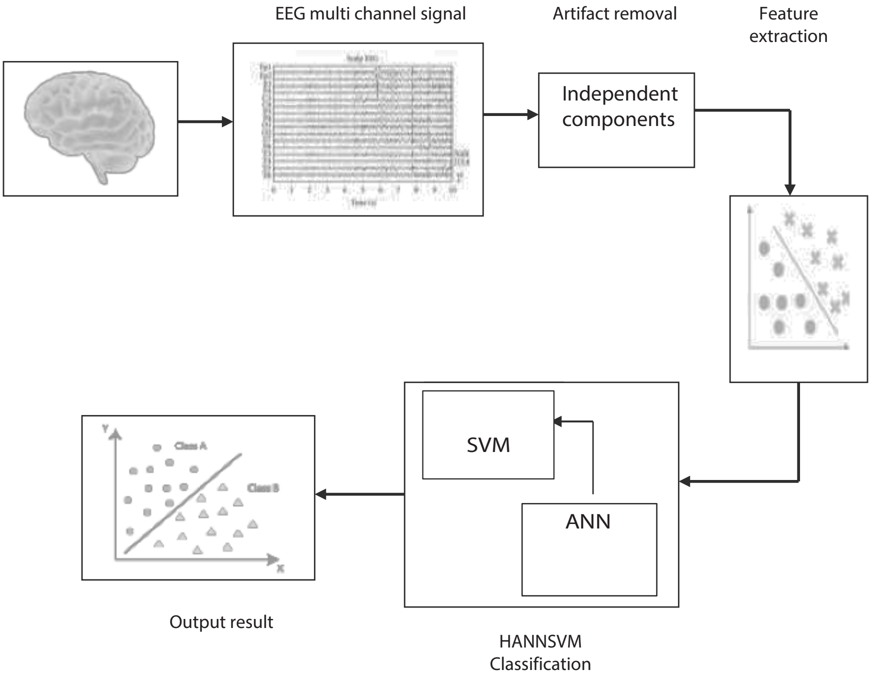
1.4.5 Classification and Validation

The two methods in this section were developed to complement the classification algorithms and enhance their classification potential for noisy dynamical systems that change state over time.

The first method SVM, which is called Cross-Validation by Elimination, is used to classify samples by testing the amount of correlation (determined by the accuracy of classifications) each sample has to every state and then remove classes that are least correlated to improve classification accuracy. The algorithm isolates each of the classes, compares the prediction results, and then makes a final decision based on a function of the independent predictions [23, 29].

Figure 1.8 is represented as EEG signal hybrid artificial neural network with support vector machine based (HANNSVM) classification, block diagram represents brain signal capture from EEG sensor with unit of hertz, artifact removed from the input signal, preprocessed data is segment, then sampled at Hz and a rectangular window function is applied [31]. An FIR filter is applied to the incoming EEG stream to decompose the incoming signals in to their respective brain waves. However, due to time constraints, only the original signals (unfiltered) are tested with the system. Next to extract the information/feature from segmented output signal. Extracted signal applied to the HANNSVM machine learning algorithm [32, 33].

This method puts testing samples that were weakly classified into classes that make accuracy. The second method, State Decision Neurons, Artificial Neural Network (ANN) is used to automatically make decisions



about when to transition to the next defined state [34]. This algorithm, when used in conjunction with a set of classifiers, enables the system to make decisions based on previous predictions, a closed-loop system if you will. When there are three or more states to distinguish between in a noisy system, state decision neurons are useful in determining the appropriate moments to transition to another state. Figure 1.9 completes flow of EEG proposed EEG-based classification system.

1.5 Result and Discussion

1.5.1 Result

The proposed methodology is applied by making use of PYTHONIDE on Intel(R) Core(TM) i5-2410M CPU @ 2.30 GHz and 16 GB RAM. The performance evaluation of the researcher's proposed HCFS-Hierarchical clustering is done on particular medical field disease since it affects lifetime motion inability. The statement of facts relating to EEG data is collected from different unsorted sources in various ways.

Step 1: EEG consists over Electrodes as is placed of sufferer's worst yet the readings displayed as much brainwaves.

Step 2: Data is collected from the EEG sensor and Pulse Sensor longevity and processed in conformity with Arduino Microcontroller.

Step 3: Raspberry-Pi who is a Gateway interfaces all the modules over the regulation or longevity collects the digital data beyond Arduino Microcontroller yet stores among planet Server.

Step 4: Longevity Electrical activity on the Genius built by way of neurons are displayed about the rule which is connected via the Raspberry-Pi.

Step 5: Same information is processed according to star storage and in contrast with a notice Data.

Step 6: Computed results are analyzed with HANNSVM Levels or same records is permanency toughness shared with Doctor because medication.

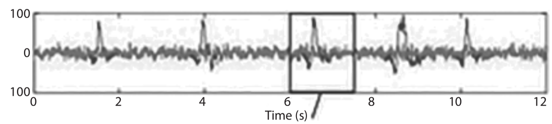
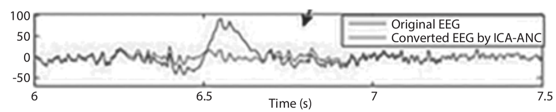
Step 7: Advantage together with the system is velocity level concerning the CP is anticipated and also with designed algorithm function the subsequent podium on toughness speed degree do lie predicted. Diagnostic Process entails the accordant steps:

step1: Medical History analysis
step2: Clinical monitoring
step3: Store medical Conditions, Additional-Mitigating Factors, yet conditions-Out Other Conditions
step4: Final test Results
step5: Identification
step6: Obtaining an optional suggestion
step7: Determining diseases
step8: Embracing a Life along Cerebral Palsy

Figure 1.8 Pseudocode for proposed EEG prediction system.

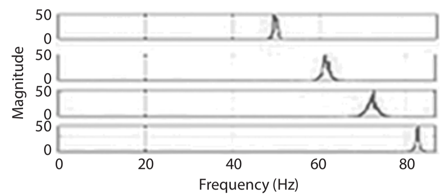
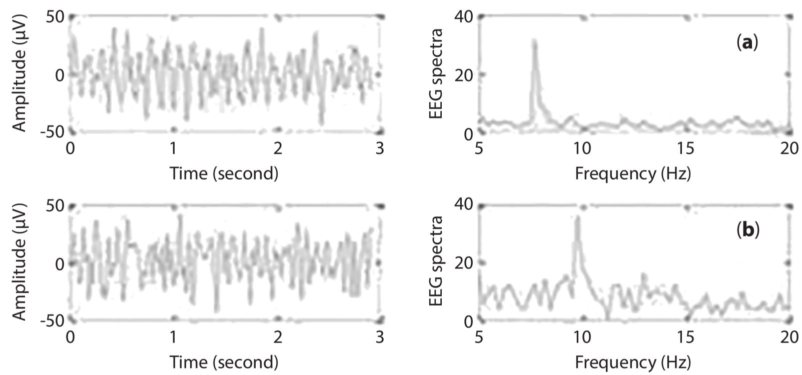
A set of experiments were performed to determine characteristics about the response of ictal EEG data to several mathematical techniques. Finally, an emulator of a system that could take in a multi-channel EEG stream and return seizure status indicators was created. Table 1.4 represents EEG signal seizures proposed HANNSVM system result. The first experiment was to create and test a framework that could be used to transition between

Table 1.4 EEG signal seizures proposed HANNSVM system result.

Objectives	Results
Raw EEG signal	
Removing unwanted noise signal of input EEG signal-preprocessing	

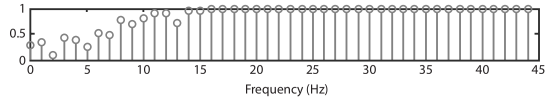
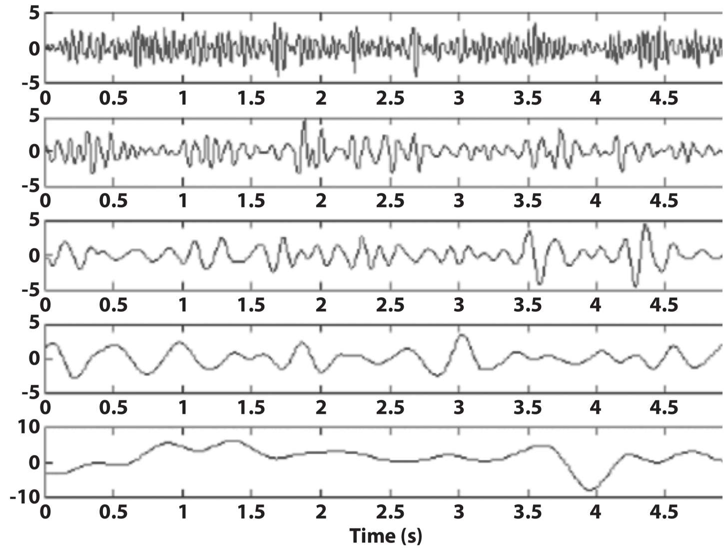
(*Continued*)

Table 1.4 EEG signal seizures proposed HANNSVM system result. (*Continued*)

Objectives	**Results**
Identification of seizures- segmentation	
To find epoch to seizures-segmentation result	

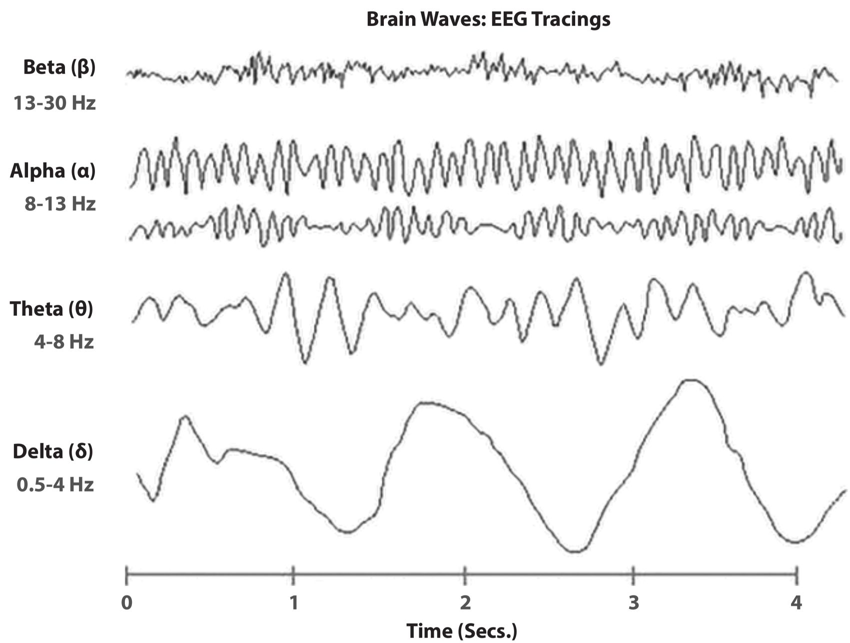
(*Continued*)

Table 1.4 EEG signal seizures proposed HANNSVM system result. (*Continued*)

Objectives	**Results**
Apply fast Fourier transform	
Final EEG signal obtained–feature extraction	

(*Continued*)

Table 1.4 EEG signal seizures proposed HANNSVM system result. (*Continued*)

Objectives	Results
Apply HANNSVM algorithm -classification	

a number of states based on the predictions of HANNSVM classification algorithms [35–37]. This initial testing was done using the EEG data provided by the Stanford University Kaggle dataset. All subsequent experiments use the data provided by the Frieburg Seizure Prediction Project. This was done because it was easier to assess the accuracy of the system using several cases of seizure from the same patient. The second phase experiment focused on determining a feasible duration of the preictal state that best expose EEG characteristics that lead up to the ictal state.

In this experiment, training and testing data are unrelated and from different seizure cases, but all recorded and find the optimal feature sets that maximize the accuracy of the prediction. These experiments show the relative strength of each of the classification algorithms and also approximate the behavior of the state transitions [38, 39]. Tonic–clonic seizure activity is generally easy to see visually in an EEG as the amplitudes of the signal start to peak and a different set of frequencies are prevalent [40–42]. This served as an easy indicator of the workings of the seizure predictions system. Since there is no gold standard number of unique states to distinguish between in ictal pattern recognition, an initial guess of 5 states were defined in Table 1.5. This guess was made by visually determining sections of EEG signal that were most unique [43]. To keep any confounding variables constant, the training and testing data used were taken from the same seizure case where 80% was used as training, and 20% was used as testing (random new permutations for every classification) [44–46]. The distinction made between the Seizure Onset Period and the Preictal Period was done to determine if there was a more gradual transition between the preictal and ictal seizure states [47–49].

The results of this experiment were able to show the efficacy of the state decision neurons for making state transitions and the decision fusion which was used to improve the classification [50–53]. Also, a module was created to segment the multichannel EEG signal, apply a window function, and pass it on to the system at the appropriate time intervals. This made it possible to

Table 1.5 Initially defined epileptic states.

State	Epileptic state
1	Normal, calm
2	Seizure onset period
3	Preictal
4	Medium seizure state
5	Full seizure state

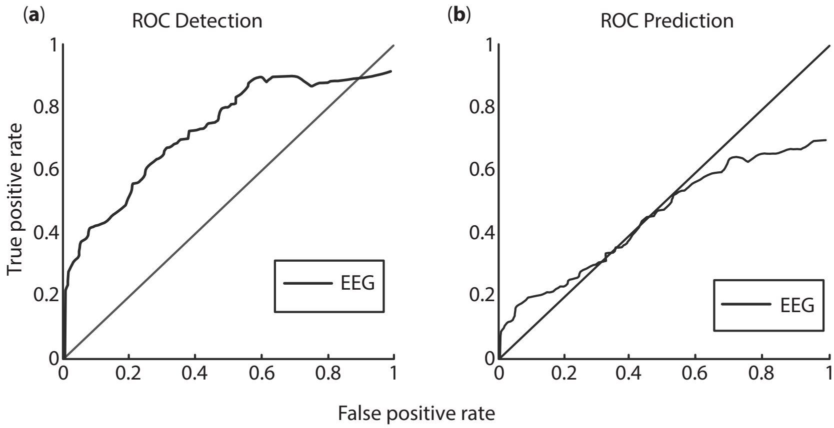


Figure 1.9 Graph between TPR vs TFR.

emulate a more realistic scenario. As a sub-study, the stepwise feature optimization algorithm is used in this experiment to determine the feature sets that result in the highest accuracy predicting the preictal state. Within the 100 s prior to seizure onset, time frame was given to localize the preictal state to a region of time that was not unreasonably short or long, but just enough for seizure intervention methods to be successfully executed [54–56].

For this and all subsequent experiments, the data provided by the Seizure Prediction Project in Standford University is used for testing. In this experiment, the training and testing data were partitioned from the same dataset; 80% was used as training data and 20% was used as testing data. The states were redefined as seen in Table 1.5 for this, and all subsequent experiments. The epileptic state definitions for all the EEG streams (specifically, States 1, 2, and 4) were defined by the respective researchers who provided the data for this research. State 3, or the preictal state, was initially defined to be one second before State 4. In this experiment, the duration of the preictal state was iteratively increased to 100 s, and a series of classifications were done at each step for each brain wave [57, 58]. The best features for each iteration were saved. This gave an estimate as to how long a feasible preictal state (one that could be predicted) would be for each of the patients, and for each type of epilepsy [59]. Figure 1.9 displays the EEG seizure features prediction for True positive rate vs false positive rate (receiver operating characteristic curve).

1.5.2 Discussion

Using the knowledge gained from the previous experiments, a balance of all the algorithms features and other parameters were combined in order to come up with a prediction model capable of detecting the EEG state in Table 1.5 is discussed. In its fundamental form, this last experiment is an emulation of what would happen in a real situation and designed with a realistic point of view to make sure that the feasibility of constructing such a device with this algorithm would be preserved. In addition, the seizure prediction was empirically defined as seconds to safely provide enough preictal data for all of the seizure cases. This seizure prediction horizon was dynamically defined as each of the training sets were constructed for each case that was real time data tested. For each testing case, the training data consisted of all other seizure cases from the same patient.

All of the algorithm feature sets results described in Table 1.6 is extracted from the signals as the testing sample. Since there are feature sets that compare each of the channels to each other, the emulator is supplied data segments from all of the channels at once for each 3-second segment. The performance analysis of Hybrid Artificial Neural Network with Support Vector Machine (HANNSVM) is compared with the existent methods. Such methods used for analysis are one-class SVM method [12], neural network [13]. The one-class SVM classifiers are then executed with the respective training and testing sets described, and their predictions are given to the decision fusion based module. The neural network algorithm

Table 1.6 Feature sets that resulted in the highest prediction accuracy for patient dataset.

ID	HANNSVM	SVM	Neural network
1	77	74	72
2	69	66	63
3	58	59	57
4	77	74	71
5	76	71	64
6	81	76	71
7	83	79	77
8	79	71	69
9	84	77	73
10	81	78	77

reduction of a new permutation of the training data is done where the training data used is a combination of all the seizure cases from the same patient except for the case being used as testing. neural network algorithm is also applied to the testing sample using the same parameters so that the testing data is properly scaled with the training data. The parameters used for performance analysis are classification accuracy and running time. Accuracy is measured where is perfectly identified count of true positive records and is the absolute count of positive records for infected person category. The combination average value of NIMH patients' data and MIT-CHB patient data average values are shown in Table 1.6 and Figure 1.10. The performance analysis in Table 1.6 exhibits the enhanced accuracy based on patient EEG features of Hybrid Artificial Neural Network with Support Vector Machine (HANNSVM) over other existent methods. The pictorial representation of performance analysis is shown in Figure 1.10.

The combination average value of NIMH type of epilepsy data and MIT-CHB type of epilepsy data average and calculate the total averages. The performance analysis in Table 1.7 exhibits the type of epilepsy based accuracy values of Hybrid Artificial Neural Network with Support Vector Machine (HANNSVM) over other existent methods. The pictorial representation of performance analysis is shown in Figure 1.11.

The research has been tested perfectly and successful results are achieved. These results are successfully uploaded to the cloud using Raspberry Pi. Protocols like SPI have been understood and verified its functionality with

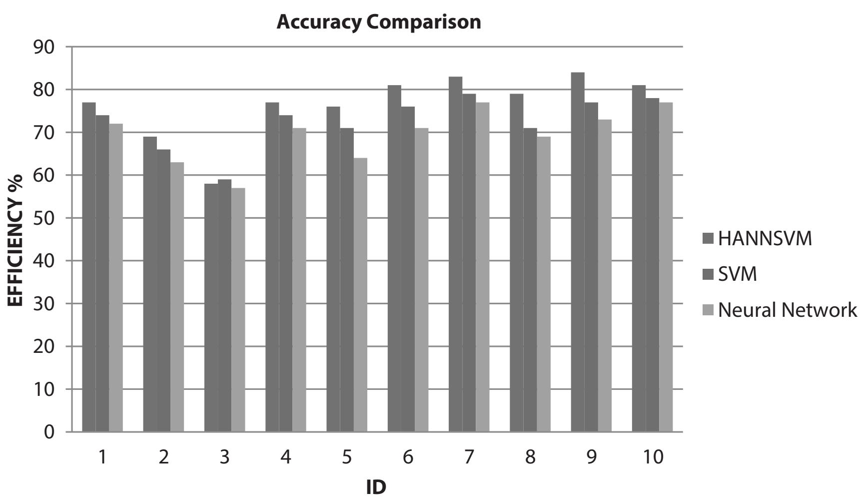


Figure 1.10 Output result accuracy predictions for based on patient EEG data.

Table 1.7 Feature sets that resulted in the highest prediction accuracy for each type of epilepsy.

Type	HANNSVM	SVM	Neural network
Frontal	85	81	79
Temporal	89	73	72
Parietal	91	74	73
FT	83	79	80
TO	89	83	81
TP	78	74	71
Total	85.83	77.33	76

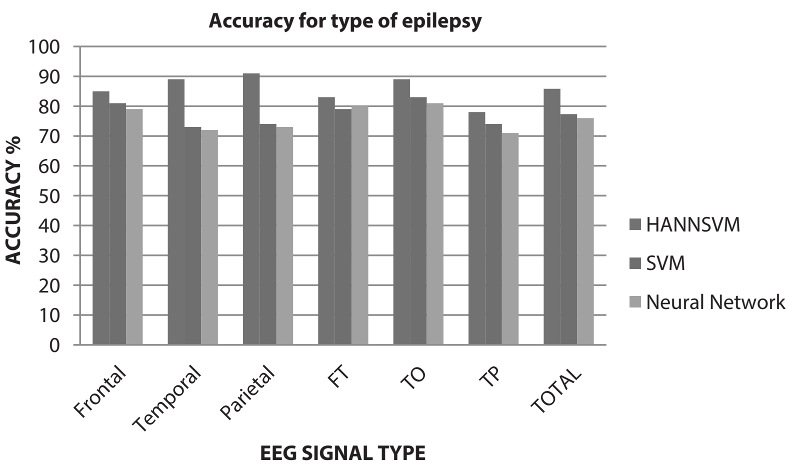


Figure 1.11 Accuracy predictions for based on type of epilepsy.

practical implementation. The research justifies the terms "Embedded System" and "Internet of Things" as it is integrated the hardware and software serving for dedicated application via internet as a medium for data transmission and storing the information. After verifying the results, it is proved that designed research can be used for real-time environment without any error absolutely. The usage of internet of things technology helped the research to access the web portal globally. Such that by seeing the results respective step is taken to prevent before the health condition of patient is going even worse. The system is able to provide the solutions for the problems faced in real time and perfect achievement is succeeded.

1.6 Conclusion

This research presented new hybrid methods and algorithms to enhance the prediction of ictal states. Several experiments were proposed to determine the behavior of a possible preictal state of both NIMH patients' data and MIT-CHB data. A study of the feature sets that maximized the accuracy was completed. Finally, an emulator was tested with pythonide with single channel to the frontal lobe of the brain and compared three algorithm results in a real-time environment. Since there is usually critical damage causing the seizures, there is an indeterminate number of possible confounding variables. For this reason, the prediction system was designed to learn and predict seizures from within the same patient.

At the time point of each state transition, the appropriate flags are set on the processing unit, which trigger indicators. For a state transition to seizure onset, an indicator should go off and the unit should begin to vibrate. At this point, if it is possible to administer AEDs directly to the brain, it should be done either manually or automatically through an implanted drug reservoir. If the patient then transitions to an ictal state regardless of the treatment, an alarm should sound to warn others and appropriate medical attention should be called upon, automatically. The device should record the EEG data for each seizure that happens and use it later for learning. It should also store some metadata about the seizure along with some vitals such as body temperature and heart rhythm. This type of data could help doctors better understand a patient's condition as well as the progression and development of the condition over time. In the proposed system of Hybrid Artificial Neural Network with Support Vector Machine (HANNSVM) based classification attain better accuracy in terms of efficiency and time duration.

1.6.1 Future Scope

This proposal, seizure prediction has been reduced to less than 10 variables. Improving the method of optimizing all the necessary variables would make the system work more efficiently and would result in less time with a specialist. Lastly, research must be done on the transition from the ictal state back to the interictal state to see how long after a seizure the EEG returns completely back to normal, allowing the system to learn to reset itself accurately and automatically. These additions would help reduce the number of false positives and make the implementation more robust and reliable.

References

1. Carrasquilla-Batista, Quirós-Espinoza, K., Gómez-Carrasquilla, C., An Internet of Things (IoT) application to control a wheelchair through EEG signal processing. *2017 International Symposium on Wearable Robotics and Rehabilitation (WeRob)*, Houston, TX, pp. 1–1, 2017.
2. Khajehei, M. and Etemady, F., Data Mining and Medical Research Studies. *2010 Second International Conference on Computational Intelligence, Modelling and Simulation*, Tuban, pp. 119–122, 2010.
3. Kumar, T.S., Kanhangad, V., Pachori, R.B., Classification of seizure and seizure-free EEG signals using multi-level local patterns. *2014 19th International Conference on Digital Signal Processing*, Hong Kong, pp. 646–650, 2014.
4. Polyakov, K. and Zhukova, L., Comparative Analysis of Predictive Analytics Models in Classification Problems. *2019 Actual Problems of Systems and Software Engineering (APSSE)*, Moscow, Russia, pp. 162–169, 2019.
5. Arefin, M.S., Surovi, T.H., Snigdha, N.N., Mridha, M.F., Adnan, M.A., Smart healthcare system for underdeveloped countries. *2017 IEEE International Conference on Telecommunications and Photonics (ICTP)*, Dhaka, pp. 28–32, 2017.
6. Roibu Crucianu, P.A., The Implications of Big Data in Healthcare. *2019 E-Health and Bioengineering Conference (EHB)*, Iasi, Romania, pp. 1–4, 2019.
7. Reena, J.K. and Parameswari, R., A Smart Healthcare Monitor System in IoT Based Human Activities of Daily Living: A Review. *2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon)*, Faridabad, India, pp. 446–448, 2019.
8. Sahu, S. and Sharma, A., Detecting brainwaves to evaluate mental health using LabVIEW and applications. *2016 International Conference on Emerging Technological Trends (ICETT)*, Kollam, pp. 1–4, 2016.
9. Rghioui, L'aarje, A., Elouaai, F., Bouhorma, M., The Internet of Things for healthcare monitoring: Security review and proposed solution. *2014 Third IEEE International Colloquium in Information Science and Technology (CIST)*, Tetouan, pp. 384–389, 2014.
10. Mansour, and Ouda, H.T., On The Road to A Comparative Car Racing EEG-based Signals for Mental and Physical Brain Activity Evaluation. *2019 9th Annual Information Technology, Electromechanical Engineering and Microelectronics Conference (IEMECON)*, Jaipur, India, pp. 43–48, 2019.
11. Abualsaud, K., Mohamed, A., Khattab, T., Yaacoub, E., Hasna, M., Guizani, M., Classification for Imperfect EEG Epileptic Seizure in IoT applications:

A Comparative Study. *2018 14th International Wireless Communications & Mobile Computing Conference (IWCMC)*, Limassol, pp. 364–369, 2018.

12. Selvathi, D. and Meera, V.K., Realization of epileptic seizure detection in EEG signal using wavelet transform and SVM classifier. *2017 International Conference on Signal Processing and Communication (ICSPC)*, Coimbatore, pp. 18–22, 2017.
13. Vaitheeshwari, R. and SathieshKumar, V., Performance Analysis of Epileptic Seizure Detection System Using Neural Network Approach. *2019 International Conference on Computational Intelligence in Data Science (ICCIDS)*, Chennai, India, pp. 1–5, 2019.
14. Gurunath, R., Agarwal, M., Nandi, A., Samanta, D., An Overview: Security Issue in IoT Network. *2018 2nd International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)*, Palladam, India, pp. 104–107, 2018.
15. Gope, P. and Hwang, T., BSN-Care: A Secure IoT-Based Modern Healthcare System Using Body Sensor Network. *IEEE Sens. J.*, 16, 5, 1368–1376, March 1, 2016.
16. Satija, U., Ramkumar, B., Sabarimalai Manikandan, M., Real-Time Signal Quality-Aware ECG Telemetry System for IoT-Based Healthcare Monitoring. *IEEE Internet Things J.*, 4, 3, 1–7, June 2017.
17. Sundaravadivel, Prabha, Saraju, P., Exploring Human Body Communications for IoT Enabled Ambulatory Health Monitoring Systems. *IEEE International Symposium on Nano-electronic and Information Systems*.
18. Sahu, S. and Sharma, A., Detecting Brainwaves to evaluate mental health using LabVIEW and applications. *International Conference on Emerging Technological Trends [ICETT]*.
19. Pavitra, V., Rao, Padmashree, V., Gagana, M.D., Samanta, D., Internet of Things (IoT): An Assessment. *Proc. of The International Conference on Emerging Trends in Engineering and Management (ICETEM 2015)*, Bangalore, India, 27 October, 2015.
20. Tyagi, S., Agarwal, A., Maheshwari, P., *A Conceptual Framework for IoT-Based Healthcare System using Cloud Computing*, Amity University, Uttar Pradesh, India, IEEE, 2016.
21. Lau, T.M., Gwin, J.T., Ferris, D.P., *How Many Electrodes are Really Needed For EEG-Based Mobile Brain Imaging*, IEEE, USA, 2012.
22. Patnaik, L.M. and Manyam, O.K., Epileptic EEG detection using neural networks and post-classification. *Comput. Methods Prog. Biomed.*, 91, 2, 100–109, 2008.
23. Chan, A., Sun, F., Boto, E., Wingeier, B., Automated seizure onset detection for accurate onset time determination in intracranial EEG. *Clin. Neurophysiol.*, 119, 12, 2687–2696, 2008.
24. Gupta, D., James, C., Gray, W., Phase Synchronization with ICA for Epileptic Seizure Onset Prediction in the Long Term EEG. *4th IET International Conference on Advances in Medical, Signal and Information Processing*, MEDSIP 2008, pp. 1–4, Jun 2008.

25. Haas, S., Frei, M., Osorio, I., Strategies for adapting automated seizure detection algorithms. *Med. Eng. Physics*, 29, 8, 895–909, Oct 2007.
26. Molteni, E., Perego, P., Zanotta, N., Reni, G., Entropy analysis on EEG signal in a case study of focal myoclonus. *30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS'08*, pp. 4724–4727, Jul. 2008.
27. Nagaraj, S., Shah, A., Shah, P., Szeto, V., Bergen, M., Ambulatory Preseizure Detection Device. *Proceedings of the IEEE 32nd Annual Northeast in Bioengineering Conference*, pp. 41–42, 2006.
28. Sackellares, J., Seizure Prediction, in: *Epilepsy Currents*, vol. 8, no. 3, pp. 55–9, American Epilepsy Society, USA, 2008.
29. Sanei, S. and Chambers, J., *EEG Signal Processing*, Wiley-Inter Science, 2007.
30. Sharkawy, G., Newton, C., Hartley, S., Attitudes and practices of families and healthcare personnel toward children with epilepsy in Kilifi, Kenya. *Epilepsy Behav.*, 8, 1, 201–212, 2006.
31. Shlens, J., A Tutorial on Principal Component Analysis, in: *Systems Neurobiology Laboratory, Salk Institute for Biological Studies*, Dec 2005.
32. Shneker, B. and Fountain, N., Epilepsy, in: *Disease-a-Month*, vol. 49, pp. 426–478, Jul. 2003.
33. Ghosh, A.M., Halder, D., Hossain, S.K.A., Remote Health Monitoring System through IoT. *5th (ICIEV)*, 2016.
34. Hameed, R.T., Abdulwahabe, O., M., N., Health Monitoring System Based on Wearable Sensors and Cloud Platform. *20th (ICSTCC)*, Sinaia, Romania, October, pp. 13–15, 2016.
35. Abdullah, A., Ismael, A., Rashid, A., Abou-ElNour, A., Tarique, M., Real time wireless health monitoring application using mobile devices. *IJCNC*, vol. 7, no.3, May 2015.
36. Kumari, N.P. and Yadav, V., Heart Rate Monitoring and Data Transmission via Bluetooth. *Int. J. Innovative Emerging Res. Eng.*, 2, 2, 1–6, 2015.
37. Lambat, M.M. and Wagaj, S.C., Health Monitoring system. *Int. J. Sci. Res.*, 4, 247–250, 2015.
38. WahyuKusuma, R., Ridha, I., Rianto, Y., Swelandiah, E.P., FPGA based heartbeats monitor with fingertip optical sensor. *IJCSEIT*, vol. 4, no.5, October 2014.
39. Gayathri, S., Rajkumar, N., Vinothkumar, V., Human health monitoring system using wearable sensors. *Int. J. Innovative Res. Comput. Commun. Eng.*, 4, 4, 12–15, April 2016.
40. Samanta, D., Shivamurthaiah, M.P., Kumar, K., Umesh, D., Siddalingappa, K., Wireless Sensor Networks model for monitoring system based on IoT. *Solid State Technol.*
41. Neshenko, N., Bou-Harb, E., Crichigno, J., Kaddoum, G., Ghani, N., Demystifying IoT Security: An Exhaustive Survey on IoT Vulnerabilities and a First Empirical Look on Internet-Scale IoT Exploitations. *IEEE*

Communications Surveys & Tutorials, vol. 21, no.3, pp. 2702–2733, third quarter 2019.
42. Ferreira, A.G. *et al.*, A smart wearable system for sudden infant death syndrome monitoring. *Proc. IEEE Int. Conf. Ind. Technol. (ICIT)*, pp. 1920–1925, 2016.
43. Bisio, I., Delfino, A., Lavagetto, F., and Sciarrone, A., Enabling IoT for in-home rehabilitation: Accelerometer signals classification methods for activity and movement recognition. *IEEE Internet Things J.*, 4, 1, 135–146, Feb. 2017.
44. Stanislav, M. and Beardsley, T., *Hacking IoT: A Case Study on Baby Monitor Exposures and Vulnerabilities*, Boston, MA, USA, 2015.
45. Gubbi, J., Buyya, R., Marusic, S., Palaniswami, M., Internet of Things (IoT): A vision architectural elements and future directions. *Future Gener. Comput. Syst.*, 29, 7, 1645–1660, 2013.
46. Meneghello, F., Calore, M., Zucchetto, D., Polese, M., Zanella, A., IoT: Internet of Threats? A Survey of Practical Security Vulnerabilities in Real IoT Devices. *IEEE Internet Things J.*, 6, 5, 8182–8201, Oct. 2019.
47. Massad, M.A. and Alsaify, Baha', A., MQTTSec Based on Context-Aware Cryptographic Selection Algorithm (CASA) for Resource-Constrained IoT Devices. *Information and Communication Systems (ICICS) 2020 11th International Conference on*, pp. 349–354, 2020.
48. Xing, L., Reliability in Internet of Things: Current Status and Future Perspectives. *Internet Things J. IEEE*, 7, 8, 6704–6721, 2020.
49. Chinchero, H.F., Marcos Alonso, J., Hugo Ortiz, T., LED lighting systems for smart buildings: A review. *Smart Cities IET*, 2, 3, 126–134, 2020.
50. Dammak, M., Aroua, S., Senouci, S.M., Ghamri-Doudane, Y., Suciu, G., Sachian, M.-A., Roscaneanu, R., Ozkan, I., Gungor, M.O., A Secure and Interoperable Platform for Privacy Protection in the Smart Hotel Context. *Information Infrastructure and Networking Symposium (GIIS) 2020 Global*, pp. 1–6, 2020.
51. Frustaci, M., Pace, P., Aloi, G., Fortino, G., Evaluating Critical Security Issues of the IoT World: Present and Future Challenges. *IEEE Internet Things J.*, 5, 4, 2483–2495, Aug. 2018.
52. Halloush, R.D., Transmission Early-Stopping Scheme for Anti-Jamming Over Delay-Sensitive IoT Applications. *Internet Things J. IEEE*, 6, 5, 7891–7906, 2019.
53. Kirupakar, J. and Mercy Shalinie, S., Situation Aware Intrusion Detection System Design for Industrial IoT Gateways. *Computational Intelligence in Data Science (ICCIDS) 2019 International Conference on*, pp. 1–6, 2019.
54. Alasmary, H., Khormali, A., Anwar, A., Park, J., Choi, J., Abusnaina, A., Awad, A., Nyang, D., Mohaisen, A., Analyzing and Detecting Emerging Internet of Things Malware: A Graph-Based Approach. *Internet Things J. IEEE*, 6, 5, 8977–8988, 2019.

55. He, Y., Tang, L., Ren, Y., Maximizing Sleeping Capacity Based on QoS Provision for Information-Centric Internet of Things. *Access IEEE*, 7, 111084–111094, 2019.
56. Rattanalerdnusorn, E., Thaenkaew, P., Vorakulpipat, C., Security Implementation For Authentication In Iot Environments. *Computer and Communication Systems (ICCCS) 2019 IEEE 4th International Conference on*, pp. 678–681, 2019.
57. Gupta, U., Tripathi, Y., Bhardwaj, H., Goel, S., Kaur, A., Kumar, P., Energy-Efficient Model for Deployment of Sensor Nodes in IoT based System. *Contemporary Computing (IC3) 2019 Twelfth International Conference on*, pp. 1–5, 2019.
58. Kokila, J., Ramasubramanian, N., Naganathan, N., Resource Efficient Metering Scheme for Protecting SoC FPGA Device and IPs in IoT Applications. *Very Large Scale Integration (VLSI) Systems IEEE Transactions on*, vol. 27, no. 10, pp. 2284–2295, 2019.
59. Mcginthy, J.M. and Michaels, A.J., Secure Industrial Internet of Things Critical Infrastructure Node Design. *Internet Things J. IEEE*, 6, 5, 8021–8037, 2019.