Development of Machine Learning Based Epileptic Seizureprediction using Web of Things(WoT)

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Abstract

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A significant chronic neurological illness called epilepsy and identified by examining Brain signals that Brain Neurons' produce. In order to generate messages and communicate with bodily organs, neurons are intricately coupled to one another. Electrocorticography (ECoG) and Electroencephalogram (EEG) media are frequently used to detect these brain impulses. These signals generate a large amount of data and are complicated, noisy, non-stationary andnon-linear. As a result, it is tough to identify seizures and learn about knowledge relating to the brain. Without sacrificing performance, machine learning classifiers can classify EEG data, detect seizures, and highlight pertinent meaningful patterns. As a result, numerous researchers have created a variety of seizure detection methods combining statistical characteristics and machine learning classifiers.The biggest difficulties lie in choosing the right classifiers and characteristics. The purpose of this work is to demonstrate a machine learning methodology for using WoT to detect epileptic seizures.

Keywords- Epilepsy; EEG; Brain; seizer; PyEEG;

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1. INTRODUCTION-

The Greek and Latin words "epilepsia" (means "seizure" "to seize upon") are the source of the word epilepsy. It is a severe neurological condition with distinctive traits that is prone to recurrent seizures. The

Babylonian treatise on medicine, which was written more than three thousand years ago, contains a context for epilepsy. This illness affects all mammal species, including rats, dogs, and cats in addition to people. The term "epilepsy" is unremarkable and equally spread around the world, yet it offers no hints as to the kind or severity of the seizures. The neurological condition epilepsy is characterised by aberrant brain activity that results in seizures or episodes of strange behaviour, sensations, and occasionally loss of consciousness.

Epilepsy can strike any person. Men and women of different ages, races, and cultural ba ckgrounds can develop epilepsy. Recurrent seiz ures are a common symptom of epilepsy, which is characterised by an imbalance in the electric al rhythms of the brain. In individuals with seizu res, abrupt and synchronised electrical energy b ursts that may momentarily alter their awarene ss, movement-
s, or sensations disturb the regular electrical pat tern by Selvakumari et al (2019).

Around 49 million people worldwide suffer with epilepsy, a chronic, non-communicable brain disorder. Recurrent seizures are its defining feature. Seizures are brief bursts of spontaneous movement that might affect either a portion of the body (partial) or the entire body (generalised), and they can occasionally be followed by loss of consciousness and control over bowel or bladder function. Unwarranted Electrical discharges' in a cluster of Brain Cells cause seizure episodes. Such discharges can occur in various areas of the brain. The smallest muscular jerks or attention lapses can be seizures, as well as severe convulsions that last for a long time. The frequency of seizures can also vary, from fewer than one per year to several per day. Not all seizures indicate epilepsy.Two or more unprovoked seizures are considered to be an epileptic seizure. Written accounts of epilepsy date as far back as 4000 BCE, making it uniqueoldest documented medical diseases in the World. Epilepsy has been shrouded in fear, misinformation, prejudice, and social shame for millennia. The quality of life for those who have the condition and their family may be negatively impacted by this stigma, which persists in many nations today by Chen S et al (2019)

a. Signs and symptoms-

Seizures can have a variety of characteristics, depending on where in the brain the disruption first appears and how far it develops. Temporary symptoms include loss of awareness or consciousness as well as impairments in movement, mood, or other cognitive processes, as well as changes of sense (including vision, hearing, and taste). Both physical issues (such as fractures and bruising from seizures-related traumas) and psychological issues, such as anxiety and sadness, are more common in people with epilepsy. Similar to this, patients with epilepsy have a risk of dying prematurely that is thrice higher than that of general population, with rural areas and low- and middle-income countries having the highest rates of early mortality.Many of the epilepsy-related causes of death, particularly in lower and middle incomes nations, can be avoided, including falls, drowning, burns, and extended seizures by Shoeb A et al (2010).

b. Rates of disease-

A large amount of the global disease burden is accounted for by epilepsy, which affects about 50 million individuals globally. Between 5 - 10 per 1000 peoples are thought to be affected by active epilepsy at any given moment, defined as having ongoing seizures or needing treatment. Each year, epilepsy affects an estimated 5 million people worldwide. Epilepsy is thought to be diagnosed in near to 50 out of 100,000 peoples annually in higher-income countries. This number can reach 139 per 100 000 in low- and middle-income nations. About 49 million people worldwide suffer from epilepsy, which contributes significantly to the burden of disease. The estimated prevalence of active epilepsy, which is defined as experiencing ongoing seizures or requiring treatment, is between 4 and 10 per 1000 persons.

Worldwide, an estimated 5 millions of peoples suffer with Epilepsy each year. In lower- and middle-incomes countries, this figure can reach 139 per 100 000 byLahmiri S (2018)

c. Causes-

Epilepsy cannot be spread. Though various underlying diseases can cause epilepsy, in roughly 50% of cases around the world the disease's origin is still unknown. The following subcategories of causes of epilepsy exist: structural, genetic, infectious, metabolic, immunological, and unknown. There are now a number of causes that have been proposed. The primary cause is disruption of brain's electrical activity, which may result from a variety of factors, including birth defects, a lack of oxygen during labour, and low blood sugar levels. About 50 million individuals worldwide have epilepsy, with 100 million developing it at least once in their lifetime. It makes up 1% of all diseases in the globe, and its prevalence is estimated to be between 0.5 and 1%. The primary sign of epilepsy is when a patient has several seizures. It results in an abrupt breakdown or atypical brain activity that prompts an uncontrollable change in a patient's behavior, feeling, and faint.Seizures often lasts a few seconds to some minutes, & they can be occur at any moment and without anfeeling. This results in severe injuries like burns, fractures, and occasionally even death by Al Ghayab (2019)

d. Treatment-

Seizures are manageable. With the proper administration of antiseizure medications, up to 71% of patients with epilepsy could go seizure-free. When considering stopping anti-seizure medication, pertinent clinical, social, and personal variables should be taken into account after two years without seizures. The two most reliable indicators of seizure recurrence are a known aetiology for the seizure and an abnormal electroencephalography (EEG) pattern by Lahmiri S, (2018).

e. Seizure type -

Neuro-experts divide seizures into two primary types based on the symptoms, partial and generalised, as shown (figure 1). A partial seizure, known as a "focal seizure," exclusively affects a portion of the cerebral hemisphere. Complex-partial and Simple-partial seizures are the two varieties. In simple-partial, patient retains awareness but struggles to speak clearly. The term "focal impaired awareness seizure" refers to a condition in which a person experiencing a complex-partial becomes disoriented about their surroundings and begins acting erratically, such as chewing and mumbling. On the other hand, generalised seizures swiftly disrupt entire brain networks and cause damage to all brain areas.Although there are many different forms of generalised seizures, they can be broadly categorised into 2 groups: non-convulsive&convulsive by Abualsaud K et al (2015).

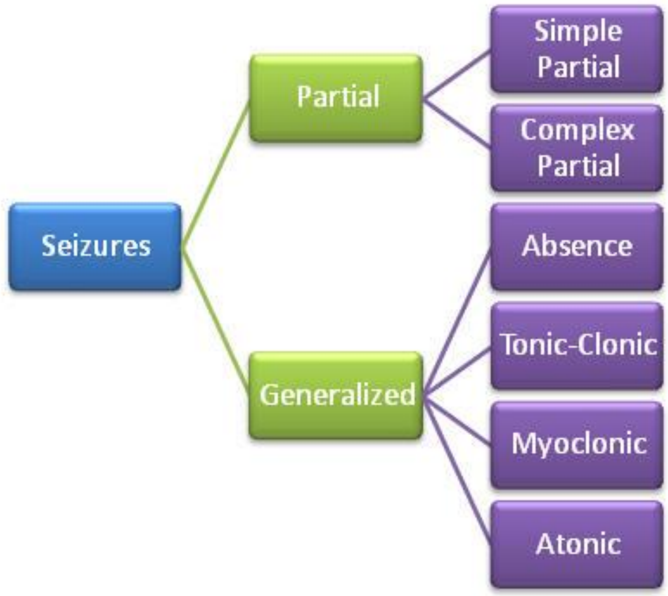

Figure 1. Classification of seizure.

2. LITERATURE SURVEY-

Seizure detection was done using the entropy features' processed dataset. In different study, Chen et al(2019). used a raw EEG dataset and has 8 entropy features, including sample,approximate, fuzzy,spectral, Shannon,permutation, conditional, correction conditional. That processed data then categorised into 3 class values: "inter-ictal,""ictal," & "normal stage," with an accuracy of 99.50%. Selvakumari et al (2019), suggested a technique that made use of the 4 features entropy, variance,energy and RMS. Based on those attributes, detection was carried out with a reported accuracy of 95.63% using SVM and Bayesian classifiers.But they didn't provide the precise percentage of seizure locations, but the technology is also capable of locating the seizure region in the brain.

Song et al (2010)uses ELM and NN to create classification models (BPNN). Their overall statistics demonstrate 95.60% classification accuracy and shorter execution times. Shoeb et al (2010) used SVM with the vector feature to perform seizures' detection on the organised dataset from the CHB-MIT, and they evaluated their accuracy to be 96%.

Doraiet al (2010)projected the idea of Epochs, which entails breaking down the information into shorter time intervals. On these epoch EEG datasets, they also used ensemble of 4 "blackbox" techniques: KNN,LDA, SVM andCVE. With this method, seizures can be predicted 65 seconds in advance.

Before detecting the seizure, Birjandtalab et al. (2016)divided EEG data in2 classesviz seizure and nonseizure, using a Gaussian mixture model (GMM), and achieved 90% accuracy. He brought up the topic of class inequality in their datasets as well.

Amin, Malik et al. (2015) used the DWT method to extract relative energy characteristics, and 4 classifiers—MLP,SVM, KNN, & Nave Bayes—were used for classification. The results reveal that SVM has a 98% accuracy rate, outperforming the other classifiers.

K. Abualsaud et al. (2015) had suggested a system for automatic seizure identification on noisy EEG signal utilising the ensemble of 'black-box' classifiers. However, because all four classifiers were "black boxes," the ensemble approach did not deliver the anticipated level of accuracy.

Lahmiri et al. (2018) used SVM with GHE to categorise "non-seizure"&"seizure" cases and discovered 100% accuracy within a shorter amount of time. The fact that the authors assert good seizure detection accuracy in a short amount of time is a good sign in this case. The number of times the seizure can be identified, however, was not specified by the authors.

Using idea of information Gain Theory, Al Ghayab et al. (2019) were able to extracts and score the significant features from an EEG signals datasets with a 100% accuracy rate.The seizure case classification is performed using the least square-SVM (LS-SVM). Furthermore, the authors were unable to investigate any additional related elements of knowledge discovery because of the "blackbox" nature of applied classifiers.

On managed datasets with good sets of features', including frequency-domain,time-domain, time-frequency domains, & non-linear features, Zabihi.et. al.(2013)used SVM classifier to detect patient-specific seizures. Their model's performance has averaged a sensitivity and specificity of 93.78% and 99.05%, respectively. It is remarkable in this case that they ignore a crucial element—line, length—from literature that is often used in seizures' detection.

Hencecontend that the CHB-MIT datasets is unbalanced because a seizure only lasts a few seconds within an hour or so of recording. A method for anticipating an epileptic seizure in real time has been developed by Teixeira et al (2014). The machine learning classification techniques SVM, radial basis functions neural networks (RBF), and multilayer perception neural networks are used to forecast medical events (MLP).

The seizure detection analysis raise a number of intriguing research queries, such as choosing appropriate statistical features'& machine learning classifier for reduction of computation time due to the dataset's high volume and high dimensions, & the most important piece of absent information from ML classifiers is determining the precise points of seizures at the brain lobes.

3. ROLE OF RESEARCHERS IN EPILEPTIC SEIZUREDETECTION-

For better results, ML is frequently used to biological and health data sets. In particular, ML by Sreenivasulu et al (2022) and data mining researchers and scientists are vigorously involving in suggesting ideas for improved seizure detection. ML has been extensively used to extract sensible and important patterns from a variety of domain datasets. It has a big and prospective impact on how other disciplines, like healthcare, solve their challenges. On brain datasets, machine learning applications for Seizure Detection, Epilepsy Lateralization, discriminating seizure sates, &localisation can be observed. Different ML classifiers, including SVM, ANN, decision trees, decision forests, and random forests, have accomplished this.Undoubtedly, a lot of evaluations on seizure detection have been done in the past along with the classifiers,applied features, and stated accuracy without aiming on the difficulties data scientists confront when working with dataset of neurological illnesses. This article offers thorough analysis of ML applications for detecting epileptic seizures and other associated knowledge finding tasks by Bahubali K Shiragapur (2020).

4. FRAMEWORK (SEIZURE DETECTION) -

Here, we provide a visual representation of the model used to identify seizures in an EEG/ECoG seizure dataset. Data preparation,Data collection, applying ML classifiers, & performance evaluation are the four processes that make up the process.

a. Data collection

The collection of the brain signals dataset is a prerequisite. Various monitoring tools are employed for this. EEG and ECoG are typically the most commonly used devices since their electrodes or channels are glued into place on the scalp in accordance with 10-20 connections to EEG device, delivering timely information about voltage fluctuations as well as temporal and spatial information. The EEG monitoring device places EEG channels on subject's scalp, reads these electrical signals, and shows the raw signals on the screen. Additionally, the analyst has carefully observed these raw signals and divided them into "non-seizure" &"seizure" stages.

b. Data transformations

The conversion of signal data into 2D table format is the critical next step after data gathering. This facilitates analysis and provides crucial information, such as seizure detection. Because it hasn't been processed yet, this data is raw. Therefore, providing pertinent information won't be appropriate. Various feature selection methodologies have been used for the processing. In this step, the dataset is also presented as supervised, which means, it offers potential class-values for the class attribute.

c. Dataset preparation

Data processing is a crucial phase in the transformation of data that allows for the extraction of valuable information from gathered raw dataset. Many feature extraction methods have been applied. These techniques are typically used on the dataset of retrieved EEG signals. The dataset gets more useful after feature extraction processing, which ultimately aids the classifier in retrieving superior knowledge.

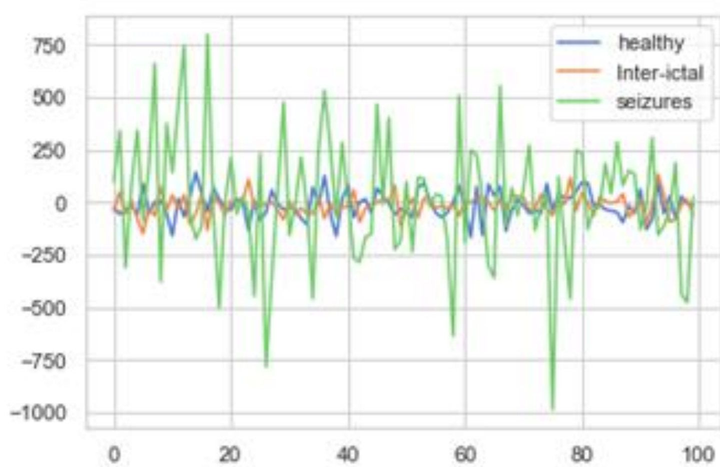

Figure 2. Graphical display (Loaded dataset)

The extraction of useful information from the obtained raw dataset is made possible by the processing of data, which is a vital step in the transformation of data. Numerous features extraction methodsare used as a result. Usually, these techniques are used todataset of recovered EEG signal. Raw dataset expands in terms of numerous statistical measure values. PyEEG is a Python software that solely extracts features from EEG/MEG segments. Because of this, it is unable to import data in various formats or export features to a classifier. This is because according to the modular and compositional principles of building open source software, small programmes with simple interfaces that can function well together are preferred to large monolithic systems.

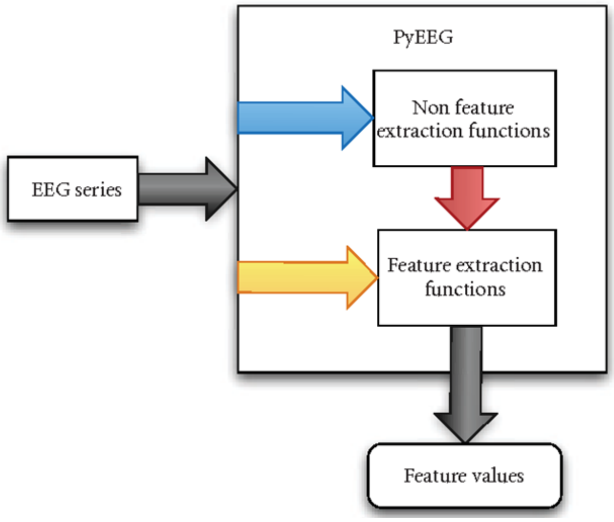

Figure 3. PyEEG Library

There are two sets of functions in PyEEG.

- Preprocessing.
- Feature extraction functions.

5. Applying Machine Learning –

Different unsupervised &supervised MLtechniques have been employed to acquire a high seizure detection rate & discover pertinent knowledge from EEG processed datasets.

i. Classification

Dataset in classification has collection of "nonclass attributes" & "class attribute." These are the main parts, and as they are both strongly associated with prospective classification, their relevant information is crucial. The term "target attribute" refers to the "class attribute" C, which includes multiple classes values, as non-seizure &seizure. The term "non-class attributes" or "predictors" refers to characteristics A = A1,A2.A3,...An. On the processed EEG dataset, common classifiers for seizure identification include SVM, decision tree, and decision forest.

ii. Evaluation of Performance

Accuracy of findings obtained are used to compare various approaches. Tenfold cross-validation is the most widely used training method, where every fold, or one horizontal segment's of the datasets, is utilised as the training datasets and the other 9 segments becomes used as the testing dataset. Performance of classifiers is typically evaluated using metrics of recall,precision, &f-measure in addition to accuracy. Thisis based on 4 possible classification outcomes' —

TN- True-Negative, TP-True-Positive, FN- False- Negative &
(FP+TP) is defined as a ratio of True Positives' to all cases rec

6. DATABASE AVAILABLE-

i. Children Hospital Boston-MIT EEG dataset-

The dataset was created by Children's Hospital Boston at MIT (CHB-MIT) is openly available on physionet server [15]. With the help of the Cygwin utility, which communicates with the physionet server, it is simple to gather. It lists how many EEG recordings of seizures and other brain activity each CHB patient has had. 23 patients make up the dataset; 5 men (3-22 yrs old) and 17 women (1-19 years old). Every patient has several seizure and non-seizure records in the .edf format, which depict the spikes with seizure start & end times and are easily seen via "EDFbrowser" browser.Main dataset are in 1D format and contain EEG signals which are acquired using several channels that are positioned on the surface of brain. These dataset signals were all captured at 256Hz frequency.

ii. Epilepsy CentreECoG Dataset, University of California

Electrocorticogram (ECoG) signal collection from an epileptic patient was made accessible to the public by the Epilepsy Center at University of California (UCSF). This was initially obtained using 12 electrodes (invasive)& non-invasive implantation of 76 electrodes on the scalp (64-electrodes). There are 16 files total in it. Eight of these files (F1 to F8) are categorised as "pre-ictal," which refers to the period just prior to the seizure. The remaining files provide data from the "ictal" stage. The overall sampling time is 10 seconds, and the frequency used to sample the data is 400 Hz (or 400 cycles per second).As result, totally has (400cycles/s × 10 s) 4000cycles in everyfile.

iii. The Freiburg—EEG dataset

The dataset collected from hostile EEG recordings of Twenty one patients with medically intractable focal epilepsy (8 males and 13 females, ages 10 to 50). It was captured during an intrusive presurgical epilepsy monitoring procedure at the Freiburg University Hospital's Epilepsy Center in Germany. Out of Twenty patients, thirteen patients had 24hrs of recordings, and 8 had lesser than 24hrs. Together, these interictal recordings capture 88 seizures.

iv. Bonn University—EEG dataset

Said dataset is divided into 5 subsets, each of which is designated by the letters (A–E) and contains 100 single-channel recordings with a duration of 23.6sec that were recorded using the worldwide 10–20 electrode placement technique. With the same 128-channel amplifier system channel, all of the signals are recorded.

v. BERN‑BARCELONA—EEG dataset

The said dataset included 3750 bivariate focal & 3750 bivariate non-focal EEG files from five individuals with pharmacoresistant temporal lobe epilepsy. Following surgery, two patients experienced just auras and no other seizures, leaving three patients seizure-free. An intracranial strip and depth electrodes were used to record multichannel EEG data. The electrodes were implanted using the 10-to-20 placement. Depending on whether or not EEG signals were collected with more than 64 channels, they were either sampled at 512 Hz or 1024 Hz. They were able to identify the regions of each patient's brain where their seizures began based on the intracranial EEG recordings. For the aim of seizure localisation, this dataset is suitable.

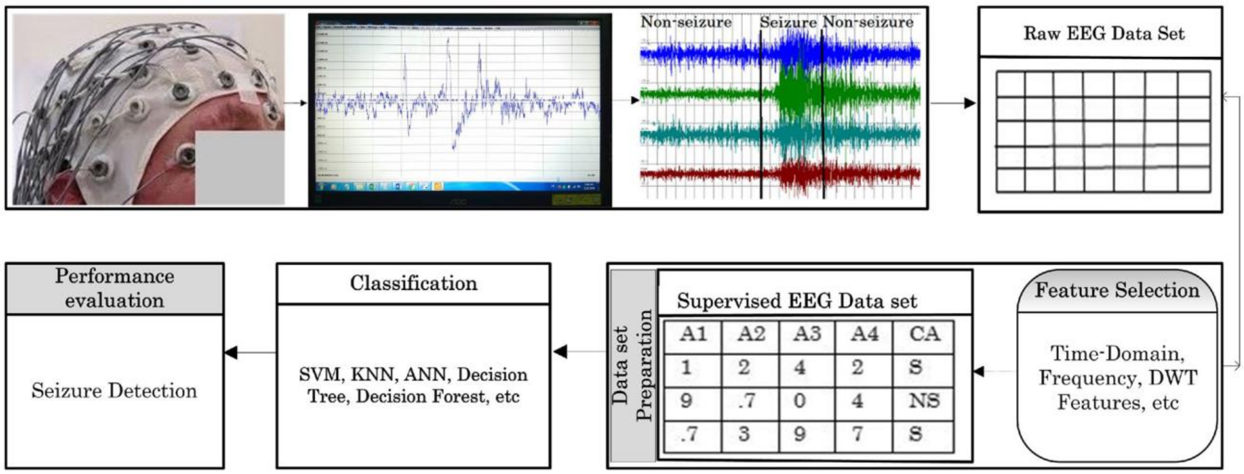

Figure 4. Basic Model (Epileptic Detection).

7. FEATURE EXTRACTION-

Numerous statistical techniques, including LPC, kurtosis, mean, auto-correlation, and PCA, are taken into consideration. These attributes are taken into account when training the network for additional classification.

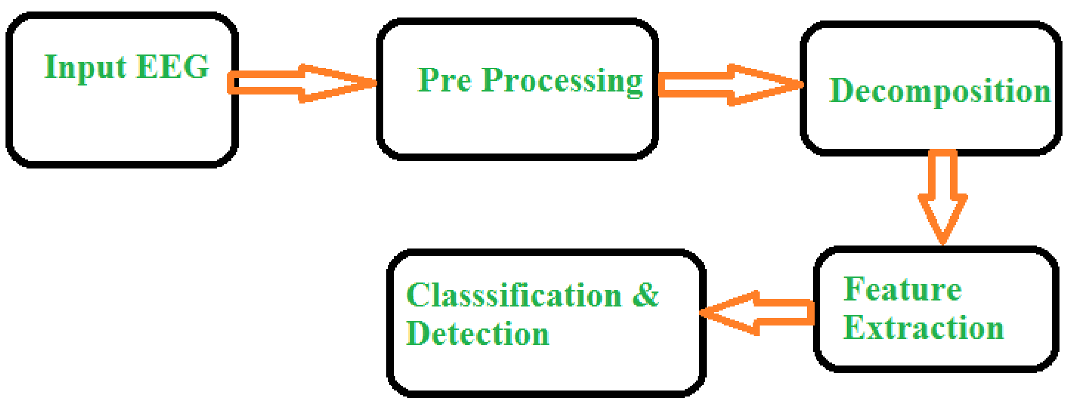

Figure 5. Schematics of proposed system.

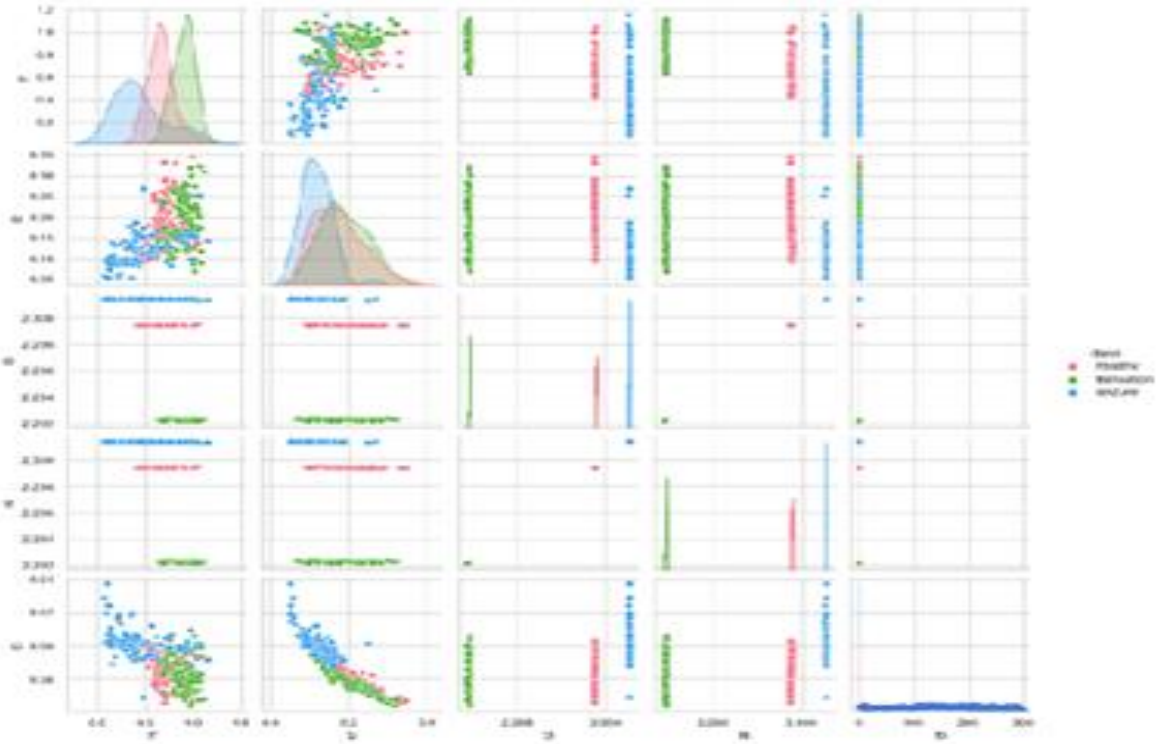

Figure 6. Graphical display of extracted features

8. CLASSIFICATION

A fresh observation is classified; this is done using training data that have known category membership as the basis for classification. There are numerous techniques used for classification, including neural networks such back-propagation, LVQ, SOM, feed-forward, normalised correlation, K-nearest neighbour (KNN), Hamming distance, SVM, and weighted Euclidean distance.

SVM, is one of the most used supervised training approaches, and it is used to address problems with classification & regression. However, it is primarily applied to Machine Learning Classification issues. The extreme vectors and points that help create the hyperplane are chosen via SVM. The SVM approach is based on support vectors, which are utilised to represent these extreme situations.

In SVM, a decision boundary called a hyperplane is used to divide two different groups. Popular Kernel operations include:

1. Polynomial;
2. Linear;
3. Gaussian/RBF;

$$K(x,y) = (x \times y + 1)^d$$
$$K(x,y) = x \times y$$
$$K(x,y) = exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right)$$

9. SEIZURE LOCALIZATION/ PREDICTION-

After a seizure has been successfully identified, localisation is a crucial step in epileptic surgery. Surgery can usually stop isolated seizures that come from either the right or left side of Brain. Seizure monitoring tools, likeECoG& EEG, are quite useful in locating the seizure. For EEG, the electrodes/channels are implanted both invasively and non-invasively (for ECoG). Their positioning, which aids in pinpointing the seizure area, is based on the 10/20 (10-20) International standard. Seizure localization refers to the process of locating the area of the brain that is being affected by a seizure. Anti-epileptic medicines (AED) can treat some forms of seizures, such as "tonic-clonic," although patients with partial seizures may occasionally need surgery.

Locating seizure location is a crucial and difficult challenge for neurologists & neurosurgeons to handle this issue. Finding the point/region/location/focal area where a seizure is starting is the surgical aim. A seizure's location can be determined using the 10-20 positioning technique. To locate a seizure, computational & ML methods have recently been used. Figure 8 displays a number of medical event timelines, including the "interictal" time period where no seizures occur. Preictal will sound the alert at the time indicated by the Seizure Prediction Horizon (SPH). Following the SPH is the Seizure Occurrence Period (SOP). At SOP, the seizure is anticipated to happen.In the postictal phase following the seizure period, no seizures are seen. The cumulative time delay between SPH and SOP should be greater than 5 minutes as a general rule to prevent a dangerous situation. The major goal is to use wearable technology to identify and detect SOP on the patient's side. Additionally, IoT is used to process this data remotely. The block diagram displays a comprehensive wireless Smart Web of Things (SWOT) architecture for a user-end prototype that can monitor epileptic seizure activity. Through currently used smartphone devices, the user end observatory device will be connected to the clinical side. The block diagram for epileptic seizure detection & prediction utilising signal transform and statistical techniques is shown in Figure 5.Furthermore, these smart medical devices are necessary in today's world since they enable remote health status monitoring and patient location tracking. The generated warning events can also be communicated to family members and clinical observers for preventive action.

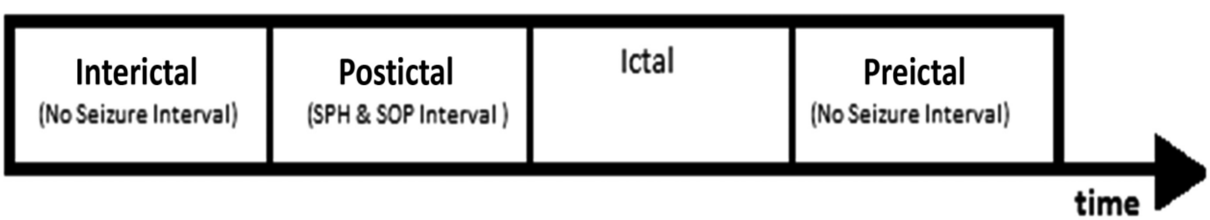

Figure 7. Seizure event / time activity.

10. RESULTS-

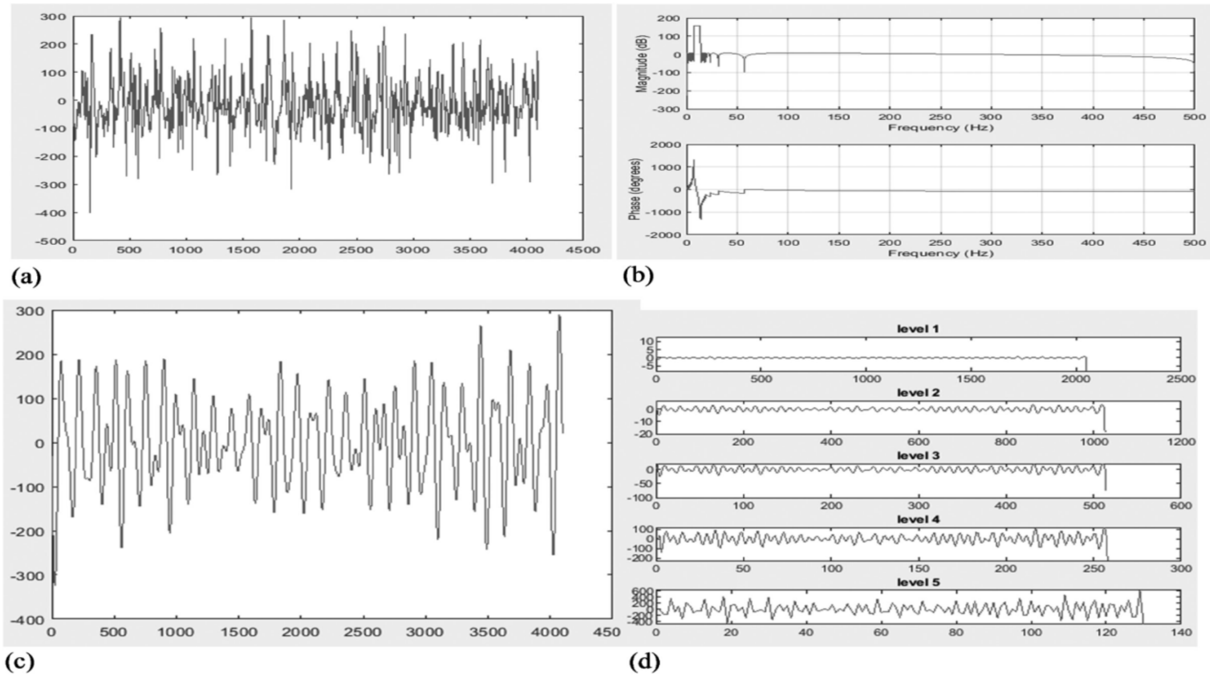

Figure 8- Qualitative analysis of proposed system on normal EEG signal: (a) input normal EEG signal, (b) magnitude and phase plot of the filter, (c) filtered signal, (d) wavelet decomposition level 5.

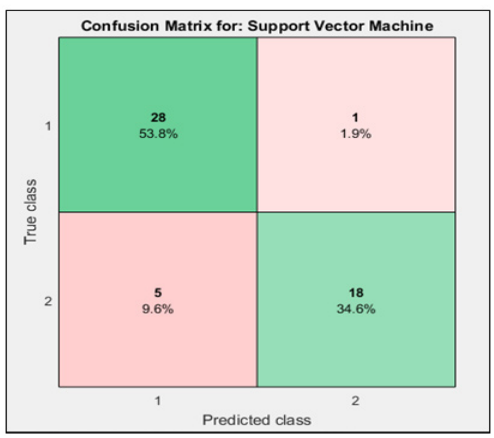

Figure 9. Confusion matrix.

The SVM makes the following prediction:-

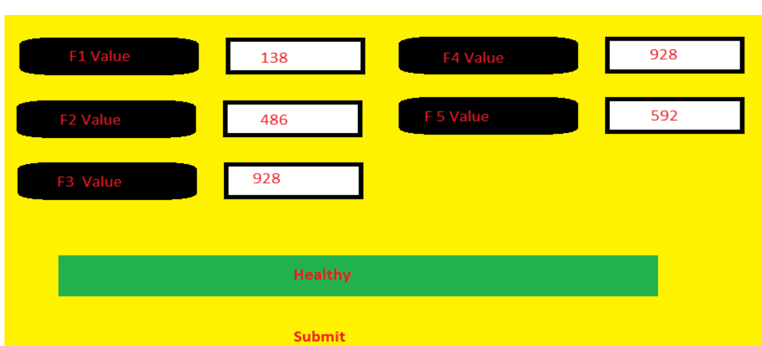

Figure 10. Patient's data recognize as 'Healthy'

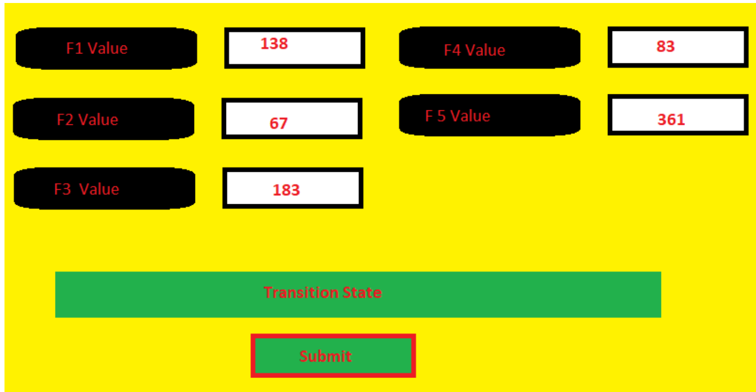

Figure 11. Patient data recognize as in 'Transition State'

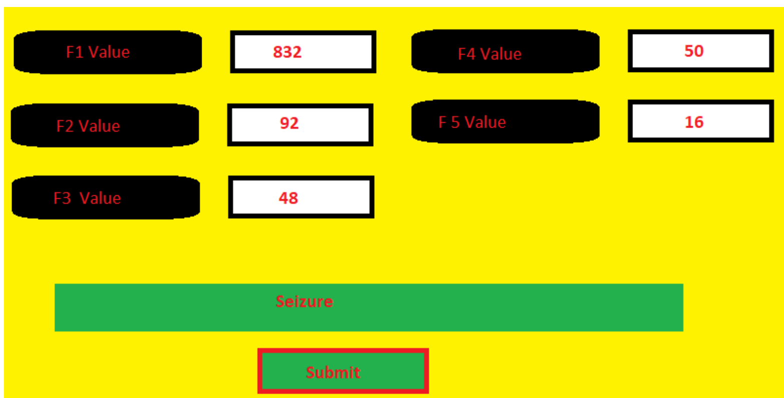

Figure 12. Patient detected as having 'Epileptic Seizure'

11. CONCLUSION-

In thisarticle, machine learning is used to detect epilepsy. The dataset is trained using the SVM algorithm, and accuracy of 81.66% is attained. The Jetson Nano provides the recognition speed for real-time implementation. All of the dependencies needed to implement SVM are supported by Jetson Nano. When used with the Jetson Nano, accuracy and performance are improved. The technology for automatically classifying the epileptic and normal EEG signals has been put into place. From online sources, EEG signals of healthy and also epileptic patients were gathered. The Chebyshev filter was used to preprocess the EEG signals. Several features, including LPC, kurtosis, mean, auto-correlation, and PCA, are retrieved from the filtered signal.These features are fed into a SVM as input. SVM makes the final determination of whether seizures are present in an EEG signal or not. The occurrence of a seizure event is predicted using a further filtered signal. The Web of Things can be used to scale up the application.

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