Detection of EEG Spikes Using Machine Learning Classifier

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ABSTRACT

Epilepsy is a common brain disorder. Approximately 1% of global population suffers from this disease. Epilepsy is characterized by a transient disorder of the neuronal system and its unpredictable nature. Epileptic seizures falls under two categories: partial and generalized, the difference lies in the occurrence region of the brain. Seizures can occur for all races, ages, but they are more common in younger and older demographics. Epileptic seizures not only harm the sensory, motor, and functional aspects of the body, but they also affect the consciousness, memory, and cognitive activities of epileptic patients. Therefore, it is of great practical significance to develop an effective prediction and detection approach for epileptic seizures to save the life of the people. EEG is painless and convenient; it is the most popular detection approach for epilepsy diagnosis. The detection of epileptic seizures involves the manual scanning of EEG signals, which is error-prone and time-consuming. Hence, it is urgent to develop effective and reliable techniques for seizure detection via EEG signals. Selection of feature is an important step in developing reliable models. Therefore, understanding signals' statistical properties is very important as data recording or using the different datasets setting the paramteres in each case is different. Several classifiers have been tested and evaluated for EEG epileptic seizure detection to discriminate between seizure and non-seizure states. SVM classifier is the most common technique; the evaluations indicated that our model achieved the more effective classification than some previously studied methods. Hence, it can be said as computer-assisted clinical diagnosis of seizures bears a potential, which not only relieves the suffering of patient with epilepsy to improve quality of life, but also helps the neurologists, clinicians to reduce their workload and help them to make decisions more quickly, accurately, and effectively. Both traditional feature extraction techniques statistical and machine learning classifiers are considered for study and successfully classified the data as spike or non spike with higher efficiency. Conventional feature extraction techniques commonly used are statistical parameters as mean, median, mode average etc. time domain features. EEG is a signal acquisition tool from cerebral electric discharges. In this paper, we have used Support Vector Machines (SVM) for classification of spike signals morphology. The SVM is a supervised classification method using kernel functions. It could help in improvement of diagnosis of Epilepsy.

Key words: **Electroencephalogram, Support Vector Machine, Epileptic seizure, Machine Learning, Spikes**

1. INTRODUCTION

Human brain processes and coordinates the information of huge activities of the body. Electroencephalogram (EEG) is the recording of electrical activity of the brain by attaching some electrodes on the scalp that records the potential difference between the electrodes which is called electroencephalography[1]. It is painless and harmless as it does not pass any electricity into the brain or our body [2].

Spikes are transient signals that range from 20 milliseconds to 70 milliseconds and having amplitudes greater than 100[3].

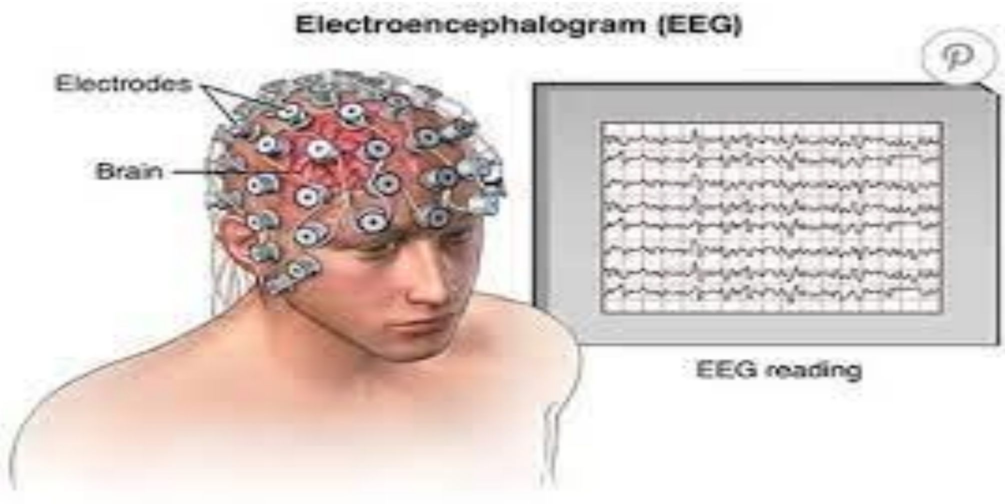

Fig. 1. Electroencephalogram is the recording of electrical activity of the brain from scalp. (Adapted from German Neuroscience Centre: Electroencephalogram) [4].

Epileptic seizures falls under two categories: partial and generalized, the difference lies in the occurrence region of the brain. Seizures can occur for all races, ages, but they are more common in younger and older demographics. Epileptic seizures not only harm the sensory, motor, and functional aspects of the body, but they also affect the consciousness, memory, and cognitive activities of epileptic patients.

EEG is a useful medical tool as it has the ability to record both normal and abnormal electrical activity of the brain. The EEG signals are classified in five different frequency bands as shown in Table 1.

Table 1. EEG frequency bands [2]

Frequency band	Frequency	Brain states
Gamma (γ)	>35 Hz	Concentration
Beta (ß)	12-35 Hz	Anxiety dominant, active, external attention, relaxed
Alpha(α)	8-12 Hz	Very relaxed, passive attention
Theta(θ)	4-8 Hz	Deeply relaxed, inward focused
Delta(δ)	0.5-4 Hz	Sleep

Generalised seizures occur when the whole brain is affected by abnormal electrical activity. The young person becomes unconscious, if sometimes only briefly. Partial or Focal seizures occur when one area (or lobe) of the brain is affected by abnormal electrical activity. The symptoms and level of consciousness depend on the area of the brain involved.

2. LITERATURE REVIEW

A variety of techniques were developed for epileptic seizure detection using EEG signals in previous research. The basic two steps involved in seizure detection using the various proposed methods are feature extraction and classification techniques. Extracting important features from EEG signals is very crucial step to improving classification performance. Relevant features can be extracted from different domains, including the time domain, frequency domain, and/or time-frequency domain.

There are several methods that extract time domain features for epileptic seizure detection including radial basis function neural networks based on principal component analysis (PCA) [6]. [7] extracted time domain features using amplitude and phase coupling measures based on three different coupling approaches. [6] presented a PCA-based neural network to detect epileptic seizures. [8] used fractional linear prediction to discriminate non-seizure and seizure EEG signals. In frequency domain analysis, the main methods include fast Fourier transform[9], higher-order spectra [10] , power spectral analysis [11] , eigenvectors [12], [9] extracted the relevant features from raw EEG signals using fast Fourier transform, and built a hybrid system to detect epileptic seizures. [10] made a comparative study of the feature extraction from the power spectrum and the higher-order spectra, and the experimental results showed that the selected higher-order spectra features outperformed the power spectrum. 13] extracted continuous wavelet transforms (CWT) and bi-spectrum features, and built a number of classifiers to perform both two-way and three-way classifications. [10] evaluated an EEG spectrum from 4 to 24 Hz with univariate comparisons and multivariate comparisons, and the experimental results demonstrated that EEG spectral analysis could be used to demonstrate awareness in patients with severe brain injury. [12] extracted features using eigenvector methods, and the experimental results demonstrated that the features obtained by the eigenvector methods could adequately represent EEG signals.

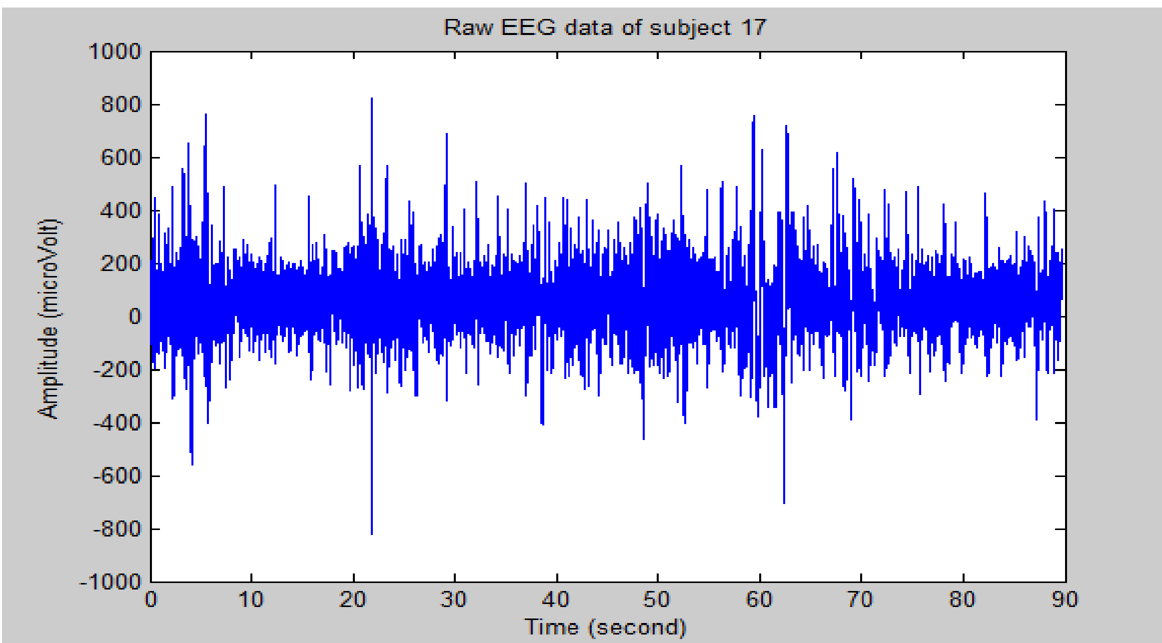

Figure 2. Raw EEG data of a subject in time domain [5].

In the time-frequency domain, the main methods include wavelet transform [14], wavelet packet decomposition[15];[16], multi-wavelet transform[17], Stockwell transform[18], empirical mode decomposition (EMD) [19], and so on. [14] used empirical wavelet transform to divide raw EEG signals into rhythms and extract relevant features. [16] transformed EEG signals into sub-signals using wavelet packet decomposition, and wavelet packet coefficients were then fed into the autoregressive model to compute autoregressive coefficients, which were used as extracted features. Peker et al., (2015)19 extracted relevant EEG features using a dual-tree complex wavelet transform at various levels of granularity to obtain size reduction. [17] used multi-wavelet transforms and extracted features to identify seizures in EEG signals. [18] transformed raw EEG signals into the time-frequency domain using Stockwell transform, and the amplitudes of Stockwell transform in five sub-bands were extracted to construct feature vectors. [20] employed EMD to decompose raw EEG signals, and the second-order difference plot of the decomposed components was utilized as a feature for seizure detection.

Apart from the time-frequency domain analysis, several approaches based on non-linear features were applied to EEG signals after decomposition. [21] assessed the diagnostic performance of Lyapunov exponents in EEG signals. [22] applied recurrence quantification analysis to raw EEG signals and sub-bands for epileptic seizure detection. [23] combined correlation dimension with standard deviation and the largest Lyapunov exponent for epileptic seizure detection.

Table 2 Summary of conventional feature extraction techniques and machine learning classifiers used [33].

Author	Year	Features	Classifier	Performance (%)
O. Faust et al.	2010	PSD	RBF SVM	Acc = 98.33
Oweis	2011	EMD + MEMD	Euclidean Clustering	Acc = 94.00
Marcus and Dragan	2012	Bilinear TFD	SVM/	Acc = 99.30
Arslan et al.	2013	SVD	SVM	Acc = 99.00
Gajic et al.	2014	Wavelet	Quadratic Classifier	Acc = 98.50
Jaiswal et al.	2015	EMD, Wavelet, Morphological filters	Fuzzy Clustering	PI = 98.03, QV = 23.82
Rajaguru et al.	2015	Morphological filters	ANN	Acc = 98.33
Li et al.	2016	DD-DWT	LS-SVM	Acc = 99.36
Sharma and Pachori	2017	TQWT	LS-SVM + FD	Acc = 100
Sharma et al.	2018	MMSFL-OWFB-based KE	SVM	Acc = 100
Wani et al.	2018	DWT	ANN	Acc = 95.00
Naser et al.	2019	DWT and approximation and abe entropies	SVM	Acc = 98.75
Lamhiri and Shmuel	2019	Hurst exponent	k-ANN	Acc = 100
Osman and Alzahrani	2019	SOM	RBFNN	Acc = 97.47
Mahjoub et al.	2020	TQWT, IMFs, MEMD	SVM	Acc = 98.78
Raluca et al.	2020	DWT	ANN	Acc = 91.10
Ozlem et al.	2020	Ensemble EMD	KNN	Acc = 97.00
Khaled	2020	NA	Random Forest	Acc = 97.08

Regarding classification, the detection results or output is decided by the performance of the selected classifiers. In previous studies, the most frequently used classifiers included decision trees [24] , random forests [25] , artificial neural networks [26], support vector machines (Jaiswal and Banka,2017)27, extreme learning machines [16], ensembles of gradient-boosted decision trees [28] convolutional neural networks [29] long short-term memory networks [30], etc. Among these classifiers, artificial neural networks are frequently used due to their good adaptability, generalization capability, and easy implementation [31] Deep learning-based approaches were also applied to EEG signal classification in recent years [29;32]. In automated epilepsy detection systems, generally Machine learning algorithms are used (Table 2).

Epilepsy is a unpredictable neurological disease that is accompanied by disturbed movements of the body, loss of consciousness, and also loss of muscle control [34]. In most of the cases for epileptic patients, seizures are controlled by giving anticonvulsant therapy. But for about 25% of epileptic cases, no treatment is available +yet. Hence, a reliable and effective prediction method to predict the onset of seizures is very important as it could improve the life of epileptic patients who are constantly under pressure of the random seizure occurrences. Hence the present work was undertaken with following objectives.

- Recording & evaluation of drug induced EEG spikes and transient waves.
- Analysis and identification of features for classification of EEG spikes.

Epileptic seizures not only harm the sensory, motor, and functional aspects of the body, but they also affect the consciousness, memory, and cognitive activities of epileptic patients.

A block diagram of the key stages of this research is shown in Figure3. The methodology followed a traditional machine learning approach: (1) data were collected and labeled; (2) the data were appropriately preprocessed; (3) features were selected and extracted; (4) a classifier was trained; and (5) the performance of the system is evaluated.

2.1 Epileptic Seizure Detection System

This section provides a general overview of an epileptic seizure detection system. A typical system consists of the following stages, as shown in Figure 3:

1. Data acquisition,
2. preprocessing,
3. Feature extraction,
4. Classification
5. Performance analysis and evaluation.

Fig. 3: Block diagram of an epileptic seizure detection system

3. MATERIALS & METHODS

- ***Subject***: Young White Rats are considered for the study, (Permission from Ethical committee was taken earlier).
- ***Development of EEG spikes and Transients***: (By intracranial injection of Penicillin), Stainless steel screw electrodes were attached on to the scalp and signals were recorded.
- ***Recording of brain signals***: The brain signals was digitally acquired with the help of "Biopac student lab software" available in the Bio Medical Instrumentation Laboratory.
- ***Feature Extraction*** (both time and frequency domain features) were extracted.(statistical parameters and power spectrum are considered)
- ***Classification***: Support Vector Machine (SVM) is used to classify the given EEG signal as epileptic or non epileptic.

In order to record the signal, 350 gm and 270gm wt.of white rats were used for experimentation, (Permission from Ethical Committee was taken earlier). For this, 1.6 gm/ kg body weight urethane was given as anesthesia which was irreversible. Single dose Penicillin (25 units in 5 µL of saline) was prepared and injected using 1ml insulin disposable syringe, intracranial at depth of 2mm in the cortical region to induce seizure after 15 min of giving anesthesia.

Sampling Frequency was 250 samples/sec.
Bandpass filter was applied (0.5-40Hz).

3.1 Feature Processing

Feature processing refers here to feature selection, transformation, and extraction. The selection and extraction of "good" features, is an important machine learning topic which directly influences the performance of a classification system in terms of its accuracy, The features used in this research were selected after a literature review. However, these features have been reported in successful seizure detection algorithms.

3.2 Feature Extraction

Data processing is a decisive step to extract meaningful information from the collected raw dataset. As such, diferent feature extraction techniques have been used; as shown in Table 3 These methods are generally applied to the extracted EEG signal dataset. After feature extraction processing, the dataset becomes more informative that it ultimately helps the classifer for retrieving better information. Feature extraction techniques commonly include time domain, frequency domain and time–requency analyses, entropy and wavelet analysis etc.[35].

Table 3: Feature extraction methods and features used on EEG signal dataset

Feature Extraction Methods	Relevant Features
Time-Domain Features	Mean, variance, mode, median, max, min, standard deviation
Frequency-Domain Features	Power spectral Density (PSD)

3.3 Time Domain Feature Analysis:

Raw EEG epileptic signals are a function of time. So, features extracted and calculated on these signals are called time domain features.

3.4 Statistical Parameters

Statistical parameters being used are mean, median, mode, standard deviation etc. These are the features calculated to differentiate between normal and a seizure event [36].

Here, X be the sequence used for feature extraction,

X=[x[0],x[1]……x[N−1]]
equ. (1)

Where, N is the length of the sequence.

The most common statistical parameters used in extracting features are as follows:

$$Mean = \frac{1}{n}\sum_1^n x_i$$
(2)

$$Median = \left(\frac{N+1}{2}\right)^{th}$$
(3)

$$SD = \sqrt{\sum_1^n (X_n - Mean)\frac{2}{n-1}}$$
(4)

$$Max = Max[x_n]$$
(5)

$$Min = Min[x_n]$$
(6)

3.5. Frequency Domain Feature Analysis

Signal transformation is actually conducted to describe the details of the frequency of the signal to get some useful information. The power spectral density (PSD) method is used to calculate and analyze the features [37].

3.6 Power Spectrum Density

- The power spectral density (PSD) represents the power distribution of EEG series in the frequency domain and used to evaluate the abnormalities of the brain.
- The power spectral density (PSD) of the signal describes the power present in the signal as a function of frequency, per unit frequency.

- Power spectral density is commonly expressed in watts per hertz (W/Hz).
- The FFT samples the signal energy at discrete frequencies whereas PSD deals with stochastic signals (a random signal).

4. Classification

Applying machine learning classifiers

To achieve a high accuracy of seizure detection rate and explore relevant knowledge from the EEG processed dataset, different supervised and unsupervised machine learning have been used. The following classifiers have been popularly used in seizure detection. SVM, is applied to the processed EEG dataset for seizure detection

4.1 Performance evaluation

The accuracy of the obtained results is used to evaluate performance of different methods. The most popular training approach is tenfold cross-validation, where each fold, i.e., one horizontal segment of the dataset is considered to be the testing dataset and the remaining nine segments are used as the training dataset [38].

Except for the accuracy, the performance of the classifiers is commonly measured by the following metrics as Precision, Recall, and F-measure. These are based on four possible classifcation outcomes—True-Positive (TP), True-Negative (TN), False-Positive (FP), and FalseNegative (FN) as presented in Table 4.

Support Vector Machine (A Machine Learning Classifier)

Support Vector Machine is a machine learning classifier used in biomedical signal processing, suitable for binary classification. It is a discriminative classifier which intakes training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. Here, Margin is actually the perpendicular distance between the closest data points and the hyperplane on both sides. The best optimized line (hyperplane) with maximum margin is termed as Margin Maximal Hyperplane. The closest points where the margin distance is calculated are the support vectors. Kernels are mathematical functions for transforming data using some linear algebra. Different SVM algorithms use different types of kernel functions [39].

Table 4: Classification outcomes

Acronym	Detection type	Real world scenario
TP	True positive	If a person suffers to 'seizure' and also correctly detected as a 'seizure'
TN	True negative	The person is actually normal and the classifer also detected as a 'non-seizure'
FP	False positive	Incorrect detection, when the classifer detects the normal patient as a 'seizure' case
FN	False negative	Incorrect detection, when the classifer detects the person with 'seizure(s)' as a normal person. This is a severe problem in health informatics research

This table describes each parameter metric considering seizure and non-seizure case.

Precision is the ratio of true-positives to the total number of cases that are detected as positive (TP+FP) (Siddiqui et al. 2020). It is the percentage of selected cases that are correct, as shown in Equation. Precision = TP / TP + FP × 100%

High precision means the low false-positive rate. Recall is the ratio of true-positive cases to the cases that are actually positive. Equation 2 shows the percentage of corrected cases that are selected.

Recall = TP/ TP + FN × 100%

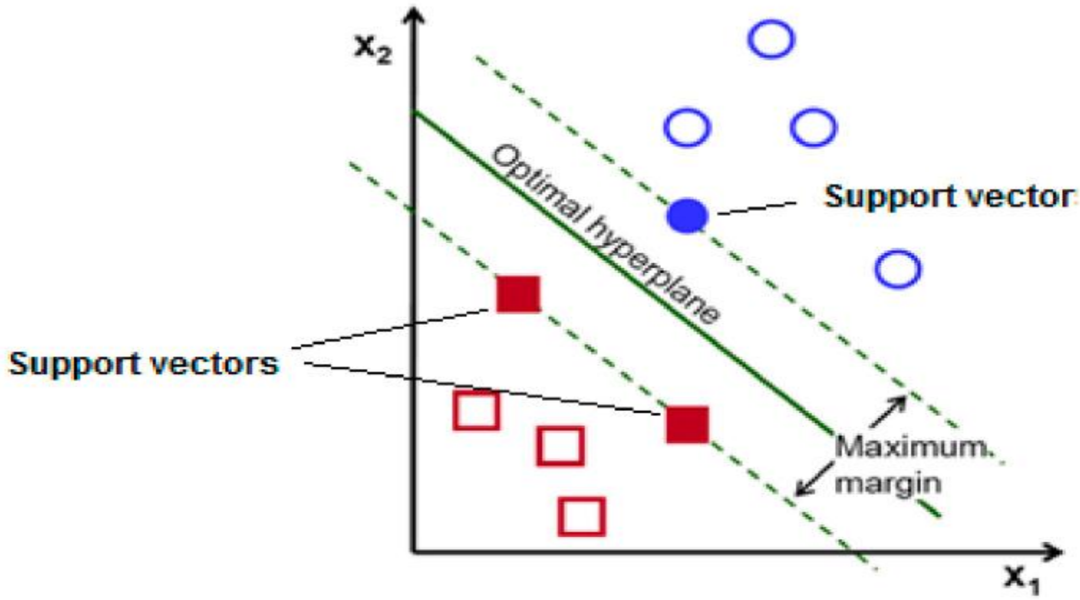

Fig.4 An example of a separable problem in a 2D space [36].

Support Vector Machine (SVM)

- SVM is a useful technique for data classification.
- The SVM is a supervised learning algorithm that uses a kernel trick to transform input data into higher dimensional space, after which it segregates the data via a hyper-plan with maximal margins.
- Due to its ability to manage large datasets, the algorithm is widely used for binary classification problems in machine learning [40].

The optimum hyperlane is found as follows:

$W.x_i + b \geq +1$, if $y_i = +1$

$W.x_i + b \leq +1$, if $y_i = -1$

Where, x_i is the i^{th} input vector ($x \in R^N$), y_i is the class label of the i^{th} input ($y \in \{-1, +1\}$),

w is the weight vector which normal to the hyperplane, and the b is the bias. Optimal hyperlane is found by two margins which parallel to the optimal hyperplane.

Margins are found by

$W.x_i + b \leq \pm 1$

The input vectors that determine the margins are called as support vectors.

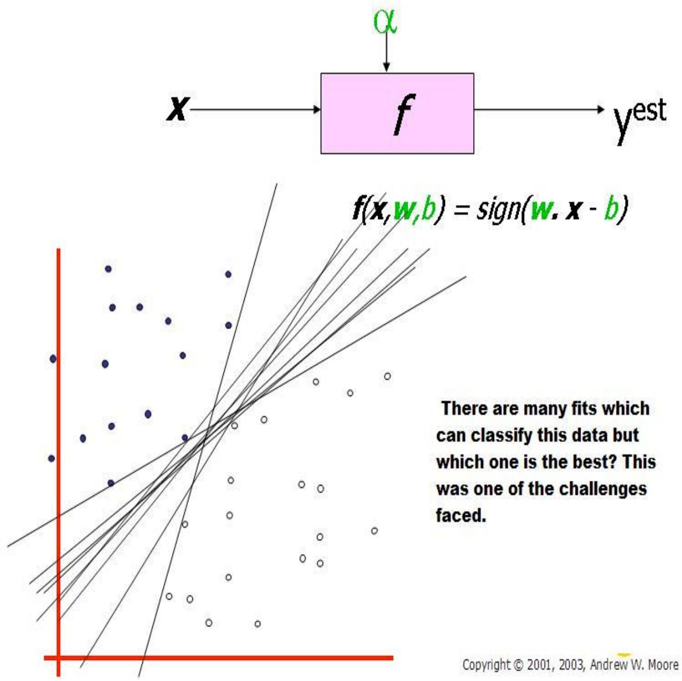

Fig. 5 There are many linear classifiers (hyper planes) that separate the data. However only one of these achieves maximum separation. It gives the maximum margin classifier (Taken from Andrew W. Moore slides 2003).

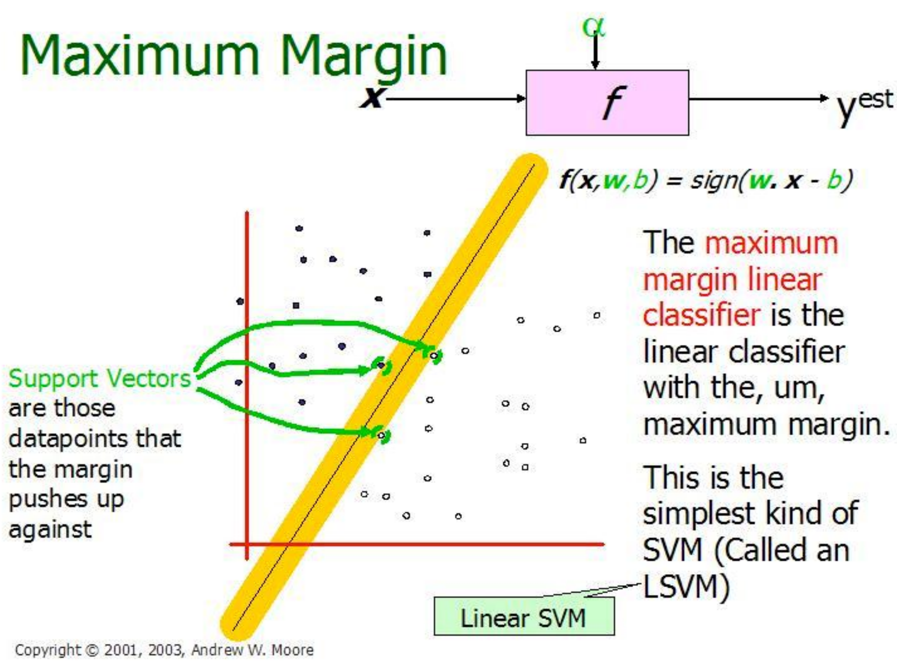

Fig. 6 It gives the maximum margin classifier (Taken from Andrew W. Moore slides 2003)

When a Machine Learning model is built various evaluation metrics are used to check the quality or the performance of a model. For classification models, metrics such as Accuracy, Confusion Matrix, and ROC curve are used. It measures the performance of Machine Learning classification model and looks like a table-like structure. This is how a Confusion Matrix of a binary classification problem looks like:

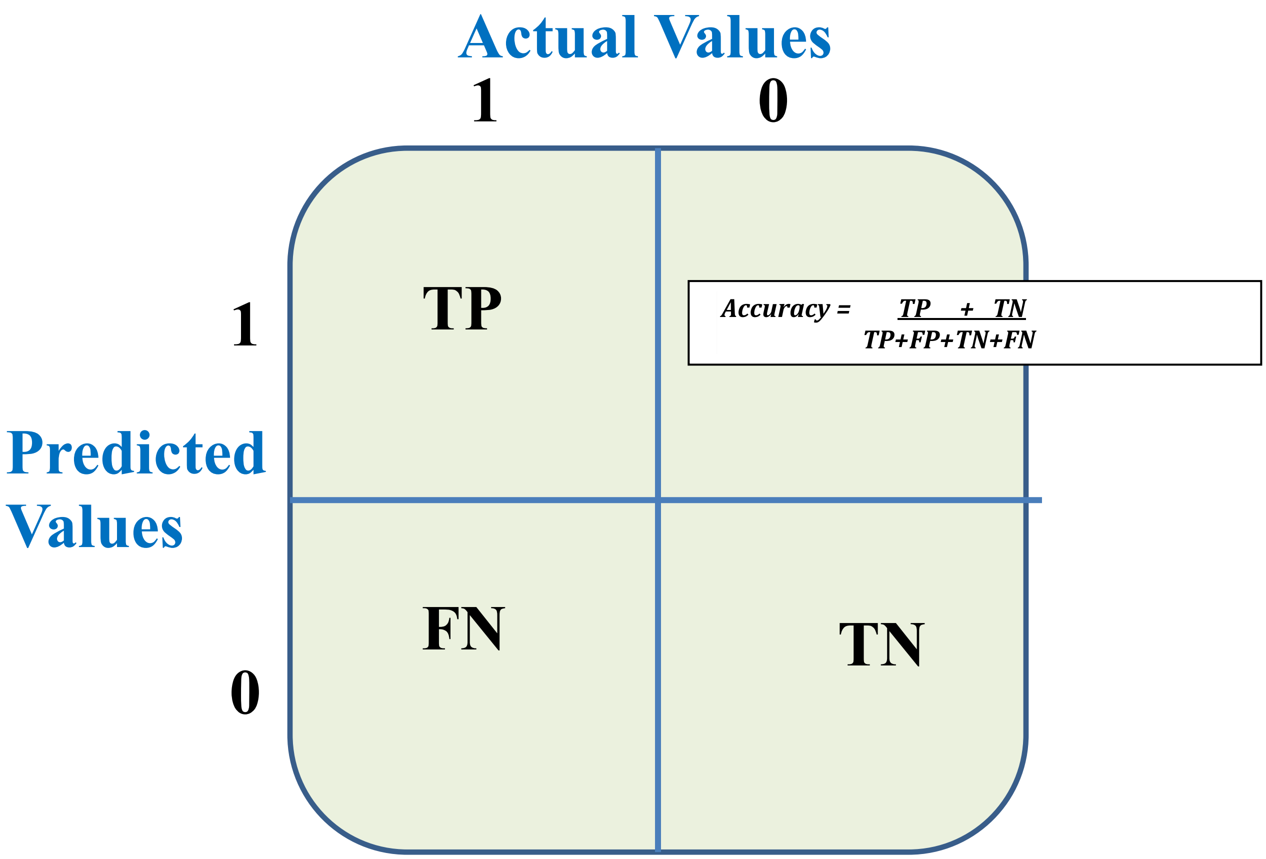

Fig.7 Elements of Confusion Matrix

Elements of Confusion Matrix

- TP: True Positive: The values which were actually positive and were predicted positive.
- FP: False Positive: The values which were actually negative but falsely predicted as positive.
- FN: False Negative: The values which were actually positive but falsely predicted as negative.

Receiver operating characteristic curve (ROC)

- ROC graphs (receiver operating characteristic curve) are useful for organizing classifiers and visualizing their performance.
- Classifiers that give curves closer to the top-left corner indicate a better performance.

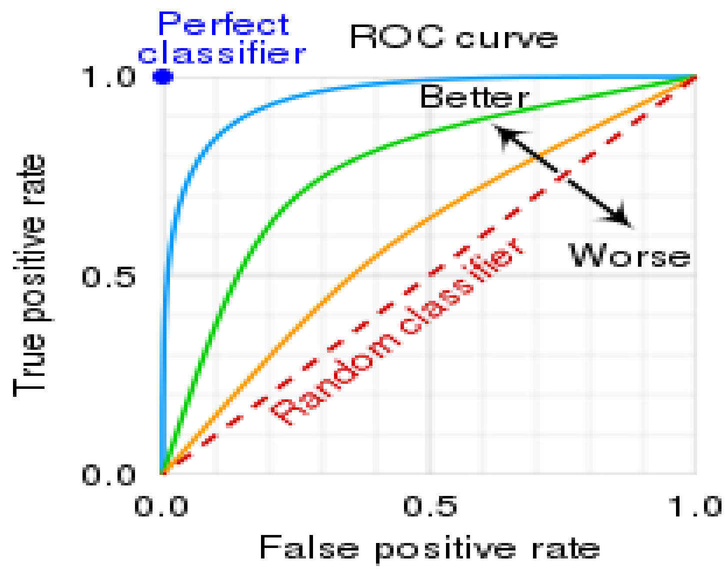

Fig. 8 The ROC space for a "better" and "worse" classifier [41].

5. RESULTS

(Injecting Penicillin 25 units in 5 μL of saline water to anesthetic rats)
Data recorded (0.5 -40Hz), (Sampling Frequency 250/sec)

Fig.9 Intracranial electrode insertion in adult white rats to record the EEG signal

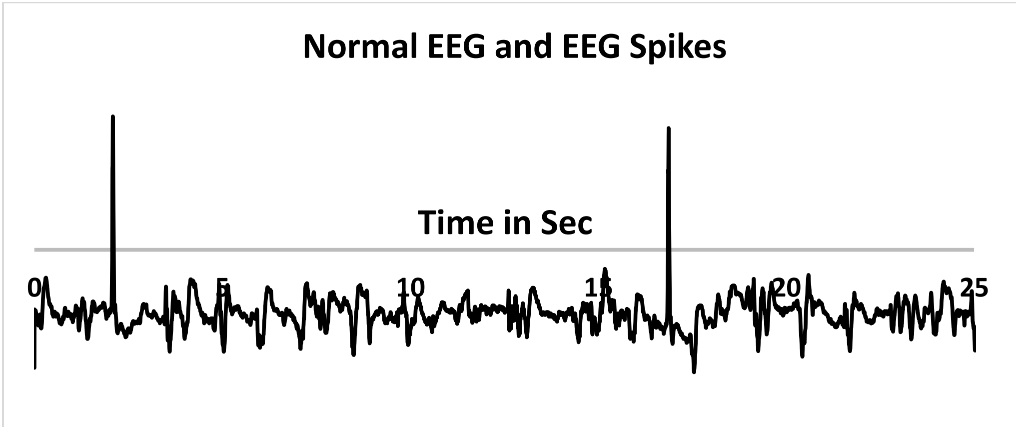

Fig.10: Graph showing Normal vs. EEG Spikes

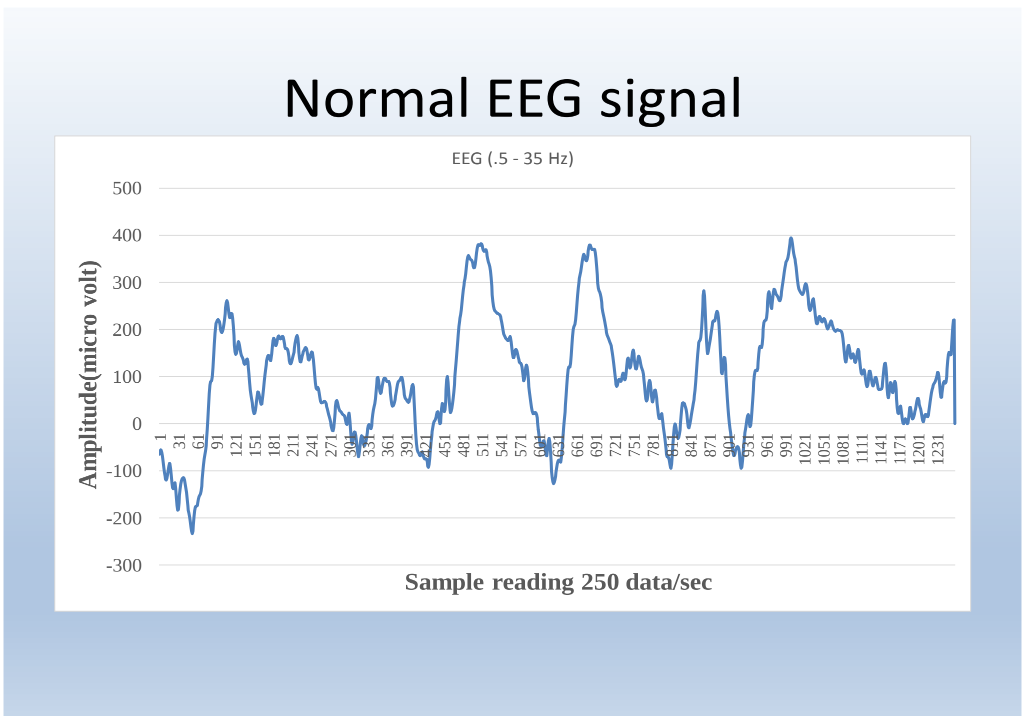

Fig. 11 showing Normal EEG signal, X axis Sample data; Y axis amplitude (µ volt).

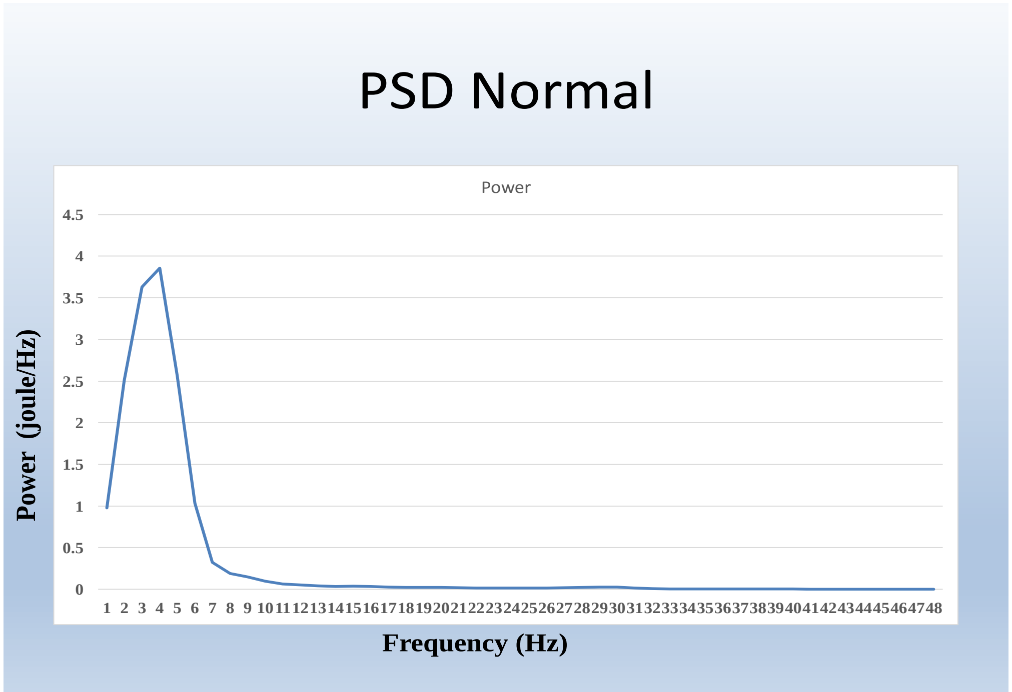

Fig.12. Power Spectral Density (Normal) X axis Frequency (Hz); Y axis Power(Joule/Hz).

For extracting the features of the signal power division at each frequency, the power spectral density (PSD) is calculated and analyzed.

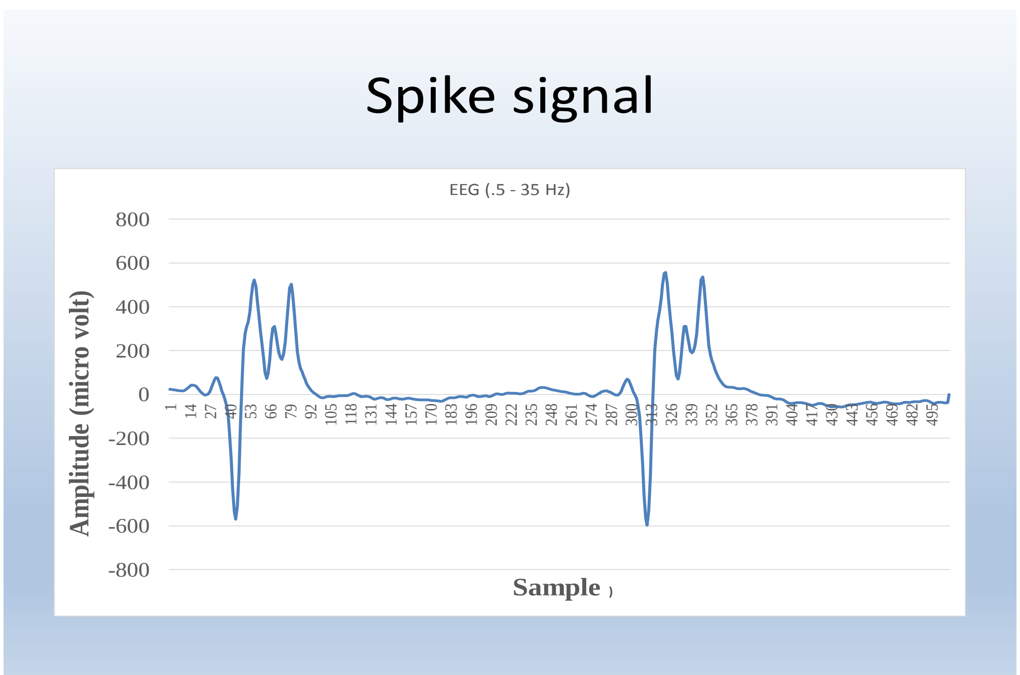

Fig 13. Showing Spike Signals

Spike Signals having amplitudes (µ volt) greater than normal EEG signal. Spike is a transient signals with a short spike on the EEG ranging from 20 milliseconds to 70 milliseconds with amplitudes greater than 100. Studies have shown that spike numbers vary significantly a few minutes before epileptic seizures begin (Slimen et al. 2020).

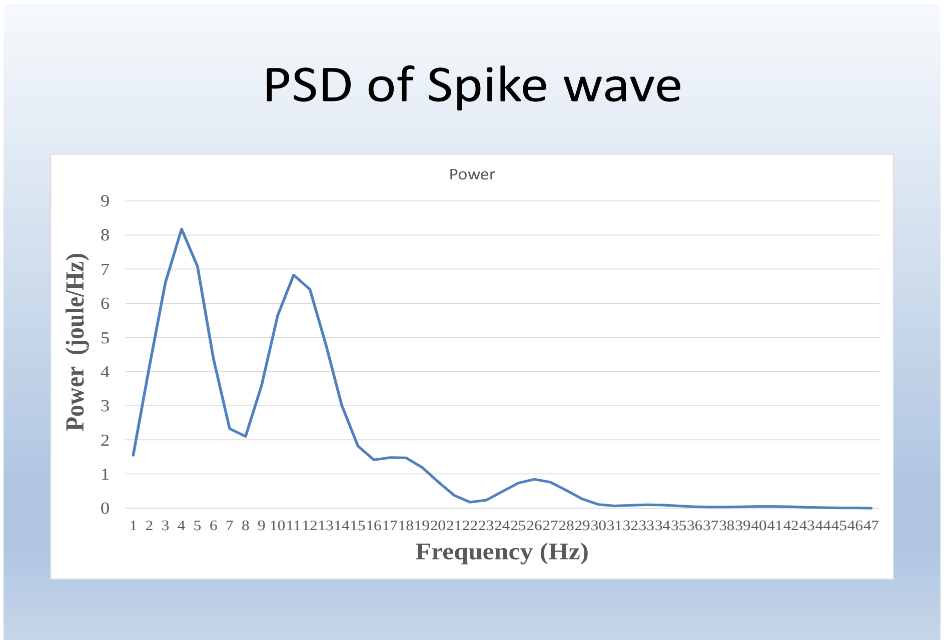

Fig. 14 Showing PSD of Spike Signal

Power spectral density (PSD) analysis is a method for evaluating the distribution of power in a signal over a range of frequencies.

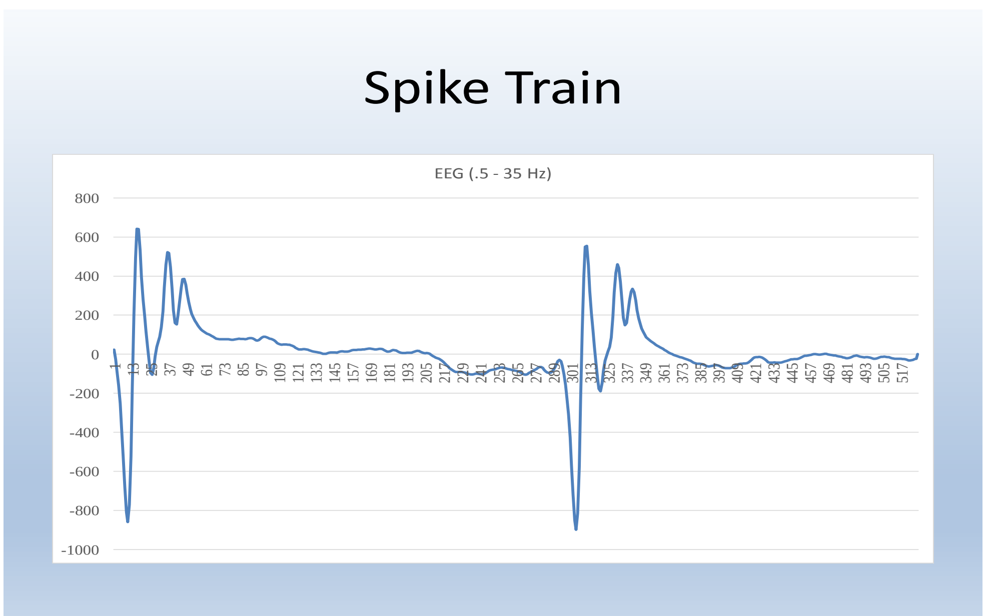

Fig. 15 Showing Spike Train

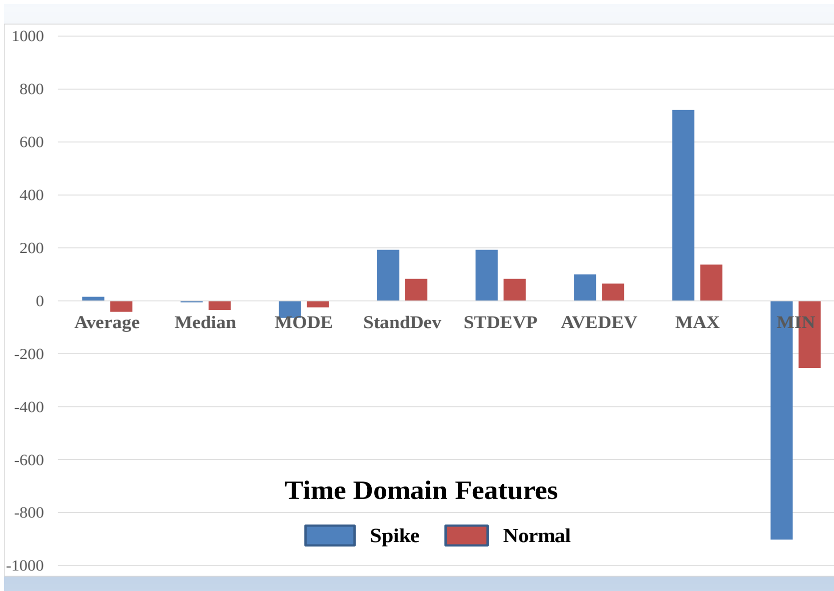

Fig. 16 Showing Statistical Parameters as Time Domain Features

Researchers have been using the statistical parameters such as mean, median and mode, standard deviation etc. to differentiate between non-epileptic and epileptic conditions because the statistical analysis and recording of EEG signal, parameters of EEG signals for various conditions is different. Therefore, these parameters are calculated as features to differentiate between non epileptic and epileptic event.

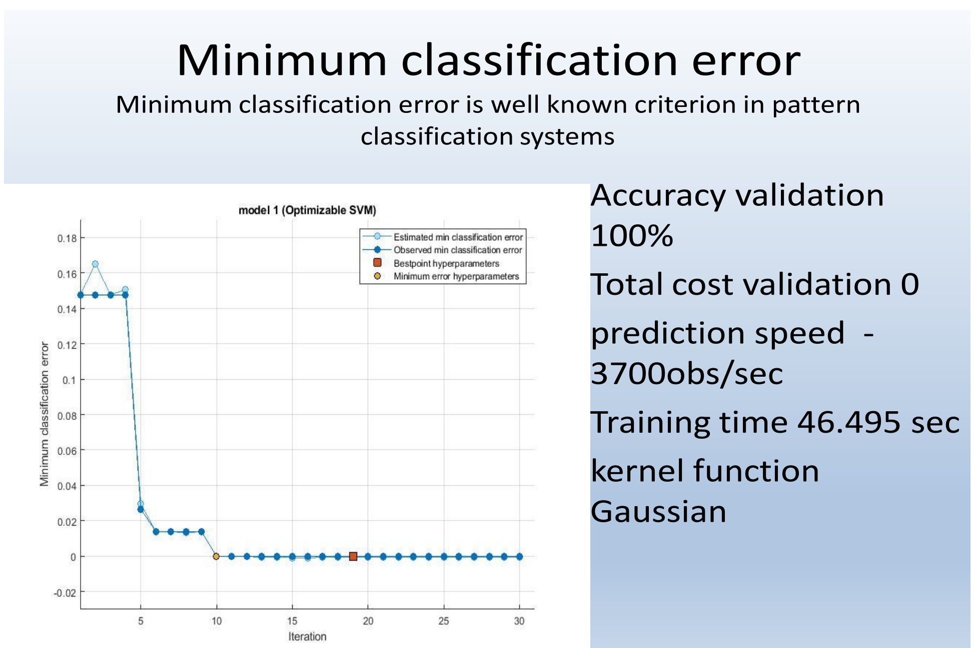

Fig. 17 showing Minimum Classification Error

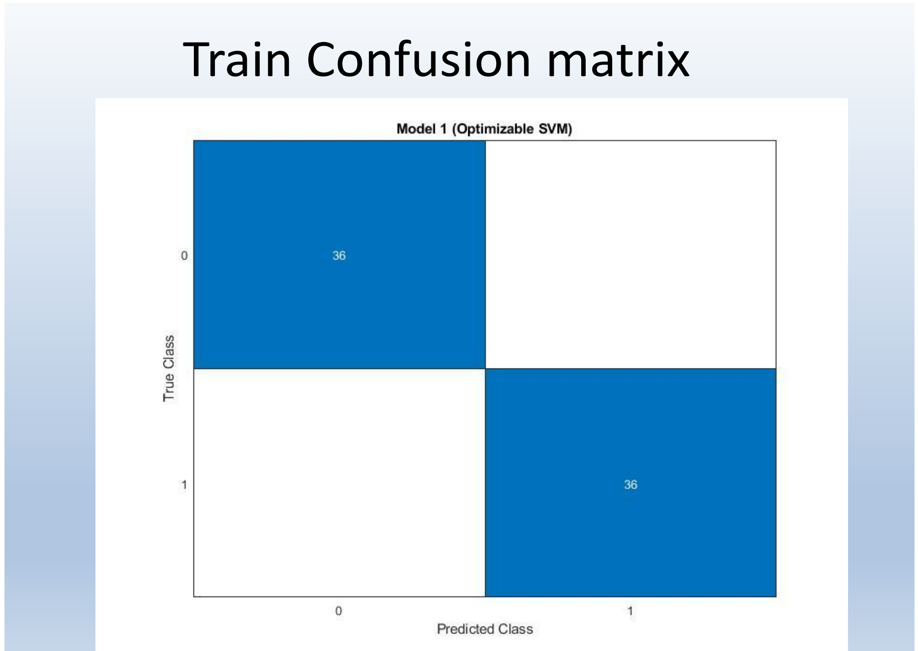

Fig. 18 Showing Train Confusion Matrix

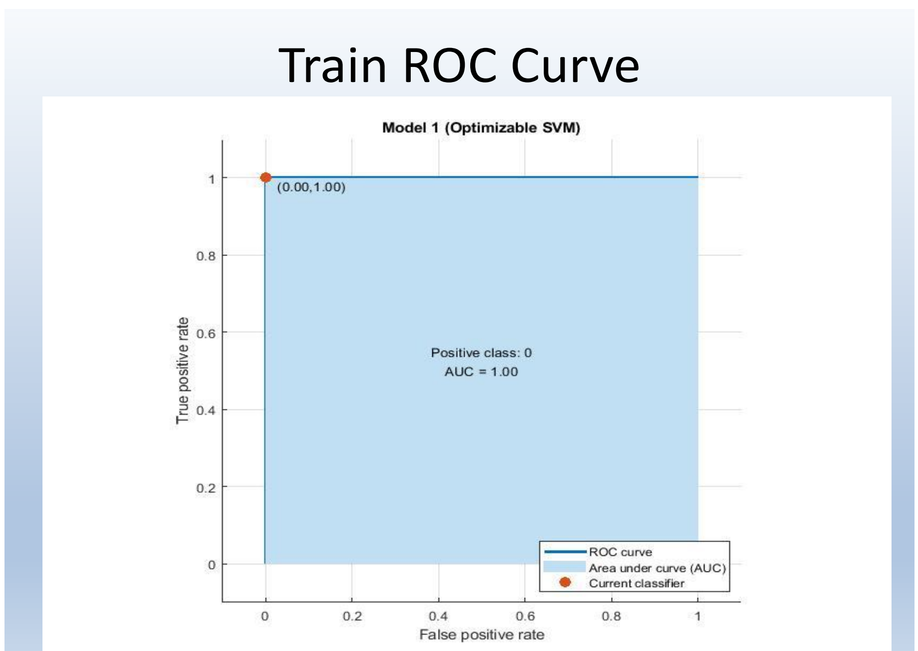

Fig. 19 showing Train ROC Curve

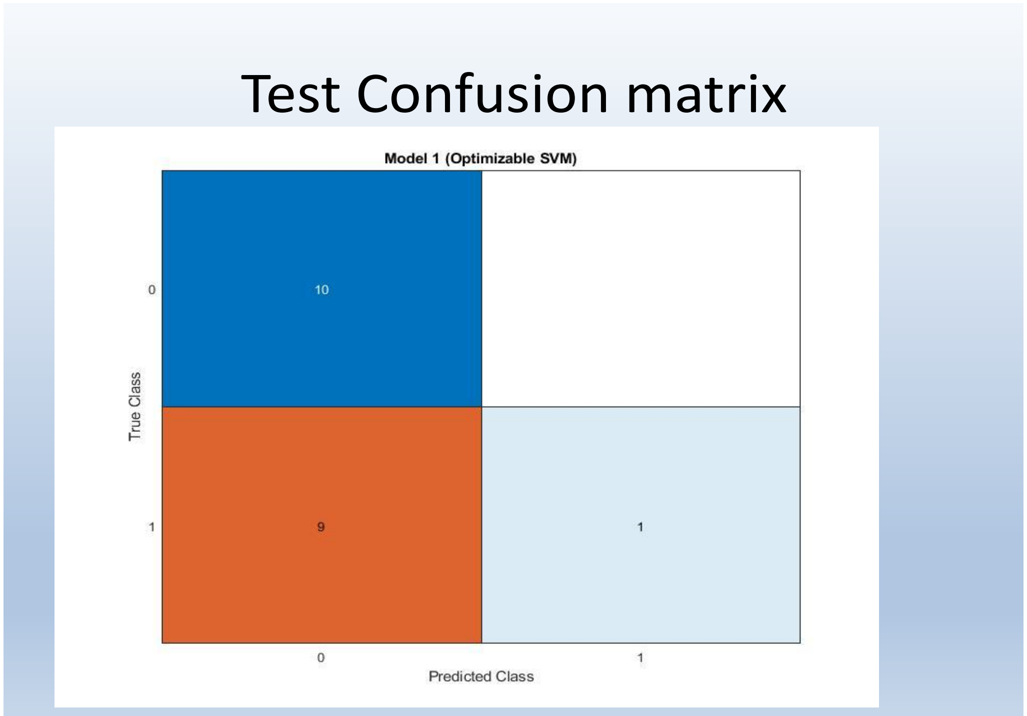

Fig. **20 showing Test Confusion Matrix**

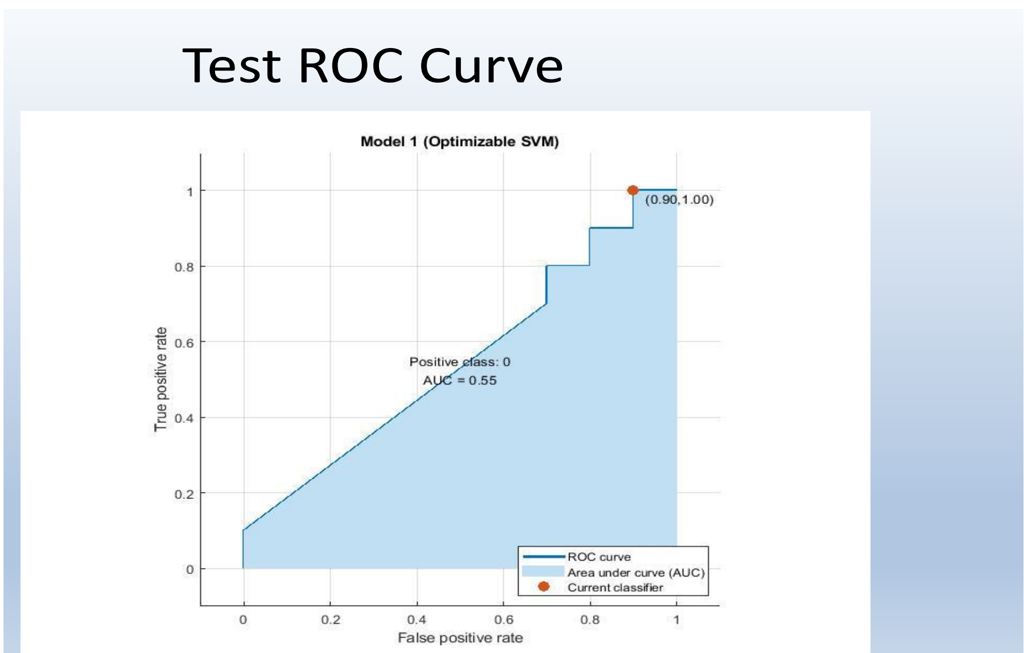

Fig. 21 showing Test ROC Curve

Table 5: Five-fold percentage accuracy obtained in classification of Control and the Epilepsy group using support vector machine .

Five-fold percentage accuracy obtained in classification of Control and the Epilepsy group using support vector machine

		Five fold Accuracy(%)			
	1	2	3	4	5
Training Dataset 80%	100	93.1	95.8	91.7	92.5
Testing Dataset 20%	55	65	100	100	100
Box Constraint c	807.71	961.27	993.58	977.19	963.47
Kernel Scale gamma	13.82	3.32	4.56	1.92	1.40

Selection of feature is an important step in developing reliable models. Therefore, understanding signals' statistical properties is very important as data recording or using the different datasets setting the parameters in each case is different. Several classifiers have been tested and evaluated for EEG epileptic seizure detection to discriminate between seizure and non-seizure states. ANN and SVM classifiers are the most common techniques; SVM is easy and fast as compared to ANN. But ANN is more robust technique during the training of ANN under supervised learning, the input vector is presented to the network, which will produce an output vector. This output vector is compared with the desired/target output vector.

The evaluations indicated that our model achieved the more effective classification than some previously studied methods. Hence, it can be said as computer-assisted clinical diagnosis of seizures bears a potential, which not only relieves the suffering of patient with epilepsy to improve quality of life, but also helps the neurologists, clinicians to reduce their workload and help them to make decisions more quickly, accurately, and effectively.

6. DISCUSSION

To understand the spikes morphology, classification tools are required. [42] in their studies reported that with each kernel there is at least one classifier which exactly predicts the class of morphology of the test sample. The polynomial and sigmoidal kernels were the best because the best classifiers of these kernels have the smallest number of support vectors (19 for the polynomial kernel and 20 for the sigmoidal kernel). [43] developed a tool for preprocessing of Brain Computer Interface (BCI) data that classified threshold crossings in a tunable manner and it was beneficial for decoding. Neural network-based spike classifier has the potential to reduce the need of human intervention in removing noise from the neuronal data. The tunable classifier is a step toward preprocessing methods that optimize and stabilize online decoding performance. [44] demonstrated an efficient VLSI implementation of a spike-based learning algorithm that solves both *memory encoding* and *memory preservation* problems, by using binary synaptic weights that are updated in a stochastic manner. The results reported demonstrate the correct functionality of the spike-based learning circuits for the difficult case of random patterns. [45] reported machine learning approach for personalized detection of focal EEG abnormalities, such as spikes and sharp waves, necessary for the automated assessment of the clinical implications of a recording. Despite not directly comparable, the presented method has higher sensitivity (=97 %) and smaller FP rate (=0.1 min-1) than most approaches proposed in the literature, thus constitutes a useful tool for automated assessment of interictal discharges in sleep EEG. [46] reported the method for converting an ANN into an SNN (Spiking neural networks)that enables low latency classification with high accuracies. It yields improved performance without increased training time. The presented analysis and optimization techniques boost the value of spiking deep networks as an attractive framework for neuromorphic computing platforms aiming for fast and efficient pattern recognition. Futher, we need to increase the number of dataset and to introduce the characteristic ''SLOW WAVES'' which we did not take into account in this work.

7. CONCLUSION

Data set was very small, hence, it needs further studies to evaluate and compare the performance of different classifiers. In the future, we intend to further optimize our model to achieve the classification of multiple-levels of epileptic seizure. Future work might look into the prospects of Deep learning classifiers and comparing the performance analysis.

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REFERENCES

[1] R. Mukherjee, S. S. Dhar and K. Tara, "Prediction of Disorder of Brain using EEG Signal Processing in MATLAB GUI Platform," 2017 2nd International Conference on Electrical & Electronic Engineering (ICEEE), 2017, pp. 1-4, doi: 10.1109/CEEE.2017.8412847.

[2] M. Kalaivani, V. Kalaivani,, V. Anusuya Devi. Analysis of EEG Signal for the Detection of Brain Abnormalities. International Journal of Computer Applications® (IJCA) (0975 – 8887) International Conference on Simulations in Computing Nexus, ICSCN-2014.

[3] I. B. Slimen, L. Boubchir and H. Seddik, "Epileptic seizure prediction based on EEG spikes detection of ictal-preictal states", J. Biomed. Res.., 34, 3, pp. 162–169, 2020.

[4] German Neuroscince Centre: Electroencephalogram, URL: https://www.gncdubai.com/treatments/neurological-eeg/, (Accessed on Nov.5, 2021)

[5] C.-K. A. Lim and W. C. Chia, "Analysis of Single-Electrode EEG Rhythms Using MATLAB to Elicit Correlation with Cognitive Stress," International Journal of Computer Theory and Engineering, vol. 7, pp. 149-155, 2015.

[6] G.D. Samanwoy, A. Hojjat, D. Nahid, "Principal component analysis-enhanced cosine radial basis function neural network for robust epilepsy and seizure detection." IEEE Trans. Biomed. Eng., 2008, pp.55, 512–518.

[7] Q. Wei, Y. Wang, X. Gao, S. Gao, "Amplitude and phase coupling measures for feature extraction in an EEG-based brain–computer interface." J. Neural Eng., 2007, pp.4, 120–129.

[8] V. Joshi, R.B. Pachori, A. "Classification of ictal and seizure-free EEG signals using fractional linear prediction." Biomed. Signal Process. Control., 2014, pp.9, 1–5.

[9] K. Polat, S. Günes, "Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform." Appl. Math. Comput., 2007, 187, pp.1017–1026.

[10]C.K. Chua, V. Chandran, R.U. Acharya, C.M. Lim, "Application of higher order spectra to identify epileptic EEG." J. Med. Syst., 2011, 35, pp.1563–1571.

[11] A.M. Goldfine, J.D. Victor, M.M. Conte, J.C. Bardin, N.D. Schiff, "Determination of awareness in patients with severe brain injury using EEG power spectral analysis." Clin. Neurophysiol., 2011, 122, pp.2157–2168.

[12]E.D. Übeyli, "Analysis of EEG signals by implementing eigenvector methods/recurrent neural networks." Digit. Signal Prog., 2009, 19, pp.134–143.

[13]C. Ieracitano, N. Mammone, A. Hussain, F.C. Morabito. "A novel multi-modal machine learning based approach for automatic classification of EEG recordings in dementia", Neural Networks, 2020, pp.123, 176–190.

[14] A. Bhattacharyya, M. Sharma, R.B. Pachori, P. Sircar, U.R. Acharya, "A novel approach for automated detection of focal EEG signals using empirical wavelet transform.", Neural Comput. Appl.,2016, pp.29, 47–57.

[15] T. Li and M. Zhou, "ECG classification using wavelet packet entropy and random forests", Entropy, 2016, pp.18, 285.

[16] Y. Wang, Z. Li, L. Feng, C. Zheng, W. Zhang, "Automatic Detection of Epilepsy and Seizure Using Multiclass Sparse Extreme Learning Machine Classification", Comput. Math. Method Med., 2017, pp.6849360.

[17] L. Guo, D. Rivero, A. Pazos, "Epileptic seizure detection using multiwavelet transform based approximate entropy and artificial neural networks", J. Neurosci. Methods, 2010, 193, pp.156–163.

[18] H. Kalbkhani and M.G. Shayesteh, "Stockwell transform for epileptic seizure detection from EEG signals", Biomed. Signal Process Control, 2017, 38, pp.108–118.

[19] M. Peker, B. Sen, D. Delen, "A Novel Method for Automated Diagnosis of Epilepsy using Complex-Valued Classifiers", IEEE J. Biomed. Health Inform., 2015, 20, pp.108–118. Entropy 2020, 22, 140 22 – 25.

[20] R.B. Pachori and S.Patidar, "Epileptic seizure classification in EEG signals using second-order difference plot of intrinsic mode functions", Comput. Meth. Programs Biomed., 2014, pp.113, 494–502.

[21] N.F. Güler, E.D. Übeyli, I. Guler, "Recurrent neural networks employing Lyapunov exponents for EEG signals classification" Expert Syst. Appl., 2005, 29, pp.506–514.

[22] M. Niknazar, S.R. Mousavi, B.V. Vosoughi, M. Sayyah, "A new framework based on recurrence quantification analysis for epileptic seizure detection" IEEE J. Biomed. Health Inform., 2016, 11, pp.572–578.

[23] G.D. Samanwoy, A. Hojjat, D. Nahid, "Mixed-band wavelet-chaos-neural network methodology for epilepsy and epileptic seizure detection" IEEE Trans. Biomed. Eng., 2007, 54, pp.1545–1551.

[24] H.W. Hu, Y.L. Chen, K. Tang, "A novel decision-tree method for structured continuous-label classification", IEEE Trans. Cybern., 2013, 43, pp.1734–1746.

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

[26] O. Kocadagli, R. "Classification of EEG signals for epileptic seizures using hybrid artificial neural networks-based wavelet transforms and fuzzy relations", Expert Syst. Appl., 2017, 88, pp.419–434.

[27] A.K. Jaiswal, H. Banka, "Epileptic seizure detection in EEG signal with GModPCA and support vector machine", Bio-Med. Mater. Eng., 2017, 28, pp.141–157.

[28] M. Shoaran, M. Farivar, A. Emami, "Hardware-friendly seizure detection with a boosted ensemble of shallow decision trees", In Proceedings of the 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC 2016), Orlando, FL, USA, 16 August 2016; pp.1826–1829.

[29] F. Achilles, F. Tombari, V. Belagiannis, A.M. Loesch, S. Navab, "Convolutional neural networks for real-time epileptic seizure detection", Comput. Methods Biomech. Biomed. Eng. Imaging Vis., 2016, 6, pp.264–269.

[30] K.M. Tsiouris, V.C. Pezoulas, M. Zervakis, S. Konitsiotis, D.D. Koutsouris, D.I. Fotiadis, "A Long Short-Term Memory deep learning network for the prediction of epileptic seizures using EEG signals", Comput. Biol. Med., 2018, 99, pp.24–37.

[31] W.Ren, M.Han, "Classification of EEG Signals Using Hybrid Feature Extraction and Ensemble Extreme Learning Machine" Neural Process. Lett., 2019, 50, pp.1281–1301.

[32] A. Craik, Y. He, J.L. Contreras-Vidal, "Deep learning for Electroencephalogram (EEG) classification tasks: A review" J. Neural Eng. 2019, pp.16, 031001.

[33] S. Saminu et al., Application of Deep Learning and WT-SST in Localization of Epileptogenic Zone Using Epileptic EEG Signals. Appl. Sci., 12, pp. 4879. 2022, https://doi.org/10.3390/app12104879.

[34] Noor Kamal Al-Qazzaz, Sawal Hamid, Bin Mohd Ali , Siti Anom Ahmad , Mohd Shabiul Islam and Javier Escudero. Selection of Mother Wavelet Functions for Multi-Channel EEG Signal Analysis during a Working Memory Task. Sensors 2015, 15, 29015-29035; doi:10.3390/s151129015.

[35] S. Saminu et al., "Hybrid feature extraction technique for multi-classification of ictal and non-ictal EEG epilepsy signals", Elektrika, J. Electr. Eng., 19 pp. 1–11, 2020, doi: 10.11113/elektrika.v19n2.219.

[36] S. Saminu,et al., A Recent Investigation on Detection and Classification of Epileptic Seizure Techniques Using EEG Signal. Brain Sci. 20;11 (5):pp.668. 2021, doi: 10.3390/brainsci11050668.

[37] L. Orosco, A.G. Correa and E.L. Leber, "Epileptic seizures detection based on empirical mode decomposition of EEG signals", In M.K. Günel, edt., Management of Epilepsy-Research, Results and Treatment. In-Tech Publishing, Vienna, Austria, pp. 3–20, 2011.

[38] Siddiqui, M.K., Morales-Menendez, R., Huang, X. et al. A review of epileptic seizure detection using machine learning classifiers. Brain Inf. **7**, 5 (2020). https://doi.org/10.1186/s40708-020-00105-1.

[39] E. Alickovic, J. Kevric and A. Subasi, "Performance evaluation of empirical mode decomposition, discrete wavelet transform, and wavelet packed decomposition for automated epileptic seizure detection and prediction", Biomed. Signal Process. Control., 39, pp. 94–102, 2018.

[40] Amin HU, Mumtaz W, Subhani AR, Saad MNM and Malik AS (2017) Classification of EEG Signals Based on Pattern Recognition Approach. Front. Comput. Neurosci. 11:103. doi: 10.3389/fncom.2017.00103.

[41] Fawcett, T. (2006) An Introduction to ROC Analysis. Pattern Recognition Letters,27,861-874.https://doi.org/10.1016/j.patrec.2005.10.010.

[42] Ousmane Khouma et al. Novel Classification Method of Spikes Morphology in EEG Signal Using Machine Learning. Procedia Computer Science 148 (2019) 70–79.

[43] Issar et al. A neural network for online spike classification that improves decoding accuracy. J Neurophysiol 123: 1472–1485, 2020. doi:10.1152/jn.00641.2019.

[44] Mitra, S; Fusi, S; Indiveri, G (2009). Real-time classification of complex patterns using spike-based learning in neuromorphic VLSI. IEEE Transactions on Biomedical Circuits and Systems, 3(1):32-42. DOI: https://doi.org/10.1109/TBCAS.2008.2005781.

[45] Zacharaki et al. (2016). Spike pattern recognition by supervised classification in low dimensional embedding space. Brain Informatics, 3:73–83; DOI 10.1007/s40708-016-0044-4.

[46] Peter U. Diehll et al.(2015). Fast-Classifying, High-Accuracy Spiking Deep Networks Through Weight and Threshold Balancing. DOI: 10.1109/IJCNN.2015.7280696.