Epileptic Seizure Prediction Based On Features Extracted Using Wavelet Decomposition And Linear Prediction Filter

Janga vijaykumar E Srinivasa Reddy Tucha Kedir Elemo

Abstract: Epilepsy is a brain disorder triggered by abnormal neuronal activity and hallucinations of epileptic cases are of primary interest. The EEG is the rhythmic discharge from the local or entire brain which usually takes seconds to minutes. Indices of irregular electrical activity in the brain are synchronous and almost frequent pulses and rapid bursts, which are also usually regarded as seizures. In this analysis, the energy filter (LP) linear prediction bias specifies the input and offset periods of the EEG signal. The occurrence of pulses and high waves in EEG seizures is controlled by an updated linear predictor device. All expected EEG pulse cycles are used for production and measurement purposes in this study and device output is calculated with a ROC graph. This uses the Wavelet approach for extract signals features and LightGBM purpose of classification. The methodology proposed contributes significantly to treatment of epileptic seizures because the ictal EEG is first administered with a changed linear estimation bias. The findings of the suggested method are evaluated using ROC, which indicates that seizures were 95.6% effective. The suggested solution was effective with high accuracy and faster training time.

Keywords: Epilepsy, Epileptic seizure, wavelet transform, Feature extraction

1 INTRODUCTION

Epilepsy is considered a condition in which people are suffering from a brain control disorder [1]. Although more than fifty million people around the world are infected with epilepsy [2], in the United States, epilepsy has impacted approximately three million patients. The third most common brain disorder is epilepsy [3]. In the meantime there are various possible triggers of epilepsy, including a genetic deficiency that occurs in abnormal neuronal activity or neuron migration. Early diagnosis may be helpful for the management of epilepsy although the main cause of epilepsy remains unknown. Epilepsy is the second most common nerve disorder in China and is second to headache. The specific diagnosis and prediction of epilepsy are therefore significant. Many work concentrated on EEG pulse detection and interpretation to both diagnose and treat epilepsy. Fast detection of epileptic seizures means that it is enough time before it actually happens because a medication will prevent an attack. Epileptic seizures involve 4 different states: Pre-ictal, which is a condition that happens before the convalescence begins, ictal, which starts with the onset of the seizure and finishes with an attack, post-ictal and interictal, which begins after the first post-ictal confiscation period and stops before the beginning of a pre-ictal cycle with concurrent confiscation. Fig. 1 shows three different channel input states. In fact, seizures can be expected when the preictal stage starts. The prediction of the preictal state presence indicates the attack. The analysis thus aims to predict the presence of preictal symptoms with epileptic seizures. Machine learning methods for the detection of epileptic seizures are used.

- *Janga vijaykumar E Srinivasa Reddy Tucha Kedir Elemo*
- *.vijaykumar.janga@gmail.com*
- *.esrreddy67@yahoo.com*
- *.tuchakedir@gmail.com*

Such learning models include EEG signal detection, signal preprocessing, feature extraction functionality and finally classification between seizure states. Seizure identification needs good features that show a significant change in various brain functions. Seizure classification against nonseizure. A safe EEG aids in diagnosing epileptic seizure in the subject, while interictal (intersecting time between two consecutive seizures) epileptic seizure classification (ictal) is essential for the seizure alert and detection system [4]. In the past, different methods for seizure classification based on frequency domains have been suggested and established, such as Fourier [5, 6]. Fourier methods and time-frequency methods of short-time transformation (STFT) [7] have also been used for this purpose. Window size is important in STFT to decide the balance between frequency and time resolution [8]. By using the wavelets model [8, 9] and its form like the discrete wavelet, the EEG signals for epilepsy are pre-analyzed by the authors ' description in [10]. In [11] the authors experimented similarly with a dual-tree complex wavelet (DTCWT) for decomposition and abstraction dependent on the Fourier quick transform logarithm (FFT). The classifier of nearest neighbor (NN) was used for extracted items. Specific machine learning methods have been used for separating the ictal from interictal and healthy nonseizure. Feature extraction is an essential part of this process and affects the model's control of discrimination [12].

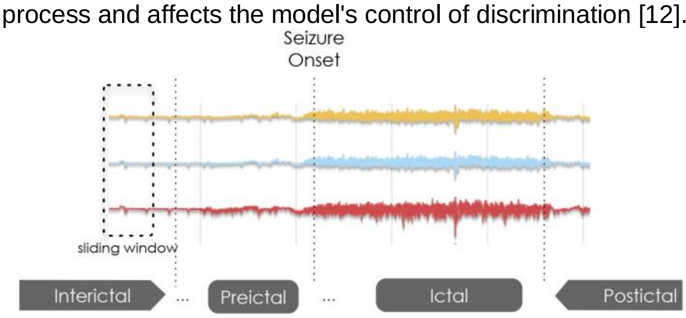

***Fig. 1**. Input states of three different channels*

Even with good training efficiency which deals with features of high-dimensional suffers from time burden and accuracy degrades. So, in this paper we design an efficient lightGBM that have advantage of leaf strategy with less memory usage better suitable for EEG utilities.

2 BACKGORUND WORKS

The irregular electrical activity that spread through the brain cortex is epileptic seizure. In the deep brain or epileptic focuses primary and secondary types are produced, Spikes and sharp waves of EEG signal are intermittent high-tension waveforms, and can signify a seizure. On the other side, bursts or intense pulses that arise interictal in epileptics or in people with genetic epilepsy loss are referred to as epileptics. Such irregular fast and slow waves can be mixed and, if a lot of them in a paroxysmal way disrupt relatively normal EEG rhythms, they become extremely epileptic as shown in Fig.2.

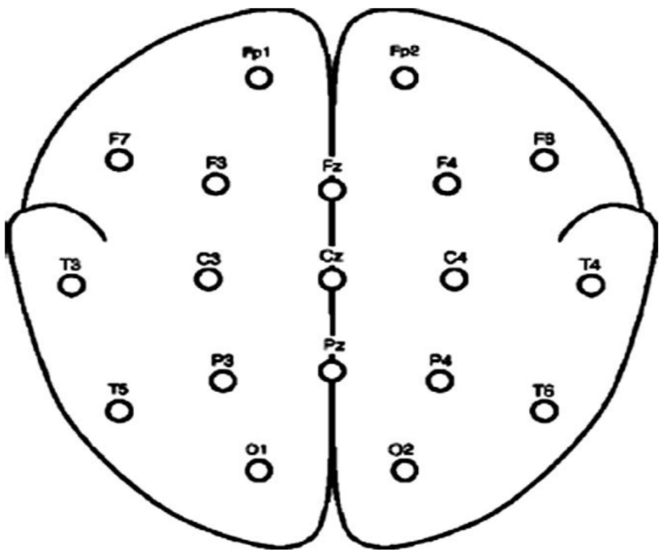

***Fig. 2**. Standard 10–20 electrode placement scheme for recording EEG signals [13]*

That level, though, is followed by inherent complications which may create variations as of true results. The following problems are labeled:

- When there is a change in placement of electrodes as mentioned in [14], it results in the errors occurrence in the EEG recording cases. The collected data should also be objective and relevant to the basic truth.
- The difficulty gets a feature vector of lower dimensions over the entire brain contains several functions.

Many algorithms for selection of features are also required to pick relevant features. It is limited amount of reference items, it is difficult to obtain a general pattern. In the main applications the training data over-fitness results in the poor functionality of the system and even worsens when affected by the noise.

3 METHODS AND METHODOLOGY

As an indication for the epileptic seizure through EEG records the basic outline of the proposed scheme can be used. The proposed method will encourage efforts to understand the underlying mechanism for the production of the epileptic EEG signal and to prediction the seizures in the Fig. 3. The system suggested comprises of five essential stages.

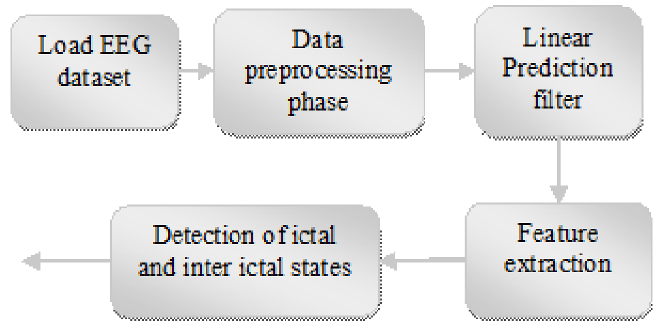

***Fig. 3**. Block diagram of the proposed scheme*

Data recordings of EEG:

Dataset 1:

The EEG database included the epileptic ictal and inter-ictal EEG records essential to develop and validate the process. Such impulses are recorded with a 128-channel 12-bit EEG system with 173.5 measurements per second and with a band-pass filter of 0.53–40 Hz. A total of 250 different records with a length of 23.6s are divided into five categories (A–E). Categories A and B are registered in international 10-20 electrode positioning schemes of healthy volunteers in the open eye and closed eye positions respectively. Inter-ictal histories of five epileptic cases are C and D groups. The electrodes are mounted on the epileptic focuses of group C and on the opposite hemisphere hippocampus of group D. Class E documents are all epilepsy events.

Data preprocessing phase:

The EEG consists of the artifact contaminated data, which happens because either the faulty cable or the action of the subject during EEG recordings. To detect objects, a strong detector is required that is capable of detecting even if it involves noise. The signal of interest for noise with potential interference-artifacts is measured by a rigorous subspace detection method. For each class, the current model assumes a Gaussian distribution, signal of interest and non-interest in the region. Epileptic seizure detection with modified linear predictive filter: Linear predictive filter is an adaptive filter as shown in Fig. 4 by reference. In this analysis, a linear predictive (LP) filter is used to determine optimal coefficients using the autocorrelation function. By means of LP coefficients, the signal value in p from the previous measurements is estimated at instant t. The difference in expected and actual values is known as an error in prediction or modeling.

To be specific the output of the Linear Prediction filter is

$$\hat{s}(n) = -\sum_{k=1}^{p} a_p(k) s(n-k) \quad (1)$$

and the corresponding error between the observed sample s(n) and the predicted value $\hat{s}(n)$ is

$$e(n) = s(n) - \hat{s}(n) \quad (2)$$

by minimizing the sum of the squared error we can determine the pole parameters $a_p(k)$ of the model.

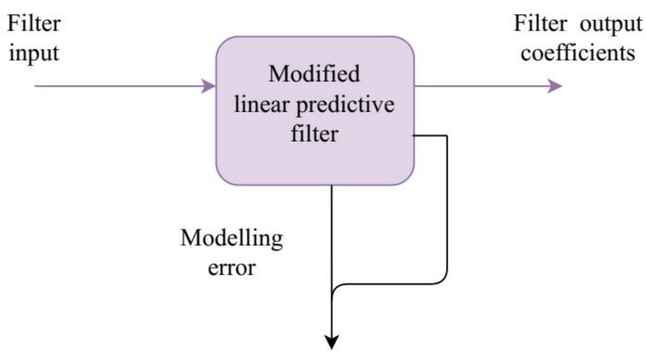

***Fig. 4**. Modified linear prediction filter, input/output signals*

The result of differentiating the sum above with respect to each of the parameters and equation the result to zero, is of p linear equations

$$\sum_{k=1}^{p} a_p(k) r_{ss}(m-k) = -r_{ss(m)} \quad \text{Where m=1, 2,….p} \quad (3)$$

Where $r_{ss(m)}$ represent the autocorrelation of the sequence s(n) defined as

$$r_{ss(m)} = \sum_{n=0}^{N} s(n)s(n+m) \quad (4)$$

The equation above can be expressed in matrix form as

$$R_{ss}a = -r_{ss(m)} \quad (5)$$

Where $R_{ss}a$ is a pxp autocorrelation matrix, r_{ss} is a px1 autocorrelation vector, and a is a px1 vector of model parameters.

The gain parameter of the filter can be obtained by the input-output relationship as follow:

$$s(n) = -\sum_{k=1}^{p} a_p(k) s(n-k) + Gx(n) \quad (6)$$

Where X(n) represent the input sequence.

The equation can be further put in the error model as given by

$$Gx(n) = s(n) + \sum_{k=1}^{p} a_p(k) s(n-k) = e(n) \quad (7)$$

then

$$G^2 \sum_{n=0}^{N-1} x^2(n) = \sum_{n=0}^{N-1} e^2(n) \quad (8)$$

if the input excitation is normalized to unit energy by design, then

$$G^2 \sum_{n=0}^{N-1} x^2(n) = \sum_{n=0}^{N-1} e^2(n) = r_{ss}(0) + \sum_{k=1}^{p} a_p(k) r_{ss}(k) \quad (9)$$

Where G^2 is set equal to the residual energy resulting from the least square optimization.

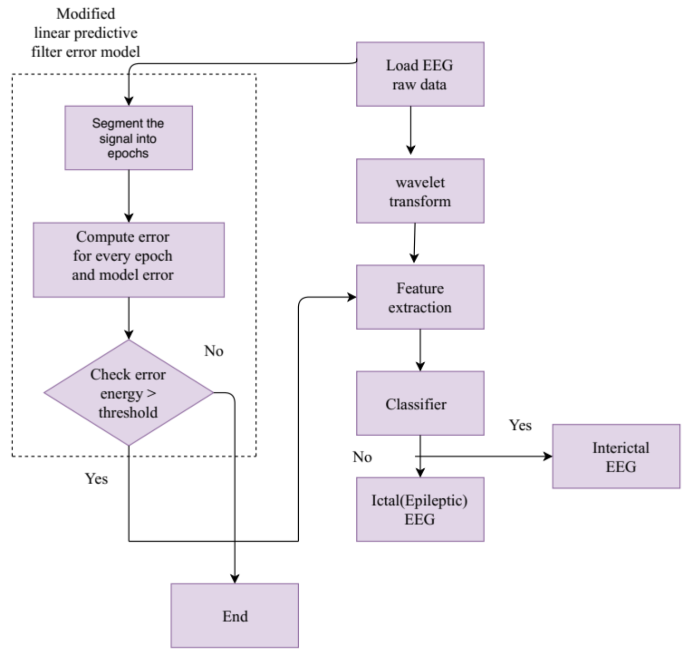

***Fig. 5**. Block diagram of the proposed scheme*

Features extraction using wavelet decomposition:

The abstraction of features is used to reduce the details in the signal to the wanted ones and to reduce signals sophistication. A multiresolution classification is used during discrete wavelet analysis to decompose a given signal x(t), which is focused on two basic functions, wavelets and scaling functions, into ever finer details.

$$x(t) = \sum_k 2^{\frac{j}{2}} a_{j_0}(k) \varphi\left(2^{j_0} t - k\right) + \sum_{j=j_0}^{\infty} 2^{\frac{j}{2}} d_j \sum_k 2^{\frac{j}{2}} \quad (10)$$

$$d_j(k) \Psi\left(2^j t - k\right)$$

Where the functions φ(t) and ψ(t) are the essential scaling and the mother wavelet respectively. In the extension described, the first summation reflects an approximation of x(t) according to the scale index of j_0, while in the second term the greater j (finer scales) is used to provide more detail. In this wavelet expansion the coefficients are called the discrete wavelet transformation (DWT) of the x(t)... These coefficients can be determined by orthogonal wavelets

$$a_j(k) = \int_{-\infty}^{\infty} 2^{\frac{j}{2}} x(t) \varphi\left(2^j t - k\right) \quad (11)$$

$$d_j(k) = \int_{-\infty}^{\infty} 2^{\frac{j}{2}} x(t) \Psi\left(2^j t - k\right) \quad (12)$$

Where $a_j(k)$ and $d_j(k)$ are the wavelet approximation and detail coefficients, respectively. In the DWT, the frequency axis is divided into dyadic intervals towards the lower frequencies, while the bandwidth length decreases exponentially.

Classifier Implementation:
To work effectively decrease errors in training process of classification, a gradient booster machine (GBM) has been built to increase the predictive efficiency of a sample. There are many classifiers and machine learning models that can be used to identify EEG data and it is challenging to choose the one that is most appropriate for the study of multiclass EEG data. We address the most commonly adopted Adaboost classifications and the proposed LightGBM classification introduced in this paper in the section.

Adaboost Classifiers:
The underlying principle behind Adaboost is that the weight of classifier and the data sample be set in each iteration to insure that unexpected results are predicted correctly. If a machine learning algorithm embraces weights on the training set, it can be used as a base classifier.

Gradient boosting machine classifier:
It works on iteration based that has the property of transforming the weak learners to powerful learners by providing suitable weights. It has three elements of functionality: feature training error, predictive learner with weak nature and a weak loss reduction model to integrate poor learners.

LightGBM Classification:
While developing a decision tree, LightGBM employs leaf-wise development techniques. When each decision tree is trained and the data are separated, two methods can be used: standard and step-wise. The strategy of the level preserves a balanced tree, while the strategy of the leaf separates the leaf that reduces the damage the most.

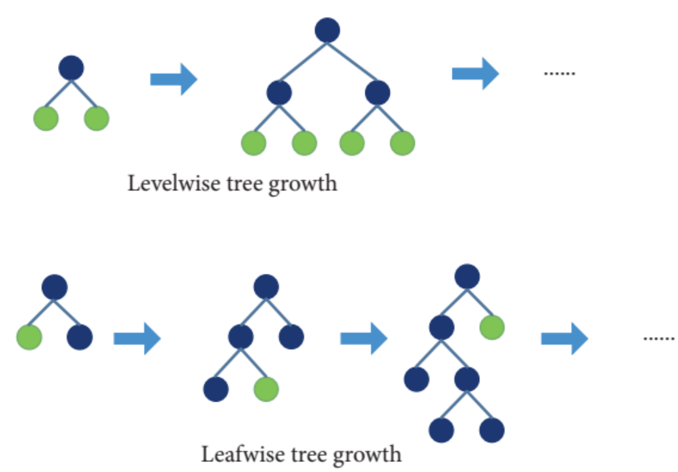

Fig. 6*. Learning process of LightGBM*

An example showing the difference between leaf and weed development. Level-specific training is known as a type of regularized instruction since leaf-specific training will create any tree that can provide level-specific training, whereas the reverse does not apply. As a consequence, the leaf-specific training is more prone to overfit, however useful, as Fig.6 indicates. For large datasets this is a better choice and the only option available in lightGBM [14-15].

4 RESULT AND DISCUSSIONS

EEG results were screened and all processing and interpretation were carried out using Intel core i3, 2.4 GHz with 4 GB RAM laptop in Matlab (Mathworks) 2017a and EEG toolbox. The features extraction step is the most important step, which differentiates between left and right signals by their characteristics, so that features extractions simplify the classification method and also increase its accuracy. Classification using gradient boosting algorithms requires a large number of training examples and time. Many problems occur during testing, such as over-fitting, but the network has not trained to generalize to new situations. To evaluate and make comparisons of the performance of the models, the following metrics are considered. Area under Curve (AUC): It is a measurement of the area under the Receiver Operating Curve (ROC) being a plot of true positive rate verses false positive rate. Sensitivity (Sen): It is the process of checking for state when corresponding state is existed. Sen = TP/(TP+FN).

Specificity:
It is the process of checking for state when corresponding state is not existed. Spec= TN/(TN+FP).

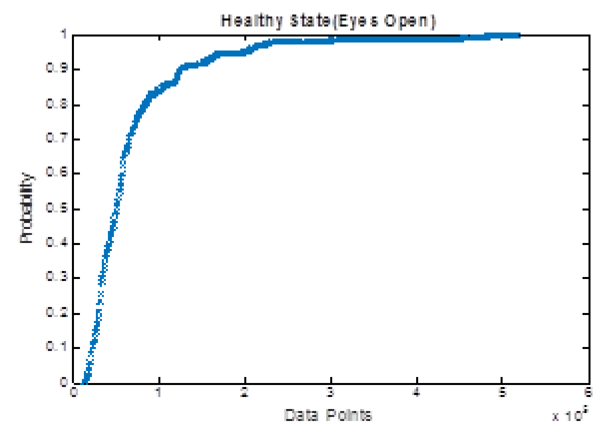

Fig. 7*. Healthy state of subject when eyes open*

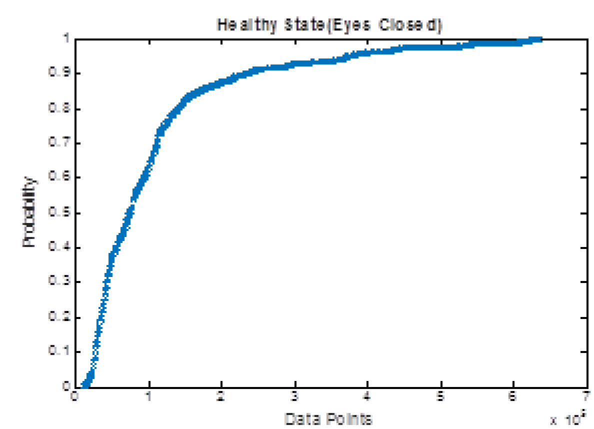

Fig.8*. Healthy state of subject when eyes closed*

From Fig. 7-8 indicates that the overall performance of the process when open eyes and closed eyes of healthy subjects when applied to proposed technique achieves 88% (44/50) for open eyes and 100% for closed eye scenarios. The open-eye healthy volunteer group recorded a lower success rate, respectively. Such false positive elements are due to the lack of a normal, eye-like alpha pattern. Open eyes absorb prevailing alpha frequencies, so the background noise is modeled rather than the signal itself on the linear prediction filter.

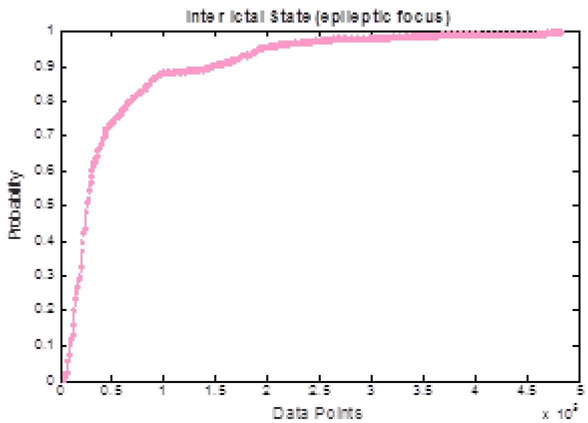

Fig. 9. *Error energy distribution of Inter ictal state of epileptic focus*

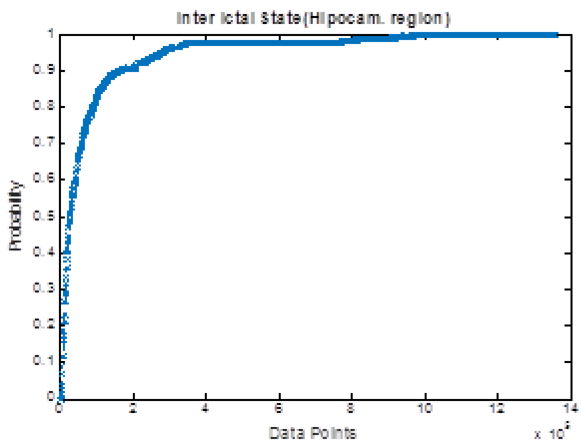

Fig. 10. *Error energy distribution of Inter ictal state of Hipocam region*

From the Fig. 9-10 indicates that while both the hippocampus area and the epileptic focus are captured in the inter-ictal recordings, standard 10-20 positioning structures are used for ictal condition and for stable reports. In these cases, the overall success rates for epileptic focus were reached at 96% (48/50), for the hippocampus region at 94%(47/50) and for ictal state at 92% (46/50).

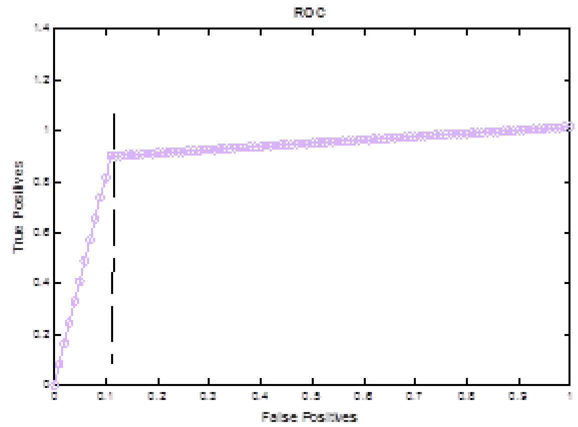

Fig. 11. *ROC curve plot*

Fig. 11 indicates the result of the system of the ROC study. ROC sensitivity and specificity values are measured. The large area of the ROC shows a high sensitivity of the system. ROC analysis that shows 93.6% performance in seizure identification.

Table .1. *Comparison of training errors in the classifiers*

	Adaboost training error	*Gradient Boost Machine error*
With DWT feature extraction	*0.1571*	*0.1125*
With Autoregression (AR) feature extraction	*0.2785*	*0.1821*
With Common Spatial Pattern (CSP) feature extraction	*0.2000*	*0.1482*

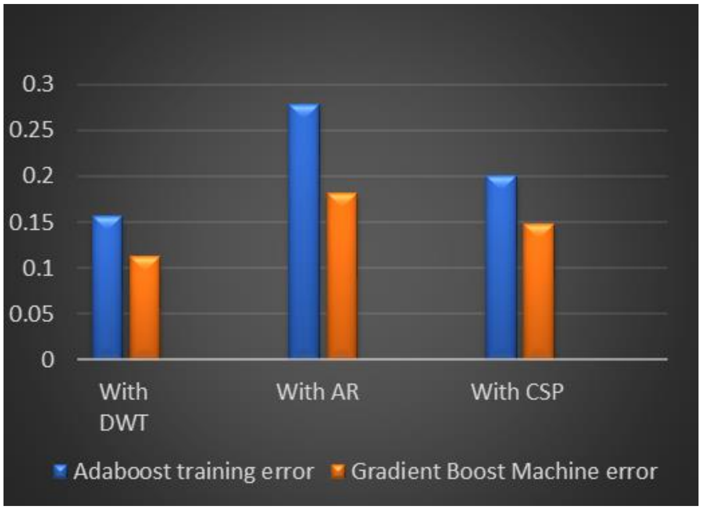

Fig. 12. *Comparison of Training Error in the classifiers*

Fig.12 shows that gradient boost machine classifier is having less training error when combined with DWT feature extraction outperforms as related to Adaboost with other feature extraction techniques.

5 CONCLUSION

EEG offers additional epilepsy detection information that have techniques of feature extraction, selection that affect the EEG classification considerably. The types of electrodes used and the technique used in feature extraction influence the work procedures, some pre-processing is done before the extraction process, but also the extraction method is so essential, and some approaches (such as wavelets) need not be pre-processed when used, while some are not functioning well unless a pre-processing procedure is conducted. DWT is used to generate more powerful features to achieve higher results compared to statistical methods. The proposed scheme is capable of providing better robustness with the assistance of modified LP filter requires fewer training time, which simplifies the system with a robust detection rate. Light Gradient boost machine (LGBM) could achieve a higher accuracy and less computation complexity on EEG states, that provides lower training errors.

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Authors Bio-data

Mr Janga Vijaykumar,Research Scholor in computer Science Department,University college of Engineering,Acharya Nagarjuna university,Guntur.He has done his MTech from JNTU,Hyderabad. He published his works in 8 international journals and attended 2 international conferecnes.His ares of reaserach interest are Artificial Intelligence,Machine Learning and Kowledge Extraction systems.

Prof E Srinivasa Reddy, Professor & Dean -University college of Engineering, Acharya Nagarjuna University-Guntur. He was also worked as the principal -University college of Engineering, Acharya Nagarjuna University. He obtained his MS and MTech from BITS Pilani and Visweswaraya Technological university respectively. He completed his PhD from Acharya Nagarjuna University in 2008.He had 25 years of teaching and 10 years of research & 15 years of Administrative Experience with the publications count over 80 including prestigious journals and conferences. His area of research interest includes Digital image processing, pattern recognition.

Tucha Kedir Elemo is working as Dean, College of Informatics, Bulehora University, Ethiopia. He has done his masters from symbiosis international university, Pune in 2017. His research areas are machine learning and Artificial intelligence.