Detecting Epileptic Seizures Using Electroencephalogram: A Novel Frequency Domain Feature Extraction Technique for Seizure Classification using Fast ANFIS

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ABSTRACT
Epileptic seizures usually results in a mixture of temporal alterations in perception and behavior. Epilepsy is considered to be one of the highly frequent neurological disorders. A considerable manner for detecting and examining epileptic seizure behavior in humans is Electroencephalogram (EEG) signal examination. EEG classification is a significant process in Brain Computer Interface (BCI) that offers a new dimension in human computer interface, directly linking a computer with human thinking. Identification of the epileptic EEG signal has been performed manually. Recently, automated epileptic seizure identification with the help of EEG signals has become an active of research. This paper presents an implementation of automated epileptic EEG detection system. In this paper, frequency domain feature extraction is carried out through Fast Fourier Transform to the process of classifying EEG signals. For classification this paper uses Fast Adaptive Neuro-Fuzzy Inference System (ANFIS) which utilize the modified Levenberg–Marquardt algorithm for learning. Experimental results show that the proposed system results in higher accuracy of classification at lesser time.

Keywords
Electroencephalogram, Epilepsy, Adaptive Neuro-Fuzzy Inference System, Modified Levenberg–Marquardt Algorithm.

1. INTRODUCTION
Electroencephalogram (EEG) is represented as the representative signal consisting information of the electrical activity created by the cerebral cortex nerve cells. This has been a highly used signal in clinical evaluation of brain behaviors and in the diagnosis of epilepsy. The Electroencephalograph (EEG) signal includes large data regarding the activities of the brain. EEG gathered from scalp electrodes, is a superposition of a large number of electrical potentials obtained from various sources.

Epilepsy is a general word that combines various kinds of seizures. Epilepsy is featured by unprovoked, recurring seizures that poke the nervous system. Seizures or convulsions are temporary modifications in brain functions because of abnormal electrical action of a group of brain cells that present with apparent clinical symptoms and gatherings [25]. Epilepsy may be resulted by a number of unconnected situations such as damage outcome from high fever, stroke, toxicity, or electrolyte imbalances [26]. The disease epilepsy is featured by an unexpected and repeated malfunction of the brain that is named as seizure. Epileptic seizures replicate the clinical signs of excessive and hyper synchronous behaviors of neurons in the brain [23]. Around one in every 100 persons will contain a seizure at situations in their life [24].Epilepsy and seizure are two different words where in seizures are the indications of epilepsy and epilepsy is the fundamental tendency of the brain to generate an unanticipated break of electrical energy. Epilepsy can be separated into two kinds such as idiopathic epilepsy and symptomatic epilepsy. First is a type of epilepsy in which the reason for the epilepsy remains untouched while in the second type a concrete result is detected. The indicative epilepsy is characteristically determined through any one of the succeeding behaviors like stroke, serious illness in the nervous system, harsh injury to the skull and more.

This paper intends to provide a better technique for EEG classification. In the proposed technique, the Frequency Domain Features (FDF) is calculated for each signal and this FDF is used as a feature for classification. For classification, Fast Adaptive Neuro-Fuzzy Inference System (FANFIS) is used in this paper.

2. RELATED WORK
Han *et al.,* [1] proposed an EEG signal classification technique for epilepsy diagnosis based on AR model and Relevance Vector Machine (RVM). It can better split the ictal EEG signals [11] from the inter-ictal signals. This works includes three phases: initially, EEG characteristics are gathered from the signals according to AR models, and then the act of these characteristics is analyzed. In the next phase, based on the act of the characteristics, feature choice was introduced among feature extraction and classifiers. In the last phase, RVM is executed with various AR models, various kernel widths, and various subsets of the characteristics for the purpose of getting an overview of the technique.

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Sukanesh *et al.,* [2] put forth a fuzzy techniques and hierarchical aggregation functions decision trees for the classification of epilepsy risk levels from EEG signals [6, 7, 8]. Statistical spectral feature extraction for classification of epileptic EEG signals is suggested by Seong *et al.,* [3]. The author provides a novel statistical technique along with a simple classification technique that can differentiate epileptic EEG signals [10] from normal EEG. The statistical technique gathers highly important spectral characteristics by maximizing statistical distance among the epileptic and the normal power spectrums. The power spectrum density of EEG signals is calculated with the help of multi-taper technique. A linear technique based on the Fisher discriminant analysis classifies the chosen spectral characteristics as either the epileptic or the standard class from the EEG recordings [17, 18, 19].

Panda et al., [4] given a technique for classification of EEG signal using wavelet transform and Support Vector Machine (SVM) for epileptic seizure diction. Classification of EEG for Epilepsy Diagnosis in Wavelet Domain Using Artificial Neural Network and Multi Linear Regression is suggested by Ercelebi *et al.,* [5].

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3. Methodology

In this approach, Frequency Domain Feature Extraction (FDFE) is carried out for better results.

3.1 Feature Extraction

Feature Extraction is a procedure of identifying a feature or a feature vector from a pattern vector. Features consist of most important data necessary for pattern processing. In this paper, frequency domain feature extraction is carried out. The central frequency, RPEB, and the Itakura distance mentioned are the examples of frequency domain features. In this paper, 3 features are utilized for the comparison of classifier's performance namely central frequency, mean of the absolute amplitude and the Itakura distance [2, 3].

Central frequency calculates the center frequency of the signal in frequency domain. The definition give is

$$f_c = \int_{f_L}^{f_H} fP(f)df \Big/ \int_{f_L}^{f_H} P(f)df \tag{1}$$

As sampled discrete data is used, above equation can be changed as follows.

$$f_c = \sum_{f=f_L}^{f_H} fP(f) \Big/ \sum_{f=f_L}^{f_H} P(f) \tag{2}$$

Mean of the absolute amplitude is a different way to measure power spectrum in frequency domain. If the magnitude of the time-domain signal is big, the magnitude of the frequency domain signal is also big. As shown in Table 1, EEG signals of different sleep stages have different rhythms and different magnitudes, and thus, this can be one of the feature parameters. Here is the definition.

$$A_m = \int_{t=t_1}^{t_f} |S(t)| \quad A_m = \sum_{t=t_1}^{t_f} |S(t)| \tag{3}$$

Itakura distance is used widely in speech recognition. It computes the distance between 2 AR processes. In this paper, 2 EEG channels namely Fpz-Cz and Pz-Oz are present and therefore Itakura distance between 2 EEG channels is measured. If AR processes of Fpz-Cz and Pz-Oz are given by $a_x = [1 - a_1 - a_2 \ldots a_p]$ and $a_y = [1 - a_1 - a_2 \ldots - a_p]$ respectively, then the minimum square error (MSE) for the Fpz-Cz is

$$MSE_{x,x} = a_x^T R_x(p) a_x \tag{4}$$

where the Rx(p) is the autocorrelation matrix for the Fpz-Cz of size p+1. Similarly, the MSE of the Pz-Oz passing through the Fpz-Cz is

$$MSE_{x,y} = a_y^T R_x(p) a_y \tag{5}$$

The Itakura distance of Fpz-Cz to Pz-Oz difined as

$$d_{I_{xy}} = \log\left(\frac{MSE_{x,y}}{MSE_{x,x}}\right) \tag{6}$$

Through reverse computation, the Itakura distance of Pz-Oz to Fpz-Cz, can be calculated as

$$d_{1_{yx}} = \log\left(\frac{MSE_{y,x}}{MSE_{y,y}}\right) \tag{7}$$

Combining (6) and (7), the symmetric Itakura distance is calculated as

$$d'_{1_{xy}} = \frac{1}{2}(d_{1_{xy}} + d_{1_{yx}}) \tag{8}$$

3.2 Fast Fourier Transform

FFT is used in this approach for the feature extraction. It has a computational complexity of nlog(n), where n is the number of samples. It is the fastest transformation process between time and frequency domain.

Once the FFT coefficients are obtained, various more expressive features can be extracted which are listed below:

A. Spectral Centroid:

This represents the balancing point of the spectral power distribution

$$C_t = \frac{\sum_{n=1}^{N} M_t[n] \cdot n}{\sum_{n=1}^{N} M_t[n]} \tag{9}$$

Where $M_t[n]$ is the magnitude value of the spectrum at position (frequency) n.

B. Band Energy:

Band energy expresses the energy of the subbands normalized by the total energy of the signal.

C. Spectral Roll-Off (SRO):

Measures the frequency below which a certain amount of spectral energy resides. It measures the "skewness" of the spectral shape [29]. Mathematically, it is expressed as

$$SRO = \sum_{n=1}^{R_t} M_t[n] \tag{10}$$

These mentioned features are computed for every segment and then used for the classification of EEG signals. 128 FDF values are provided for every EEG segment and determine four FDF values from every EEG segment and make use of them for the purpose testing and training the FANFIS.

3.3 Classification using FANFIS

The classification technique used in this paper is Fast Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithm.

The ANFIS [22] is a framework of adaptive technique to assist learning and adaptation. This kind of framework formulates the ANFIS modeling highly organized and not as much of dependent on specialist involvement. To illustrate the ANFIS architecture, two fuzzy if-then rules according to first order Sugeno model are considered:

$$Rule\ 1: If\ (x\ is\ A_1)\ and\ (y\ is\ B_1)\ then\ (f_1 = p_1 x + q_1 y + r_1)$$

$$Rule\ 2: If\ (x\ is\ A_2)\ and\ (y\ is\ B_2)\ then\ (f_2 = p_2 x + q_2 y + r_2)$$

where x and y are represents the inputs, A_i and B_i indicating the fuzzy sets, f_i indicates the outputs within the fuzzy region indicated by the fuzzy rule, p_i, q_i and r_i shows the design parameters that are determined while performing training procedure. The ANFIS architecture to execute these two rules is represented in figure 1, in which a circle shows a fixed node and a square shows an adaptive node.

All the nodes in the initial layer are adaptive. The outcome from these adaptive nodes is fuzzy membership grade of the inputs that are indicated by:

$$O_i^1 = \mu_{A_i}(x) \quad i = 1,2 \tag{11}$$

$$O_i^1 = \mu_{B_{i-2}}(y) \quad i = 3,4 \tag{12}$$

where $\mu_{A_i}(x), \beta_{B_{i-2}}(y)$. can allow any fuzzy membership function. For instance, if the bell shaped membership function is utilized, $\mu_{A_i}(x)$ is given by:

$$\mu_{A_i}(x) = \frac{1}{1 + \left\{\left(\frac{x - c_i}{a_i}\right)\right\}^{b_i}} \tag{13}$$

where a_i, b_i and c_i is nothing but the parameters of the membership function which controls the bell shaped functions accordingly.

In the second layer, the nodes are fixed. These nodes are named with M, indicating that they perform as a simple multiplier. The outcome of this layer can be given by:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \quad i = 1,2 \tag{14}$$

which represents the firing strengths of the rules.

Also, the nodes in third layer are fixed. They are named with N, indicating that they are occupied in a normalization function to the firing strengths from the earlier layer.

The outputs of this layer can be represented as:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{15}$$

which represents the normalized firing strengths.

All nodes that are in fourth layer are adaptive. The outcome of the entire node in this layer is just the multiplication of the normalized firing strength with the first order polynomial. As a result, the outcome of this layer is represented by:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \quad i = 1,2 \tag{16}$$

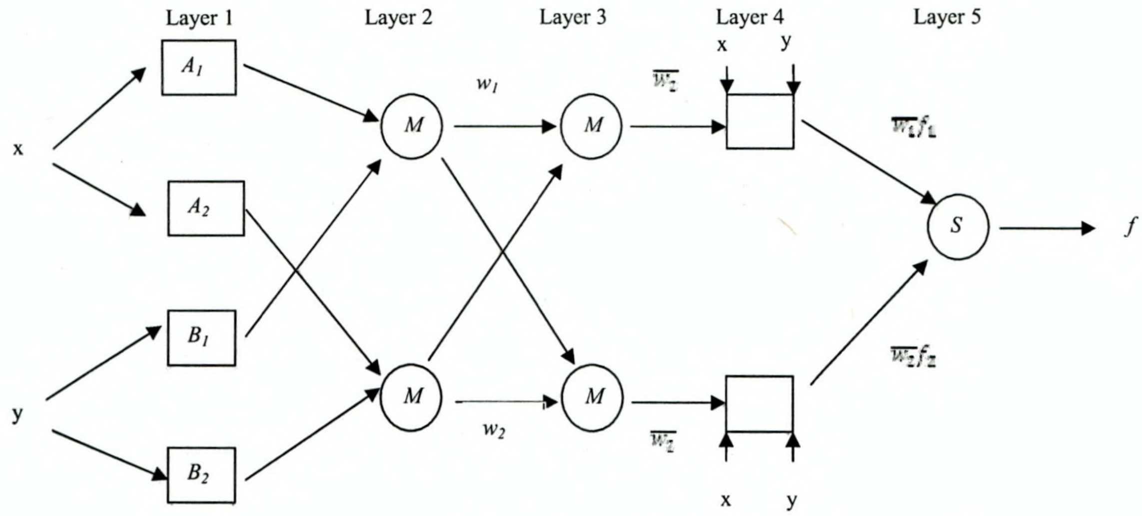

Figure 1: ANFIS Architecture

There is only one node named 'S' in the layer 5. This nodes performs the addition of all the incoming signals. Thus, the overall output of the model is given by:

$$O_i^5 = \sum_{i=1}^{2} \bar{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \tag{17}$$

It can be distinguished that layer 1 and the layer 4 are adaptive layers. Layer 1 composes of three adjustable parameters like a_i, b_i and c_i that is related to the input membership functions.

These parameters are represented as premise parameters. In layer 4, there exists three adjustable parameters . namely p_i, q_i and r_i, related to the first order polynomial. These parameters are called consequent parameters.

3.4 Learning algorithm of ANFIS

The intention of the learning algorithm is to adjust all the modifiable parameters such as $\{a_i, b_i, c_i\}$ and $\{p_i, q_i, r_i\}$, for the intention of matching the ANFIS output with the training data.

If the parameters such as a_i, b_i and c_i of the membership function are unchanging, the outcome of the ANFIS model can be given by:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \tag{18}$$

Substituting Eq. (15) into Eq. (18) yields:

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2 \tag{19}$$

Substituting the fuzzy if-then rules into Eq. (19), it becomes:

$$f = \bar{w}_1 (p_1 x + q_1 y + r_1) + \bar{w}_2 (p_2 x + q_2 y + r_2) \tag{20}$$

After rearrangement, the output can be expressed as:

$$f = (\bar{w}_1 x) p_1 - (\bar{w}_1 y) q_1 + (\bar{w}_1) r_1 + (\bar{w}_2 x) p_2 + (\bar{w}_2 y) q_2 + (\bar{w}_2) r_2 \tag{21}$$

which is the linear display of the changeable resulting parameters like p_1, q_1, r_1 and p_2, q_2, r_2. The least squares distance method can be used to identify the optimal values of these parameters easily. If the basis parameters are not changeable, the search space turns to be larger and directs to allowing for large time for convergence. A hybrid technique combining the least squares distance measure and the gradient descent method is used for the purpose of solving this drawbacks. The hybrid algorithm contains a forward pass and a backward pass. The least squares method that functions as a forward pass is used for the purpose of determining the outcome parameters with the no alterations in the premise parameters. Once the optimal consequent parameters are identified, the backward pass starts directly. The gradient descent method that functions as a backward pass is used to fine-tune the premise parameters equivalent to the fuzzy sets in the input domain. The outcome of the ANFIS is determined by utilizing the outcome parameters gathered in the forward pass. The output inaccuracy is used to modify the principle parameters with the help of standard back propagation technique. It has been accepted that this hybrid method is very proficient in training the ANFIS. Learning can be fast up in ANFIS using Modified Levenberg-Marquardt algorithm which in turn results in Fast ANFIS (FANFIS)

3.5 Modified Levenberg-Marquardt Algorithm

A Modified Levenberg-Marquardt algorithm is used for training the neural network. Considering performance index is $F(w) = e^T e$ using the Newton method the equation obtained is as follows:

$$W_{K+1} = W_K - A_K^{-1} . g_K \quad (22)$$

$$A_K = \nabla^2 F(w)|_{w=w_k} \quad (23)$$

$$g_k = \nabla F(w)|_{w=w_k} \quad (24)$$

$$[\nabla F(w)]_j = \frac{\partial F(w)}{\partial w_j} = 2 \sum_{i=1}^{N} e_i(w). \frac{\partial e_i(w)}{\partial w_j} \quad (25)$$

The gradient can write as:

$$\nabla F(x) = 2J^T e(w) \quad (26)$$

Where

$$J(w) = \begin{bmatrix} \frac{\partial e_{11}}{\partial w_1} & \frac{\partial e_{11}}{\partial w_2} & \cdots & \frac{\partial e_{11}}{\partial w_N} \\ \frac{\partial e_{21}}{\partial w_1} & \frac{\partial e_{21}}{\partial w_2} & \cdots & \frac{\partial e_{21}}{\partial w_N} \\ & & \vdots & \\ \frac{\partial e_{KP}}{\partial w_1} & \frac{\partial e_{KP}}{\partial w_2} & \cdots & \frac{\partial e_{KP}}{\partial w_N} \end{bmatrix} \quad (27)$$

$J(w)$ is called the Jacobian matrix.

Then, the Hessian matrix is to be found. The k, j elements of the Hessian matrix yields as:

$$[\nabla^2 F(w)]_{k,j} = \frac{\partial^2 F(w)}{\partial w_k \partial w_j} = 2 \sum_{i=1}^{N} \left\{ \frac{\partial e_i(w)}{\partial w_k} \frac{\partial e_i(w)}{\partial w_j} + e_i(w). \frac{\partial^2 e_i(w)}{\partial w_k \partial w_j} \right. \quad (28)$$

The Hessian matrix can then be expressed as follows:

$$\nabla^2 F(w) = 2J^T(W).J(W) + S(W) \quad (29)$$

$$S(w) = \sum_{i=1}^{N} e_i(w). \nabla^2 e_i(w) \quad (30)$$

If $S(w)$ is small assumed, the Hessian matrix can be approximated as:

$$\nabla^2 F(w) \cong 2J^T(w)J(w) \quad (31)$$

Using equations (23) and (31), the Gauss-Newton method is obtained as follows:

$$W_{k+1} = W_k - [2J^T(w_k) \cdot J(w_k)]^{-1} 2J^T(w_k)e(w_k) \quad (32)$$

$$\cong W_k - [J^T(w_k) \cdot J(w_k)]^{-1} J^T(w_k)e(w_k)$$

The advantage of Gauss-Newton is that it does not require calculation of second derivatives. There is a problem the Gauss-Newton method is the matrix $H = J^T J$ may not be invertible. This can be overcome by using the following modification.

Hessian matrix can be written as:

$$G = H + \mu I \quad (33)$$

Suppose that the eigen values and eigenvectors of H are $\{\lambda_1, \lambda_2, \ldots \ldots, \lambda_n\}$ and $\{z_1, z_2, \ldots \ldots, z_n\}$.Then:

$$\begin{aligned} Gz_i &= [H + \mu I]z_i \\ &= Hz_i + \mu z_i \\ &= \lambda_i z_i + \mu z_i \\ &= (\lambda_i + \mu) z_i \end{aligned} \quad (34)$$

Therefore the eigenvectors of G are the same as the eigenvectors of H, and the eigen values of G are $(\lambda_i + \mu)$. The matrix G is positive definite by increasing μ until $(\lambda_i + \mu) > 0$ for all i therefore the matrix will be invertible.

This leads to Levenberg-Marquardt algorithm:

$$W_{k+1} = W_k - [J^T(w_k)J(w_k) + \mu I]^{-1} J^T(w_k)e(w_k \quad (35)$$

$$\Delta w_k = [J^T(w_k)J(w_k) + \mu I]^{-1} J^T(w_k)e(w_k) \quad (36)$$

As known, learning parameter, μ is illustrator of steps of actual output movement to desired output. In the standard LM method, μ is a constant number. This work modifies LM method using μ as:

$$\mu = 0.01 e^T e \quad (37)$$

Where e is a $k \times 1$ matrix therefore $e^T e$ is a 1×1 therefore $[J^T J + \mu I]$ is invertible.

Hence, if actual output is out of range than preferred output or likewise, errors are huge so, it converges to preferred output with large steps.Similarly, when quantity of error is very less then, actual output approaches to preferred output with soft steps. Thus, error oscillation greatly minimizes.

4. EXPERIMENTAL RESULTS

The proposed technique is evaluated using around 5000 signals are collected during that period which includes both normal and abnormal signals. The Frequency Domain Feature (FDF) values are calculated for both normal and abnormal signals. With this obtained FDF, the classifier is trained and fewer signals obtained as a result of dimensionality reduction are used for testing the proposed technique. The parameters used for evaluating the proposed technique are average classification accuracy and the time required for classification. The testing phase is carried out by providing varied number of data points such as 500, 1000, 1500, 2000, 2500, 3000, 3500, 4000, 4500 and 5000.

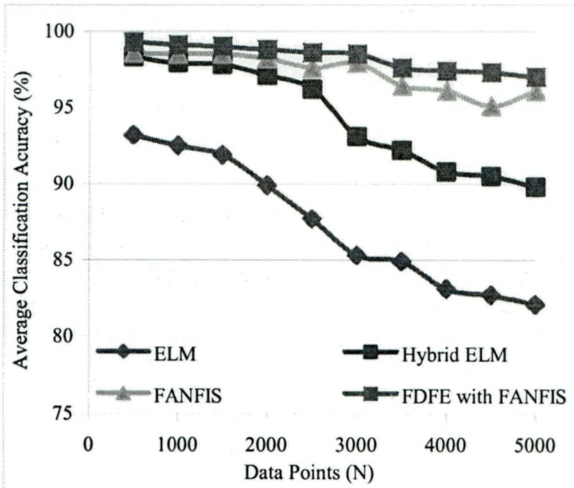

Figure 2: Average Classification Accuracy comparison

Figure 2 shows the average classification accuracy resulted when using ELM, Hybrid ELM, Fast ANFIS and FDFE with FANFIS techniques. From the figure, it can be observed that the average classification accuracy decreases as the data points supplied for testing increases. It can be observed that the overall resulted classification accuracy is better for the proposed FDFE with FANFIS technique than the existing techniques such as ELM, Hybrid ELM and FANFIS.

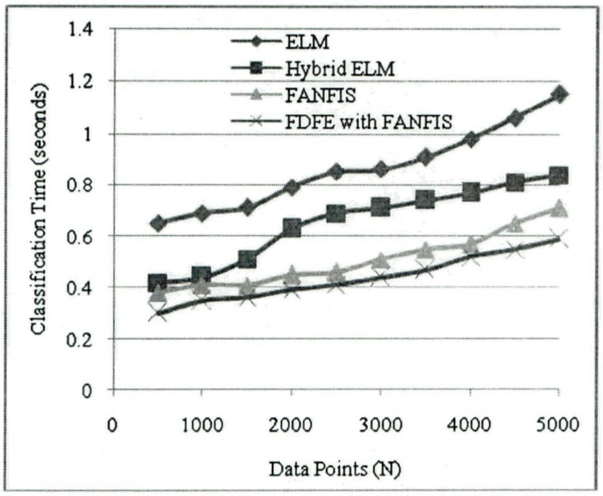

Figure 3: Classification Time Comparison

Figure 3 shows the classification time required for using ELM, Hybrid ELM, Fast ANFIS and FDFE with FANFIS techniques. From the figure, it can be observed that the classification time increase as the data points supplied for testing increases. Overall, the classification time required is lesser for the proposed FDFE with FANFIS technique than the existing techniques. These results suggests that the proposed technique FDFE with FANFIS results in better classification accuracy than the existing technique and also the processing requires only lesser time for classification.

5. CONCLUSION

Careful analyses of the EEG records can provide valuable insight and improved understanding of the mechanisms causing epileptic disorders. The main technique used in epilepsy diagnosis is EEG signal analysis. As EEG signals are non-stationary, the conventional method of frequency analysis is not highly successful in diagnostic classification. Various techniques exist for EEG classification to detect epilepsy, but all the existing techniques lack some performances like classification accuracy, classification time, etc. To overcome those difficulties, this paper provides a better technique for EEG classification by means of Frequency Domain Feature Extraction (FDFE) using FFT. With this feature, the classifier is trained and tested for detecting the occurrence of epilepsy. For classification, this paper uses Fast ANFIS (FANFIS). The experimental result shows that the proposed technique results in better accuracy in lesser time when compared to the existing techniques. Also, the classification time is much reduced for the proposed technique.

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