



HFD and MCFET Based Feature Extraction Technique for Detection of Epilepsy Using ANN Classifier

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ABSTRACT

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A neurological disorder called Epilepsy which causes the sudden occurrence of epileptic seizures. The electroencephalogram (EEG) is the recorded electrical activities of the brain to examine the epileptic patient through EEG pattern for diagnosis. Epileptic seizure is one of the abnormality or brain disorder in which seizure patterns shows large spikes for specific time domain or area. This work mainly focused on detecting the Epileptic seizures or Epilepsy through the extracted feature like Higuchi Fractal Dimension (HFD) and Masking and Check-in based feature extraction technique (MCFET). Three scaling features of HFD viz. fractal dimension, the standard deviation of fractal dimension and scaling factor while twenty masking and check-in-based features of the upper and the lower envelope along with ten features of the Discrete Wavelet Transform (DWT) coefficients (Table 1) from raw EEG signals are required as input to the Artificial Neural Network (ANN) for classifications. The overall performance is improved in terms of Accuracy, Sensitivity, Specificity through both HFD and MCFET features. Further, the overall accuracy using HFD and MCFET based feature extraction technique around 98% with a bit of computational time of about 1 second by reducing the training percent from 80% to 60%.

1. INTRODUCTION

Electroencephalogram is a diagnostic tool for the prediction of Epilepsy. As per the World Health Organization (WHO) fact sheet, over 2% of the world population suffer from a persistent neuronal disease known as Ictal or Epilepsy with uncertain seizure signals. Epilepsy can be occurred almost all ages of people and majorly it divides in two parts i.e. Internal and External. Internal Epilepsy occurs due to stress, lack of oxygen during birth and genetically transfer through parents while external Epilepsy occurs due to severe head injury and excess consumption of alcohol during stress. This brain electrical activity is read through Electroencephalogram. Electroencephalograms appear to be complicated assemblies of disorganized, randomly superimposed, and varying activity of Epileptic seizures.

MCFET is a statistical technique for extraction of stationarity behaviour of EEG signal while HFD is the pattern recognition approach in which different fractal dimension parameter values identify the class of EEG signal. Detection of Epilepsy or concurrent seizure in EEG signal requires the following steps:

1. Extraction of MCFET and HFD parameters.
2. Classification based on above parameters using Artificial Neural Network classifier with little computational time.

Others works based on seizure prediction algorithms discussed in this section 1.1.

1.1 Related works on seizure prediction algorithm

Choubey and Pandey [1] proposed K-Nearest Neighbor

(KNN) classification technique and MCFET for detection and classification of EEG signal samples. While in their other work, they have used a combination of statistical parameters to detect epilepsy and EEG classification using Artificial Neural Network (ANN) and K-Nearest Neighbour(K-NN) classifiers [2]. This approach is limited to HFD parameters with maximum accuracy of 91.33%. In another work, Bilal et al. [3] used multiresolution dynamic mode decomposition (DMD) to detect Epilepsy whereas, Imtiaz et al. [4] used the six main blocks for seizure sample data reduction together with other supporting blocks for efficient classification. Zeng et al. [5] analyzed the Visibility Heights Entropy of Hierarchical Neighbors for detecting Epileptic seizures. Zhao et al. [6] used three entropies (Spectral Entropy, Renyi Entropy, and Approximate Entropy) for epileptic seizure detection. Another work carried out by Chen et al. [7] reached eight entropies for seizure detection in which optimised performance with an accuracy, sensitivity and specificity of 99.50%, 100.00%, and 99.40% respectively and compared the results with traditional machine learning methods. Yuan et al. [8] developed a Deep Learning model to detect Epileptic seizures. This paper transforms the EEG segment into the time-frequency domain and then adds a sparsity and selectivity constrain module to detect effective EEG channels. Andy et al. used an SVM classifier to detect seizure signals from EEG signals. A Bayesian optimization algorithm has been used to optimize the hyper-parameters of SVM with extracted features like entropy and connectivity on publicly available CHB-MIT database. Hussein et al. [9] worked on a critical review for Focal and Non-Focal Epilepsy. This paper mainly reviews on

EMD, Entropy, Tensors, DWT and Dynamic Analysis-based feature extraction techniques for detecting the Epileptic seizure from EEG signal. Satapathy et al. [10] classified EEG signals using RBF neural network with Particle Swarm Optimization (PSO) technique and produced a maximum accuracy of around 99% compared to the other techniques. Saminu et al. [11] reviewed standard statistical features like mean, median, skewness, kurtosis, curve length, and DWT to detect Epileptic seizures from EEG signals. The current progress on Epileptic Seizure detection based on automatic seizure detection using deep and machine learning technique which require complex optimization approach for improving performance parameter in terms of Accuracy and Sensitivity. From the above study, it is clearly analyzed that the existing Epileptic seizure detection techniques have the following drawbacks:

- Reduction of the statistical features reduces the performance parameter like accuracy and sensitivity.
- Detection of three classes (Ictal, Pre-ictal, and Normal EEG signals) without using any pre-processing algorithm.
- Variable time slot of EEG signal samples for recording.
- Complex Optimization Approach.

This work aims to develop an Artificial Neural Network based classification technique with reduced statistical features like HFD and MCFET to solve these issues. Also, this work classifies three sets of EEG data classes. Class A and B for Normal (Healthy) EEG signal samples, class B and C for Pre-Ictal EEG signal samples, and class C for Ictal EEG signal samples based on pattern recognition and identification technique.

The main research objectives of this work are depicted in this Section 1.2.

1.2 Research objectives

The step-by-step sequence of this research work for seizure prediction are:

- Extraction of MCFET and HFD based features.
- Training of the extracted features.
- Classification of Ictal, Pre-ictal and Normal (Healthy) signals and also detect Epilepsy using ANN-based classification with little computation time.

The rest of this work is divided into three sections. Section 2 discusses feature extraction while Section 3 shows performance parameters and results using ANN Classifier. In the last, Conclusion with Future Work depicted in Section 4.

1.3 Data set description

EEG datasets consist of total 500 channels provided by the University of Bonn, Germany. Each channel is of 23.6s duration according to the international 10-20 electrode system.

Table 1. Data set description

Class	No of Channels	State
Z (Set A)	100	Normal EEG data with eyes close
O (Set B)	100	Normal EEG data with open eyes
N (Set C)	100	Inter-ictal (State before Epileptic Seizure)
F (Set D)	100	Inter-ictal (State before Epileptic Seizure)
S (Set E)	100	Ictal or Epileptic Seizure

2. FEATURE EXTRACTION TECHNIQUE

2.1 Higuchi fractal dimension based feature extraction technique

The length of irregular curve with small number of points used in Higuchi method for the approximation of fractal dimension at multiple scale [12, 13]. Geometrical shape of EEG samples at different scales is the feature input for the EEG segments classification depicted in the work of Nandy et al. [13] which is based on non-linear techniques. Three scaling features required for classifications are Fractal Dimension FD, which measures the complexity of series, SFD, the standard deviation of the fractal dimension; and Sb, the standard deviation of the scaling factor in which k is the hopping interval of signal. These feature values as input to the ANN classifier. According to the algorithm proposed by Higuchi [12], for HFD calculation shown in Figure 1, as Fractal Dimension (FD) can be calculated using a LS fitting procedure as $Y=aX+b$, where, $a=D_f$ according to the formula as Eq. (1).

$$D_f = \frac{n \sum (x_k \cdot y_k) - \sum x_k \sum y_k}{n \sum x_k^2 - (\sum x_k)^2} \quad (1)$$

where, $y_k = \ln(Z_{\text{mean}})$ and $x_k = \ln(1/k)$ for $k=1, 2, 3, \dots, k_{\text{max}}$.

n denotes the number of k values for which linear regression is calculated ($2 \leq n \leq k_{\text{max}}$). The standard deviation of D_f can be calculated as Eq. (2).

$$SD_f = \sqrt{\frac{n \cdot [\sum y_k^2 - D_f \sum x_k y_k - b \cdot \sum y_k]}{(n-2) \cdot [n \cdot \sum x_k^2 - (\sum x_k)^2]}} \quad (2)$$

where, $b = \frac{1}{n} (\sum y_k - D_f \sum x_k)$ with standard deviation as Eq. (3).

$$S_b = \sqrt{\frac{1}{n} \cdot SD_f^2 \cdot \sum x_k^2} \quad (3)$$

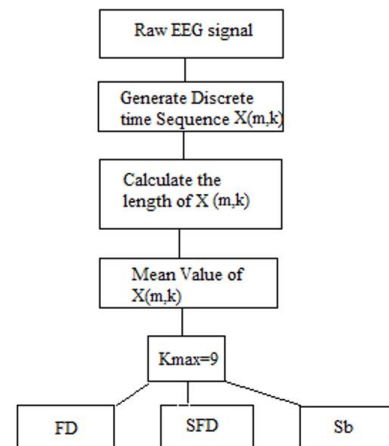


Figure 1. Higuchi fractal dimension-based feature extraction

2.2 MCFET algorithm

The MCFET works on the stationary behavior of EEG signals during masking. This technique offers a large volume of useful and important vector sets with minimum information loss. The basic steps of this algorithm are to transform a EEG samples using fast Fourier transform that's divide time domain

signals into frequency domain. It is actually a single sinusoidal oscillation at different frequencies. After that the process for mask generation is applied to the given EEG samples, in which the threshold value is fixed at 5.5 for better extraction of features. And this value estimates the length between two peak points, upper and lower after providing the masking over the signal. According to the study [1], algorithm for feature extraction from MCFET as explained in Figure 2.

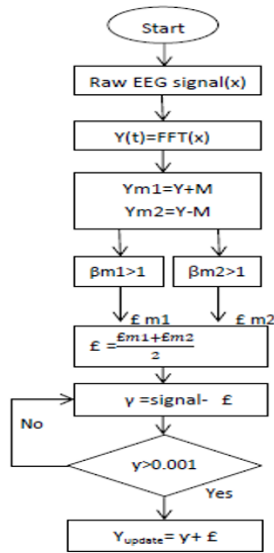


Figure 2. Flowgraph of MCFET algorithm

Apply check-in function to calculate the following parameters for ϵ ;

$$\forall_{update} = \gamma + \epsilon \quad (4)$$

$$\forall_{final} = (1/\pi) * \forall_{update} \quad (5)$$

Compute the SNR, variance, and standard 2 deviation for \forall_{final} , which helps us extract the features with large feature values for better classification purposes.

3. PERFORMANCE PARAMETER AND RESULTS

Performance parameter such as Accuracy, Sensitivity, Selectivity and ADR determine the effectiveness of the detection model. This is based on the values of TP, TN, FP, and FN of confusion matrix. Detection of Epileptic sample from the total EEG samples characterizes model performance.

3.1 Accuracy

The correct classification EEG data samples to the total number of the correct and incorrect EEG data samples defined Accuracy as Eq. (6).

$$\text{Accuracy}(\%) = \frac{\text{True Positive} + \text{True Negative}}{(\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative})} * 100(\%) \quad (6)$$

3.2 Selectivity

Selectivity for the ictal segment defined from the False rejection as Eq. (7). It characterizes the rejection of False data from EEG sample.

$$\text{Selectivity}(\%) = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} * 100(\%) \quad (7)$$

3.3 Sensitivity

Epileptic seizure(ictal) data segments from EEG data segments defined as Eq. (8). It is based on the selection of correct data.

$$\text{Sensitivity}(\%) = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} * 100(\%) \quad (8)$$

3.4 Specificity

Specificity for Pre-ictal segment defined as Eq. (9).

$$\text{Specificity}(\%) = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}} * 100(\%) \quad (9)$$

3.5 Average detection rate

Average of Selectivity and Sensitivity defined as Eq. (10).

$$\text{ADR}(\%) = \frac{\text{Sensitivity} + \text{Specificity}}{2} * 100(\%) \quad (10)$$

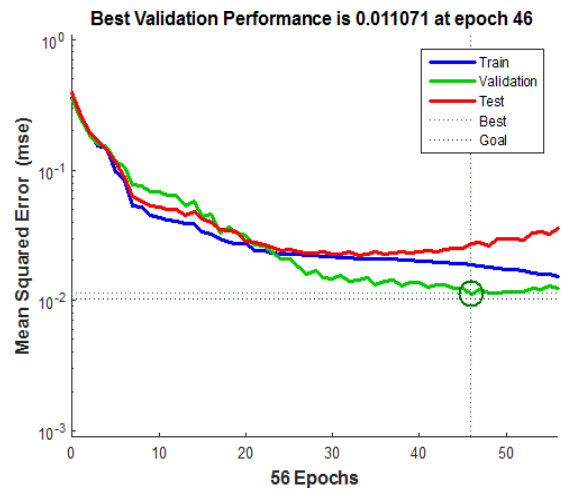


Figure 3. Performance plot for 80% trained data with MSE and epoch

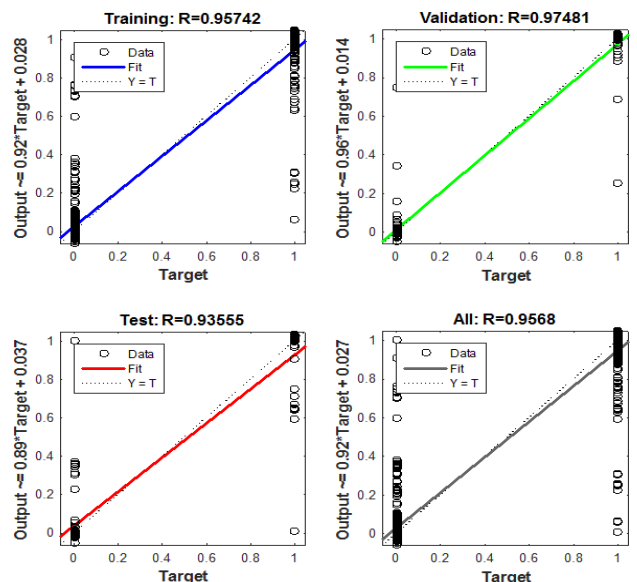


Figure 4. Training and validation plot for 80% trained data

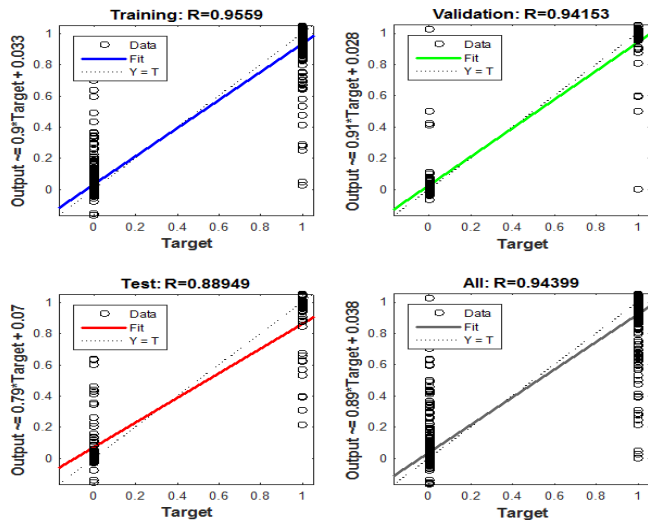


Figure 5. Regression plot for 80% trained data

Table 2. Feature details

S.No.	Features	Name of Sub features
1	HFD	Fractal Dimension (Df)
		Sdf
		Sb
		Maximum Value (Mx) of the EEG data set
		Minimum Value (Mn) of the EEG data set.
		Mean of Upper Envelope (MU).
		Mean of Lower Envelope (ML).
		The variance of Upper Envelope (VARIANCE1).
		Signal to Noise Ratio of Upper Envelope (SNR1)
		Standard Deviation of Upper Envelope (STDTN1).
2	MCFET	The variance of Upper Envelope (VARIANCE2).
		Standard Deviation of Upper Envelope (STDTN2).
		DWT Approximate and Detail Coefficients of 4096 samples (Selecting only 10 DWT Features)

Table 3. Classification based on HFD+MCFET parameters for ANN classifier

ANN Based Classification			
Training (%) = 80%, Time = 4 Sec			
Confusion Matrix			
	Ictal	Pre-ictal (Interictal)	Normal (Healthy)
Ictal	95	4	1
Pre-ictal (Interictal)	1	96	3
Normal (Healthy)	0	3	97
Accuracy (%) = 97.333%			
Selectivity (%) = 96.06%			
Sensitivity (%) = 96%			
Specificity (%) = 67.12%			
Average Detection Rate (%) = 81.56%			

Table 3, 4 and 5 shows ANN based classification which uses 23 input hidden layer and 3 output layer with trainlm activation function. Table 2 for 80% trained data having Accuracy of about 97.11% with a computational time of one

second. Network performance plot in terms of mean square error and epoch as shown in Figure 3, Figure 6 and Figure 9 for 80%, 70% and 60% respectively. The best validation performance is 0.011071 at epoch 46 for 60% trained data. Figure 4, Figure 7 and Figure 10 represent the training and validation plot for 80%, 70% and 60% trained data, respectively. Lastly, Figure 5, Figure 8 and Figure 11 represent regression plots for different training and testing percentage ratios.

Table 4. Classification based on HFD+MCFET parameters for ANN classifier

ANN Based Classification			
Training (%) = 70%, Time = 7 Sec			
Confusion Matrix			
	Ictal	Pre-ictal (Interictal)	Normal (Healthy)
Ictal	94	3	3
Pre-ictal (Interictal)	1	97	2
Normal (Healthy)	0	4	96
Accuracy (%) = 97.111%			
Selectivity (%) = 95.75%			
Sensitivity (%) = 95.66%			
Specificity (%) = 67.16%			
Average Detection Rate (%) = 81.4134%			

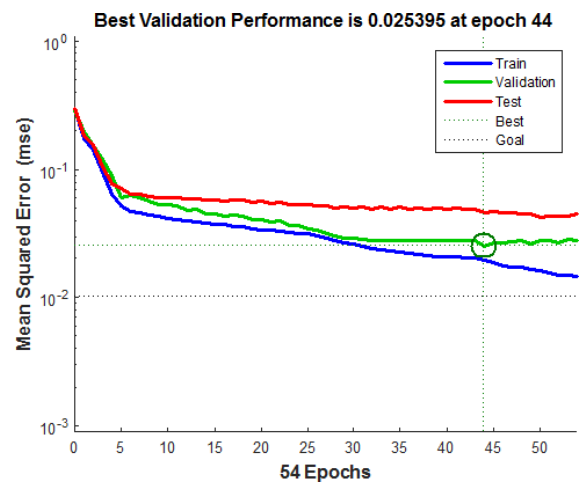


Figure 6. Performance plot for 70% trained data

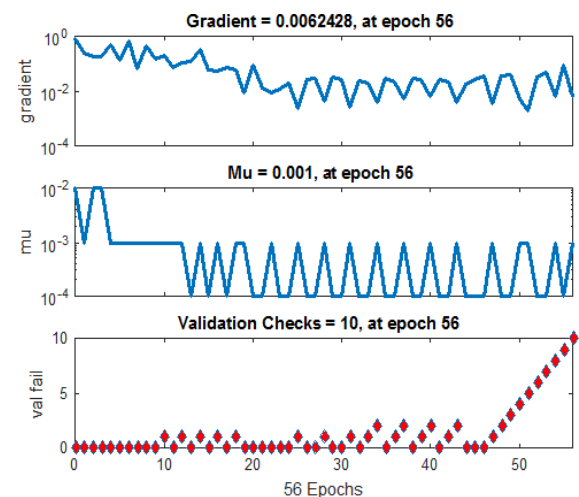


Figure 7. Training and validation plot for 70% trained data

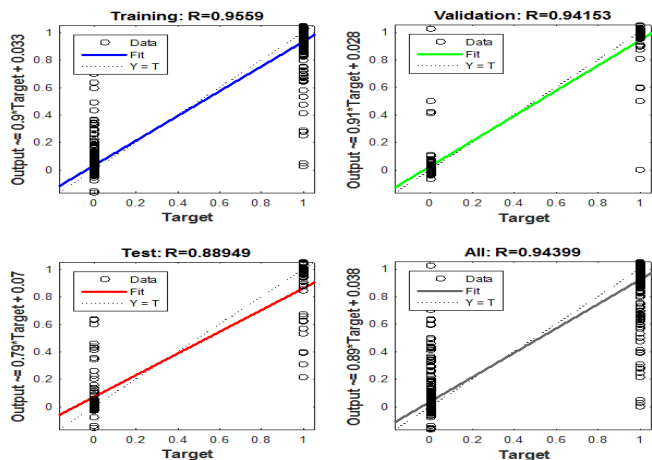


Figure 8. Regression plot for 70% trained data

Table 5. Classification based on HFD+MCFET parameters for ANN classifier

ANN Based Classification			
Training (%) = 60%, Time = 7 Sec			
Confusion Matrix			
	Ictal	Pre-ictal (Interictal)	Normal (Healthy)
Ictal	96	2	2
Pre-ictal (Interictal)	2	97	1
Normal (Healthy)	0	2	98
Accuracy (%) = 98.00%			
Selectivity (%) = 97.00%			
Sensitivity (%) = 97.00%			
Specificity (%) = 67.00%			
Average Detection Rate (%) = 82.00%			

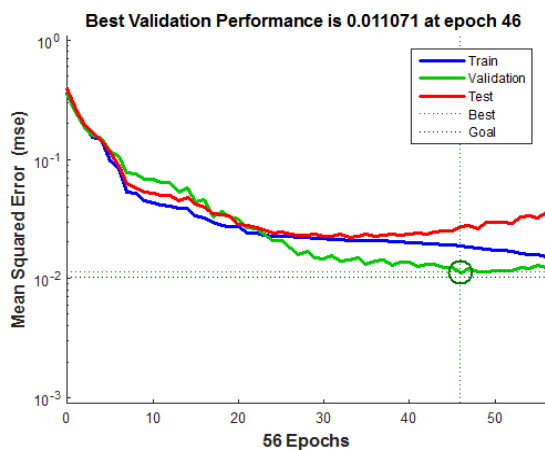


Figure 9. Performance plot for 60% trained data with MSE and Epoch

Table 6. Comparison of the proposed technique with the benchmark

Test Cases	Group	Measures	RBFN with GD [11]	RBFN with PSO [11]	RBFN with IPSO [11]	Proposed Method (MCFET+HFD)
Test Case-1	Set D & E	Accuracy	93	94	92	97
		Sensitivity	93.4	96	96	97
		Specificity	94	95	93.66	97
Test Case-2	Set AD & E	Accuracy	95	92	93	98
		Sensitivity	96.1	93	93.33	97
		Specificity	97	94	95.21	98
Test Case-3	Set A & E	Accuracy	92	93.6	95	99
		Sensitivity	94	95	98	98.6
		Specificity	97	98.3	98.6	100

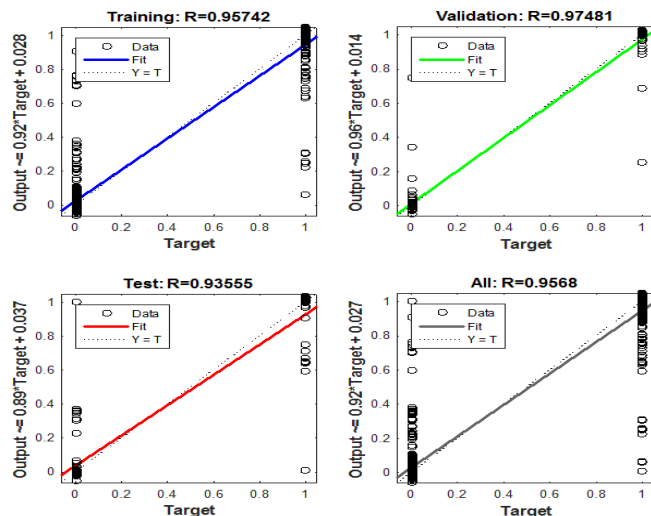


Figure 10. Training and validation plot for 70% trained data

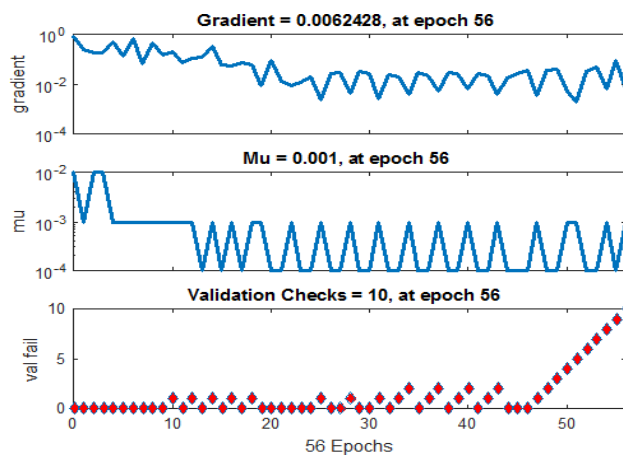


Figure 11. Regression plot for 60% trained data

3.6 Comparison with other existing techniques using different set of classes

The Table 6 shows three test cases in which classes of healthy EEG signal with Epileptic signal are considered in terms of Accuracy, Sensitivity and Specificity and compared Proposed Method with EEG classification technique using RBFN with GD, PSO and IPSO optimization technique. Accuracy, Sensitivity and Specificity is around 98% for all 3 test cases. The Proposed method for the three test cases is superior in terms of Accuracy without optimization and little computation time using simple HFD and MCFET features directly from the EEG signal.

4. CONCLUSION AND FUTURE WORK

The primary work of this paper is to reduced accuracy and computation time. Accuracy for detecting Epileptic seizures becomes around 98% with both HFD and MCFET features with a reduction of training percentage ratio. It is the simplest assessment technique for the detection of Epileptic Seizure without Optimization and reduction of feature. The average computational time for detecting Epileptic seizures varies from 4 to 7 seconds, with an average detection ratio of about 82%. It can be further improved by using an optimized algorithm at the preprocessing stage before the EEG signal classification. Accuracy can be improved further by using various optimization algorithms after extraction of various statistical features.

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