

# Intelligent Epileptiform Transients of EEG Signal Classifier

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**Abstract**— The electroencephalogram (EEG) is signal produced in the brain, because of the information flow through the communication of several neurons. It is really low amplitude signal. To understand the individual disorder disease, EEG signal have to be assessed carefully. One particular disease is epileptic seizure recognition. An epileptic seizure is a transient symptom of abnormal excessive of neuronal activity in the brain. Among seizures, the EEG of an individual with epilepsy may be seen as periodic epileptic form transients (ETs) which contain of spikes or sharp waves. The goal of this paper is to discover and classify epileptic form transients. Feed forward back propagation artificial neural network (FFBPNN) and radial basis function neural network (RBFNN) are being used to categorize (ETs). Three features are extracted, the waveform shape, frequency domain, and wavelet coefficient sets. The primary goal of the paper is to recognize the realistic feature collection which can perform satisfactory classification performance. FFBPNN had provided the best classification performance with wavelet coefficient set.

**Keyword-** EEG, epileptic form transients (ETs), artificial neural network (ANN), radial basis neural network (RBNN), wavelet transform

## I. INTRODUCTION

Electroencephalography (EEG) is the biomedical device that measures the electrical power activity of the brain using electrodes located along the scalp. Usual human brain shows different rhythmic activity, however disorder in brain can transform the rhythmic design structure. The electrical power activity of the brain is registered over a short while period, generally 20–40 minutes. The brain signals ranges from  $0.5\mu\text{V}$  to  $100\mu\text{V}$  in amplitude. EEG signals are grouped predicated on their frequency range: alpha ( $\alpha$ ), theta ( $\theta$ ), beta ( $\beta$ ), delta ( $\delta$ ), and gamma ( $\gamma$ ) [1]. Small Amplitude of the EEG signal is polluted by various artifacts that registered in the signal and altered its originality [2]. Artifacts are split up into two organizations [3]:

- 1) Physiologic signals which are produced by brain exterior sources such as; heart, eyes, muscles, tongue etc.
- 2) Non- physiologic signals which are generated by electrical equipment such as 50 Hz power line interference.

Irregular EEG activity can be sectioned off into epileptiform and non-epileptiform activity. An epileptic seizure is thought as a transient symptom of unnatural excessive or synchronous neuronal activity in the brain. Between seizures, the EEG of an individual with epilepsy may be seen as infrequent epileptiform transients (ETs) that contain of spikes or sharp waves which can carry on for 20-70ms or 70-200ms respectively. Event of ETs usually signifies repeated seizure in patients after an initial seizure. Thus it becomes important to discover ETs from a professional medical standpoint. However, the artifacts raise the difficulty to detect ETs [4]. Building a classifier with sufficient feature established to find ETs in EEG signal is the key goal of this paper.

## II. RELATED WORKS

A lot of works has been referred to in the literature for the EEG signal classification. The comprehensive evaluation of EEG information for an epileptic patient utilizing wavelet transforms was done by Adeli et.al [5]. By using logistic regression and Artificial Neural Networks, the seizure recognition was done automatically in EEG by Alkan et.al [6]. To classify the epilepsy from EEG signals, a Radial Basis Function Neural Network model was originated by Aslan et.al [7]. By using discrete wavelet transform and Approximate Entropy, Ocak diagnosed the epileptic seizures automatically [8]. The epileptic seizures diagnosis using the likelihood distribution predicted on equal frequency discretization was symbolized by Orhan et.al [9].

Tzallas et al. discovered that Peak Frequency, along with 15 other features, provided accuracies between 78.11% and 86.18% when classifying transient occasions in EEG recordings [10]. In [11], it was discovered that Peak Frequency only achieved a precision accuracy of 54.06%. A possible description for low accuracies could be that the frequency of peaks will decay as time passes. If the window that the optimum Peak Frequency is extracted from is too large, this decaying of the peak could make clear why some creators have observed less accuracy when working with only the Peak Frequency to detect seizures [12]. Wang and Lyu [13] discovered that median frequency exhibited significant dissimilarities between seizure and non-seizure patients. By segmenting the EEG signal into five independent frequency bands for delta ( $\delta$ :  $0.5 \leq f \leq 4\text{Hz}$ ), theta ( $\theta$ :  $4 \leq$

$f \leq 8\text{Hz}$ ), alpha ( $\alpha$ :  $8 \leq f \leq 12\text{Hz}$ ), beta ( $\beta$ :  $12 \leq f \leq 25\text{ Hz}$ ), and gamma ( $\gamma$ :  $25 \leq f$ ), it was possible to forecast 79 of 83 seizures with a level of sensitivity value of 95.2%.

### III. DESIGN AND METHODS

#### A. Datasets

The datasets found in this paper were extracted from Clemson University "eegNet"[14]. The 20 patients' dataset (D100) was provided. The signal is sampled at frequency rate of 256 Hz. Each patient was provided a 30-second duration signal segment. There have been 3 files to point the facts of the dataset D100: a text file details all the natural data; an 'annot.csv' file details the annotated segments; a 'class.csv' file details the classes.

#### B. Feature Sets

1) *Waveform Morphology Feature Set*: An epileptiform transient (ET) is a peak obtaining the following differentiating features [15].

- 1) There's a relatively large and soft slope accompanied by a comparatively large and soft slope of reverse polarity.
- 2) The apex of the ET is razor - sharp.
- 3) Although both edges may be of unequal span, the period of an ET is obviously between 20 and 70 ms. This length of time can be explained as the amount of the first and second half wave period.

A style of an ET that offers the properties explained above is a triangular waveform, shown in Fig. 1. [15].

A couple of six waveform features extracted from the distinctions of the natural data using the triangle model:

1. First Half Wave Amplitude (FHWA),
2. First Half Wave Duration (FHWD),
3. First Half Wave Slope (FHWS),
4. Second Half Wave Amplitude (SHWA),
5. Second Half Wave Duration (SHWD),
6. Second Half Wave Slope (SHWS),

FHWS & SHWS are computed corresponding to these formulas:

$$\text{FHWS} = (\text{FHWA}) / (\text{FHWD}) \quad (1)$$

$$\text{SHWS} = (\text{SHWA}) / (\text{SHWD}) \quad (2)$$

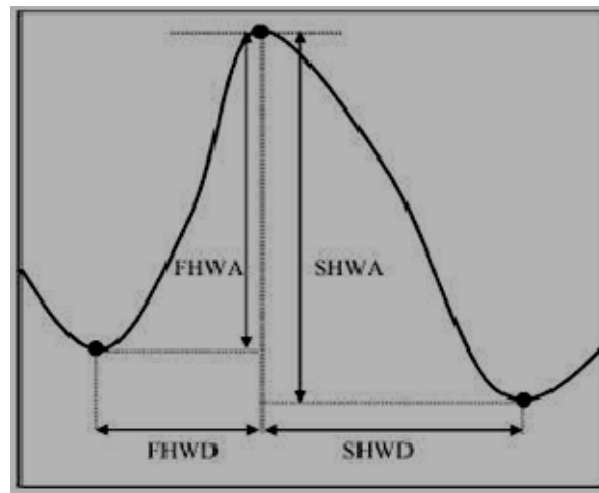


Fig. 1: ET shape feature

2) *Frequency Feature Sets*: An ET has two parts: A razor - sharp apex accompanied by a sluggish wave. The sharpened apex and the slow moving wave are composed of different frequencies. Theoretically, the energy of the sharpened apex is the most significant and the energy of the sluggish wave is the next most significant in the frequency domain. Through the use of the Fast Fourier Transform on the natural data, we get the frequency spectrum. Theoretically, the most significant peak in frequency site corresponds to the razor - sharp apex of ET and the next greatest maximum in frequency site corresponds to the slow moving wave of ET.

Power spectral density (PSD) is an optimistic real function of a frequency varying associated with a fixed stochastic process, or a deterministic function of their time. It describes the way the power of a signal or time series is allocated within frequency site. We presume the greatest optimum peak in PSD corresponds to the sharpened apex of ET and the next greatest optimum peak in PSD corresponds to the sluggish wave of ET. We also extracted four features using PSD:

1. Largest amplitude value in PSD.
2. Frequency of the most significant peak.
3. Second most significant amplitude value in PSD.
4. Frequency of the next greatest peak.

3) *Wavelet Feature Set*: To investigate the registered EEG signal, multiresolution analyses have to be performed. The wavelet transform decomposes signals over dilated and translated wavelets and evaluate the time progression of frequency transients. Inside our task we choose Symlet wavelet of order 9 (Sym 9) from Symlets family as the mother wavelet since Sym 9 have the highest relationship correlation coefficients with the epileptic spike among the list of wavelet bases available in the Mat lab toolbox [16]. A rectangular window was created by 64 temporal samples to acquire EEG signal segments. We deconstructed these signal segments into 4 levels. Then there are 5 sub group bands: 4 detail sub groups (D1-D4) and one approximation sub group (A4). For every sub band, we've 35, 21, 14 and 10 fine detail wavelet coefficients at the first, second, third and fourth levels respectively, and 10 approximation wavelet coefficients at the fourth level. If we use all the coefficients as suggestion, it'll be a high dimensions vector with how big is 90. To lessen the dimensions of the feature established, we then used the following statistical features to classify the EEG signals rather than using the initial wavelet coefficients:

1. Maximum of the wavelet coefficients in each one of the 5 sub group bands (D1, D2, D3, D4 and A4).
2. Minimum of the wavelet coefficients in each one of the 5 sub group bands.
3. Mean of the wavelet coefficients in each one of the 5 sub group bands.
4. Standard deviation of the wavelet coefficients in each one of the 5 sub group bands.

Thereupon, altogether we've 20 features for wavelet-based feature set [17].

### C. Classification

After the features have been chosen, a classifier must be designed and trained. The classifier's performance is based greatly on the characteristics of working out data. The classifiers we've considered are:

1. Feed forward back propagation artificial neural network (FFBPNN).
2. Radial basis function neural network (RBFNN).

1) *FFBPNN*: Artificial Neural Networks are recognized to facilitated classifier design and execution. ANN can study from experience and put into action complex decision areas although working out period can be long. The feed forward network framework is a favourite and useful ANN composition. Typically the most popular training algorithm, specifically back propagation method, can be used. A typical back-propagation training architecture has one input layer, one output layer, with at least one hidden layer. Figure 2 shows the normal structure of a multi-layer feed forward (MLFF) network. In this paper, we designed the FF network with one hidden layer. The neurons used in the input layer are equivalent to the size of the input vector,  $d$ , while the neurons used in the hidden layer are  $2d+1$  [18]. And two neurons are used in the output layer, which point out the result format is a two dimensions vector,  $[0 \ 1]^T$  or  $[1 \ 0]^T$ .

2) *RBFNN*: The RBF net is a network that includes a similar framework as feed forward network but with a layer of radial basis models. The hidden-layer of RBF unit utilizes a Gaussian activation function, using known centers as Gaussian function's mean, while the output units are simple linear models [11]. The two steps involved with training the RBF net are:

1. Make use of other clustering algorithm (e.g. c-means) to look for the RBF unit centers and so supplement the hidden-layer.
2. Evaluate the hidden layer to output layer weights.

RBFNN is one of the most basic forms of Neural Network comprising exactly three layers, namely input, hidden, and output layer. The restriction of only three layers helps it be simpler and in some way the effective neural network architecture (as shown in Fig. 3). The thought of RBFNN has been produced from function approximation, an RBF network positions a number of RBF neurons in the area identified by the predictor parameters. This space has as much dimensions as there are predictor parameters. The Euclidean distance is computed from the point being evaluated to the center of every neuron. The RBF is so called because the radius distance is the disagreement to the function. The output of RBFNN will depend on the distance of the input from confirmed stored vector. There are many kernel functions found in RBFNN, such as Gaussian, Multi-quadric, Inverse Multi-quadric, Mexican hat, etc. Each one of the functions has its benefits with regards to the data domain they may be used. We use to validate the performance of Gaussian basis function in RBFNNs for recognition of epileptic seizure [19].

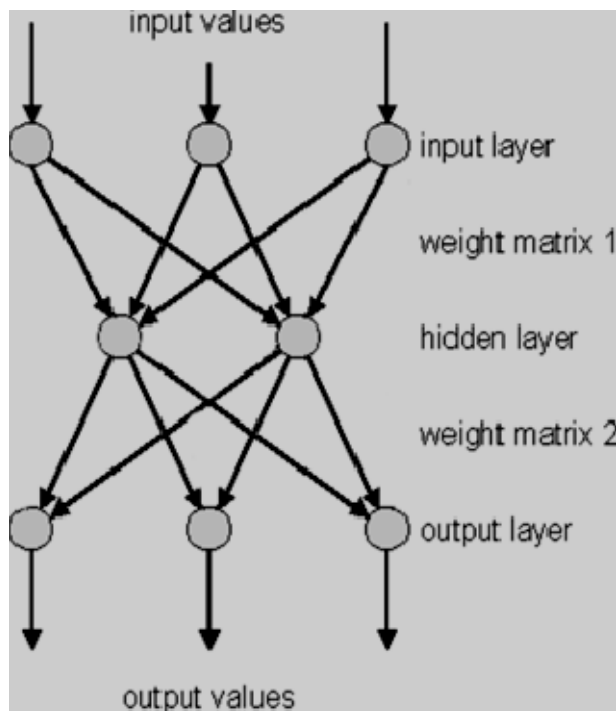


Fig. 2: multilayer feed forward network

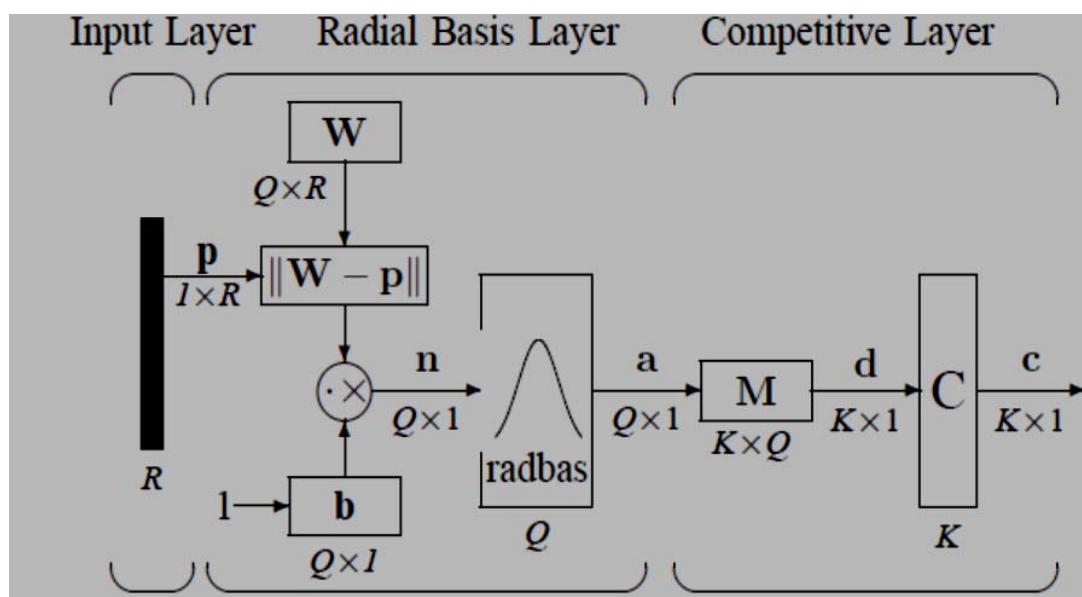


Fig. 3: RBFNN typical structure

#### IV. RESULTS and DESIGN

A lot of the results are derived from dataset D100. It had been pre-processing, feature extraction, and classification in MATLAB 2013 environment. The performance of FFBNN and RBFNN classifier is likened with the aid of two parameters level of sensitivity, and specificity. Level of sensitivity is a system's capacity to identify positive events. Specificity is a system's capacity to identify negative activity. These guide lines can be determined in line with the following formulas:

$$\text{Sensitivity} = TP / (TP + FN) \quad (3)$$

$$\text{Specificity} = TN / (TN + FP) \quad (4)$$

Where:

TP (true positive) signifies the amount of events designated as AEP signal by both the annotation and our classifier.

FP (false positive) represents the amount of events designated as AEP signal by our classifier not by the annotation.

TN (true negative) signifies the amount of events which were neither designated as AEP signal by our classifier nor by the annotation.

FN (false negative) represents the amount of AEP signal events designated by the annotation that have not designated by our classifier.

Presently there are two classes; a circumstance refers to "AEP" and "non AEP" class. Due to the various morphologies of ETs, it is difficult to choose an acceptable size for a dataset which is large enough for training and classification. We designed a "leave half out" method, called cross-validation training by patient method, showing the pattern of level of sensitivity, and specificity as the size of training dataset varies. The description of training by patient strategy is shown below. It has the following steps:

Step 1: For every trial, randomly break out D100 into 2 mutually exclusive 50-patient subsets. The first is for testing (ST); the other is designing for training (H). For H, arbitrarily choose 10 patients' data and create a 10-patient training collection (H1). Utilize the same solution to create a 20-patient training set (H2), a 30-patient training set (H3), a 40-patient training set (H4) and 50-patient training set (H5).

Step 2: Build the two "classifiers" respectively using the five training packages,  $H_i, i=1, 2 \dots 5$ .

Step 3: Apply the classifiers on ST.

Step 4: Iterate Step one to Step three to appointed studies (inside our case, 100 tracks), till all the studies are finished.

Figures 4 – 9 illustrates the level of sensitivity and specificity cross validation results for both classifiers FFBPNN & RBFNN of D100 FFT, waveform, & wavelet feature sets. These results can be summarized and tabulated in table I.

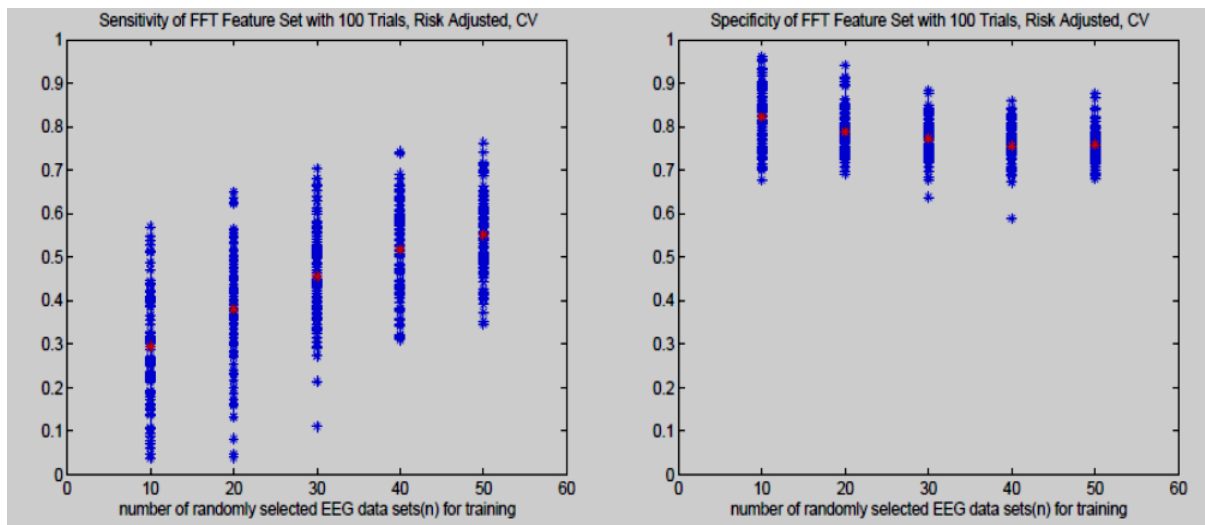


Fig. 4: sensitivity & specificity for FFBPNN with FFT feature set.

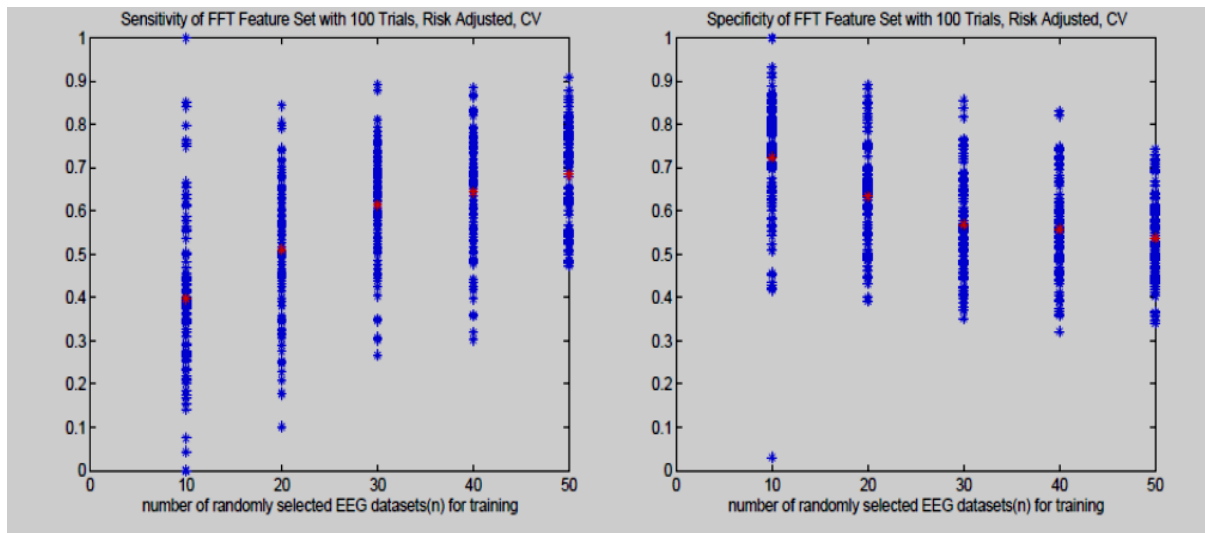


Fig. 5: sensitivity & specificity for RBFNN with FFT feature set.

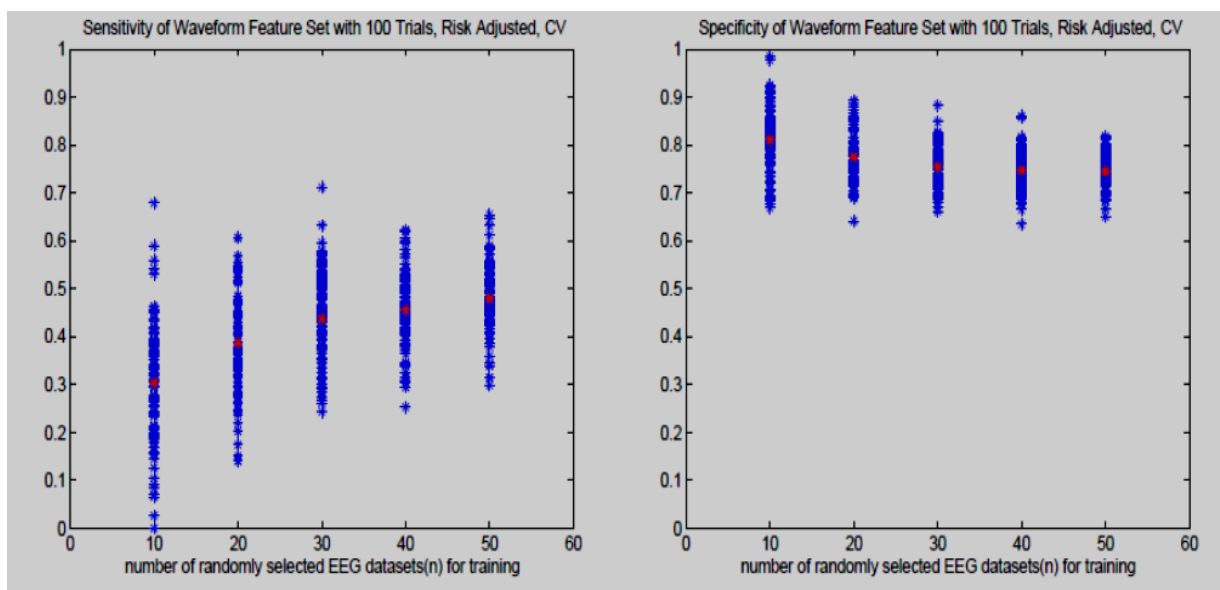


Fig. 6: sensitivity & specificity for FFBPNN with waveform feature set.

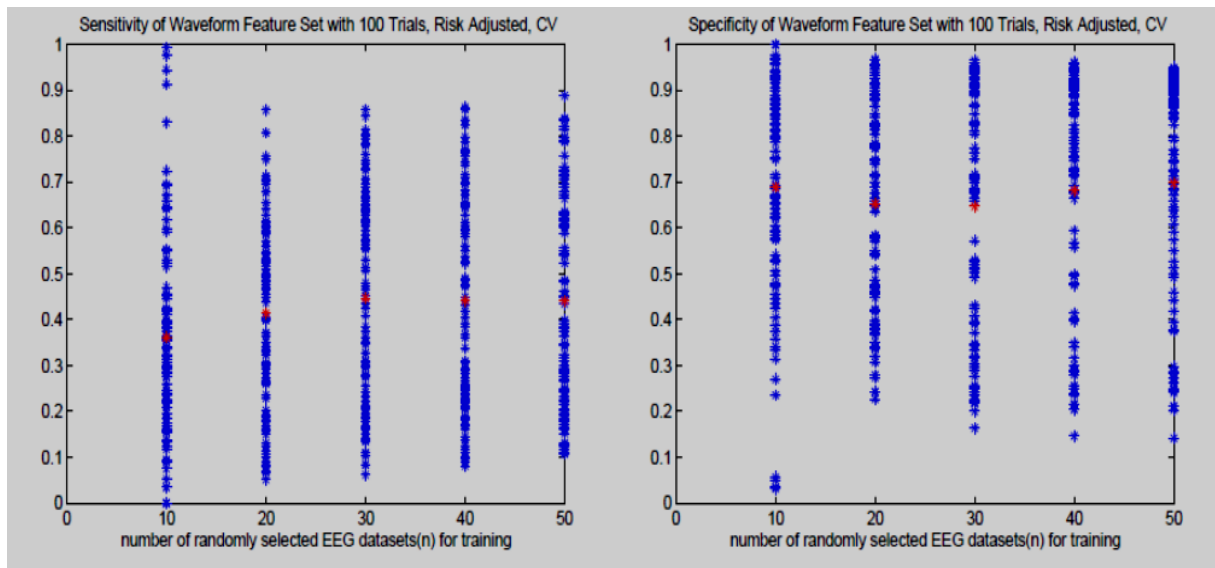


Fig. 7: sensitivity & specificity for RBFNN with waveform feature set.

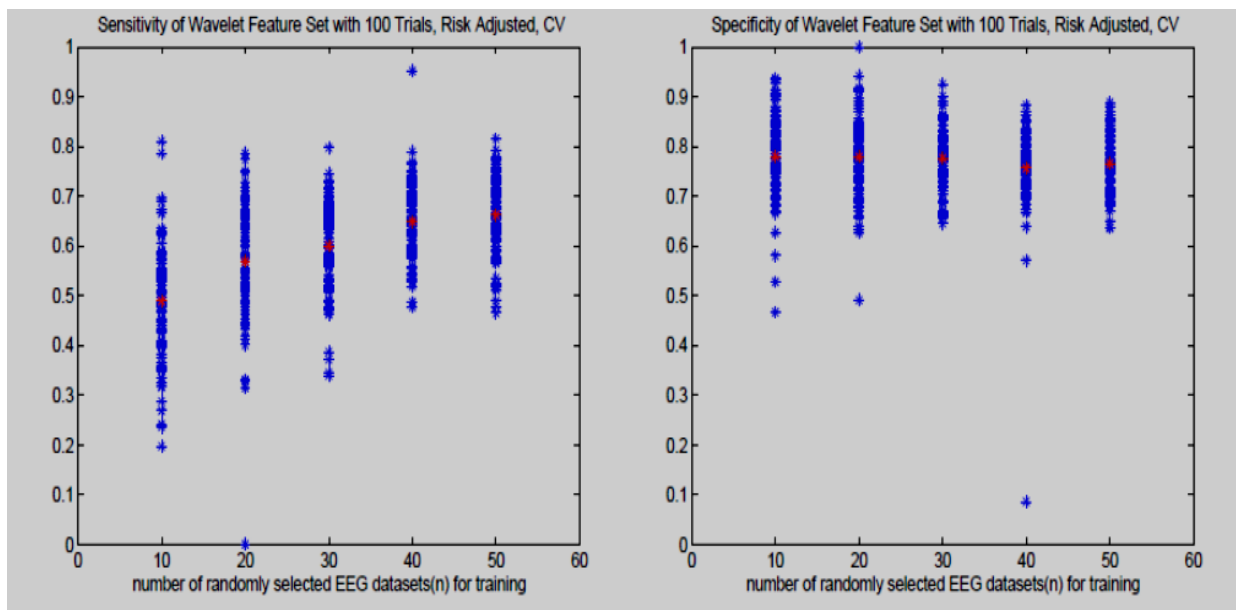


Fig. 8: sensitivity & specificity for FFBPNN with wavelet feature set.

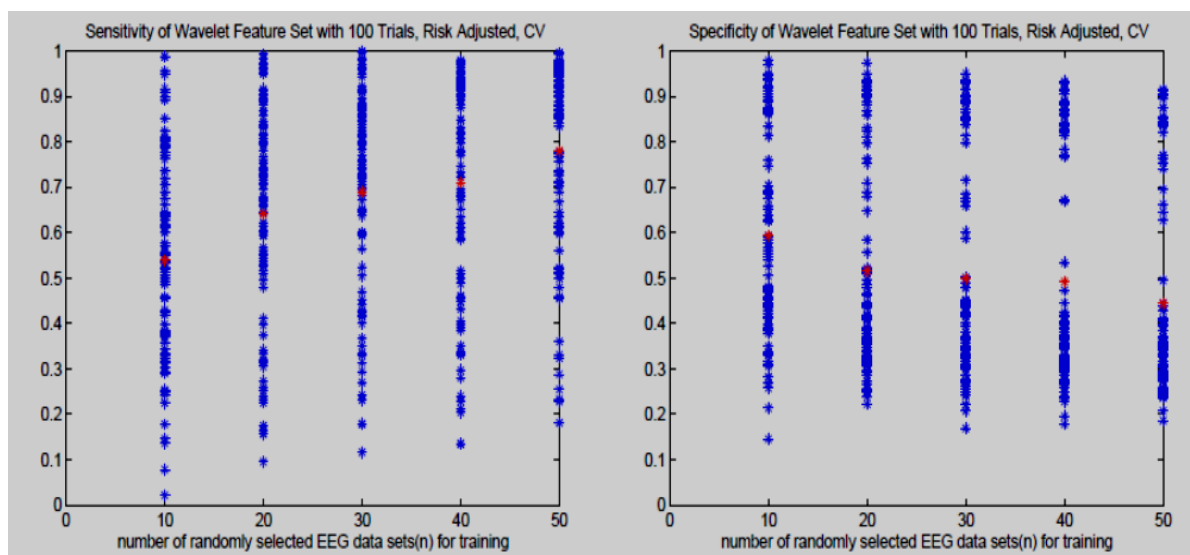


Fig. 9: sensitivity & specificity for RBFNN with wavelet feature set

TABLE I  
 Mean Sensitivity & Specificity for FFBPNN & RBFNN Classifiers

FEATURES	validation	FFBPNN		RBFNN	
		sensitivity	specificity	sensitivity	specificity
FFT	10	28.78%	82.78%	39.76%	73.75%
	20	34.56%	79.61%	49.93%	62.94%
	30	42.38%	77.32%	60.85%	56.73%
	40	48.70%	76.11%	61.25%	55.58%
	50	52.34%	76.11%	65.12%	53.47%
	average	41.352	78.386	55.382	60.494
WAVEFORM	10	30%	80.71%	35.32%	69.28%
	20	35.42%	77.24%	40.54%	63.36%
	30	40.87%	75.48%	41.87%	63.35%
	40	41.32%	75.06%	41.06%	69.74%
	50	45.87%	75%	41.06%	70.05%
	average	38.708	76.698	39.97	67.156
WAVELET	10	48.23%	77.59%	53.24%	59.87%
	20	54.87%	78.19%	63.56%	51.36%
	30	58.97%	77.73%	67.98%	50.04%
	40	60.37%	76.58%	68.31%	49.68%
	50	62.48%	76.58%	75.69%	44.83%
	average	56.984	77.334	65.756	51.156

### V. CONCLUSION

We have carried out various feature sets; waveform morphology, frequency, & wavelet and two classification methods; FFBPNN, & RBFNN to classify the "AEP" and "nonAEP" situations. We also assessed the results using level of sensitivity & specificity. Based on the results we can conclude:

- 1) RBFNN with wavelet features produces the best level of sensitivity (65.756%) and most affordable specificity (51.156%).



2) The variances of RBFNN classifier results are always large than corresponding results of FFBPNN. The explanation for this large span is that we now have overlaps of AEP and nonAEP datasets and elements of the features aren't carrying out a Gaussian distribution even as we assumed for RBFNN.

3) Taking into considering the level of sensitivity and specificity performance, the wavelet feature sets achieved relatively the better results than other feature sets.

4) Reviewing table 1 we can summarized that the specificity is obviously better than related sensitivity. That is because of the unbalanced patient information since there are just 31 patients providing AEP data segments while all the 100 patients providing nonAEP data segments.

5) When the size of training sets grows, the level of sensitivity of the classifier typically raises while specificity decreases.

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