



# **Feature Extraction of Epilepsy Seizure Using Neural Network**

Meenakshi, Dr. R.K Singh

M. Tech scholar, KNIT Sultanpur, Uttar Pradesh, India

Electronics Engg. Dept., KNIT Sultanpur, Uttar Pradesh, India

**ABSTRACT:** The neural network classifies, extract Features to identify the EEGs according to the percentage distribution of energy features. An area of great interest is the development of device that incorporate algorithms capable of detecting early onset of seizures or even predicting those hours before they occur. This lead time will allow for new types of interventional treatment. In the near future patient's seizure may be detected and treated well before any physical harm. Epilepsy is one of the most common neurological disorders with a widespread 0.6-0.8% of the world's population. One-third of the patients achieve sufficient seizure control from medicine and other 8-10% benefit from respective surgery. For the remaining 25% of patients, no sufficient treatment is currently available. There are number of researchers present in literature and still going on regarding automated detection of epileptic seizures. The work proposed by A Subasi [1] in 2005 decomposition of EEG signal applied to artificial neural network and the work proposed by D Najumnissa [2], the features are considered and modified using neural network. Feature extraction is most important for their classification of healthy and unhealthy subjects. Here we are using pattern recognition for feature extraction using some parameters.

**KEYWORDS:** Epilepsy, EEG, Artificial Neural Network, Feature Extraction

## **I.INTRODUCTION**

The EEG electroencephalography signals are generally used for the epilepsy diagnosis and the epileptic Seizure detection because they can provide valuable insight into disorders of the brain activity[3] Due to complex interactions between billions of neurons, the recorded EEG signals are manifested as non stationary, complex and they also consist of many sinusoidal component of different frequency bands[4]. Artificial Neural Networks (ANN) are widely used in the detection of the class of signal in many biomedical signal analysis because they have better predictive power than signal analysis Techniques [5-7].

**Table.1 Classification of Healthy and Unhealthy subject based on frequency range**

<b>Type</b>	<b>Frequency</b>	<b>Features</b>
Delta	0.5-4 Hz	It is primarily associated with deep sleep, serious brain disorder.
Theta	4-8 Hz	Theta wave arises from emotional stress or disappointment and unconscious material, creative inspiration and deep mediation.
Alpha	8-13 Hz	When the brain is in relaxation state.
Beta	13-30 Hz	When the brain is associated with active attention, mental activities.
Gamma	>30 Hz	It is associated with various cognitive and motor functions.

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## II. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks provide information in a similar way as the human brain does. The neural network is composed of a large number of highly interconnected processing neurons working in parallel to solve a specific problem [8]. In the human brain a typical neurons collects signal from others through a short section called dendrites. The neuron sends out spikes of electrical activity with a long thin portion known as an axon, which splits spikes into thousands of branches. Artificial Neural Networks consist of two layers an input layer containing the input variable to the problem and output layer containing the solution of the problem. Pattern recognition can be implemented by using a feed forward[9].Neural Network that has been trained shown in figure(1).During training the network is trained to associate output with input patterns[10-13]. When the network is used, it identifies the input pattern and tries to output

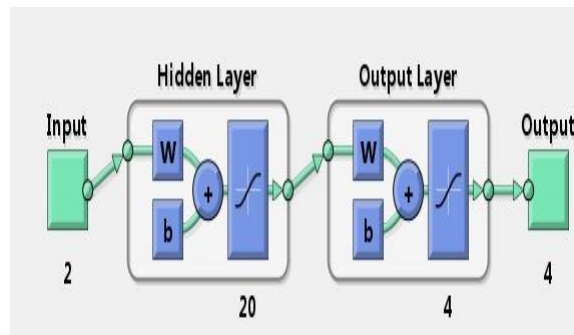


Fig.1 Neural Network

the associated output pattern. In this scheme, each node with message searches for possible path nodes to copy its message. Hence, possible path nodes of a node are considered. Using NSS, each node having message selects its path nodes to provide a sufficient level of end-to-end latency while examining its transmission effort. Here, it derives the CSS measure to permit CR-Networks nodes to decide which licensed channels should be used. The aim of CSS is to maximize spectrum utilization with minimum interference to primary system. Assume that there are M licensed channels with different bandwidth values and  $y$  denotes the bandwidth of channel  $c$ . Each CR-Networks node is also assumed to periodically sense a set of M licensed channels.  $M_i$  denotes the set including Ids of licensed channels that are periodically sensed by node  $i$ . suppose that channel  $c$  is periodically sensed by node  $i$  in each slot and channel  $c$  is idle during the time interval  $x$  called channel idle duration. Here, it use the product of channel bandwidth  $y$  and the channel idle duration  $x$ ,  $t_c = xy$ , as a metric to examine the channel idleness. Furthermore, failures in the sensing of primary users are assumed to cause the collisions among the transmissions of primary users and CR-Networks nodes.

## III.EEG DATA

Healthy subject and epileptic EEG subject are used separately to test the performance of the proposed method.

EEG Hardware	Brain Amp. Amplifier
Kind of electrode	Ag/Agcl
Hardware reference	Electrodes , Neurofeedback
Sampling Rate	1000 Hz
Hardware filter	Hum notch filter
Software filter	Band pass filter
Other Hardware	None
Patient state during reading	Relax sitting on chair

In epileptic EEG database the data set IV for Brain Computer Interface (BCI) [14-17] contain EEG recording from two subjects during two kind of task which are the epilepsy and healthy human. The recording was made using Brain Amp amplifier and a 128 channel. Ag/Agcl electrode cap from ECI 118 EEG channel were measured. Analysis have been done for each data Here we are taking some fixed channel data which are more important for classification of signal.



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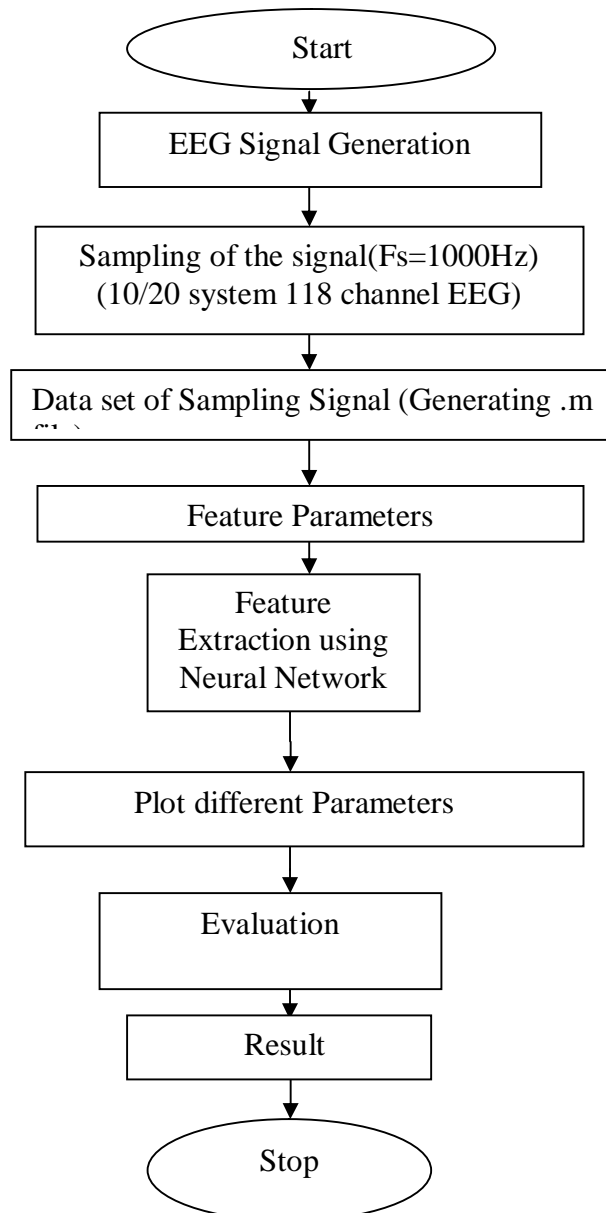
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## IV. FEATURE EXTRACTION

Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully preferred it is predictable that the features set will extract the applicable information from the input data in order to perform the desired task using this summary representation in place of the full size input [18]. Feature extraction involves simplify the amount of resources required to illustrate a large set of data exactly. When performing analysis on complex data one of the major problem is the number of variables implicated. Analysis with a large number of variables requires large amount of memory and calculation power or classification algorithm which over fits the training sample. Feature extraction is a general term for methods of constructing combinations of the variables to get about these problems while still relating the data with sufficient accuracy [19].

## V. FLOW CHART OF FEATURE EXTRACTION TECHNIQUES



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(An ISO 3297: 2007 Certified Organization)

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Pattern recognition, feature extraction is a special form of dimensionality decline. When the input data to an algorithm is too large to be processed and it is assumed to be disgracefully unnecessary (much data, but not much information) then the input data will be transformed into a reduced representation set of features.

## Feature Parameters:

**I. Minimum-** Minimum value of cluster

Min= $\min(K_i)$ , where  $i=1, \dots, n$

**II. Maximum-** Maximum value of cluster

Max= $\max(K_i)$ , where  $i=1, \dots, n$

**III. Mean-** Mean value of the absolute values of each channel signal.

$$F_i = \frac{1}{n} \sum_{j=1}^N |S_{ij}|^2$$

A feed forward neural network is an artificial neural network where connections between the units do not form a bound of cycle. The feed forward neural network was the first and possibly simplest type of artificial neural network. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes to the output nodes [20]. There are no cycles or loops in the network. Feed forward networks have one-way connections from input to output layers. They are most commonly used for forecast, pattern recognition, and nonlinear function fitting. Supported feed forward networks include feed forward back propagation, cascade-forward back propagation, feed forward input-delay back propagation, linear, and perception networks.

**Two layer feed forward network:** A two-layer neural network capable of calculating XOR. The numbers within the neurons represent each neuron's explicit threshold. The numbers that explain arrows represent the weight of the inputs. This net assumes that if the threshold is not reached, zero (not -1)[21] is output. Note that the bottom layer of inputs is not always considered a real neural network layer as shown in Fig 3

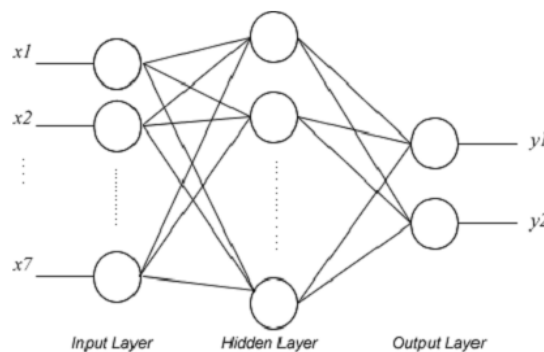


Fig.3 Neural Network Calculating XOR

## VI. PERFORMANCE

**Mean square error (MSE):** It is a network performance function. It measures the network's performance according to the mean of squared errors. Mean squared error (MSE) of an estimator is one of many ways to quantify the difference between values implied by an estimator and the true values of the quantity being estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. MSE measures the average of the squares of the errors [22]. The error is the amount by which the value implied by the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate. As shown in fig below Fig 4.

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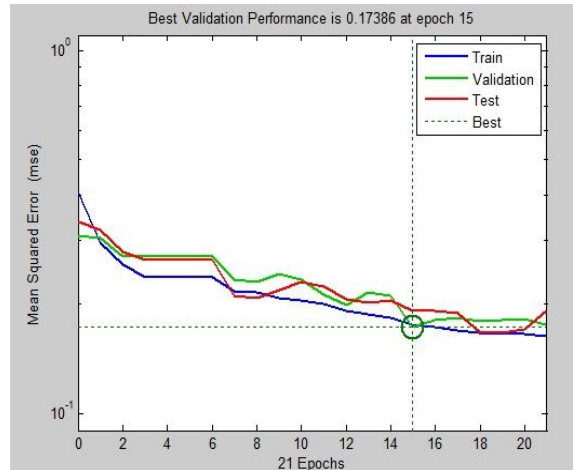


Fig.4- Performance analysis

After extracting the features from feature parameters The comparison is done between these feature parameters and performance is checked by classifying the data using this two methods the classifier work is done by Neural Network[23]. The methods are compared for performance before that the data is trained by neural Network pattern recognition tool box. Gradient is plotted and checked for the accuracy shown below in Fig 5.

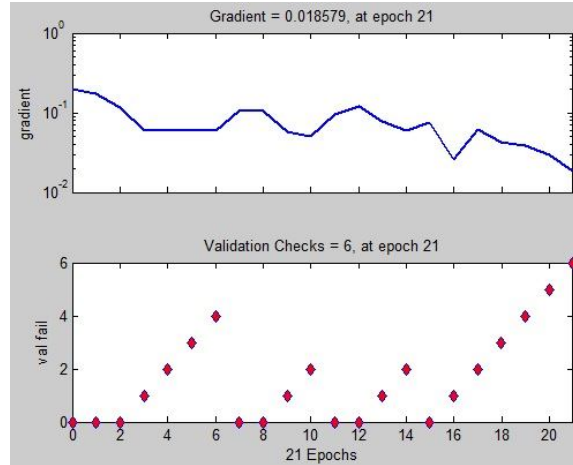


Fig5- Gradient Validation

In the field of artificial intelligence, a confusion matrix is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one. Each column of the matrix represents the instance in a predicted class, while each row represents the instances in an actual class. If a classification system has been trained to differentiate between cats, dogs and rabbits, a confusion matrix will summarize the results of testing the algorithm for further inspection. As shown in Fig 6

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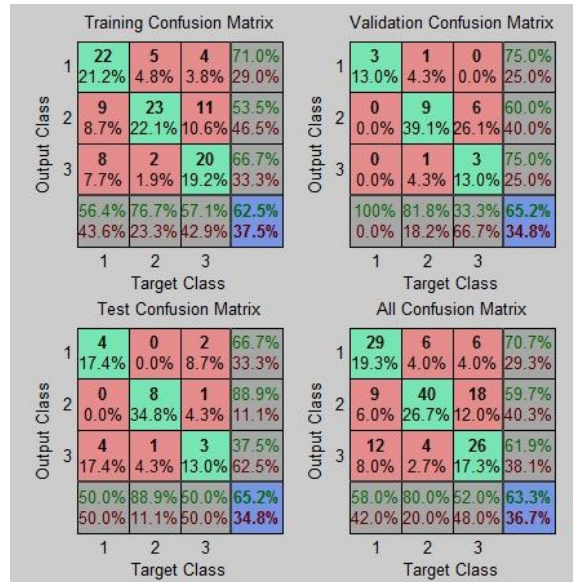


Fig 6-Confusion matrix

In signal detection theory, a receiver operating characteristic (ROC), or simply ROC curve, is a graphical plot which illustrates the presentation of a binary classifier system as its inequity threshold is varied. ROC analysis provides tools to select possibly optimal models and to discard suboptimal ones separately from (and prior to specifying)[24] the cost context or the class division. ROC analysis is related in a direct and natural way to cost benefit analysis of diagnostic decision making. ROC is been used in medicine, radiology, biometrics, and other areas for many decades and is increasingly used in machine learning and data mining research. As shown in below Fig 7

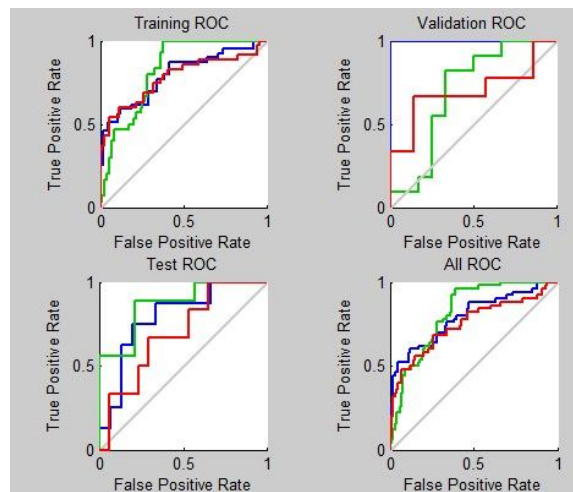


Fig 7-ROC

## VII. RESULT & DISCUSSION

An artificial neural network using pattern recognition that classifies subjects as having or not having an epileptic seizure provides a valuable diagnostic decision support tool for neurologist treating potential epilepsy. In pattern recognition we evaluate the percentage differ in healthy and unhealthy subjects in confusion matrix. Using the confusion matrix and Receiver Operating Characteristics (ROC) we summarized the feature difference between healthy and unhealthy subject. Features are extracted using feature parameters method. It evaluated for their performance using pattern recognition tool box from the obtained results it has observed that the feature parameter extraction gives better



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accuracy comparison to the other feature extraction method. Further Research is needed to find more accurate memory architectures and its appropriate training algorithms.

## VIII. FUTURE SCOPE

Advantage of EEG Signal Extraction-Feature extraction and classification are used for investigation of the following clinical problems [18-20]. (i) Monitoring alertness, coma, and brain death. (ii) Locating areas of damage following head injury, tumour, and stroke. (iii) Testing afferent pathways (by evoked potentials). (iv) Monitoring cognitive engagement (alpha rhythm). (v) Producing biofeedback situations. (vi) Controlling anesthesia depth (servo an aesthesia). (vii) Investigating epilepsy and locating seizure origin. (viii) Testing epilepsy drug effects. (ix) Assisting in experimental cortical excision of epileptic focus. (x) Monitoring the brain development. (xi) Testing drugs for convulsive effects. (xii) Investigating sleep disorders and physiology. (xiii) Investigating mental disorders. (xiv) Providing a hybrid data recording system together with other imaging modalities.

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