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Automatic Support System for Classifying Brain Signal

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Abstract— The diagnosis system presents to classify the EEG brain signal of patient to distinguish between normal and abnormal as tumor and epilepsy with better classification accuracy. The prediction of the brain tumor is a demanding problem, due to the cells complex structure. The artificial neural network classifies the stage of brain signal that is tumor case or epilepsy case or normal. The human study of the signal is time consuming, inaccurate and needs intensive trained person to avoid diagnostic errors. The system uses the back propagation with feed forward for classification with the supervised training and non knowledge based classification. Decision making was performed in feature extraction using Principal Component Analysiswith help of learning samples. The work of the BPN classifier was evaluated in terms of training performanceand classification accuracies. The test samples will be classified using network parameters and its features. The system gives improved performance accuracy for different test samples.

Keywords— Artificial Neural Network(ANN), Back Propagation Network (BPN), Feature Extraction, Principal Component Analysis(PCA), Electroencephalogram (EEG).

I. INTRODUCTION

In Recent years,automated classification and detection of Tumors in brain using different brain signals is triggered by the necessity of high meticulousness when dealing with a human life. Also, the computer aid is demanded in medical institutions due to the fact that it could improve the results than the human analysis where the false cases must be at a very flat rate. It has been declared that double reading of medical images could lead to better Tumor detection. But the cost inferred in double reading is very high, and so good software to assist humans in medical institutions is of great interest nowadays. A traditional method of monitoring and diagnosing the diseases depends on detecting the presence of particular features by a human observer. Due to large number of patients in intensive care units and the need for continuous observation of such conditions, several techniques for automated diagnostic systems have been developed in recent years to attempt to solve this problem. Such techniques work by transforming the mostly qualitative diagnostic criteria into a more objective quantitative feature classification problem. Automated classification of Brain signals by using some prior knowledge like intensity and some anatomical features is proposed. Currently there are no methods widely accepted therefore automatic and reliable methods for Tumor detection are of great need and interest. The application of BPN in the classification of data for EEG signals problems are not fully utilized yet. These included the feature extraction and classification techniques especially for CT images problems with huge scale of data and consuming times and energy if done manually.

At present, Brain–Computer Interfaces (BCI) is the best feasible way of providing the communication between the human and the system by means of brain signals. By using this BCI the patients can put across their views or needs by means of their brain signals just by thinking process. The signal classification module is composed of the obtained EEG signal features extraction and the transformation of these signals into device instructions. The EEG classification tactic depends on the inducement and, thereby, the reaction to detect motor imagery, event related potentials, slow cortical potentials, or steady-state evoked potentials. The predicted EEG drives the classification to some precise feature extraction methods.

Feature extraction involves a data reduction method which will be applied to each signal for converting multi band to single band data using PCA. PCA is mathematically defined as an orthogonal linear transformation. PCA is also sensitive to the scaling of variables.Principal Component Analysis is used to reduce the large dimensionality of the data and multi spectral band reduction through extracting features like *mean value,covariance*, *Eigen values*, *Eigenvectors*and *Eigen faces.*It is useful for discriminating the pattern of different signals with limited features. The signal reduction is used to explain the majority of its variability compared to multiband features.

Neural networks are predictive model based on the action of biological neurons.Back propagation algorithm is finally used for classifying the pattern of malignant and benign tumor. The performance of the Back Propagation network was evaluated in terms of training performance and classification accuracies. The system uses the back propagation with *feed forward* for classification. There are two main phases which are *training and testing phase.* BPN will automatically select the correct type of network based on the type of target variable.

The back-propagation learning rule can be used to adjust the weights and biases of networks to minimize the sum squared error of the network. The advantage of using BPN is that it is usually much faster to train BPN network than a multilayer network and also they generate accurate predicted target probability scores

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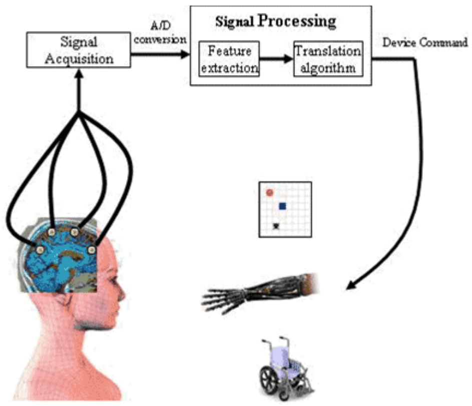

Figure 1: Brain-Computer Interface

II. SYSTEM ANALYSIS

Electroencephalography (EEG), a non-invasive recording technique, is one of the commonly used systems for monitoring brain activity. EEG data is simultaneously collected from a multitude of channels at a high temporal resolution, yielding high dimensional data matrices for the representation of single-trial brain activity.EEG Signals are classified using Neural Network. Feature extraction of EEG signals is core issues on EEG based brain mapping analysis. The classification of EEG signals has been performed using features extracted from EEG signals. Many features have proved to be unique enough to use in all brain related medical application.

In existing, they mainly focused to observe distinctive spatio-temporal brain patterns at intervals a group of event connected responses. They introduced a completely unique classification formula, the spatially weighted FLD-PCA (SWFP), that relies on a ballroom dance linear classification of event-related responses, mistreatment fisher linear discriminant (FLD) classifier and principal element analysis (PCA) for spatiality reduction. They also used discriminant element Analysis (HDCA), introduced by Parra, et al. 2007. They also used a modified version of HDCA, discriminant principal component analysis formula (HDPCA). Finally they compared single-trial classification accuracies of all the 3 algorithms. It is found that HDPCA significantly increased classification accuracies compared to the HDCA.

There is also some limitationusing these methods. It is not applicable for multiple signals for abnormal detection in a short time. They used shift invariant property and there occurs a loss of details due to shift invariant property. Although HDPCA increased the classification accuracies compared to HDCA, still the accuracy need to be improved for better classification to find the exact result.

III. PROPOSED WORK

The main objective is to design an ANN based EEG classifier which distinguishes between the EEG signal of a normal patient and that of a brain tumor patient.

Classification of signal from EEG for brain abnormal Detection based onPrincipal Component Analysis and Artificial Neural Network.

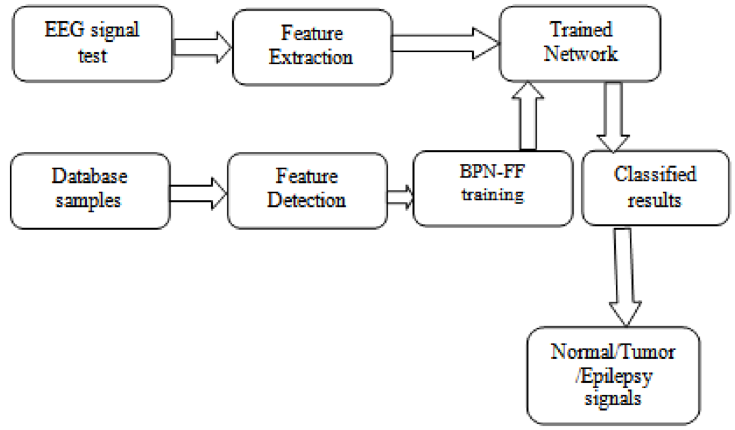

Figure 2: Proposed system block diagram

The purpose of PCA is to reduce the large dimensionality of the data. PCA is an effective tool for analyzing data and finding patterns in it. It is a form of unsupervised learning and data compression is possible. By projecting the data from higher dimensional into a lower dimensional space that precisely characterizes the state of the process, dimensionality reduction methods can significantly simplify and progress process monitoring procedures.

Back propagation network gives fast and accurate classification and is a promising tool for classification of the signals. The back propagation and feed forward algorithms are often used together. Feed-forward describes how neural network processes and recalls patterns.

A. Feature Extraction Using Pca

Feature extraction is related to dimensionality reduction. Here it is done using Principal component analysis. PCA is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn

has the highest variance possible under the constraint that it be orthogonal to (i.e., uncorrelated with) the preceding components. Principal components are guaranteed to be independent only if the data set is jointly normally distributed. Principal component analysis is mainly used for *feature extraction* process which involves eliminating the redundant data from given samples.

PCA STEPS:

- Input.
- Subtract the mean

- Calculate the covariance matrix
- Calculate the eigenvectors and Eigen values of the covariance matrix
- Choosing components and forming a feature vector
- Deriving the new data set.

Mean value is calculated by taking average of inputs. *Difference matrix is* calculated by taking difference between input and its matrix value. *Covariance* is calculated by multiplying difference matrix and its inverse. Each Eigen value is proportional to the portion of the "variance" (more correctly of the sum of the squared distances of the points from their multidimensional mean) that is correlated with each Eigen vector. Finally Using those set of Eigen vectors we can construct Eigen faces.

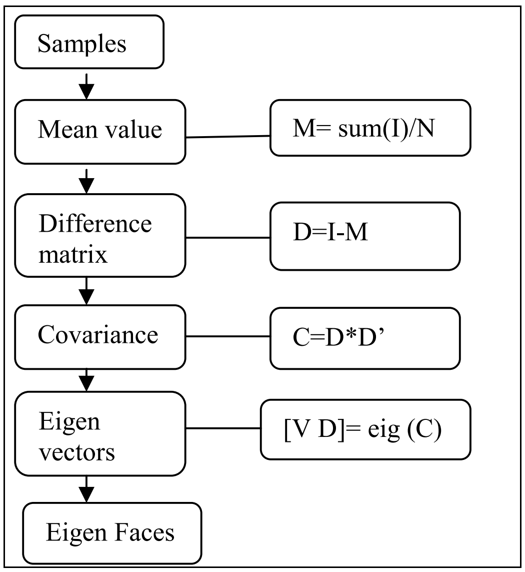

Figure 3:Algorithm flow of Feature Extraction

B. Process Of Artificial Neural Network

The selection of the name “neural network” was one of the great successes of the Twentieth Century. It certainly sounds more exciting than a technical description such as “A network of weighted, additive values with nonlinear transfer functions”. A typical artificial neural network might have a hundred neurons. In comparison, the human nervous system is believed to have about $3x10^{10}$ neurons.

Types of Neural Networks:

- Artificial Neural Network
- Back propagation networks
- General Regression Neural Networks

This network has an input layer (on the left) with three neurons, one hidden layer (in the middle) with three neurons and an output layer (on the right) with three neurons. There is one neuron in the input layer for each predictor variable. In the case of categorical variables, N-1 neurons are used to represent the N categories of the variable.

The following diagram illustrates a perception network with three layers:

Input Layer: The input layer distributes the values to each of the neurons in the hidden layer.

Hidden Layer: Arriving at a neuron in the hidden layer, the value from each input neuron is multiplied by a weight (w_{ji}).

Output Layer: Arriving at a neuron in the output layer, the value from each hidden layer neuron is multiplied by a weight (w_{kj}).

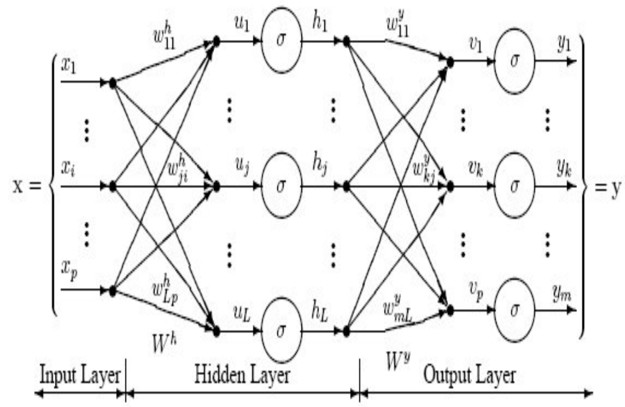

Figure 4: The Multilayer Neural Network Model

C. Back Propogation With Feed Forward Network

Back Propagation (BPN) and General Regression Neural Networks (GRNN) have similar architectures, but there is a fundamental difference: Probabilistic networks perform classification where the target variable is categorical, whereas general regression neural networks perform regression where the target variable is continuous. If you select a BPN/GRNN network, DTREG will automatically select the correct type of network based on the type of target variable.

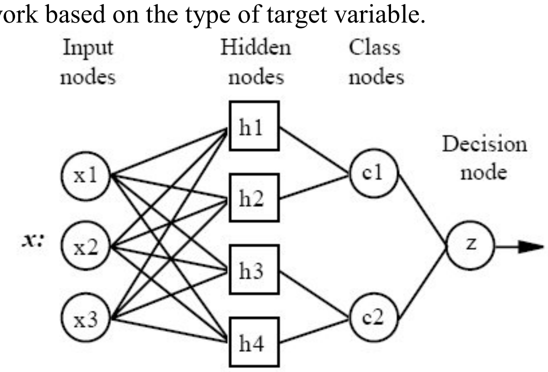

Figure 5: Architecture of BPN

D. Back Propagation with feed forward Algorithm:

Consider a network with a single real input x and network function F. The derivative F’(x) is computed in two phases: Feed-forward: the input x is fed into the network. The primitive functions at the nodes and their derivatives are evaluated at each node. The derivatives are stored.Back propagation: The constant 1 is fed into the output unit and the networkis run backwards. Incoming information to a node is added and the result is multiplied by the value stored in the left part of the unit. The result is transmitted to the left of the unit. The result collected at the input unit is the derivative of the network function with respect to x.

STEPS OF THE ALGORITHM

The back propagation algorithm is used to compute the necessary corrections, after choosing the weights of the network randomly. The algorithm can be decomposed in the following four steps:

i) Feed-forward computation
ii) Back propagation to the output layer
iii) Back propagation to the hidden layer
iv) Weight updates

The algorithm is stopped when the value of the error function has become sufficiently small.The classifier will classify the input test sample into three classes such as normal, tumour and epilepsy cases.

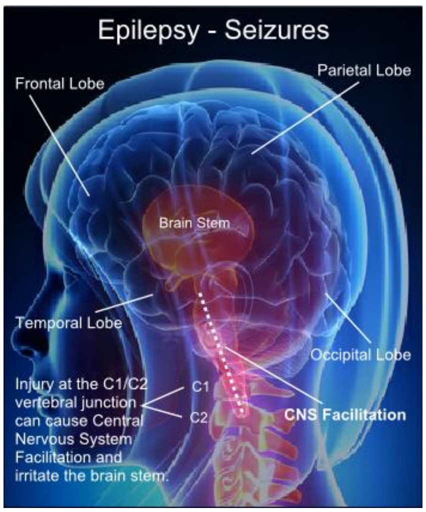

Figure 6: Image of Epilepsy

IV. CONCLUSION

The project presented an automated brain diseases diagnosis system with the supervised back propagation with feed forward neural network to detect abnormality such as tumor and epileptic case. Inorder to improve the system performance, the classifier has trained with the features of principal components. The simulated system provided that the better classification accuracy of input samples and compatibility in this diagnosis.

V.FUTURE ENHANCEMENT

In our proposed method, although we are able to handle high-dimensional data since we do not need to compute or to keep the covariance matrix, PCA might not be preferable in estimating the principal directions for such kind of data. Therefore, we will pursue the study of these issues in our future work and multiple disease predication analysis the same method.

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