

EEG Signal Classification Using Artificial Neural Network and Principal Features Analysis for Brain Diseases Diagnosis

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Abstract: *The project proposes an automatic support system for stage classification using artificial neural network for brain tumor and epilepsy detection for medical application. The detection of the brain tumor is a challenging problem, due to the structure of the tumor cells. The artificial neural network will be used to classify the stage of brain EEG signal that is tumor case or epilepsy case or normal. The manual analysis of the signal is time consuming, inaccurate and requires intensive trained person to avoid diagnostic errors. Back Propagation Network with image and data processing techniques was employed to implement an automated Brain Tumor classification. Decision making was performed in two stages: feature extraction using Principal Component Analysis and the classification using Back Propagation Network (BPN). The performance of the BPN classifier was evaluated in terms of training performance and classification accuracies. Back Propagation Network gives fast and accurate classification than other neural networks and it is a promising tool for classification of the Tumors.*

I. Introduction

Automated classification and detection of Tumors in different medical signals is motivated by the necessity of high accuracy when dealing with a human life. Also, the computer assistance is demanded in medical institutions due to the fact that it could improve the results of humans in such a domain where the false negative cases must be at a very low rate. It has been proven that double reading of medical images could lead to better Tumor detection. But the cost implied in double reading is very high, that's why good software to assist humans in medical institutions is of great interest nowadays. Conventional methods of monitoring and diagnosing the diseases rely 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.

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.

II. Existing Approches

- Manual analysis
- Distance based signal classification

KNN Classifier

In pattern recognition, the k-nearest neighbor algorithm (k-NN) is a method for classifying objects based on closest training examples in the feature space. k-NN is a type of instance-based learning, or lazy learning where the function is only approximated locally and all computation is deferred until classification. The k-nearest neighbor algorithm is amongst the simplest of all machine learning algorithms: an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of its nearest neighbor.

The same method can be used for regression, by simply assigning the property value for the object to be the average of the values of its k nearest neighbors. It can be useful to weight the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. (A common weighting scheme is to give each neighbor a weight of $1/d$, where d is the distance to the neighbor. This scheme is a generalization of linear interpolation.)

Drawbacks

- Less accuracy in classification
- Medical Resonance images contain a noise caused by operator performance which can lead to serious inaccuracies classification.

Discrete Wavelet Transform

In mathematics, a wavelet series is a representation of a square-integrable function by a certain orthonormal series generated by a wavelet. This article provides a formal, mathematical definition of an orthonormal wavelet and of the integral wavelet transform.

Drawbacks

- Loss of details due to shift variant property.

III. Proposed Method

EEG Classification for brain abnormal Detection based on GLCM Artificial Neural Network for classification

Advantages

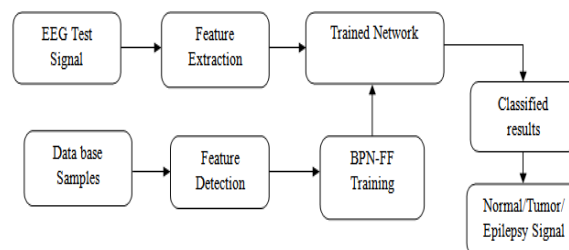
Using ANN, the need for a neurologist to analyze EEG signals is eliminated or minimized.

- Flexible in features detection.
- Time consumption is less.

Methodologies

- Principal Component analysis
- BPN with feed forward network

IV. Block Diagram



Gray-Level Co-occurrence Matrices

The Gray Level Co-occurrence Matrix1 (GLCM) and associated texture feature calculations are image analysis techniques. Given an image composed of pixels each with an intensity (a specific gray level), the GLCM is a tabulation of how often different combinations of gray levels co-occur in an image or image section. Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity (a.k.a. image texture) at the pixel of interest.

$$Energy = \sum_{i,j=0}^{N-1} (P_{ij})^2$$

Entropy feature

$$Entropy = \sum_{i,j=0}^{N-1} -\ln(P_{ij}) P_{ij}$$

Contrast feature

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij} (i - j)^2$$

Homogeneity feature

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1 + (i - j)^2}$$

Correlation feature

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i - \mu)(j - \mu)}{\sigma^2}$$

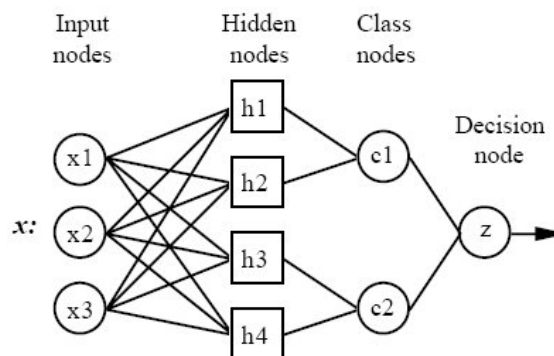
Shade feature

$$Shade = \text{sgn}(A) |A|^{1/3}$$

Back propagation networks (BPN):

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.

Architecture of a BPN:



All BPN networks have four layers:

Input layer — There is one neuron in the input layer for each predictor variable. In the case of categorical variables, N-1 neurons are used where N is the number of categories. The input neurons (or processing before the

input layer) standardizes the range of the values by subtracting the median and dividing by the interquartile range. The input neurons then feed the values to each of the neurons in the hidden layer.

Hidden layer — This layer has one neuron for each case in the training data set. The neuron stores the values of the predictor variables for the case along with the target value. When presented with the x vector of input values from the input layer, a hidden neuron computes the Euclidean distance of the test case from the neuron's center point and then applies the RBF kernel function using the sigma value(s). The resulting value is passed to the neurons in the pattern layer.

Pattern layer / Summation layer — The next layer in the network is different for BPN networks and for GRNN networks. For BPN networks there is one pattern neuron for each category of the target variable. The actual target category of each training case is stored with each hidden neuron; the weighted value coming out of a hidden neuron is fed only to the pattern neuron that corresponds to the hidden neuron's category. The pattern neurons add the values for the class they represent (hence, it is a weighted vote for that category).

For GRNN networks, there are only two neurons in the pattern layer. One neuron is the denominator summation unit the other is the numerator summation unit. The denominator summation unit adds up the weight values coming from each of the hidden neurons. The numerator summation unit adds up the weight values multiplied by the actual target value for each hidden neuron.

Decision layer — The decision layer is different for BPN and GRNN networks. For BPN networks, the decision layer compares the weighted votes for each target category accumulated in the pattern layer and uses the largest vote to predict the target category. For GRNN networks, the decision layer divides the value accumulated in the numerator summation unit by the value in the denominator summation unit and uses the result as the predicted target value.

V. Conclusion

It is easy identify the tumours in the brain and it is less time consuming and very efficient to diaganise by the doctor.

Reference

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