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Automated Epileptic Seizures Detection and Classification

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ABSTRACT

Detection of epileptic seizure activities from multi-channel electroencephalogram (EEG) signals plays a giant position inside the timely treatment of the sufferers with epilepsy. Visual identification of epileptic seizure in long-time period EEG is bulky and tedious for neurologists, which may additionally cause human errors. An automated device for accurate detection of seizures in a protracted-time period multi-channel EEG is crucial for the scientific prognosis. The features selection is based on discrete wavelet transformation (DWT).and feature extraction based GLCM. In the last stage, Probabilistic Neural Network is employed to classify the Normal and epileptic EEG signals.

Keywords : Electroencephalogram Signals, Probabilistic Neural Network, Discrete Wavelet Transformation, Gray-Level Co-Occurrence Matrix

I. INTRODUCTION

Epilepsy is a serious chronic incurable brain disease. It is a critical neurological sickness stemming from transient strange discharges of the brain electric activity, leading to uncontrollable actions and trembling seizures often manifested as sudden, transient movement, autonomic nervous or psychiatric symptoms, such as abnormalities, affecting patients' physical and intellectual development and it could even be life-threatening. Now a days EEG is the most effective manner to diagnose epilepsy. Epilepsy is diagnosed through visual examination of EEG signals to find abnormalities. However this method is not only time consuming but also leads to misdiagnosis due to subjectivity and retrospective analysis. Therefore, it is necessary to find a real time and accurate automatic detection technology.

Therefore, the analysis of epilepsy allows the selection of remedy or surgical remedy. Since the electroencephalogram (EEG) records display the mind electrical sports, they are able to offer valuable insight into problems of the brain interest [1]. In this context, the EEG recordings measured in seizure-unfastened intervals from the epilepsy patients are considered as vital additives for the prognosis or prediction process. Although the prevalence of epileptic seizures appears unpredictable, greater efforts are targeted on the development of computational fashions for computerized detection of epileptic discharges, which then can be used to expect the onset of seizure. EEG is a scientific system executed for monitoring, diagnosing, and figuring out neurological disorders associated with epilepsy. Epilepsy is a neurological sickness precipitated because of strange electric discharges inside the mind which can be characterized by way of seizures and sudden adjustments inside the electric pastime of the mind. An epileptic seizure is normally diagnosed as a sluggish-spike waveform. The unpredicted nature of those seizures makes the each day lifestyles motionless with transient impairments of perception, speech, reminiscence, recognition and can cause an accelerated danger of injury or death. The lengthy-term video-EEG recording is big milestones to now not simplest seize and examine activities however also help in the contribution of treasured medical records. Traditional techniques of studying EEG are time-ingesting and a tedious activity done by using neurologists. Visual interpretation of those lengthy-time period EEG recordings can result in human mistakes and is inefficient. The brain is a nonlinear and complex dynamic gadget, so detecting seizures by means of a single-channel EEG isn't sufficient [2]. Thus, the processing of multi-channel EEG performs a vital position in seizure detection throughout the brain. However, multi-channel EEG alerts impose the challenge of efficiently extracting beneficial facts, and therefore, best a few studies have focused on them. An ample range of research had been proposed for seizure detection. Such approach entails preprocessing, feature extraction, and classification. Selecting extensive features is crucial to distinguish among everyday and epileptic EEG indicators. Our consciousness is on making the activity of the neurological professionals clean via making the abnormality visually comprehensible by means of the usage of the multi-functions extraction techniques. So some distance, numerous automated epileptic seizure detection methods have been proposed. The automated seizure detection technique for a protracted duration of EEG recordings considers line period of EEG as a function and artificial neural networks for classification. The dataset is subjected to preprocessing, visual inspection, and artifact removal. EEG signals are decomposed into special sub-bands using discrete wavelet remodel (DWT), and line duration feature is extracted. Then the extracted features are given as input to the PNN classifier which classifies the given EEG signal as either normal or epileptic.

II. RELATED WORK

Jiang et al. proposed Seizure classification of EEG signals using transfer learning, semi supervised learning and TSK fuzzy system [4]. They implemented transductive transfer learning, semi supervised learning and task fuzzy system but this process takes longer duration to train and test the dataset. Daniel et al. proposed Epileptic focuses localization using discrete wavelet transform based on interictal intracranial EEG [5]. In that they designed a framework to use DWT and support vector machine (svm) for epileptic focus localization problem based on EEG. The major drawback was the final model did not provide good results. G. R. Suresh et al. performed analysis of lifting based DWT and MLPNN for epilepsy seizure detection from EEG [6]. The proposed model classifies the data using a multilayer perceptron neural network, which takes longer time to classify. These drawbacks are overcome by our system which uses a combination of DWT and GLCM for feature extraction and feature selection. The probabilistic neural network which has four layers of process involved is implemented for providing better classification.

III. IMPLEMENTATION DETAILS

Proposed System

The proposed system considers the EEG signals as input. Then features are extracted using the discrete wavelet transform (DWT) and GLCM. Finally the extracted features are given as input to the probabilistic neural network for classification. The figure shows the proposed model.

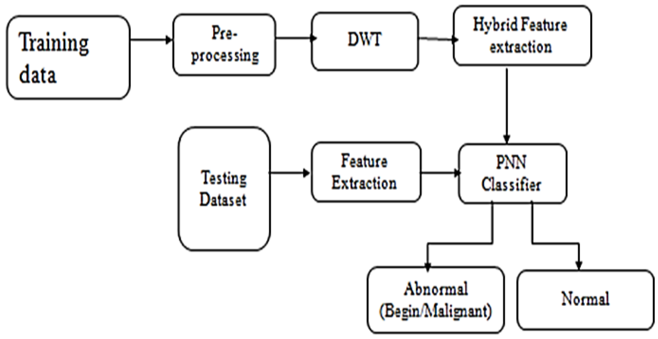

Figure 1: Block diagram of the proposed system

A. Dataset Collection

The dataset is taken from UCI Machine Learning Repository. It is a multivariate time series data having 178 features against 1 categorical attribute through 11500 instances. Each number represents a voltage signal corresponding to the brain activity at a point of time. The dataset was also collected from EEG / ERP data available for free public download, BNCI Horizon 2020 project, engineering.

B. Feature selection and extraction

Feature selection is done for filtering irrelevant or redundant features from the dataset. Feature selection is based on DWT (discrete wavelet transform). Feature extraction is used for machine learning, pattern recognition and in image processing. Feature extraction is based on GLCM(gray-level co-occurrence matrix)[9].

DWT (discrete wavelet transform)

The discrete wavelet transform (DWT) algorithm has a firm position in processing of signals in various areas of research and industry. DWT provides octave-scale frequency and spatial timing of the analyzed signal and it is constantly used to solve and treat advanced problems. It is used for signal coding to represent a discrete signal in a more redundant form which acts a preconditioning for data compression. Practical applications can also be found in signal processing of accelerations for gait analysis, image processing and in digital communications. The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations which obeys some defined rules. The set of wavelets form an orthonormal basis which is used to decompose the signal.

GLCM(gray-level co-occurrence matrix)

A co-occurrence matrix is a matrix that is defined over an image where the distribution of co-occurring pixel values occurs at a given offset. Pair of matrices can be used to generate a co-occurrence matrix. The textural features which can be extracted from the co-occurrence matrix are Correlation, Variance, Inverse Difference Moment, Sum Average, Sum Variance, Sum Entropy, Entropy, Difference Variance, Difference Entropy, Mean of Correlation, and etc. These data are given as the input for classification of data.

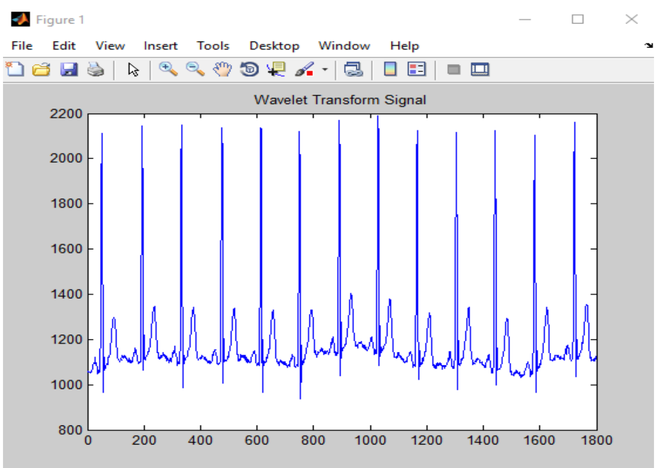

Figure 2: Feature Extraction and selection using DWT and GLCM

C. PNN Classification

A probabilistic neural network (PNN) is a widely used in classification and pattern recognition problems[10]. In the PNN, the operations are organized into a multilayered feedforward network with four layers:

- Input layer
- Pattern layer
- Summation layer
- Output layer

1. Input layer

In input layer each neuron represents a predictor variable. When there are N number of categories N-1 neurons are used in categorical variables. It standardizes the range of the values by subtracting the median and dividing by the interquartile range. In the hidden layer the input neurons feed the values to each of the neurons.

2. Pattern layer

In pattern layer the training data set has one neuron for each case in this layer. Along with the target value it stores the values of the predictor variables for the case. A hidden neuron computes the Euclidean distance of the test case from the neuron's center point and then applies the radial basis function kernel function using the sigma values.

3. Summation layer

There is one pattern neuron for each category of the target variable in PNN. Each hidden neuron has the actual target category of each training case; the weighted value from hidden neuron is fed to the pattern neuron that corresponds to the hidden neuron's category. The pattern neurons add the values for the classes.

4. Output layer

The output layer compares the weighted votes for each target category accumulated in the pattern layer and uses the largest vote to predict the target category.

D. Training and Testing

A training set is used to train a model. The training set consists of 70 percent of the EEG signals from the collected dataset. Then features are extracted and given as input to the PNN classifier. Similarly the test set comprises of 30 percent of the signals from the dataset. The below figures shows the results of training and testing.

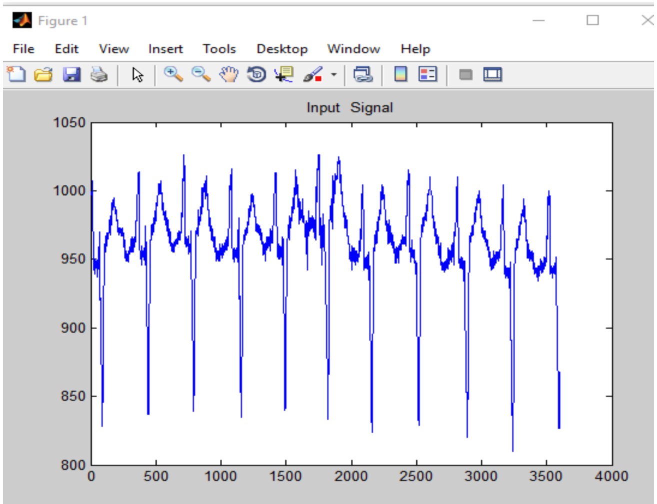

Figure 3: PNN Classification - Normal

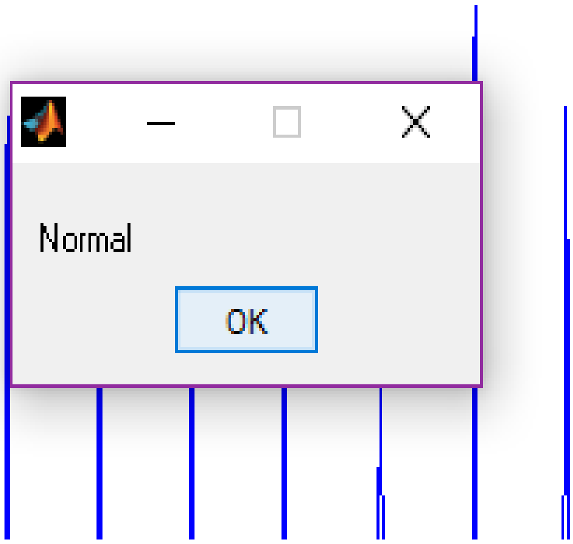

Figure 4: PNN Classification- Normal

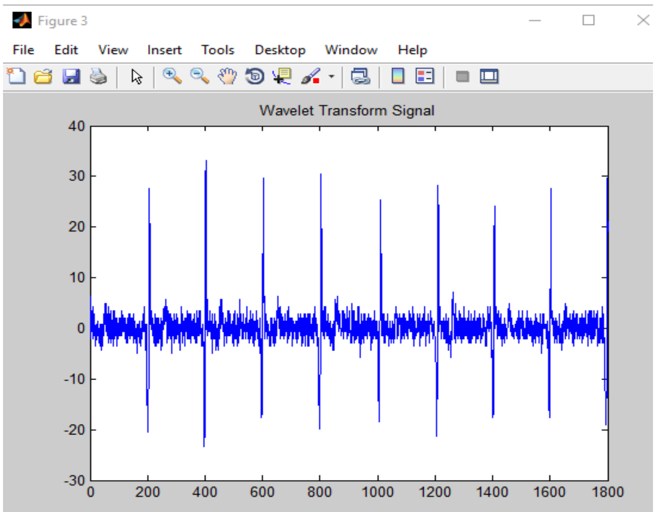

Figure 5: PNN Classification- Abnormal

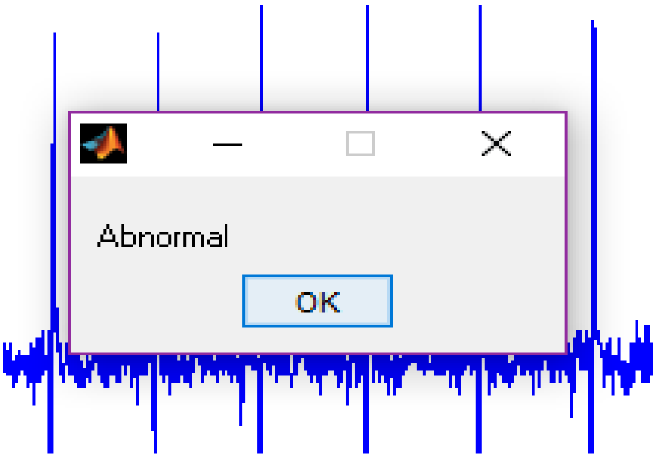

Figure 6: PNN Classification- Abnormal

IV. RESULT

Until now, not much is understood about the occurrence and mechanism underlying the epileptic seizure.Therefore, many automated epileptic detection systems have been developed using different approaches in the recent years. Such automated systems reduce the time taken to review offline the long-term EEG recordings significantly and facilitate the neurologist to diagnose and treat more patients in a given time. The model implemented detects the epileptic signals with an accuracy of 85%.

V. CONCLUSION

The study provides Detection of epileptic seizure activities from multi-channel electroencephalogram (EEG) signals. Visual identification of epileptic seizure in long-time period EEG is bulky and tedious for neurologists, which may additionally cause human errors. Therefore,an automated device for accurate detection of seizures in a protracted-time period multi-channel EEG is crucial for the scientific prognosis. The feature selection are based on Discrete wavelet transformation (DWT)and feature extraction are based on gray level Co-occurence matrix(GLCM). In the last stage, Probabilistic Neural Network is employed to classify the Normal and epileptic EEG signals. It is anticipated that the proposed algorithm will offer a faster and accurate diagnosis and also reduce the time spent on detecting seizures from long-term multi-channel EEG recordings and can be extended to more patients for long-term EEG.

VI. FUTURE WORK

In addition to the work done the idea can be further developed by connecting it to the cloud and smart application where the data set is stored on Cloud and it is moved towards an android application.

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