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A hybrid technique for EEG signals evaluation and classification as a step towards to neurological and cerebral disorders diagnosis

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Abstract

Electroencephalography (EEG) signals are commonly used to identify and diagnose brain disorders. Each EEG normal waveform consists of the following waveforms: Gamma(γ) wave, Beta (β) wave, Alpha (α), Theta (θ), and Delta (δ). The term Neurological Diseases " NurDis " is used to describe a variety of conditions that affect the nervous Epilepsy, neuro infections (bacterial and viral), brain tumors, cerebrovascular diseases, Alzheimer's disease, and various dementias are all examples of neurological disorders. Encephalitis is one of the illnesses that affects the brain. The EEG signals used in this paper were from the CHB-MIT Scalp EEG database. The discrete wavelet transform (DWT) was utilized to extract characteristics from the filtered EEG data. Finally, classifiers such as K Nearest Neighbor (KNN) and Support vector machine (SVM) were used to categorize the EEG signals into normal and pathological signal classes using all of the computed characteristics. In order to categorize the signal in a normal and anomalous group, the KNN and SVM classifiers are employed. For both classifiers, performance assessments (accuracy, sensitivity and specificity) are determined. KNN classifier accuracy is 71.88%, whereas SVM classifier accuracy is 81.23%. The sensitivity of KNN and SVM are 80.14% and 77.31%, respectively. The KNN classification specificity is 69.62% and the SVM classification specificity is 98%. Both classifiers performance is evaluated using the confusion matrix.

Keywords: Discrete wavelet transform (DWT), Support vector machine (SVM), Electroencephalography (EEG) signals, K-Nearest neighbor (KNN)

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1. Introduction

EEG is a brain record and may be simply captured in patient scalp contact using invasive electrodes. EEG tracks changes in brain neurons in ionic current voltage. EEG is most often utilized for the diagnosis of epilepsy which results in abnormalities in EEG data. Diagnosis also includes sleep problems, depth of anesthesia, coma, encephalopathy, and brain death. EEG was a diagnostic technique in the first line for tumors, stroke and other concentrated brain disorders. Usually a 20–30-minute EEG recording (plus preparation time) [20]. Brain disorders do not have specific symptoms, as their physical condition varies from patient to patient. EEG is one of the most significant diagnostic tests for epilepsy. Usually a 20–30-minute EEG recording (plus preparation time). A test to monitor electrical activity using small metal disks in the brain (electrodes) [20, 29].

EEG is regularly used for the determination of change which may, given clinical conditions, be important to diagnoses of brain disorders, including epilepsy and any seizures. The diagnosis or therapy of EEG may also be beneficial. Routine EEG is frequently insufficient to identify the diagnosis or treatment route. An EEG might be tried in such a condition during a seizure. This is called an ictal record, rather than an inter-ictal record referring to the EEG interconvulsive record. Generally, a long EEG with a time- and audio-sync capture is done for ictal capture [29, 30].

In traditional scalp EEG, electrodes are recorded on the scalp using conductive gel or paste, generally after mild abrasion is made in the scalp area to minimize resistance caused by dead skin cells. Typical electrodes are used in many systems, each with a separate wire. Certain systems employ electrical caps or networks in which electrodes are integrated, particularly where high electrode density arrays are required. The International 10-20 system for most clinical and research purposes specifies electrode placements and names [24].

A lesser number of electrodes is normally used to capture EEG from neonates. Additional electrodes may be used in the typical setup if clinical use and research need greater spatial resolution for some region of the brain. Every electrode is connected by means of a common electrode system via the other input of each differential amp. (one amplifier per pair of electrodes). These amplifiers improve the tension between the active and the reference electrodes (typically 1.000 to 100.000 times or a voltage gain of 60–100 dB).

The signal will then be filtered into analog EEG and when the deflection of the plumb goes below the paper the EEG signal will be released [16]. Most of the EEG systems are digital today, though. The amplified signal is transformed via an analog to digital converter after a non-aliasing filter. The mean analog to digital sample at the scalp EEG clinical location is 256–512 Hz. Sampling rates of up to 20 kHz are used for certain purposes of research [4].

A number of activation techniques may be employed throughout the recording process. These techniques may lead to normal or abnormal EEG activity which cannot be detected otherwise. These include: hyperventilation, photic (strobe light) stimulation, ocular closure, mental activity, and privation of sleep and sleep. The normal patient seizure medicines may be removed during (inpatient) epilepsy monitoring. Digital EEG signal may be recorded and filtered for monitoring electronically. Typical values are 0.5-1 Hz and 35–70 Hz for both high-pass filters and low-pass filters [13, 7]. The rest of this paper is organized as follows: the methodology introduced in section 2. EEG signals processing described in Section 3. Experimental results presented in Section 4, and section 5 concludes the paper.

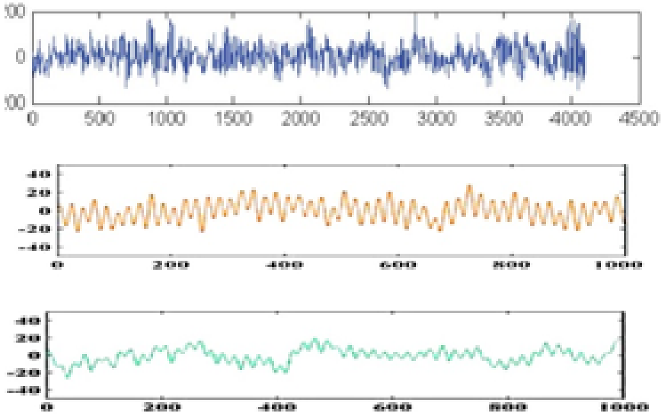

Figure 1: Various records of normal EEG signals

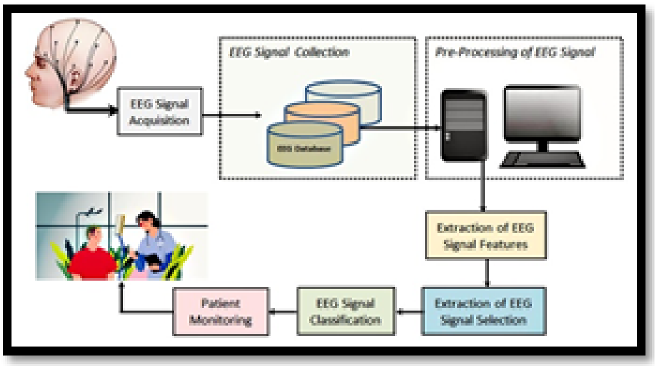

Figure 2: Overall system scheme

2. System Methodology

The following flow chart was followed to implement this application:

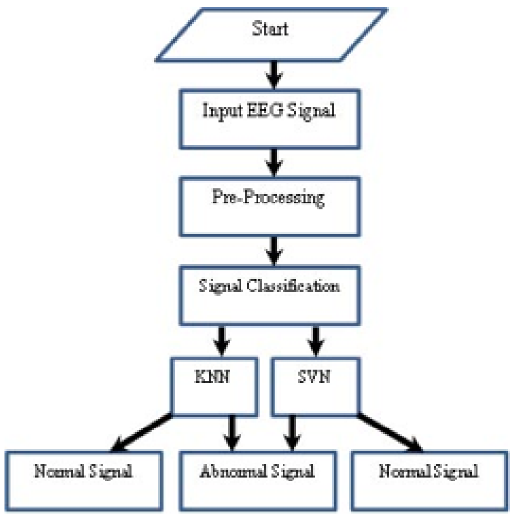

Figure 3: Flowchart of the proposed methodology

3. EEG signals processing

- Input: any biomedical signal can be entered as a system input. The input signal can be clinical, CHB-MIT Scalp EEG dataset, or direct recordings attained from the patient [17].
- Pre-Processing of EEG Signal: EEG signal has different types of noise which reduces the quality of signal providing interruption in further processing. Hence, it becomes necessary to remove these unwanted signals in order to increase the overall accuracy [27].
- Feature Extraction of EEG Signal: In order to attain the desired information, features are extracted from the filtered signals. These features act as input to the classifiers [5].
- Classification of EEG Signal: The main goal of any classifier is to categorize the signals into groups and finally reach the decision stage [23].

3.1. Input EEG signals

In this application, EEG signals were taken from the CHB-MIT Scalp EEG dataset. At the time of signal acquisition, these signals were in .eeg, .dat, or .txt format. To load the signals in MATLAB, they were converted to .mat format. 24 EEG signals were taken out of which 12 were normal signals and remaining 12 were abnormal signals. The time duration of all the signals was 1 minute and the sampling rate of about 360 Hz, respectively [23, 18].

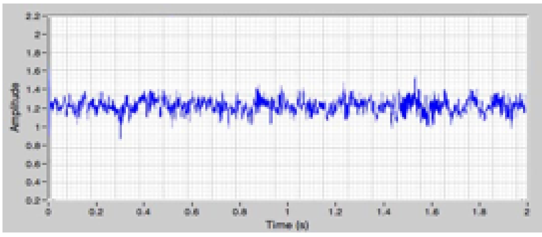

Figure 4: Normal EEG signal

3.2. Pre-processing of EEG signal

EEG signal includes many noise kinds including baseline noise, power line noise, high frequency noise, noise with equipment, muscle noise and etc. EEG is mostly affected by power line and baseline noise. Frequency of baseline noise is about 0.5 Hz [18]. Presence of such type of noise degrades the overall quality and accuracy. So, to improve the accuracy this unwanted noise must be removed. In this paper, zero phase low pass filter was used for the removal of baseline noise [10].

To attain the filtered EEG signal, following steps were implemented;

1. Zero phase signal was passed to the original EEG signal.
2. The attained EEG signal (from step 1) was then subtracted from original signal.
3. The EEG signal attained after step 2 is the filtered EEG signal [1].

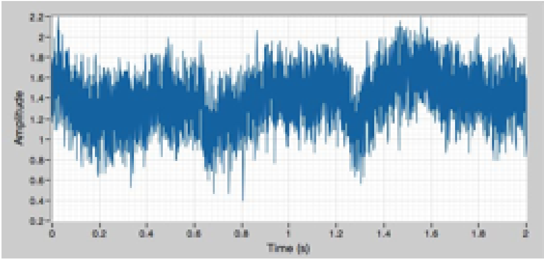

Figure 5: The input EEG signal is fed a zero phase signal.

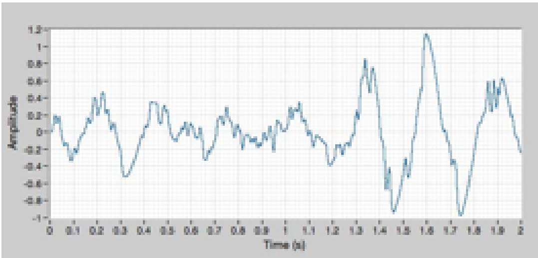

Figure 6: The filtered input EEG signal

3.2.1. *Zero phase low pass filter (ZePhLPF)*

Low-frequency transmissions are permitted whereas ZePhLPF blocks high-frequency frequencies. Such filters can be used to store filtered signal properties. It can reduce the noise influence of the original signal [31].

ZePhLPF does not reduce signal amplitude; instead, it eliminates undesirable signals. This sort of filter may filter both forward and backward. It filters signals in the forward direction, then reverses and filters the signal once again. This sort of filtering is applied to the original signal in order to achieve zero phase distortion [15].

3.3. *Feature extraction*

To attain the desired information from the filtered signal, features are extracted. Here, the 1st order statistical features of EEG are mean, median and standard deviation whereas higher order statistical features are kurtosis, skewness and variance respectively. In this paper, the following features were considered [14];

1. Mean: it is defined as the average of total number of signals.

2. Variance: it is described as the ration of sum of square of each term from mean to the number of terms in distribution.

$$Variance = \frac{\sum_{i=1}^{n}(X_i - X_{avg})^2}{n-1} \tag{1}$$

3. Standard Deviation: it is described as the amount of deviation.

4. Skewness: is defined as the distribution of asymmetry or deviation in comparison with normal distribution.

5. Kurtosis: it is described as the maximum (peak) value of EEG signal.

6. Highest frequency: This is the maximum value of the EEG signal's frequency.

7. Maximum Amplitude: This is the amplitude of the EEG signal with the greatest value [12, 2].

$$Skewness = 3 * (Mean–Median)/S.D \tag{2}$$

$$Kurtosis = \frac{\sum_{n}^{N}(y_i - y)^4}{N} \tag{3}$$

3.3.1. Discrete wavelet transform (DWT)

The majority of biological signals are non-stationary. DWT may be used to evaluate these types of signals. This approach utilizes two types of filters: low-pass and high-pass filter to split signals into distinct frequency ranges [3]. Coefficients of approximation are the result of a low pass filter (cA). Details of high-pass filter output coefficients (cD). The characteristics from the filtered signal were extracted using DWT in this paper [28].

3.3.2. Wavelet selection

One of the most essential jobs in DWT is to choose the right wavelet and the right number of decomposition stages. The sort of wavelet to choose is determined on the nature of the signal. To evaluate signals, wavelets as in, Haar, Daubechies, Symlets, Coiflets, Morlet, Mexican Hat, and others can be utilized. The Db4 wavelet was utilized to breakdown the signals in this paper [19].

The characteristics following were calculated: maximum amplitude, skewness, maximum frequency, kurtosis standard deviation, mean, and variance.

The set of calculated features were given as input to KNN and SVM for the classification of signals [9].

$$StandardDeviation = \frac{1}{N-1}\sum_{1-n}^{N}(X_n - x) \tag{4}$$

$$mean = (X1 + X2 + \ldots, Xn)/N \tag{5}$$

3.4. EEG signals classification

Classifiers in EEG signal processing are utilized to classify the signals in a proper group. Classifiers such as ANN, SVM, KNN, Fuzzy Logic System, LDA etc are widely used to classify the signals. In this paper, the classifiers such as KNN and SVM were utilized to classify the signals in a group of signal normality and abnormality [8].

3.4.1. K Nearest Neighbor (KNN)

Classifying algorithms is one of the simplest kinds. The minimal distance is determined by this method of categorization [6].

Basically, to perform the discriminant analysis, KNN classifier was developed. The distance equation (6) is given by;

$$Distanced(x, y) = \sum_{i=1}^{N}\sqrt{(x_i – y_i)^2} \tag{6}$$

The KNN method compares data from the training and test sets. The "K" value (Total neighborhood number) should be a small integer in this case. If we choose a large value for K, it is possible that the signals will be misclassified. The value of K in this text was set to 1 [25].

3.4.2. Support vector machine (SVM)

SVM is learning algorithm which is widely used for classification and regression. It can solve both binary classification and multiclass problems.

Let the training set be $(x_i, y_i)i = 1, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots I$

Where, $x_i \in R^d$ and $y_i \in (-1, 1)$ are separated by hyper plane defined as $(w * x + b = 0)$, where, $w =$ orthonormal vector of Weight related to hyper plane and $b =$ any constant term. Separation of data using hyper plane (w, b) is performed by using the function; $f(x) = sgn(w.x + b)$.

The following equation is used for input information if the hyper plane optimizes the margin; $yi(w.x + b) \geq 1$ for all values of I. The distance between hyper plane and data point is calculated using the following equation (7):

$$d((w.b), xi) = [(yi(xi.w + b))/||w||] \geq (1/||w||) \tag{7}$$

Accuracy is the phrase used to describe a system's overall performance. The accuracy is calculated as follows:

$$Acc = [(TP + TN)/(TP + TN + FP + FN)] * 100 \tag{8}$$

The ratio of the total number of correctly defined events to the total number of occurrences is known as sensitivity. Sensitivity is defined mathematically as [22];

$$Se = [TP/(TP + FN)] * 100 \tag{9}$$

Specificity is well-described as the ration of number of non-events which are rejected correctly to the total non-events count. Mathematically, specificity is given as [21];

$$Sp = [TN/(TN + FP)] * 100 \tag{10}$$

Where

TP stands for True Positive (if typical EEG signals are classified as such (Normal),
FN stands for False Negative (if typical EEG signals are labeled as such (Abnormal),
FP stands for False Positive (if typical EEG signals are labeled as such (Abnormal),
TN stands for True Negative (if typical EEG signals are labeled as such (Normal) [15**?**].

4. Experimental results

In this paper, features were extracted by utilizing discrete wavelet transform. To categorize the entering signals as normality and abnormality class, classifiers such as SVM and KNN were used. Specificity, sensitivity, and accuracy were considered for each classifier. The accuracy of KNN was better for classification of signals as compared to SVM. Hence, we conclude that although KNN is one of the simplest types of algorithms, it can be widely for the classification purposes in biomedical field. The table given below shows the percentage of accuracy, sensitivity and specificity for both KNN and SVM classifiers.

Table 1: A typical two-class confusion matrix

Normality	True Positive	False Positive
Abnormality	False Negative	True Negative

Table 2: KNN matrix confusion

TP = 70%	FP = 30%
FN = 20%	TN = 80%

Table 3: SVM Matrix Confusion

TP = 100%	FP = 0%
FN = 45%	TN = 55%

Table 4: Performance evaluation for SVM and KNN

Performance Evaluation	SVM Classifier	KNN Classifier
Specificity	98%	69.62%
Accuracy	81.23%	71.88%
Sensitivity	77.31%	80.14%

5. Conclusions

The CHB-MIT Scalp SEG database tests this technique on 48 EEG signals collected. The retrieved characteristics were the powerful features suitable for grading. The classification of signals into normal and pathological groups is utilized by both KNN and SVM classifications. The confusion matrix has shown to be one of the efficient methods for calculating performance metrics for both classifiers. For classification in normal and abdominal groups, the experimental findings of the SVM based classifier have provided the maximum accuracy of 81.23% percent.

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