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IMAGE & SIGNAL PROCESSING

An Intelligent Sleep Apnea Classification System Based on EEG Signals

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Abstract
Sleep Apnea is a sleep disorder which causes stop in breathing for a short duration of time that happens to human beings and animals during sleep. Electroencephalogram (EEG) plays a vital role in detecting the sleep apnea by sensing and recording the brain's activities. The EEG signal dataset is subjected to filtering by using Infinite Impulse Response Butterworth Band Pass Filter and Hilbert Huang Transform. After pre-processing, the filtered EEG signal is manipulated for sub-band separation and it is fissioned into five frequency bands such as Gamma, Beta, Alpha, Theta, and Delta. This work employs features such as energy, entropy, and variance which are computed for each frequency band obtained from the decomposed EEG signals. The selected features are imported for the classification process by using machine learning classifiers including Support Vector Machine (SVM) with Kernel Functions, K-Nearest Neighbors (KNN), and Artificial Neural Network (ANN). The performance measures such as accuracy, sensitivity, and specificity are computed and analyzed for each classifier and it is inferred that the Support Vector Machine based classification of sleep apnea produces promising results.

Keywords Classification of sleep apnea · Electroencephalogram · Hilbert Huang transform · Infinite Impulse Response Butterworth Band pass filter · K-Nearest Neighbors · Support Vector Machine

Introduction

A Sleep disorder is a functional abnormality of sleep that frequently occurs to human beings and animals. Some sleep disorders may cause health issues such as upper respiratory infections, allergies, weight gain and colds causing intolerable upset with mental, physical and emotional routine. Sleep Apnea is a major problem in sleep disorder leading to partial or complete stopping of breathes while sleeping. Sleep Apnea may happen in several episodes to a person throughout the night or for a short duration only during sleep. This disturbance in sleep is followed by noisy snoring that interfere the partner's sleep. Sleep apnea is a persistent situation that interrupts sleep causing extreme daytime drowsiness. The three types of sleep apnea are: Obstructive Sleep Apnea (OSA), Central Sleep Apnea (CSA), and Mixed Sleep Apnea. The OSA is a frequent and serious type of sleep disorder. It causes a complete blockage of upper airways and relaxes the throat muscles to block airflow during sleep. The symptoms for OSA are morning headaches, and loud snoring. The Central Sleep Apnea (CSA) also known as Cheyne-Stokes respiration is one type of sleep disorder in which breathes start and stop frequently while sleeping. The brain stops to send signals to the muscles that control breathing. CSA may also occur due to failure of heart and stroke. The most occurring sleep disorder is Obstructive Sleep Apnea. Another type of sleep apnea is Mixed Sleep Apnea or Complex Sleep Apnea which is a combination of both Obstructive Sleep Apnea and Central Sleep Apnea. The detection of sleep apnea is a tedious task requiring more time, effort and expertise. It is proved that electroencephalography helps in the diagnosis of sleep apnea.

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Electroencephalography is a test that monitors and records the brain activity over a period of time. It is activated by simply placing the electrodes on the scalp and is connected by wires to a computer to sense the activity of brain.

Related work

Many research works stress the role of EEG signals in the classification and detection of sleep apnea [1, 2]. It is witnessed that many machine learning strategies with different inputs were also examined in the area of sleep apnea [3]. We observed that the Support Vector Machine based sleep apnea classifier helped to achieve highest accuracy with comparison of other classifiers. Energy and variance features were used for this classification [4] and the highest accuracy obtained was around 97% for 90% of the data used for training. The thumb-rule of training and testing a designed system is to use two-third of the data for training and one-third of the data for testing. The accuracy of the Sleep apnea classifier [4] got reduced to 96.67% when 70% of the data was used for training. So it is advisable to work with a different set of feature values to obtain better classification. Sleep apnea EEG signals when denoised and smoothed making them suitable for delta band separation and computation of Delta band power ratio produces an accuracy of 84.83% and 84.07% while subjected to SVM and K-Nearest Neighbor based classifications [5]. EEG signals with reduced dc offset help in efficient division into frequency sub-bands namely alpha, beta, delta, theta, and gamma. Entropy extraction from the Multi-band EEG signals when analysed with Geometric Separability Index (GSI) provides better classification of sleep apnea based on KNN algorithm with 87.64% accuracy [6]. The band-pass filtering technique provides [7] good noise removal and extraction of the signal features when performed using Hilbert Huang Transform exhibiting effective detection of Obstructive Sleep Apnea. Detrended Fluctuation Analysis quantified power-law correlation in EEG scaling components helped to classify [8] sleep apnea using Support Vector Machine and the performance of the SVM classifier was having accuracy of 95.1%, sensitivity of 93.2% and specificity of 98.6%. The EEG data have been partitioned and organized into Reasoning Units (RU), which are used in signal segmentation and the static features namely skewness, kurtosis, mean, geomean, variance, and standard deviation are generated from wavelet packet coefficients which aid the classification of sleep apnea from normal patients using Partially Connected Cooperative Parallel Particle Swarm Optimization-Support Vector Machine Algorithm producing an accuracy of 83.66% [9]. The classification of sleep apnea using cross wavelet transform of EEG signal in combination of higher order statistics extractions obtained from the Kernel based non-linear Principal Component Analysis (KPCA) produced a sleep apnea classification system with an accuracy value of 85% [10].

Materials and methods

EEG dataset

In this work, the dataset EEG signals are taken from MIT-BIH Polysomnographic database that are visible to public and it is accessible through Physionet [11]. The MIT-BIH Polysomnographic Database is a collection of recordings of multiple physiologic signals during sleep. The physiological signals include electroencephalogram, electromyogram, electrooculogram, invasive blood pressure, respiratory wave, oxygen saturation, and cardiac volume as measured by VEST method. The database contains over 80 hours' worth of four-channel, six-channel, and seven-channel polysomnographic recordings organized in 18 records, each of which includes four files, namely Sleep/apnea annotations, Beat annotations, Signals and Header. All 16 subjects involved are male, aged 32 to 56 years (mean age is 43 years), with body weights ranging from 89 to 152 kg (mean weight is 119 kg). The signals of two subjects are segmented into two each; separated by a gap during the recording process. The remaining 14 records are all from different subjects. The EEG signals were recorded at 30 seconds interval from C3 through O1, and C4 through A1 channels covering whole night sleep.

Proposed method

This study produces an intelligent system for sleep apnea classification to distinguish the sleep apnea patients from healthy human beings using EEG signals. The EEG dataset is managed to fit for sleep apnea classification through the design of two filters using Infinite Impulse Response Butterworth Band pass filter and Hilbert Huang Transform techniques. After preprocessing, the performances of the designed filters are compared using signal to noise ratios. The filtered EEG signals are split into delta, theta, alpha, beta, and gamma frequency sub bands. Extracting the perceptive features of energy, entropy, and variance for every frequency band related to the EEG data signals is the central task of the proposed system development with effective sleep apnea classification. Finally, the feature vector of the EEG signals is fed to supervised machine learning based classifiers. Performance analysis and comparison are done to support the sleep apnea classification system to possess the appreciable accuracy (Fig. 1).

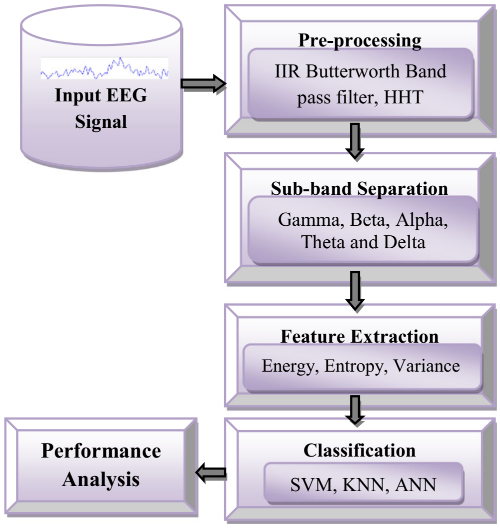


Fig. 1 Classification of sleep apnea using EEG signals

Pre-processing and sub-band separation

In the preprocessing stage, the signals of the input EEG dataset are filtered for the removal of artifacts due to eye movement, eye blinks, and muscle movements, which may be helping to execute the feature extraction and the classification sub tasks. Infinite Impulse Response Butterworth Band pass filter employs invariant technique along with pass band and Hilbert Huang Transform is a Finite Impulse Response filter which works for nonlinear data to decompose any difficult data that are used for filtering process. The Infinite Impulse Response Butterworth Band pass filter designed for this system retains the EEG sub frequencies starting from Gamma to Delta. The designed Band Pass Butterworth filter was of order 4, passband from 40 Hz to 100 Hz with sampling frequency of 250 Hz. A Hilbert Huang Transform based equiripple filter designed is of order 15, with frequency vector of [0 1], magnitude vector of [1 1], density factor of 20 and weight of 1. The filters are designed using the FDAtool in MATLAB. We identified that among the Infinite Impulse Response Butterworth Band pass filter and Hilbert Huang Transform filter, the first one exhibited better filtering performance with an increased signal-to-noise ratio in the order of cubic power of 10; this was due to reduced delay. So, we opted to use IIR Butterworth Band pass filter; and the filtered EEG signals are subjected to sub-band separation using wavelet transform. We used Daubechies wavelet to decompose the EEG signals; thereby the filtered EEG signals are split into five separate frequency bands: Gamma, Beta, Alpha, Theta, and Delta. Then these signals are fed to the sub-system which performs Feature extraction.

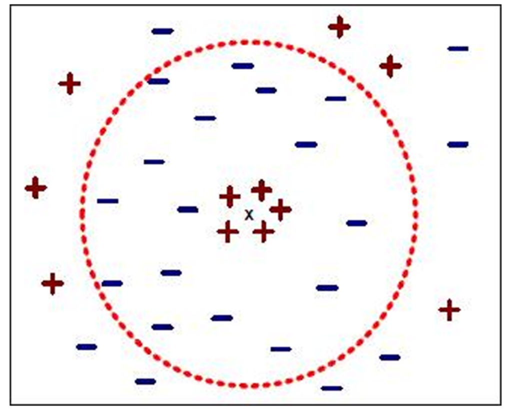


Fig. 3 Architecture of KNN

Feature extraction

In any EEG signal, statistical features represent the useful information that can be positively engaged for the classification of sleep apnea. We extracted the values for 14 features including Energy, Entropy, Standard Deviation, Variance, Mean, Median, Mode, Minimum, Maximum, Skewness, Kurtosis, Magnitude, Phase, and Frequency. Several tests were performed with different combinations of the above said 14 feature values and it

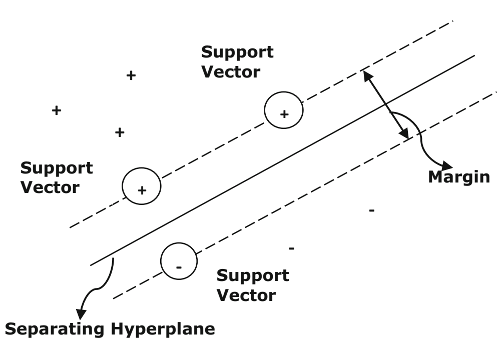


Fig. 2 Optimal-boundary hyperplane of SVM

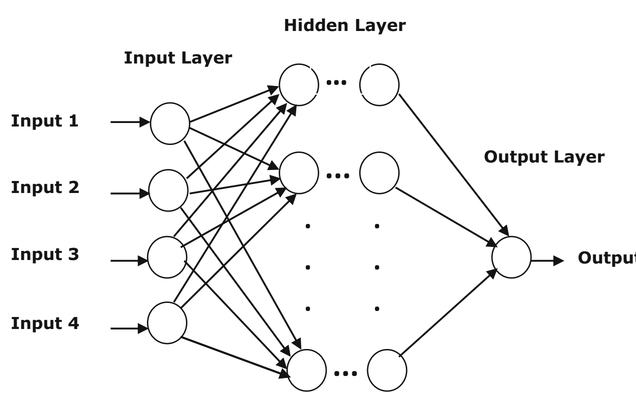
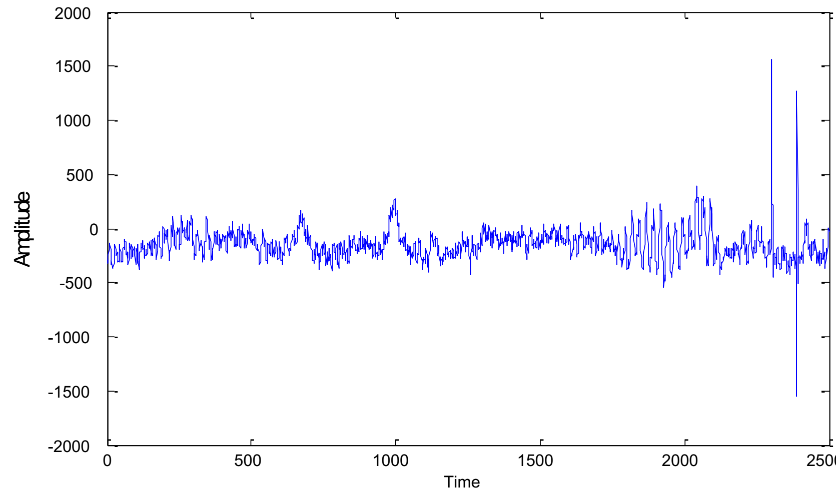


Fig. 4 Architecture of ANN

Fig. 5 Input EEG signals



was noticed that the feature values of energy, entropy and variance helped in the design of effective Sleep Apnea Classifier. We would like to state that energy, entropy and variance are the three parameters of the EEG sub-bands necessary to provide the best classification accuracy for the detection of sleep apnea.

Energy

Energy represents the strength of a signal or power of a signal to identify series in the power curve at any period of time. The statistical representation of energy is given by,

$$E = \sum_{i=1}^{N} |X_i| \tag{1}$$

Where E is the energy, N is the total number of samples and X_i is the value of samples in each epoch.

Entropy

Entropy is a spontaneous constraint in the way that can be optically differentiating a normal signal from an abnormal signal [12]. Uncertain result of the signal is measured by using the formula:

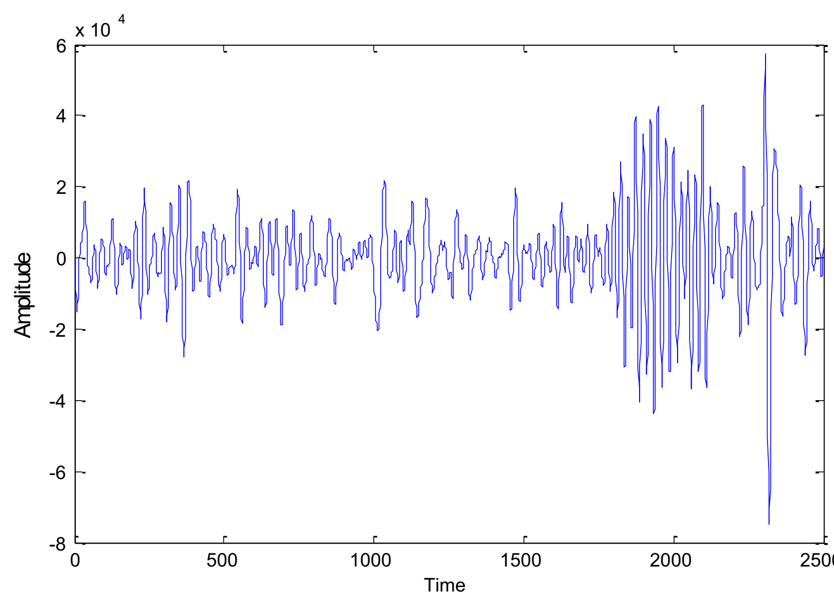
$$EN = \sum_{j=1}^{N} \left(X_j^2\right) \log\left(X_j^2\right) \tag{2}$$

Where EN is entropy, N is the total number of samples and X_j is the value of samples in each epoch.

Variance

Variance is the prospect of the squared variation of each number in a dataset from its mean, squaring the differences and

Fig. 6 IIR Butterworth band pass filter for EEG signal



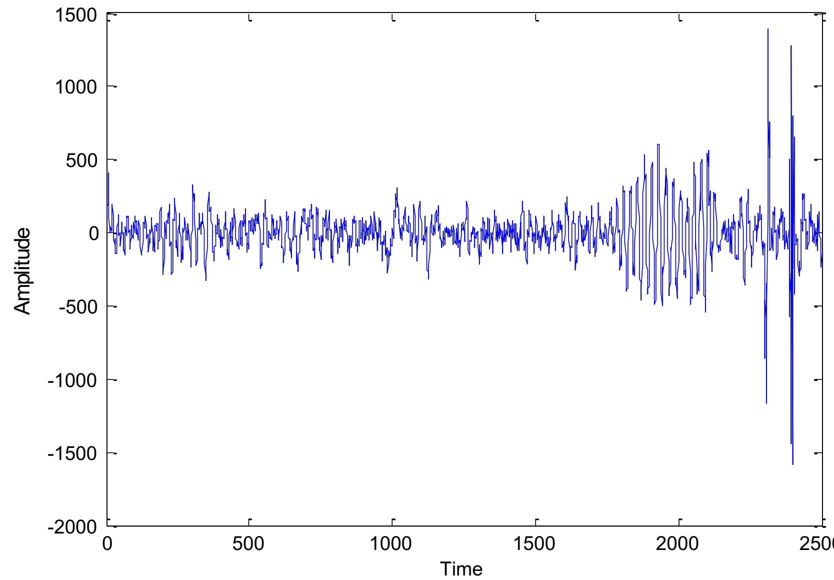


Fig. 7 Hilbert Huang transform based filter for EEG signal

dividing the sum of the squares by the number of values in the set. The formula for variance is,

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(X_i - \mu)^2 \tag{3}$$

Where σ^2 is the variance, N is the total number of samples, X_i is the value of samples in each epoch and μ is the mean value.

Classification

EEG based Sleep Apnea can be classified by designing Machine Learning Classifier Algorithms using MATLAB toolbox [13]. We made the attempt of using the following three machine learning techniques to classify sleep apnea patients from healthy human beings to study the effectiveness of those classifiers after feeding-in the feature values of energy, entropy and variance.

Support vector machines (SVM)

The Support Vector Machine is one of the main supervised machine learning algorithms which can be used for classification task through grouping of the data samples. Non-linear separable data is mapped into higher dimensional space by constructing optimal hyper planes in a multidimensional space [14] that divides various class labels and quadratic optimization dilemma is solved. The margin can be maximized by using suitable techniques for hyper plane designing to identify support vectors among the classes of data signals [15]. The kernel functions of SVM used for the design of hyper planes are Polynomial kernel, Linear kernel, and Radial Basis Function (RBF). The Hyperplane separates the data into two groups such as +1 or − 1.

The support vectors are the data points that are closest to the separating hyperplane; these points are on the boundary of the slab. The Fig. 2 given above illustrates these definitions, with "+" indicating data points of type +1 and "-" indicating data points of type −1. The hyperplane is the plane passing through the midpoint between the data sets. The hyperplane ought to produce the correct separation of class i.e., classification whatever the intended data set may be. The region bounded by the two hyperplanes will be the biggest possible margin.

Table 1 SNR values for input and filtered EEG signals

EEG Signals	Sleep Apnea EEG Signal			Normal Human EEG Signal		
	Before Filtration	After Filtration by IIR Butterworth Band Pass Filter	After Filtration by Hilbert Huang Transform	Before Filtration	After Filtration by IIR Butterworth Band Pass Filter	After Filtration by Hilbert Huang Transform
Least SNR value	3.45E+05	3.43E+09	2.52E+05	6.11E+04	3.77E+08	5.68E+04
Highest SNR value	4.98E+07	5.41E+10	1.28E+07	6.27E+06	7.90E+09	1.52E+06
Average SNR values for all Signals	9.79E+06	2.94E+10	4.89E+06	1.20E+06	3.94E+09	6.42E+05

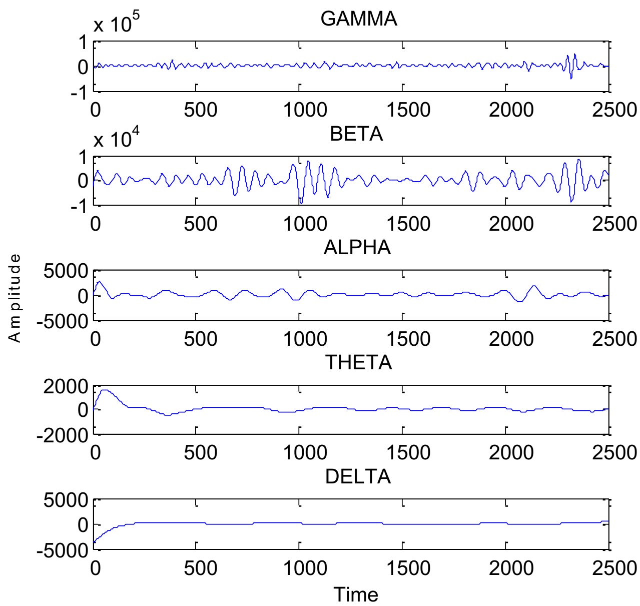


Fig. 8 Sub-band separation of EEG signal

To improve the classification performance of the SVM classifier we recommend the use of kernel functions for enhanced classification. The various types of kernel functional available with SVM are linear, nonlinear, polynomial, radial basis function (RBF), and sigmoid.

K-nearest-neighbor (KNN)

Another important machine learning classifier algorithm is the K-Nearest-Neighbor (KNN) classifier, which is a nonlinear classifier used for the classification process. The two important parameters involved in this classification are the distance metric and the number of nearest neighbors Different distance metric such as Euclidean and Mahalanobis were adopted by the designed KNN classifier to achieve good performance. Nearest Neighbor Classifiers assign a feature vector to a class based on its nearest neighbors. It compares a particular unidentified test data with training data that are available in an n-dimensional space and the calculated distance measure is used for measuring the nearness of data values. An object is classified by a majority of its neighbors. K is always a positive integer which represents the number of neighbors. The neighbors are selected from a set of objects for which the correct classification is known.

In Fig. 3, the plus symbol represents the class A data and the minus symbol represents the class B data and the dotted circle is used to separate both classes along with their nearest neighbours.

Table 2 Frequencies corresponding to different EEG signal sub-bands after decomposition

Decomposed Signals	Frequency Range (Hz)
D1(Gamma)	35 to 78
D2(Beta)	29 to 41
D3(Alpha)	13 to 23
D4(Theta)	3 to 10
D5(Delta)	2 to 6

Table 3 Average of features values for normal-human signals

Feature Name	Normal Signal Gamma	Normal Signal Beta	Normal Signal Alpha	Normal Signal Theta	Normal Signal Delta
Energy	5.68E+05	3.38E+04	4.02E+03	1.34E+04	2.09E+04
Entropy	1.012172	1.048272	1.184916	1.120183	1.08026
Variance	5.69E+05	3.38E+04	4.02E+03	1.34E+04	2.09E+04

Artificial neural networks (ANN)

The most frequently used machine learning classifier model is Artificial Neural Networks (ANN) consisting of simulated neurons joined together in different fashions to form networks of varying capacities. A huge quantity of interconnected nodes involved in information processing are coupled together to perform the classification. ANN has three layers for data processing. They are: the input layer consisting of neurons which make up the primary layer of the ANN, the hidden layer which is also a set of neurons and does the work of information processing and the results are fed to the output layer, and the third layer is the output layer, which is responsible for providing the results of classification to the world. The vital parameters involved in ANN based classifications are activation function, and learning rule.

This Sleep Apnea Classification system is developed using a Feed forward type of ANN; where the input is accessible to the network along with the weights and nonlinear activation function is utilized to direct the result to the output layer, and the miscalculation is corrected in a forward path. After network training, the dataset can be tested to perform the correct classification.

The ANN in Fig. 4 has n hidden layers in addition to one input layer and one output layer. The input is fed to the input layer and the output is obtained in the output layer.

Results and discussions

In this study, we have developed a system to classify Sleep Apnea patients and normal healthy humans using the EEG signals of 18 sleep apnea patients and we analyzed the performance of the proposed method. The input EEG signals

Table 4 Features values for decomposed sleep apnea signals

Feature Name	Signal with the highest feature values					Signal with the lowest feature values					Average feature values for all patients
	Sgl-high Gamma	Sgl-high Beta	Sgl-high Alpha	Sgl-high Theta	Sgl-high Delta	Sgl-low Gamma	Sgl-low Beta	Sgl-low Alpha	Sgl-low Theta	Sgl-low Delta	
Energy	6.61E+07	2.06E+07	1.91E+06	9.60E+05	2.31E+06	1.07E+07	1.68E+06	1.42E+05	2.89E+04	6.38E+04	7.78E+06
Entropy	0.9998	0.9999	0.9931	0.9198	0.6606	0.9991	1.0138	1.0046	1.0011	1.0406	1.00E+00
Variance	6.62E+07	2.06E+07	1.91E+06	9.60E+05	2.31E+06	1.07E+07	1.68E+06	1.42E+05	2.87E+04	6.28E+04	7.78E+06

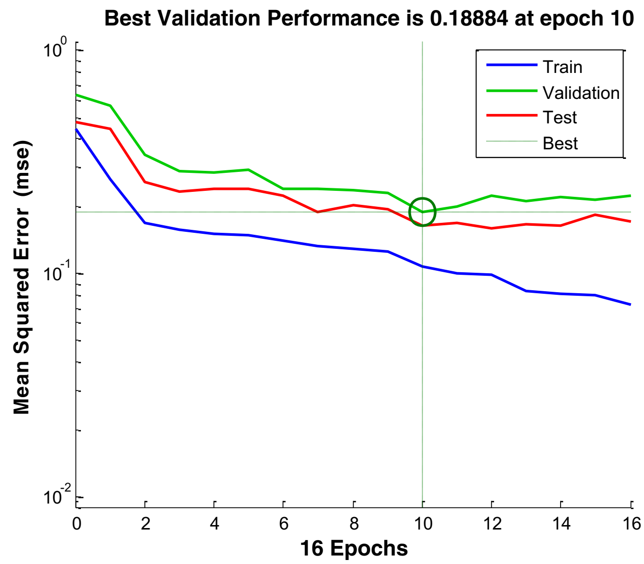


Fig. 9 Mean squared error of the ANN classifier

contain 2500 samples each for duration of 30 seconds; and are annotated with Apnea-Hypopnea Index values.

Fig. 5 shows the EEG input signal which is collected from a Sleep Apnea patient. The signal has 2500 Hz frequency ranges for a single patient or subject. The input EEG signal is displayed using MATLAB.

The input signals were filtered using Infinite Impulse Response Butterworth Band-pass Filter and Hilbert Huang Transform; and the outcomes are depicted in Figs. 6 and 7 respectively.

The signal-to-noise ratios (SNR) before and after the filtering of the EEG signals by using the above two methods are given in Table 1. The average SNR value for Sleep Apnea signals was 9.79E+06 before filtering and the same was 2.94E+10 and 4.89E+06 after filtering using IIR Butterworth Band pass filter and Hilbert Huang Transform respectively. We concluded that IIR Butterworth Band pass filter is better than Hilbert Huang Transform based filter for filtering of EEG signals for this system.

After filtering process the sub band separation task is performed through the use of Daubechies filter. Figure 8 below shows the result of sub-band decomposition into the five frequency sub-bands of Gamma, Beta, Alpha, Theta, and Delta for the Sleep Apnea signal shown above in Fig. 6. We have

Table 5 Performance analysis

Classifiers	SVM		KNN	ANN
	With RBF	With Polynomial		
Accuracy	95	99	75	86
Specificity	100	98	92	100
Sensitivity	90	100	70	75

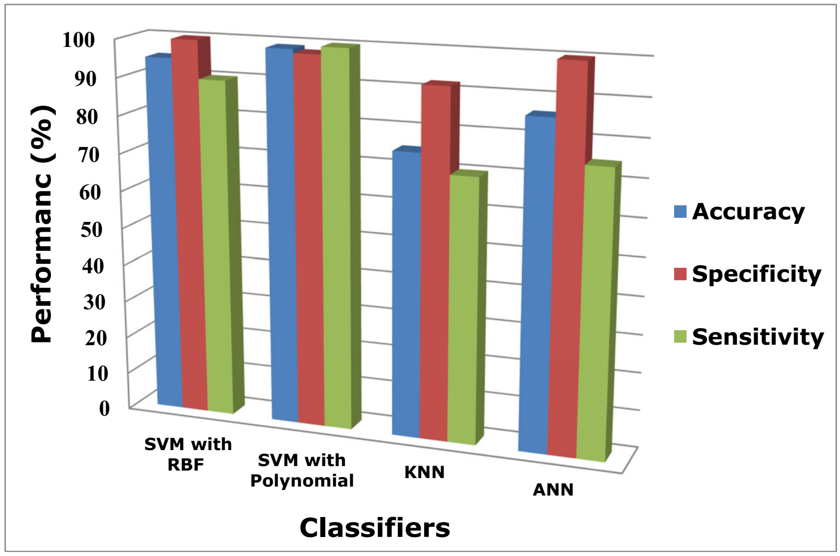


Fig. 10 Performance chart

plotted the five sub-band signals with time on X-axis and amplitude on Y-axis and we observed that the Gamma brain waves have the highest frequency when compared to other frequency band signals of the input EEG waves.

The Sub-band separation task also leads to the analysis of frequency range of the input dataset taken for the study. The results are drafted in Table 2.

We analysed the feature values for each frequency band constituting the EEG signals and observed that the energy values were 6.61E+07 and 1.07E+07 respectively for the two signals with the highest and lowest values bordering the ranges of values we obtained for all the EEG signals. Table 3 shows that the features values extracted from each frequency band wave of healthy humans EEG signals. Table 4 shows the average feature values for the five EEG sub-bands of two input EEG Sleep Apnea Signals with the highest and the lowest feature values; also the average features values for all 18 patients is represented in the last column of this table. We noticed that the feature values of the Sleep Apnea EEG signals are higher than that of normal human beings. The observed feature values are taken for further classification of sleep apnea (Fig. 9).

Sleep Apnea classification was performed with SVM, KNN, and ANN machine learning algorithms using the features extracted from the decomposed EEG signals as input data in addition to the feature values computed for EEG signals from healthy humans. The performance analysis done after the calculation of accuracy, sensitivity and specificity of the three classifiers helped to judge the effectiveness of the three machine learning strategies mentioned above.

Accuracy is a measure of the number of correct predictions divided by the total number of predictions. The accuracy of the classifier designed for this system is defined by its ability to differentiate the sleep apnea and the normal cases correctly. Mathematically accuracy can be stated as,

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{4}$$

Where,

True Positive (TP) is the number of cases correctly identified as Sleep Apnea.

False Positive (FP) is the number of normal cases incorrectly identified as Sleep Apnea.

True Negative (TN) is the number of cases correctly identified as Normal.

False Negative (FN) is the number of Sleep Apnea cases incorrectly identified as Normal.

Sensitivity is the ability of a classifier to correctly predict the true positives. The sensitivity of this system is its ability to determine the Sleep Apnea cases correctly. Mathematically, this can be stated as,

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5}$$

Specificity is the ability of a classifier to correctly predict the true negatives. The specificity of this system is its ability to determine the Normal cases correctly. Mathematically, this can be stated as,

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{6}$$

The performance analysis results for the SVM, KNN and ANN based classifiers using two-third of the data for training and one-third of the data for testing are given in Table 5.

Fig. 10 shows the performance analysis of the three types of Sleep Apnea Classifiers. It is inferred that the Support Vector based Sleep Apnea Classifier exhibits the best classification.

Conclusion

In this paper, the performances of Support Vector Machine, K-Nearest Neighbors, and Artificial Neural Network based Sleep Apnea Classifiers are analyzed using a novel feature set derived from EEG signals. The running times of all the three classifiers of sleep apnea are almost the same. It is proved that SVM based Sleep Apnea Classifier performs better when compared to the ANN and KNN based Sleep Apnea Classifiers. Also it is noticed that the polynomial kernel function of SVM helps to design sleep apnea classifiers with the highest accuracy using the proposed feature set. Our future effort will deal with the development of web-based sleep apnea classification systems which may provide assistance to physicians in their diagnosis of sleep apnea diseases.

Compliance with Ethical Standards

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

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