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Detection of Driver's Drowsiness Using Empirical Mode Decomposition

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Abstract - The necessity of a reliable system for the Detection of Drowsiness is arising now days. In recent years fatigue and Drowsiness are been treated as a dominant originator for most of calamities as that of alcohol and lead to severe physical injuries as well as economic losses and deaths. A drowsy state is defined by reduced Beta, Alpha and increased Delta, Theta frequencies. The proposed work portrays an efficient technique for discriminating Drowsy state from Normal state by investigating the frontal lobes of human brain. Primarily an FIR filter is designed to differentiate the Theta and Delta frequency bands by Empirical Mode Decomposition approach for feature extraction. For the process of classifying the distinct features a model based on Neural Network trained with the help of back propagation algorithm is used. The experimental results determine that the proposed technique is potential of investigating and identifying Driver's Drowsiness with superior accuracy of 92%, sensitivity of 100% and specificity of 98%.

Keywords - Electroencephalogram (EEG), Empirical mode decomposition (EMD), ANN, Drowsiness.

INTRODUCTION

Drowsiness is portrayed by minute state of activeness and consciousness with difficulty in being alert. At these stage chances of dropping into asleep state is very high, more particularly when involved in operating a huge machine or a simple vehicle driving. In recent studies, declaration to focus on the risk of driving with drowsiness is issued by American Academy of Sleep Medicine (AASM) [Watson. N, 2015]. The estimation based on Administration of National Highway Traffic Safety portrayed 10,000 crashes reported by police have occurred by Drowsiness [Howe, TX, 1998].

A study based on AAA standards also reported that 21% of total destructions include Drowsy Drivers, which ended up smashing persons in the years 2009 to 2013 [B. Tefft, 2014].

Huge number of calamities and disasters caused by lack of consciousness and alertness quantifies the danger of the Drowsy Driving. The sleep state of a driver is prone to lose his control on vehicle, such type of activity which results in collision with either an object ahead or moving vehicle. To prevent these calamitous unfortunate things, the mental state of a driver is very much needed to be monitored. Enormous varieties of approaches have been designed for Drowsiness state detection, which included detection of driver's cognitive state. As number of traffic accidents are growing, and hence to investigate the drowsiness state of a driver, researchers have mostly observed and stated Stage I state or light sleep as the drowsiness phase.

EXISTING WORKS

Few studies portrayed that the crashes that are caused because of the driver's drowsiness consists of a wide number of characteristics [G. Borghini, 2014]. Few Statistics attained with these criteria will not account totally for collisions or accidents occurred by drowsiness due to involvement of complexity; hence, accidents associated to driver drowsiness might be much deplorable than those revealed by statistics.

In order to overcome such type of accidents, it is very much needed to determine effective and efficient precautions to diagnose the state of drowsy and alert him before the mishap happens. Subjective measures: Which evaluate the drowsiness level depending on one's individual estimation. The frequently used scale for state of drowsiness was named as Karolinska Sleepiness scale (KSS), which is a scale with nine-points, which contain verbal anchors on every step [Otmani. S, 2005]. Hu et al. calculated the ratings of KSS with respect to drivers for a period of 5 minutes and utilised these calculations as reference for EoG signal collected [Hu, S, 2009].

Enormous number of measures was researched few of them are:

i. Vehicle-based measures: Liu et al. [Liu, C.C, 2009] published a report on present vehicle-based measures.

The former measure was most widely used one, measured by using steering angle sensors. [Thiffault. P, 2003] [Fairclough, 1999]. The latter is other type of scope which can evaluate the level of driver's drowsiness within the software itself, in a simulated environment and also gives the quality variation of Lane Position. External camera can be used to track lane in case of field experiments [Ingre. M, 2006].

Arun et.al [Arun Sahayadas, 2012] analysed the composite analysis for the state of drowsiness system, which integrates a non-intusive physiological precautions in addition to various cares by which one could exactly investigate the drowsiness state of a driver.

ii. Behavioural measures: Depend on the behaviour of the driver, which includes the eye blinking, position of head, yawning etc., a camera is used to alert the driver under such situations. [Xiao, 2009] [Yin. B, 2009].

iii. Physiological measures: Many researchers studied the correlation among physiological signals electromyogram (EMG), electroencephalogram (EEG)) and driver drowsiness [Akin. M, 2008] [Guosheng. Y, 2010]. Each method used for driver's drowsiness has its own merits and demerits. The term "drowsy" is very much similar to that of a first stage of sleep, it actually describes a rise in falling asleep. Sleep activity sections can be stated as waken-up, Non-Rapid Eye movement (NREM) and Rapid eye movement (REM). REM is again divided as Sleep stage 1, 2 and 3[Brodreck.V, 2012]. Generally, after the EEG data is collected, they are pre-processed for removal of unwanted signals by using filters or wavelet analysis to separate the band frequencies and further feature extraction would be performed. Enormous techniques were determined for extracting important features from EEG -electroencephalogram signals, those probably grabs the unique sleep dynamics.

Chin.et al [Chi -Teng Lin, 2005] developed an effective system which estimates the driver's drowsiness based on the electroencephalogram (EEG) data by collective achievement of the independent component analysis (ICA), spectrum analysis of power, evaluating the similarity, and linear regression model to compute the thought process of a driver, when driver starts a vehicle in a virtual reality (VR) to extract the distinct features of drowsy state, to know the connection between the collected brain signals, the person's thought process, and to calculate the amount of the person's wakefulness. He also listed out the person's driving error index as the major alteration amid centre of the car and the centre of the cruising lane.

Hassan et. al [Hassan Albalawi, 2018] proposed a algorithm for drowsiness detection with respect to a single channel EEG, which is best suited for portable applications with simple computations. It adopted a cumulative counter for feature extraction from 8 frequency bands, which were further processed by an SVM classifier to categorize Awake and Drowsy stages. Many researches proved that accurate Drowsiness detection was offered by EEG based approaches. N. Huang et. al in 1988 [N.E. Huang, 1998] proposed EEG based effective approach by a novel technique of decomposing EEG signals.

After the distinct features are attained, next step is to classify them into one of the classes: sleep or non-sleep. Many researches were done on classification of features based on the Bayesian regularization back propagation algorithm method, which is used from procured sets of unique features [Hsu. Y, 2013] [Boostani. R, 2017]. Very commonly adopted efficient techniques for classification are Artificial neural networks (ANN) [Ebrahimi. F, 2008]. These techniques assist in improvement of performance quality. Few studies adopted Support vector machine (SVM) method in feature classification and radial basis function neural network, which compared the computation time [Sen.B, 2014]. The proposed method designed an efficient diagnosis of drowsy level algorithm which is appropriate for wide utilization along with less complexity based on single channel, unlike Conventional methods. The EEG signals were collected from a single channel, which is achieved by fixing the electrodes at C3-A2 or C4-A1 locations on the head and data is recorded from the frontal lobes of brain. Further a band pass filter is applied to filter the unwanted data from the desired Our proposed approach decomposes the collected EEG patterns into intrinsic mode functions for extraction of features by Empirical Mode Decomposition and measures the mean Intrinsic frequencies of EEG signals. Later, it extracts discriminate features of drowsiness based on these IMF's, which are classified by an ANN model along with Feed Forward Back propagation method. The state of Drowsiness was found to be very similar to that of Alcoholics depending on the reduced amplitudes of intrinsic mode functions and reduced frequencies of Beta and Alpha waves. The proposed technique supports dominant performance based on single channel and reduced computations over other traditional approaches in the literature.

PROPOSED METHOD

The categorization of sleep stages is depicted in Figure1. Which clearly portrays that Drowsy state is the starting stage of Sleep activity.

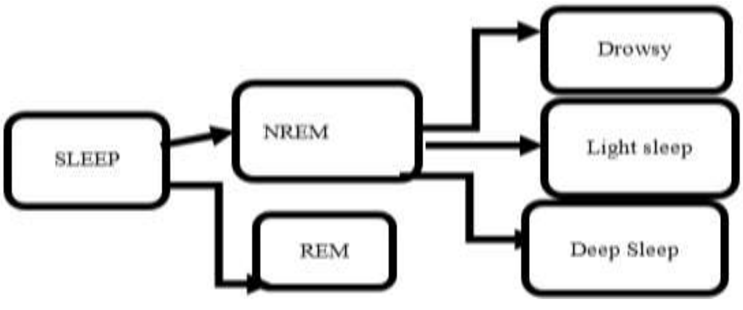

FIGURE 1 : SLEEP STAGES CLASSIFICATION

The proposed drowsiness detection methodology is composed of three dominant parts: (i) signal acquisition, (ii) extracting the features, and (iii) classifying the features in drowsy state detection. Here, we will characterize the technicality and focus its uniqueness. Figure 2. Depicts the flowchart of work process.

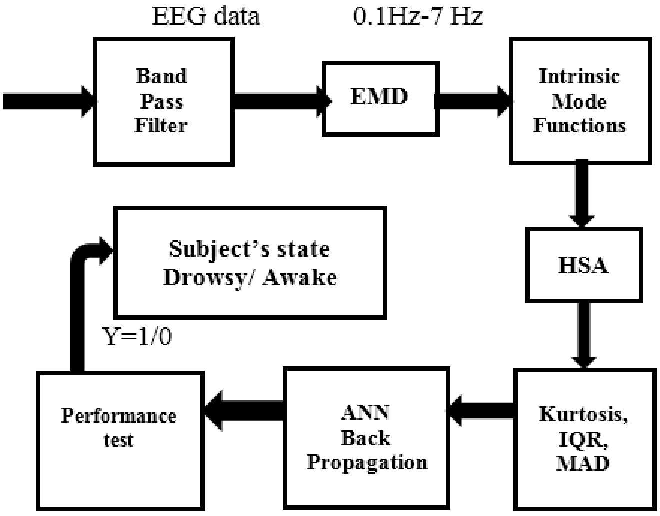

FIGURE 2

FLOW CHART OF WORK PROCESS

A. Signal Acquisition

The proposed work adopted a single channel EEG database. Normal/Awake state and Sleep Stages EEG data utilized in this work were collected from University of Bonn EEG database and the Sleep -EDF Database available in public domain [Sleep-EDF] [University of Bonn]. Every set comprises of hundred-single channel segments of EEG, each of duration 23.6sec. Every segment contains N =4096 samples, sampling frequency is 256Hz. All these EEG segments were recorded with the predefined 128- channel system and were digitized by a 12bit A/D convertor.

B. Feature Extraction

The feature extraction process constitutes of attaining the discriminate features of Drowsy and Awake EEG signals. This proposed work implemented Hilbert Huang Transform in the process of extracting the desired features. It constitutes of two important stages: 1) EMD- Empirical Mode Decomposition and 2) Hilbert Spectral Analysis.

C. Hilbert Huang Transform- HHT

Hilbert Huang Transform [HHT] attains the distinct features of Alcoholic and Normal EEG signals. It comprises of two stages: 1) EMD and 2) HSA. This technique is desirable for both the nonlinear as well as non-static data analysis in representation of energy of time frequency. A desirable path to explain this variety of a system is possible with the instantaneous frequency, which will clarify accurately the inner-wave modulations of frequency. The easiest method to find out the instantaneous frequency is with the help of HHT. The process of Hilbert Huang Transform with EMD and HSA is depicted in Figure 3.

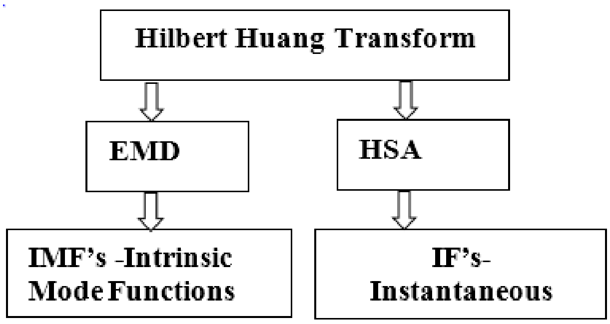

FIGURE 3

HILBERT HUANG TRANSFORM

D. Empirical Mode Decomposition (EMD) Process

The significant feature of Empirical mode decomposition [EMD] method consists of different intrinsic modes of oscillations in time series. Every intrinsic mode function is referred to as oscillation that consists of same quantity of maximum values, also no-crossings. The attained oscillations are symmetric with respect to 'common average', which are named as the ideal-values or intrinsic functions. This method of computing is named as "sifting" as shown below:

i) Calculate both highest and lowest values of x(t).

ii) i.e X_{up} (t) and X_{low} (t) should be calculated by the process of Cubic spline interpolation.

iii) Average or mean to be calculated from the highest peaks and lowest peaks, with the aid of m(t)= (X_{up} (t) +X_{low} (t)) /2.

iv) Phenomenal value, d(t) = x(t) – m(t)

Below stated two criteria of d(t) need to be tested:

a) d(t) should satisfy the above two criteria similar to the Statement of IMF (mentioned earlier) computed. Then swap the x(t) and R(t) = x(t) – d(t);

b) If the detail d(t) is detected as a non-IMF, then change the value of x(t) by d(t), and

v) 1 to 5 steps must be repeated till a single residue is attained, or we attain a individual least residual satisfying the below ending rule.

$$\text{Standard Derivation (SD)}= \sum_{t=0}^{T} \frac{|d_{k-2}(t)-d_k(t)|^2}{d_k^2(t)} \quad (1)$$

At last, the signal x(t) can be rewritten as below:

$$X(t) = \sum_{i=1}^{N}(C_j\,(t) + R(t)) \quad (2)$$

Here N portrays the accumulated final value of intrinsic modes function, $R_N(t)$ indicates the calculated remain value, it can also be attained as DC value of the particular signal. Here, C_j(t) indicates the other intrinsic modes.

E. Hilbert Spectral Analysis (HSA)

After the IMf's are attained, composite signal X(t) is written as

$$Z(t) = X(t) + iX_H(t) \quad (3)$$

Where X_H (t) represents the Hilbert transform for X(t), stated by

$$X_H(t) = \frac{1}{\pi} K \int_{-\infty}^{\infty} X \frac{(s)}{t-s}\, ds \quad (4)$$

and K as the main Cauchy term for the integral.

Exponential form of equation (2) is

$$Z(t) = A(\,t)e^{i\psi(t)} \quad (5)$$

Where B(t) =

$$B(t) = \sqrt{X(t)^2 - X_H(t)^2} \quad (6)$$

$$\psi(t) = \arctan\left(\frac{X_H(t)}{X(t)}\right) \quad (7)$$

adopting time derivative for (5)

$$Z = B\,(t)e^{i\psi(t)}(iwt)e^{i\psi(t)}\dot{A}(t) \quad (8)$$

w(t) represents the IF-the angular frequency,

$$W(t) = \dot{\psi}(t)\frac{d}{dt}\arctan\left(\frac{X_H(t)}{X(t)}\right) \quad (9)$$

Instantaneous frequency

$$f(t) = \frac{W(t)}{2\pi} \quad (10)$$

then calculating the part of overall frequency (OF) among the found IF

$$OF = \frac{\sum_{i=1}^{L} B_1(i)f(i)^2}{\sum_{i=1}^{L} B_1(i)f(i)} \quad (11)$$

B1- represents Instantaneous Amplitude,

f- represents Instantaneous frequency (IF)

These IMF and IF's are used in calculating three features i) Kurtosis, ii) IQR- Interquartile range and iii) MAD- Median absolute deviation

$$MAD = \frac{1}{N}\sum_{i=1}^{N}|x_i - \bar{x}| \quad (12)$$

F. Feature Classification

Neural Networks are widely utilised in accurate classification of various states of brain. Also, most prompt classification of Alcohol stage and Normal stages were categorized by analysing EEG signals through an ANN model [Ronzhina. M, 2012]. These are well-known for their accurate and prompt classification potentiality, efficiency and relevantly simplest implementation [Ronzhina. M, 2012]. The major part is selection of the type and particular network architecture.

Following are the layers of a typical ANN: i) Primary session, ii) multiple Middle sessions or Hidden part and iii) Output session.

The total number of middle sessions and the inner neurons totally affect the neural network classification competency [Monika Prucnal, 2017]. An ANN model with two central sections will give best accuracy with any type of analog mapping. And lot of problems in feature to be classified can be computed by ANN with a single hidden layer [Ronzhina.M, 2012] [Monika Prucnal, 2017].

The experimental result analysis for classification and identification of Alcohol state and Normal state thence prove that the adopted approach is best suited and gets the moderate control with respect to the accuracy in feature classification. The proposed technique is very useful to the clinicians and clinicians in diagnosing the decision on their patient's state. Application of such tool may assist in preparing them to decide appropriate decisions.

An EEG data is collected from 30 subjects with Alcohol content and 30 subject's EEG data pertaining to Normal condition. An individual epoch is extracted from each respective subject data, with 10 seconds epoch. 12 features were extracted based on the 2nd, 3rd, 4th and 5th IMF's respectively (i.e 4Kurtosis, 4IQR, 4MAD). The features thus extracted were used to train Neural network designed with 12 neurons at input, one neuron at the output and 15 neurons in middle section or middle layer. The method of Back Propagating the weights was implemented to make neural network. Figure 4 depicts atypical Artificial Neural Network model.

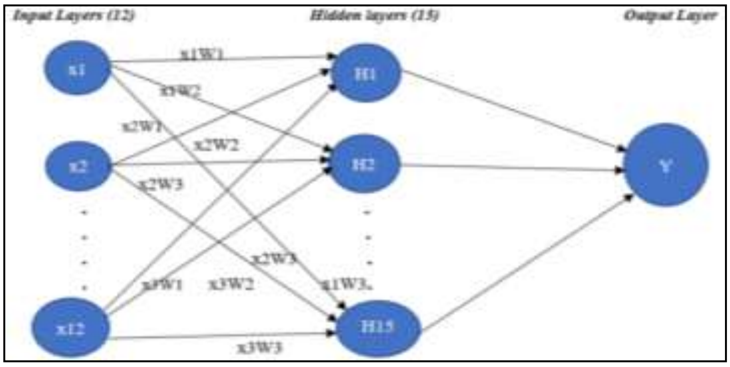

FIGURE 4

NEURAL NETWORK ARCHITECTURE

RESULTS & DISCUSSIONS

The Instantaneous Frequency indicates the IMF's numbered two till five are useful to categorize the Drowsy state and Awake state. IMF-1 is containing larger frequency oscillations and artifacts. Whereas the IMF's labelled from 2 to 4 were considered;

1.Kurtosis; 2 Inter quartile range; 3Mean absolute deviation.

Figure 5 depicts the frequency bands of Drowsy and Normal states

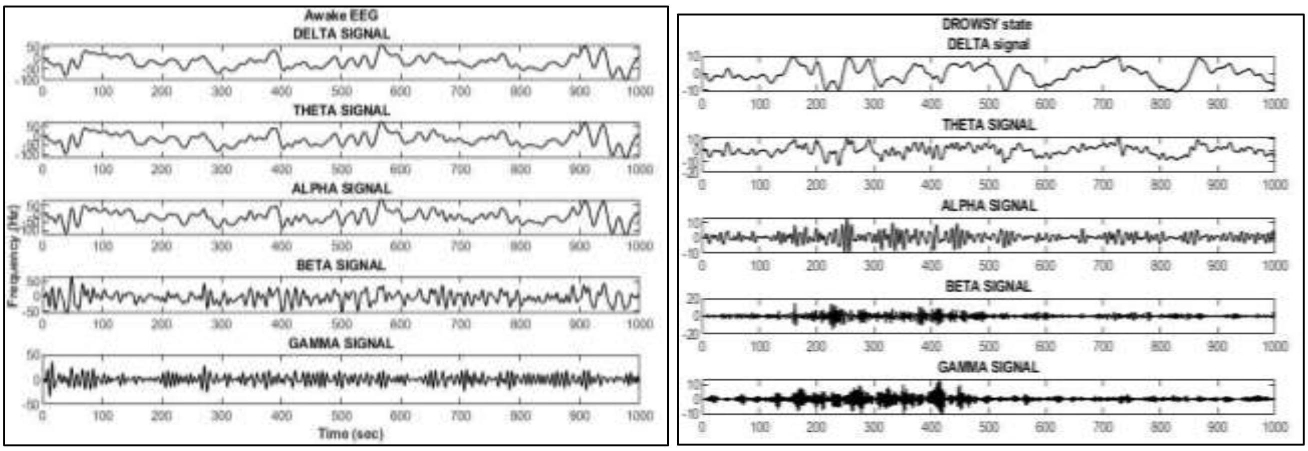

FIGURE 5

FREQUENCY BANDS OF DROWSY AND AWAKE STAGES

The Figure 5. Above depicts that Alpha signal which states the active stage of brain is found to be very low in Drowsy state than in Normal state. The power spectral densities of the five frequency bands corresponding to a Drowsy state clearly states that the /amplitude of Delta signal, which states the Sleep activity of brain is found to be high when compared to Theta Alpha and Beta frequency bands. This is depicted in Figure 6.

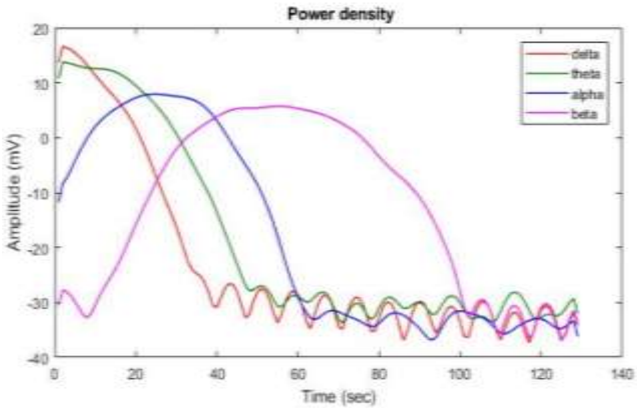

FIGURE 6

POWER SPECTRAL DENSITIES OF FREQUENCY BANDS

Figure 7 below depicts a typical Drowsy EEG signal and Awake EEG signal before and after filtering with Band pass filter of 2nd order.

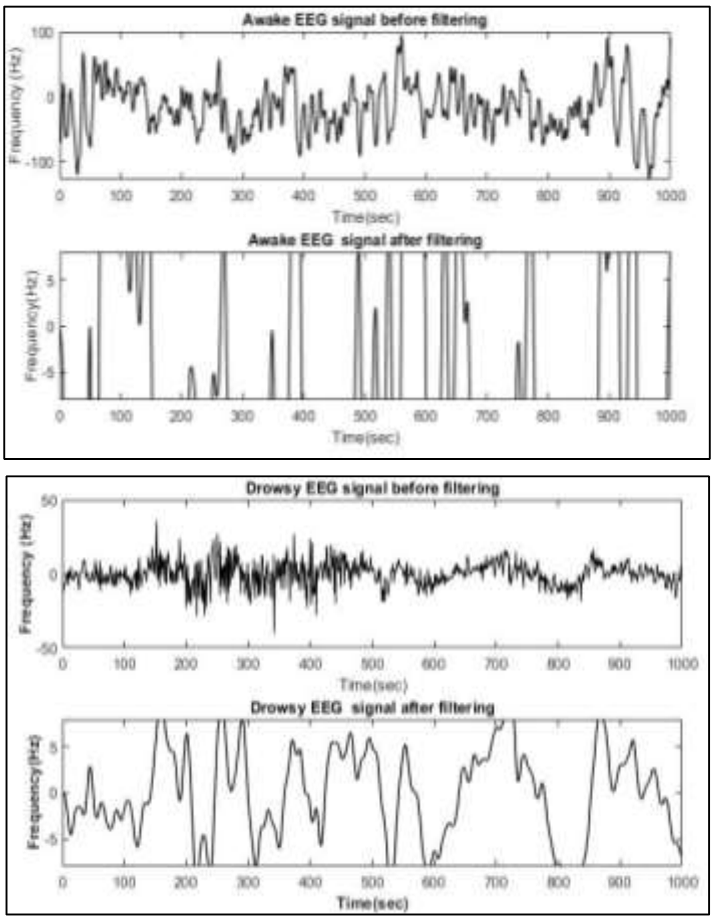

FIGURE 7

AWAKE EEG SIGNAL AND DROWSY EEG SIGNAL

The typical IMF's of both the distinct classes are depicted in Figure 8

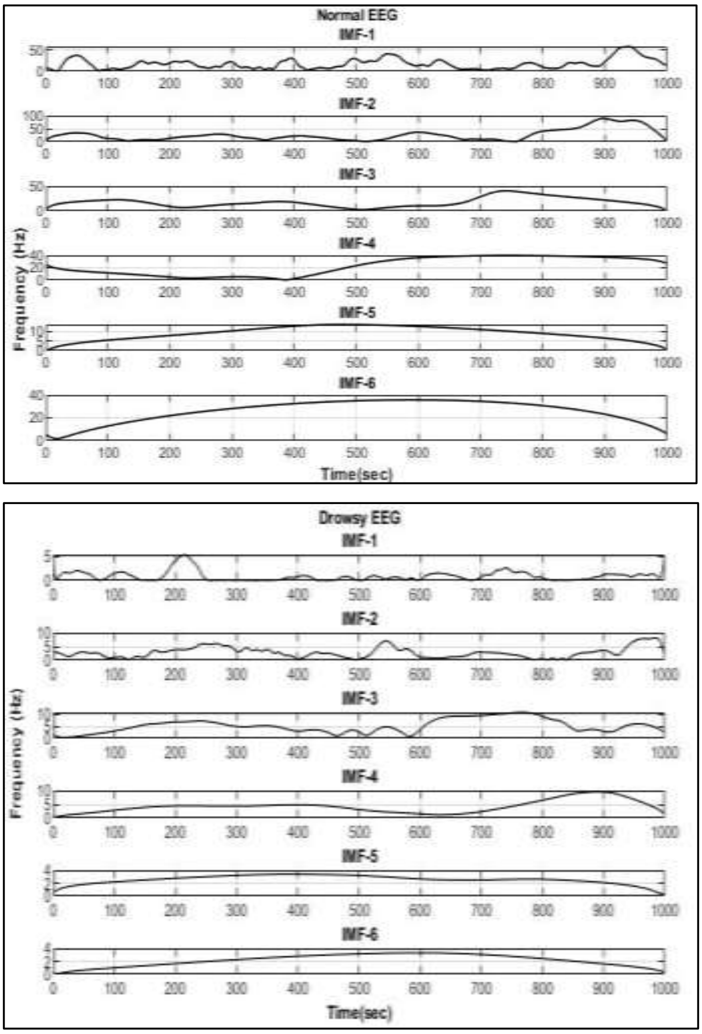

FIGURE 8

(A) NORMAL EEG IMF'S AND, (B) DROWSY EEG SIGNAL IMF'S

After Decomposition of EEG signals into IMF's by EMD algorithm, six IMFs are attained. They depict that the amplitudes of Drowsy signal falls under range of 0 to 10 Hz, whereas that of a normal / Awake signal ranges from 0 to 50 Hz

A. Performance Evaluation Metric

The measurement parameters which show the performance are totally based on the variables relation of the typical system by applying appropriate capability values namely specificity and sensitivity. The typical generalised formula are given below

$$Sensitivity = \frac{TP}{TP+TN} \times 100 \quad (13)$$

$$specificity = \frac{TN}{TN+TP} \times 100 \quad (14)$$

An accuracy and F-measure are the significant calculation parameters for computation of the dominant quality of the sleep stands for a non-sleep and sleep activity.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (15)$$

$$F - measure = \frac{2TP}{2TP+FP+FN} \times 100 \quad (16)$$

The geometric mean of sensitivity and specificity, which is computed by using equation shown below.

$$G - mean\sqrt{specificity \times sensitivity} \quad (17)$$

Here, TP- True Positive, TN- True Negative, FP-False Positive, and FN-False Negative.

Total of 60 subjects: 30 subjects pertaining to Drowsy state and 30 subjects pertaining to Awake/ Normal state were used to train ANN classifier. 40 subjects were used for testing the classifier. Performance evaluation attained 14 as True Positive, 13 as True Negative, 1 as False Positive and 2 as False Negative, which attained an accuracy of 92%.

Table 1. depicts the total no. Of training and test sets used for training the neural network

TABLE 1

TRAINING AND TEST SETS

Total no. of Subjects	90
Training Set	60
Testing Set	30

Table 2. depicts the Performance Evaluation test for the proposed method by ANN classifier.

TABLE 2

PERFORMANCE EVALUATION OF DROWSINESS DETECTION

Total no. Of Test set Subjects	True Positive (TP)	True negative (TN)	False Positive (FP)	False Negative (FN)
30	14	13	1	2

The researchers adopted various approaches for the detection of sleep stages depending on the pre-processing, feature extraction, and classification techniques. At the final stage, the segregation process was attained by adopting ANN. The comparison of SVM, Navy Bayes and the proposed classifier back propagation-based ANN is shown in Figure. 9.

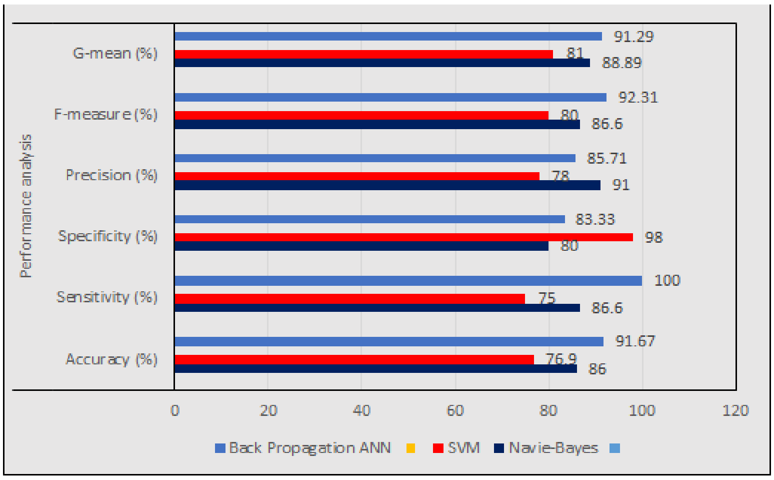

FIGURE 9

PERFORMANCE COMPARISON OF CLASSIFIERS

CONCLUSION

Awake and Drowsy EEG signals are analysed and are inspected in proposed work. Empirical mode decomposition method was used for feature extraction in computation of IMF's. The 2nd, 3rd, 4th and 5th IMFs for feature Extraction are selected based on the Instantaneous Frequency. The features extracted were classified using back propagation neural network. The proposed method was used to process the EEG signal to end up with a novel adequate tool that aids medical clinicians the probability to detect the brain signals at sleep state.

In this study, an EMD – Huang Hilbert transform based feature extraction process and feature classification based on ANN model by Back propagation algorithm was adopted. Sleep-EDF data base a publicly collected domain was taken for the study. Awake state and Drowsy stages were investigated and detected in this paper.

The proposed system brings the compatibility in providing various advantages like fast diagnosis, high accuracy of 92% better sensitivity and specificity. More accuracy can be obtained by training the ANN model under different circumstances of the subjects for Awake and Drowsy conditions.

Author Contributions

Conceptualization and main methodology by Dr.K.S. Rao and B. Anupama. Sir has given the main idea to detect the state of drowsiness and normal. Dr.K. Prabhakara Rao, original draft preparation. Software, B. Anil Kumar, has contributed for MATLAB coding and results.

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