

Ensemble Classifier Involving Deep Learning Features for Drowsiness Detection from Electroencephalograph Signals

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Abstract—Driver drowsiness detection and alerting is an important feature of smart vehicles. Prolonged driving without rest can result in accidents. The feature of drowsiness detection and timely alert can prevent accidents and save lives. With ability of low cost portable EEG headsets, mental state analysis using EEG signals has gained research importance. In this work, use of EEG signals for driver drowsiness detection is explored. Raw EEG acquired from the device is processed using empirical mode decomposition for artifact removal. Features are extracted from EEG using three different wavelet transforms and deep learning. A weighted ensemble of machine learning algorithms is proposed to detect drowsiness from the features. The performance of the proposed ensemble classifier is measured against Physionet database and the method is able to provide more than 98% accuracy.

Index Terms— Deep learning, Ensemble classifier, Neural network, Support Vector Machine, Wavelet transformation.

I. INTRODUCTION

Drowsy driving was a factor in at least 20% to 30% of the total 7,277,000 road tragedy that existed in the United States in 2016[1]. Drowsiness is a transient state of mind between awake and sleep stage. In this transient stage, brain cuts the physical signals to create relaxation. Due to this, attentiveness is lost and the person could not respond fast to events happening around his environment. When driver is drowsy, he loses control of the vehicles and this result is accidents. To prevent accidents, the driver drowsiness should be detected and alerted, so that safety of him and his co passengers can be ensured. There are many methods proposed for detecting driver drowsiness like image processing, sensors etc. But the accuracy of these systems are limited by environment constraints like low lighting, bad roads etc. Electroencephalography (EEG) is the study of brain signals. EEG signal analysis can identify various mental states like stressed, disturbed, quiet, disease, irritation, sleepiness etc. With the availability of low cost portable EEG devices, there is increasing research attention of use of these devices for various applications like stress detection, lie detection etc. This work explores the use of EEG signals for driver drowsiness detection.

II. LITERATURE SURVEY

If the study is to be used to assess a driver's performance capability, accurate and non-instructive sleepiness detection is critical. For fatigue detection, there are a lot of image processing-based approaches for monitoring eye blinking, facial expressions, yawning, eye tracking and driver's head movement have been developed as discussed by the authors of [2] [3] [4] [5] and [6]. Vehicles are equipped with cameras and sensors that continuously capture images in real time. A brief assessment of sleepiness detection approaches was published by the authors in [7]. The authors merely included a cursory overview of picture processing, yawning, and EEG detection methods. The authors of this article came to the conclusion that EEG approaches are the best for detecting sleepiness. The authors of [8] presented Independent Component Analysis (ICA) based EEG signal filtering for sleepy identification. Although experimental context is favorable, in some recent studies [9] [10] [11] have shown that choosing ICA is not the best option. The authors of [12] created Micro Electro Mechanical Systems (MEMS) EEG sensors for EEG measurements and applied PCA with linear regression to detect weariness. The functional methodology of drowsiness detection is not described in the research and both Principal Component Analysis (PCA) and linear regression are known for ineffective performance against ICA and signal loss respectively. The authors [13] proposed an unsupervised method for detecting tiredness using the power spectrum band of an EEG signal. The method gives a thorough model for sleepiness analysis, but there is no preprocessing of EEG inputs. As a result, if Electrooculograph (EOG) and Electromyograph (EMG) artifacts are present in the EEG data, it may cause a false alert. In this survey, it is obvious that the approaches receive a considerable number of votes for being superior at detecting drowsiness.

III. METHODOLOGY

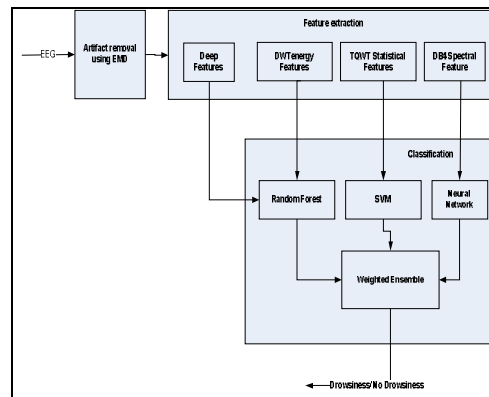


Figure 1. Proposed Methodology

The proposed methodology is as shown in Fig. 1, and the solution has following important stages as listed below:

1. Artifact removal using Empirical mode decomposition
2. Feature Extraction
3. Classification

A. Artifact Removal using Empirical Mode Decomposition

The raw EEG signal acquired from the devices must be pre-processed to remove motion artifacts introduced to driver and vehicle movement. Empirical Mode Decomposition (EMD) is used in this work for artifact removal. EMD obtains the components for the Hilbert transform by decomposing the signals into a small proportion of Intrinsic Mode Functions (IMF). Despite the fact that the EMD is criticised for being limited to a narrow band of data, this range of EEG signals is a good fit for this study. The decomposition of EEG signals through EMD technique is termed as sifting and the resultant components are recognized as IMFs. These maxima(s) forms the upper and lower envelop with mean $m1$. The difference among the data and mean is the first component of EMD. Further components are determined using $h1$ as proto-IMF. These components are first required to be cleaned to free them from artifacts. The artifacts and the signal can be separated based on their difference in peaks. A non-stationary signal is broken down into its constituents, each with a slowly fluctuating phase and amplitude [4]. These components are optimized or trained by various methods that defines a minimum threshold

and analyse the waves to define state of a person. Theoretically, the output components separates the phenomenon that transpires on different time scales. The IMFs satisfies the following requirements for a generalized Fourier decomposition: “Presence of only single zero in between two successive extrema and Local mean should always equal to zero.” The overall number of data points in an IMF component is typically limited to $\log_2 N$, N denotes the total number of data points. Through Hilbert transform, it meets all the criterias for a useful instantaneous frequency. An EMD uses an iterative method called the Sifting algorithm to deconstruct the input signal $x(t)$ into a collection of IMF.

The steps in the EMD algorithm is given below

Step 1: Initialize $r_0(t) = x(t)$, $i = 1$, $r_i(t) = r_0(t)$

Step 2: Procedure to extract the i^{th} IMF

- Initialize $h_0(t) = r_i(t)$, $J = 1$.
- Take a look at all the local minima and maxima of $h_{J-1}(t)$.
- To generate the upper and lower envelopes of $h_{J-1}(t)$, use a cubic spline to interpolate the local maxima and minima.
- Calculate the upper and lower envelopes mean $m_{J-1}(t)$.
- $h_J(t) = h_{J-1}(t) - m_{J-1}(t)$
- Set $imf_i(t) = h_J(t)$ if the stopping requirement is met; else, move to (b) with $J = J + 1$.

Step 3: $r_{i+1}(t) = r_i(t) - imf_i(t)$

Step 4: If $r_{i+1}(t)$ still have at least two extremes, set $i = i + 1$ to 2, otherwise the decomposition procedure terminates and $r_i(t)$ is the residue.

Finally, after n repetitions of the EMD method, the input signal can be reassembled as:

$$x(t) = \sum_{j=1}^n imf_j + r(t) \quad (1)$$

Fig. 2, is a flowchart depicting the EMD process.

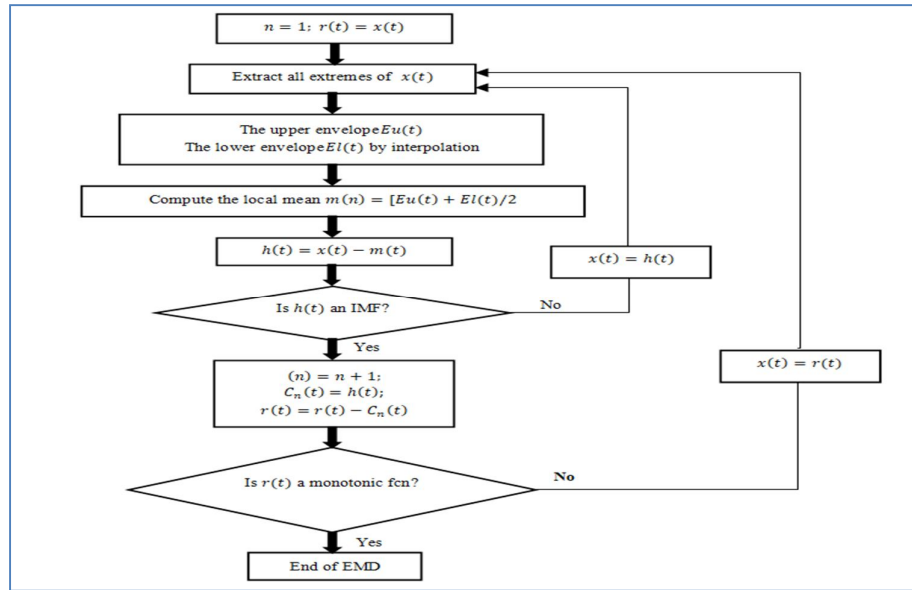


Figure 2. Flowchart of EMD

The reconstruction of EEG signal from the raw EEG signal is illustrated in Fig. 3, in which the last waveform is the residue EEG signal free from artifacts.

B. Feature Extraction

The artifact-free EEG data has four distinct properties extracted from it.

1. Discrete Wavelet Transform (DWT) energy features
2. Tunable Q-factor Wavelet Transform (TQWT) statistical features
3. Daubechies wavelet (Db) 4 spectral features
4. Deep learning features

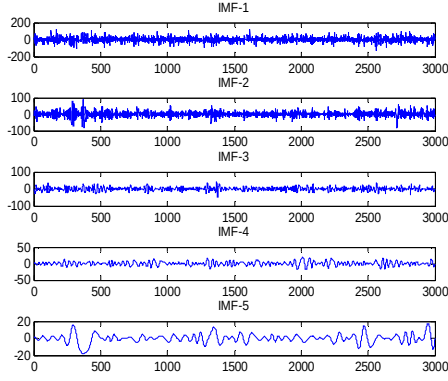


Figure 3. EEG signal artifact removal using EMD

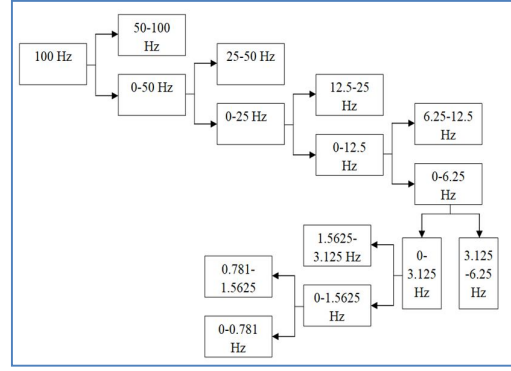


Figure 4. 7-Level Frequency Division from Discrete Wavelet Transform

DWT energy features

The variation between multiple frequency bands is best approximated by measuring amplitude in discrete levels. In this scenario, the HAAR wavelet's square function is the most appropriate filter, because the continuous signal may be described in terms of uniform sets, the components can be categorized on the basis of frequency by considering a range of their amplitudes. For example, if the maximum amplitude peak of the mother wavelet is $\frac{1}{2}$ to 1, the signal is delta. The mother value of the HAAR wavelet is given as:

$$\psi(t) = \begin{cases} 1 & 0 \leq t < 1/2 \\ -1 & \frac{1}{2} \leq t < 1 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

The scaling function is:

$$\phi(t) = \begin{cases} 1 & 0 \leq t < 1 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

For frequency classification of EEG data, the ability of wavelet decomposition is to split a mother wavelet into high and low frequency child wavelets. With a sampling frequency of 100 Hz, the signal is sampled into two daughter wavelets of Approximate Component (AC) with low frequency and Detailed Component (DC) with high frequency. The output of the first component is split into two bands: 50-100 and 0-50. The top band, 50-100, is DC, whereas the lower range, 0-50, is AC. Fig. 4. The following equation can be used to divide the initial function $x(t)$ into samples with low components:

$$C_A = Y[n]_{Low} = \sum_{k=-\infty}^{\infty} x[k]h[2n-k] \quad (4)$$

Where h is the low pass filter with a sub sampled impulse response of 2. In addition, for high-component:

$$C_D = Y[n]_{High} = \sum_{k=-\infty}^{\infty} x[k]g[2n-k] \quad (5)$$

Where, g is high pass filter with sub sampled impulse response of 2 and segmentation of AC component determines the components. In Eq. 4 and Eq. 5, the original $x(t)$ signal was replaced by the C_A in this stage.

$$C_{A1} = Y[n]_{Low} = \sum_{k=-\infty}^{\infty} C_A h[2n-k] \quad (6)$$

$$C_{D1} = Y[n]_{High} = \sum_{k=-\infty}^{\infty} C_D g[2n-k] \quad (7)$$

The energy for each level is calculated using the detailed coefficients from (9) and (11) for 7 levels DWT, where n represents the number of detailed coefficients in each level. The L denotes the current state of seven DC components. Each level has a different number of DC in each coefficient. For instance, in the first decomposition, n is 50-100, implying that $n=50$. The following is a formula for calculating energy:

$$E_L = \sum_{k=1}^n C_D(k) \quad (8)$$

The energy of the first detailed coefficient C_D is calculated for $L=1$. The energy of the 2nd DC C_{D1} is used for $L=2$. Every DC's energy ($E_1, E_2, E_3, E_4, E_5, E_6$ and E_7) is used as features for training a Random forest classifier.

TQWT statistical features

TQWT is used to extract features from oscillatory data such as EEG signals. It's a filter bank series. Each filter bank's low pass output is fed into a subsequent high pass filter in the next filter bank. Each filter bank has a low pass filter $H_0^j(w)$ and high pass filter $H_1^j(w)$. Filters are defined as:

$$H_0^j(w) = \begin{cases} \prod_{m=0}^{j-1} H_0\left(\frac{w}{\alpha^m}\right), & |w| \leq \alpha^j \pi \\ 0, & \alpha^j \pi < |w| \leq \pi \end{cases} \quad (9)$$

$$H_1^j(w) = \begin{cases} H_1\left(\frac{w}{\alpha^{j-1}}\right) \prod_{m=0}^{j-2} H_0\left(\frac{w}{\alpha^m}\right), & (1-\beta)\alpha^{j-1}\pi \leq |w| \leq \alpha^{j-1}\pi \\ 0, & \text{for other } w \in [-\pi, \pi] \end{cases} \quad (10)$$

Where

$$H_0(w) = \theta\left(\frac{w+(\beta-1)\pi}{\alpha+\beta-1}\right) \quad (11)$$

$$H_1(w) = \theta\left(\frac{\alpha\pi-w}{\alpha+\beta-1}\right) \quad (12)$$

Where, $\theta(w)$ is the Daubechies filter frequency response. J is the number of decomposition levels and it is set as 3 for this work, α is the low pass scaling factor and it is set as 0.6 for this work and β is the high pass scaling factor and it is set as 1 for this work.

Db4 spectral features

EEG signals are segmented in epochs of 5 minutes of 3000 samples for duration of 90 minutes in a non overlapping mode. A variant of Daubechies wavelet called as db4 wavelets is applied on each of the segments. The choice of db4 is due to its peculiarity of maximum number of vanishing moments and its powerful scaling. Maximum power value from power spectral analysis, mean, kurtosis, skewness, total harmonic distortion are the features extracted from the wavelet coefficients.

Deep features

Wavelet transform helps analysis of signals with dynamic frequency spectrum. Wavelet transforms are of two categories: continuous and discrete. Continuous wavelet transform is given as:

$$X_w(a, b) = \frac{1}{|a|^{1/2}} \int_{-\infty}^{\infty} x(t) \phi\left(\frac{t-b}{a}\right) dt \quad (13)$$

The mother wavelet with a scale factor of 'a' and a translation factor of 'b' is denoted as $\phi(t)$. When a continuous wavelet transform is applied to an EEG signal, a 2D scaleogram is produced, which offers extensive information on the system's state space. In this work continuous wavelet transform with Gaussian, as mother wavelet is applied onto the preprocessed EEG signal to generate the 2D scaleogram. A sample scaleogram of a EEG signal for drowsiness and non-drowsiness case is given below.

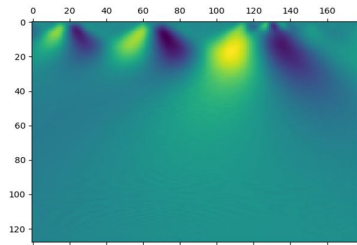


Figure 5. 2D scaleogram for drowsiness case

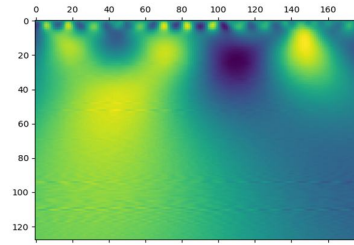


Figure 6. 2D scaleogram for non drowsiness case

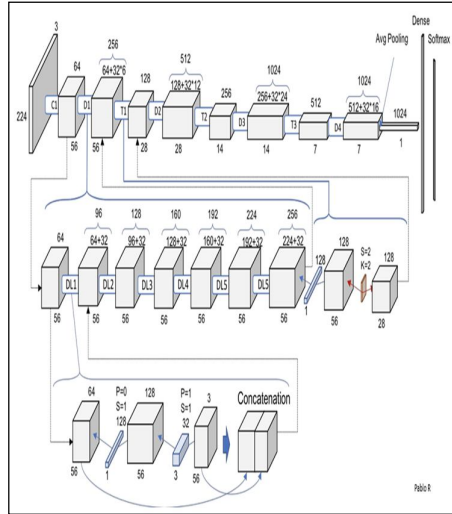
As seen from Fig. 5 and Fig. 6, there is a clear difference between drowsiness and non drowsiness case in the 2D scaleogram image. Deep learning features are extracted from the 2D scaleogram using Densenet deep learning model. Densenet was created as a response to the problem of gradient descent reducing the accuracy of high-level neural networks. The lengthy path between the input layer and the output layer in these neural networks causes the information to evaporate before it reaches its target with a few small variations. DenseNet employs concatenation (.) of the output of the previous layer with the output of the future layer, whereas ResNet uses (+) approach to merge the previous layer with the future layer. DenseNet is a network architecture that aims to improve deep learning networks while also improving training performance by using shorter links within layers. DenseNet is a convolutional neural network with each layer connected to the ones below it. The layer in the Densenet model used in this work is given in Fig. 7.

The 2D scaleogram image is mapped to 128 dimension feature vector using deep net configuration in Fig. 8. The extracted features are given to classifier for drowsiness classification.

C. Classification

Four different classifiers are trained to classify drowsiness and weighted ensemble of the results of the four classifier is done to provide the final result.

Every DC's ($E_1, E_2, E_3, E_4, E_5, E_6$ and E_7) energy is retrieved using DWT and utilised as a variable for building a Random forest algorithm. A Random forest classifier is developed by joining tree structured classifiers [14]. Every tree receives the input items, and each tree votes on an individual unit vector. The forest uses the mode from different classes with the most votes as the output class. The trees are trained for sampling in the



Layers	Output Size	DenseNet-121
Convolution	112*112	
Pooling	56*56	
Dense Block (1)	56*56	[1*1 conv] [3*3 conv] *6
Transition Layer (1)	56*56	1*1*128 conv
	28*28	
Dense Block (2)	28*28	[1*1 conv] [3*3 conv] *12
Transition Layer (2)	28*28	1*1*256 conv
	14*14	
Dense Block (3)	14*14	[1*1 conv] [3*3 conv] *24
Transition Layer (3)	14*14	1*1*512 conv
	7*7	
Dense Block (4)	7*7	[1*1 conv] [3*3 conv] *16
Output Layer(1)	1*128	1*128

Figure 7. Densenet model for feature extraction

Figure 8. Deep net model for feature extraction

establishment of N cases. This sampling is a random method that employs the bootstrap sample to replace the existing data. The training and testing of Random forest classifier is as shown in Fig. 9. The best split on these estimates breaks the node, which is made up of M variables randomly picked from M input variables ($m \ll M$). The value of m is kept constant during the training procedure. In most cases, the value of m is chosen to be M times smaller than the number of inputs. Without clipping, each tree will reach its full potential. This training generates a huge number of trees, with N_{tree} determining the maximum value. The length of tree roots (tree depth) is calculated using the node size parameter. During the testing phase, the input is given to a forest that goes through all of the trees, and each individual's classification is recorded as a vote. The winner or output is the instance that receives the most votes. About one-third of the cases are suppressed or overlooked when a tree's training data set is drawn via sampling with replacement. In the test set, this Out-of-Bag data is used to offer impartial classification error estimation. As a result, the necessity for separate test and cross validation to obtain an unbiased estimate is reduced.

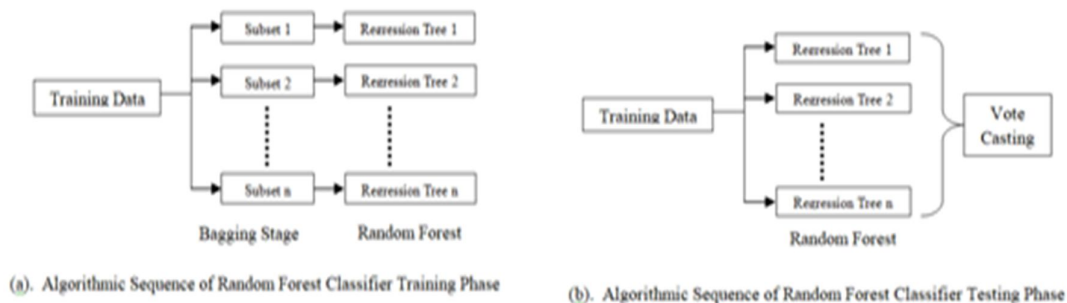


Figure 9. Random Forest classifier training and testing

Classifier C2 – TQWT statistical features + SVM Classifier.

The five statistical features extracted by applying TQWT is used as input to SVM classifier to classify two states of drowsiness or no drowsiness. SVM with Random Basis Kernel (RBF) is employed in this work. The value of gamma for RBF is set as 0.5 and C=0.10

Classifier C3 – Db4spectral features + Neural Network Classifier.

The five spectral features extracted by applying Db4 wavelet transform is used as input to Neural Network classifier to classify two states of drowsiness or no drowsiness. The neural network is used with following configuration as seen in Table I.

Classifier C4 – Deep features + SVM Classifier

SVM classifier uses the 128 dimensional deep learning features retrieved from the 2D scaleogram of EEG as input to categorise two states of drowsiness or no drowsiness.

Ensemble of the classifiers.

Weighted Ensemble of results from the four classifiers (C1, C2, C3 and C4) is done to detect drowsiness. Each classifier's output is a binary decision of drowsiness or absence of drowsiness. Classifiers' weight is computed as:

TABLE I. NEURAL NETWORK CONFIGURATION

Parameters	Values
No of Layers	3
Number of neurons in input layer	5
Number of neurons in hidden layer	11
Number of neurons in output layer	2
Training method	Levenberg – Marquardth
Learning rate	0.3
Activation function in hidden layer	tangent sigmoid function
Activation function in output layer	Logarithmic sigmoid function
Maximum number of epocs	1000

$$w(C_i) = \log \frac{1 - \text{error}(C_i)}{\text{error}(C_i)}, 1 \leq C_i \leq 3 \quad (14)$$

The error value for each classifier is determined by running a trail run. In the ensemble model, the results of C1, C2, C3, and C4 are employed. Assume that the classifier is trained on the training data, and the error rate for each classifier is calculated as 0.25 for C1 and C4, 0.14 for C2, and 0.30 for C3. The weights are calculated using the weight calculation for the error rate above. C1 and C4 get 0.47, C2 and C3 get 0.78, and C3 gets 0.36.

Assume the following outcomes are produced by the four classifiers:

C1 predicts 0, C2 predicts 1, C3 predicts 0, and C4 predicts 0 (1 – drowsiness is detected, 0 – no drowsiness). The ensemble classifier will utilize the weighted vote to get the following prediction results.

No drowsiness: $C1 + C3 + C4 = 0.47 + 0.36 + 0.47 = 1.3$

Drowsiness: $C2 = 0.78$.

The No drowsiness class has a higher weighted vote value than the Drowsiness class.

Dataset

The Sleep EDF database of sleepiness detection was obtained from physionet.org/physiobank/database/sleep-edf. On healthy males and females aged 21 to 35, horizontal EOG, FpzCz, and PzOz EEG were recorded. The samples are taken at a rate of 100 Hz. The sub mental EEG envelop, rectal body temperature, and oro-nasal airflow are all artifacts in the readings. The 'microvolt mean-root-squared' dimensions are used to read a signal. For the experimentation, there are a total of 8 recordings.

MATLAB receives the brain signals from the sleep database. Experimentation is carried out using MATLAB version 2013(a).

TABLE II. CLASSES OF SLEEP STAGES

Sleep Signal	Notation	Characteristics
S0	Wake	Low Amplitude, High Frequency
S1	Sleep stage 1	Slow Eye Movement
S2	Sleep stage 2	Spindles and K-Complexes
S3	Sleep stage 3	High Frequency, Low Amplitude
S4	Sleep stage 4	High Frequency, Low Amplitude
S5	Sleep stage 5	High Frequency, Low Amplitude REM

In MATLAB, the signals are divided into discrete format. The IMF, which are a continuous signal in discrete format, are produced by the EMD. This signal is free of artifacts and identifies the state of mind in five different sleep classes as seen in Table II. The suggested architecture's performance is assessed in terms of accuracy and

reliability. With a sampling frequency of 100 Hz, the signals are considered. The wave characteristics of sleep stages in Fig. 10 is depicted in Table II.

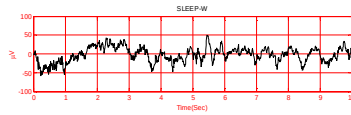


Figure 10 (a). Adults awake state of thinking

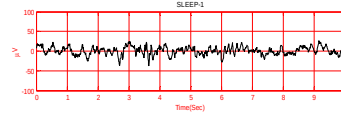


Figure 10 (b). Initial stage of drowsiness

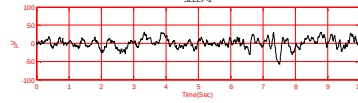


Figure 10 (c). k-complexes

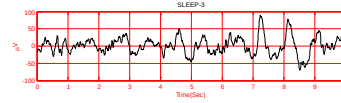


Figure 10 (d). Deep sleep-signal activity of 20%-30%

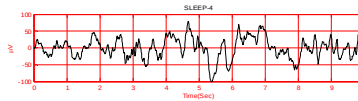


Figure 10 (e). Deep sleep-signal activity of 50%-60%

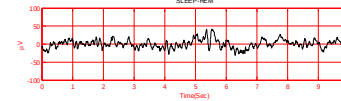


Figure 10 (f). Three periods of REM sleep

Fig. 10 (a) to Fig. 10(f) represents signal representation of sleep stages of brain. Fig. 10(a) depicts an adult's awake state of thinking. The graph shows various random features of signals, as well as low amplitude (8-13 Hz) and high frequency. These signals are generally tainted with muscular movements when the motorist closes his or her eyes or relaxes (EMG). The initial stage of drowsiness is seen in Fig. 10.(b). EEG artifacts typically have a frequency range of 4 Hz to 7 Hz. Fig. 10(c) shows k-complexes and speed spindles with a frequency range of 11Hz-16 Hz. The EMG reveals reduced muscle activity and a person's consciousness is lowered. Fig 10(d) and 10(e) show a person in deep sleep with a low frequency range of 0Hz.5-2 Hz and high amplitude. The difference between the two figures is the slow pattern of signal activity, which is 20%-30% in (d) and 50%-60% in (e). Fig. 10(f) depicts three periods of REM sleep. In the first phase, EMG is low enough to disappear. These sluggish waves are replaced by K-complexes with low amplitude and high frequency in the next phase.

IV. RESULTS AND DISCUSSION

The sample EEG signal acquired from subject is given in Fig. 11 and the result after artifact removal using EMD is seen in Fig. 12.

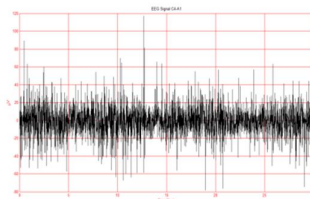


Figure 11. Original EEG signal acquired from Subject

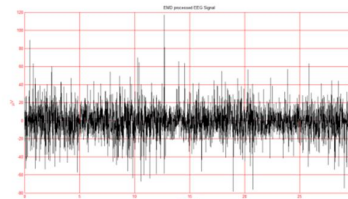


Figure 12. Artifact free EEG signal

The results of energy components due to DWT processing is given in Fig. 13.

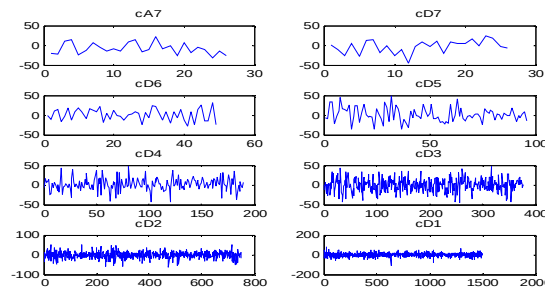


Figure 13. Various Energy Components of DC coefficients in DWT

The parameters used to evaluate the proposed solution's performance are Accuracy, Sensitivity and Specificity. The results with each of the classifiers and ensemble of the classifiers is given in Table III. In terms of accuracy, sensitivity, and specificity, the ensemble classifier outperformed the individual classifier. The accuracy parameters of several algorithms explored before are compared in Table IV. The statistics in this table are obtained from [15], which discusses categorization accuracy rates and methodologies. It is evident from this table that only a neural network can achieve good accuracy.

TABLE III. PROPOSED SOLUTION RESULTS

Method	Accuracy	Sensitivity	Specificity
DWT energy features + Random forest	97.6	95.1	94.23
TQWT statistical features + SVM	97.89	95.32	95.12
Db4 spectral features + NN	98.1	95.43	95.23
Deep learning + SVM	98.3	96.12	96.23
Ensemble classifier	98.33	96.12	95.59

TABLE IV. COMPARATIVE ANALYSIS OF ACCURACY AND RELIABILITY OF SLEEP STAGES

Reference	Signal	Method	Classifier	% Accuracy
[Wali, 2013] [15]	EEG	WT+FFT	Fuzzy 4 Classes	84.41
Proposed Ensemble model	EEG	EMD+ DWT+TQWT+Db4+ Deep learning	Random Forest + SVM + Neural Network	98.33

V. CONCLUSIONS

This paper proposes an ensemble approach for detecting driver drowsiness using EEG inputs. Four different classifiers of DWT energy features + Random Forest, TQWT statistical features + SVM, Db4 spectral features + Neural network and Deep features + SVN are trained to classify the drowsiness state. The results of the individual classifier are adaptive weighted ensemble to provide the final outcome. The proposed model is able to provide an accuracy of 98.33%, sensitivity of 96.12% and specificity of 95.59%. The performance of the proposed solution was tested against Physionet databases and experimentation with real world datasets collected from different EEG headsets is the scope of future work.

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