Drowsiness Detection using Band Power and log Energy Entropy Features Based on EEG Signals

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Abstract*: *Sleeping on the wheels due to drowsiness is one of the significant causes of death tolls all over the world. The primary reason for the sleepiness is due to lack of sleep and irregular sleep patterns. Several methods such as unobtrusive sensors, vehicle dynamics and obtrusive physiology sensors are used to diagnose drowsiness in drivers. However, the unobtrusive sensors detect drowsiness in the later stage. Whereas the physiological methods use obtrusive sensors such as electro-ocular, electro-myo and electro-encephalograms produce high accuracy in the early detection of drowsiness, which makes them a preferable solution. The objective of this research article is to classify drowsiness with alertness based on the electroencephalographic (EEG) signals using band power and log energy entropy features. A publicly available ULg DROZY database used in this research. The raw multimodal signal is processed to extract the five EEG channels. A passband filter with the cut off frequencies of 0.1 Hz and 50 Hz attenuates the high-frequency components. Another bandpass filter bank is designed to slice the raw signals into eight sub-bands, namely delta, theta, low alpha, high alpha, low beta, mid-beta, high beta and gamma. The preprocessed signals are segmented into an equal number of frames with a frame duration of 2 seconds using a rectangular time windowing approach with an overlap of 50%. Frequency domain features such as log energy entropy and band power were extracted. The extracted feature sets were further normalised between 0 and 1 and labelled as drowsy and alert and then combined to form the final dataset. The K-fold cross-validation method is used to divide the dataset into training and testing sets. The processed dataset is then trained using Discriminant analysis, k-nearest neighbour network, Binary decision tree, ensemble, Naive Bayes and support vector machine classifiers and the results are compared with the literature. The kNN classifier produces 95% classification accuracy. The developed model can provide a tool for drowsiness detection in drivers.

Index Terms*: *band power, DROZY database, drowsiness, log energy entropy, polysomnography.

I. INTRODUCTION

Road accidents are certainly a growing concern in most of the nations because of its increase in the cause of death tolls. Reports from the World health organisation (WHO) state that road accidents are the 9th leading cause of death globally [1]. Sleep-associated vehicle accidents have the highest share of traffic accidents. 30% of all fatalities and injuries have been caused by sleepiness worldwide.

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The U.S. National Highway Traffic Safety Administration (NHTSA) projected that drowsy driving is the reason for 40,000 injuries and 1,500 demises in car crashes per year [2]. These deaths could be avoided if driver drowsiness was observed correctly, and drivers were abruptly alarmed. Sleepiness is a physiological phenomenon signifying a lack of energy and motivation. There are various issues such as inadequate sleep, extended mental or physical work, long periods of stress, and anxiety, and so on. That generate fatigue in humans. Driver drowsiness has gained importance in the last 80 years. According to statistics, there is a huge requirement to build a system for monitoring the drivers and gauging their level of attention, which is also called ad Advanced Driver Assistant Systems (ADAS). There are several techniques to detect driver drowsiness, which is broadly categorized into a vehicle based, behaviour based and physiology based.

In the vehicle-based methods, the parameters such as pressure on the acceleration pedal, lane deviation, steering angle position are used to determine whether the driver is under the influence of drowsiness or not. Nowadays, modern vehicle manufactures implement one or all of the above methods in the driver assist systems as a safety measure. However, the driving environment, road marking, climatic conditions and driving skill make this method difficult to evaluate the state of the driver [2].

Another technique is to continually monitor and record the driver's motion namely eye closure, eye blink, yawning and head movements through a fixed camera with an intelligent system to discriminate between the state of the vigilance and drowsiness. Nevertheless, the critical limitation in this method is due to the reduced recognition rate under dim lighting background and the stage at which the drowsiness is detected. The behavioural method detects drowsiness only after the driver is entirely influenced by sleep.

Among the various drowsiness detection techniques, the physiology-based process involves electroencephalogram (EEG), electromyogram (EMG), electrocardiogram (ECG) and electrooculogram (EOG). The EEG method yields high accuracy and is referred to as gold standard. Thus, the physiology-based method produces high efficiency and reliability in detecting drowsiness at an early stage. The EEG signal, which is the most preferred physiological signal, has the closest association with drowsiness. The drawbacks of the EEG signals are that, as they have high temporal resolution and can be easily interfered by EMG, eye blink and electromagnetic noise [2].

Drowsy driving is a vital issue and hence need to be identified at the earliest. Drowsiness has subsequent effects. a) Driver's reduced attention to surroundings, b) Considerable delay in reaction time, and c) Affect the driver's capability to make decisions. The literature study attempts to review all the previous approaches in detecting drowsiness. Drivers involved in sleep-related crashes rate their quality of sleep was either bad or fair [3]. Missing an hour of sleep can lead to car crash risk. The only antidote for drowsiness is sleep [4].

Li and his co-authors [5] used Fp1 and O1 EEG channels to discriminate between alert and drowsy. Pranoto et al. [6] detected drowsiness in truck drivers using a speed limiter integrated fatigue analyser. The system is based on Arduino UNO, sensing the driver's body temperature and heart rate. Ribeiro et al. [7], [8] developed an EEG based drowsiness detection system based on the Sleep EDF database and used Hjorth coefficients, power spectral density and average power to classify drowsiness. Albalawi et al. [9], [10] developed a real-time drowsiness detection based on a single channel EEG signal using eight frequency bands. They computed the relative power and classified the drowsy and alert state with the support vector machine (SVM) classifier. They compared the results of the developed system with the MIT-BIH polysomnographic database. Leger et al. [11] inflight vigilance state detection using a single EEG channel for pilots. Pathak et al. [12], [13], Da Silveira et al., [14], Picot et al. [15], [16], Ogino et al. [17] researched on the using single EEG channel to classify alert and drowsy states in drivers. Hu [18] compared the different features and classifiers for driver drowsiness detection based on a single EEG channel. [19]

Alluhaibi et al. [20] discussed the various driver behaviour detection methods, their advantages and disadvantages. Mu, Hu and Min [21] detected driver fatigue using combined entropy features from the EEG signals. Belakhdar et al. [22]–[24] used a single channel EEG signal to classify drowsiness based on the average power of the delta and alpha waves. They compared the ANN and SVM classifiers for the best accuracy. They used the MIT-BIH polysomnographic dataset. Correa et al. [25], [26] extracted features using spectral and wavelet decomposition methods to classify drowsy and alert state.

In this work, we have considered the ULg multimodality drowsiness database. The database contains multimodal signals, namely five EEG channels, 2 EOG channels, 1 EMG and 1 ECG channel along with the psychomotor vigilance test (PVT) and video data. We have considered only the five EEG signals for analysis and to classify between the alert and drowsy state. We have used framing method to segment the signal into equal frames of 2 seconds using a rectangular window with an overlap of 50%. The raw signal is trimmed using a passband filter to a maximum cut-off frequency of 50Hz.

Further, each frame is segmented into eight sub-bands using a bandpass filter bank. We have extracted the log energy entropy and band power features for each of the frames. The feature set is then rescaled using a bipolar normalisation method. The feature set is labelled as drowsy and alert, and then all the alert and drowsy data are combined to form the final dataset. K-fold cross-validation technique is used. The dataset is trained using Discriminant analysis, k-nearest neighbour network, Classification ensemble, Naïve Bayes, Binary decision tree and Support vector machine classifiers and the results are compared.

The remaining of the paper is ordered as follows. The details from the literature and the proposed methodology is explained in the second part of the introduction section. The multimodality drowsiness database, data acquisition protocol and the channel selection are explained in the first part of the methods section. The second part details the preprocessing, sub-band filtering and feature extraction procedures used in this approach. Data preprocessing section details dimensionality reduction and data preparation for the six classification models. Results section projects the results followed by the discussion section discuss the outcome of this research. The conclusion section details the contributions and concludes the paper.

II. METHODS

A. DROZY Database

The publicly available ULg multimodality drowsiness (DROZY) database is considered in this research as it contains multimodal approach. The complete details of the multimodal data collection, data description and the protocol are represented in Figure 1 (Massoz, Langohr, Francois, & Verly, 2016).

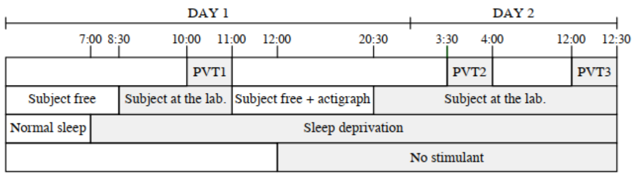

Figure 1. Protocol design during the data collection (Massoz et al., 2016)

In this research, it is planned to use the ULg multimodality drowsiness database. The database contains physiology related signals, i.e., EEG, EOG, ECG, and EMG. By using the Embla Titanium system, the signals were recorded from EEG channels C3, C4, Cz, Pz, and Fz referenced at A1 in the international 10-20 system. The vertical and horizontal EOG signals, ECG and EMG signals were also recorded at a sampling frequency of 512 Hz. Along with these signals, video signals were also recorded. The drowsiness and alert signals were recorded from 14 male and female subjects. The test was conducted in a controlled environment in three trials. Before the first trial, the subjects were asked to have a good sleep pattern for the past week. In the first trial, the subjects were asked to perform an action watching the screen. After the first trial, the subjects were asked to stay awake for 36 to 38 hours to keep them sleep deprived. In the second and third trials, the subjects performed the same previous experiment. Post the final test; the subjects were asked to take a sound sleep before they drive back home.

B. Channel selection

The experiment was conducted in three trials in two days, as mentioned in the protocol. The authors conducted an extensively used tool to measure the performance impairments due to drowsiness using a 10-minute psychomotor vigilance test (PVT). This test gives the reaction time to visual or auditory stimuli that occur at random inter-stimulus interval. Karolinska Sleep Scale (KSS), electrophysiological measurements.

1 ☐ Extremely Alert

2 ☐ Very Alert

3 ☑ Alert

4 ☐ Rather Alert

5 ☐ Neither Alert nor sleepy

6 ☐ Some signs of sleeping

7 ☐ Sleepy, no effort to stay awake

8 ☐ Sleepy, some effort to stay awake

9 ☐ Very sleepy, great effort to stay awake

Figure 2. Karolinska Sleep Scale (KSS)

The database contains PSG signals from 11 electrophysiological signals (5 EEG, 2 EOG, 1 ECG and 1 EMG) are considered. The five EEG channels are recorded from C3, C4, Cz, Pz, and Fz locations present in the central lobe of the brain. The placement of the EEG channels is depicted in Figure 4. The sensors placed around C3, C4 and Cz locations deal with the sensory and motor functions [27]. This research uses monopolar montage with C3 as a reference. The vertical and horizontal EOG signals are recorded from above and at the side of the right eye to capture the eye blinks. An ECG channel is recorded from the electrode placed on the chest, and an EMG signal is recorded from the electrode placed on the neck of the participant. The placement of electrodes is pictorially represented in Figure 3.

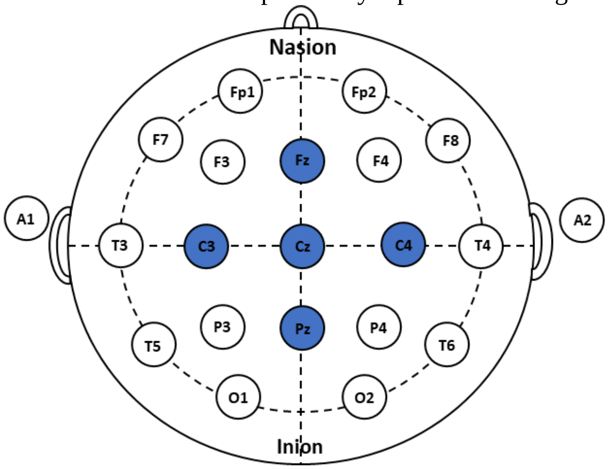

Figure 3: EEG electrode placement conferring to the international 10-20 system

III. FEATURE EXTRACTION

Dimensionality reduction plays a vital role in classifier performance. Dimensionality reduction is achieved either by feature extraction or feature selection. For both feature extraction and feature selection approach, feature evaluation criterion, the dimensionality of the feature space and optimisation procedure are required. Feature extraction is the conversion of the raw data to a dataset with the selected number of variables which contains the most discriminatory evidence. Feature extraction, on the other hand, considers the whole original data and maps the useful information into a lower dimensional space. The following section explains the signal processing and feature extraction process.

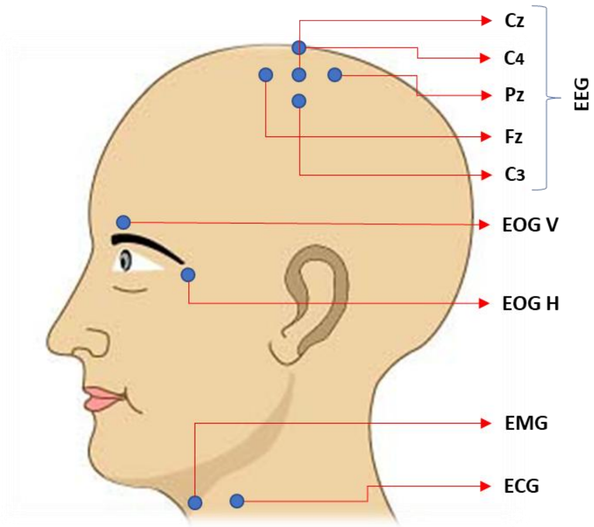

Figure 4. Multimodal electrode placement during the experiment

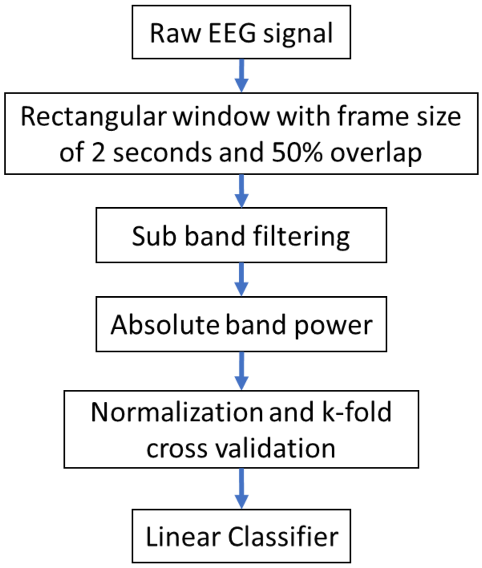

Figure 5. Flowchart of the signal processing

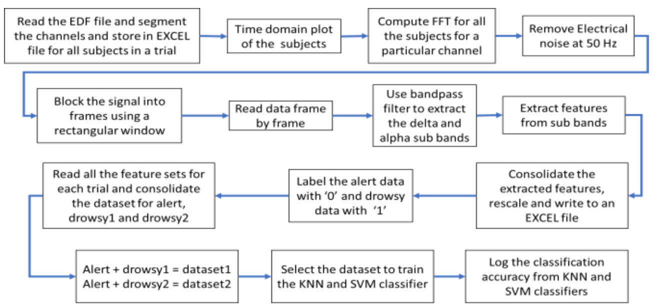

Figure 6. Block diagram of the drowsiness detection

A. EEG signal processing

EEG signals are the non-invasive physiological means of recording brain activity. It has the closest association with drowsiness. The EEG has a neural domain signal information has a high temporal resolution but can be easily interfered by EMG, eye blink and electromagnetic noise [28]. The EEG, along with the EMG, ECG, and EOG signals, remains the European data format (EDF). A MATLAB function is used to extract only the EEG signals, which are of the interest in this research. The experiment was conducted for 10 minutes, and the EEG signal contains information up to 600 seconds. The signals are recorded at 512 Hz sampling frequency. The signals include both EOG and EMG, which contribute towards the drowsiness detection. Hence the eye blink artefacts and the EMG artefacts which are removed in conventional biosignal processing is avoided in this research. The raw signal is processed directly without any artefacts removal. However, a Butterworth low pass filter with a cutoff frequency of 50 Hz is designed to attenuate the high-frequency components.

B. Subband filtering

The EEG signal is conventionally divided into alpha, beta, theta, gamma and delta waves based on their rhythms. These waves are further subdivided into low, medium and high and are extracted using a suitable bandpass filter based on their frequencies [9], [10]. A Butterworth bandpass filter bank with eight frequency bands is designed and used to extract the sub-bands of the EEG signals. Table I details the cut off frequencies for all the eight sub-bands.

C. Frame blocking, windowing and overlap

The raw signal is recorded for 10 minutes. It is difficult to apply any feature extraction methods to the whole signal. Hence the signal is divided into specific time windows (signal epochs) from the continuous EEG signal. On a trial and error method, the duration of the time windows is selected based on the performance metrics. In this case, the 2 seconds window is chosen to segment the raw EEG signal. An overlap of 50% is applied during the process of windowing.

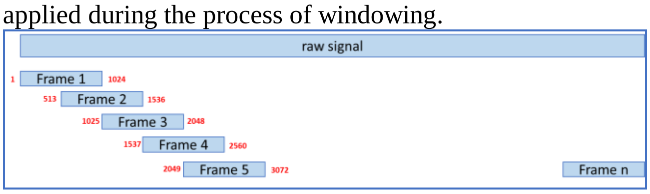

Figure 7. Frame blocking

D. Frequency transformation

During each trial of the experiment is recorded for an average of 10 minutes, which is approximately 600 seconds. All the signals are read, and the maximum length of the signal is computed and taken as reference, for those signals where the length is short, zeros are padded at the end of the signal to make all signals even. The raw EEG signal is segmented into 2 seconds pulses. After segmenting the signals into frames of 2 seconds with the windowing technique, the original raw signal grows to 300 per each subject per each trial, thereby enhancing the data. The signal is then transformed into the frequency domain by applying a Discrete Fourier transformation with the Fast Fourier Transform (FFT) algorithm.

Table I. EEG sub-band filtering

Wave	Freq range (Hz)	μV	Nature	Optimal
Delta	0.1 – 4	20 - 200	Very slow	Deep Sleep
Theta	4 – 8	20 - 100	Slow	Depressants
Low Alpha	8 – 9	20 - 60	Moderate	Relaxation
High Alpha	9–12	20 - 60	Moderate	Relaxation
Low Beta	12 – 16	2 - 20	High	Conscious
Mid Beta	16-20	2 - 20	High	Blinking, aware of self and surroundings
High Beta	20-30	2 - 20	High	Alertness, agitation
Gamma	30 – 50	3 - 5	Very high	Cognition

E. Entropy-based feature extraction

Entropy is a statistical measure that represents how much randomness is present in the signal. Entropy assesses the uncertainty of a system. Mu et al. [21] extracted spectrum entropy, approximate entropy, sample entropy and fuzzy entropy from the EEG signals. Goksu [29] used log energy entropy of wavelet packets for BCI oriented EEG analysis. Aydin et al. [30] used log energy entropy for seizure detection. The log energy entropy of '*x*' is presented in Equation 1. The log energy entropy for the delta and alpha subbands are extracted.

$$H_{LogEn}(x) = -\sum_{i=0}^{N-1} \log_2\left(\left(p_2(x)\right)\right)^2 \quad (1)$$

F. Band power

Band power returns the average power in the input signal. Foong et al. [31] used EEG band power to infer driver drowsiness. During this drowsy state, the alpha band power shows a higher value. The absolute and the relative values of each channel are obtained in the frequency band. The band power for delta, low alpha and high alpha subbands were then calculated. The following five features were computed.

a. Low alpha band power
b. High alpha band power
c. Delta band power
d. High alpha band power / Delta band power
e. Low alpha band power / Delta band power

IV. DATA PREPROCESSING AND CLASSIFICATION

Classifiers are evaluated based on the ease to interpret output, calculation time and prediction power. The feature sets contain raw information and are rescale to normalise the data between '0' and '1'. Once the feature set is extracted, the output class is labelled accordingly, and the final dataset is processed

In order to develop a binary classification, the trail 1 data are labelled as alert while the trail 2 and trial 3 data are labelled as drowsy. In this research, six classifier models were used to train and test the dataset. Dataset 1 combines the alert data from trial 1 and drowsy data from trial 2, while dataset 2 consists of trail 1 and trial 3. Both the datasets were mapped according to the state of alertness or drowsiness.

K-fold cross-validation method is used to divide the feature matrix into training and testing datasets.

K-Nearest neighbour algorithm (*k-NN*) is one of the simplest and easy to implement a supervised machine learning algorithm. The K factor is very crucial in determining the class boundaries. The boundaries become smooth with increased values of K. The training error rate and the validation error rate are the two parameters used to access for the values of K. The '**fitcknn'** function in MATLAB is used to model the KNN classifier. The '**minkowski'** method is used as a distance metric, and the number of neighbours value is chosen to be 3 in this classification method. The alert and the drowsy are defined as the two classes.

Support Vector Machine (SVM) is a supervised algorithm to be used for classification. In this method, we plot each data as a point in the n-dimensional space with the value of each feature being the value of the particular coordinate. The classification is performed by finding the hyperplane that differentiates between the two classes. Hence finding the right hyperplane becomes very crucial in SVM. By maximising the distance, also known as the margin between the nearest data point and the hyperplane will determine the right hyperplane. The kernel method is used to transform the low dimensional input space to a higher dimensional space in a non-linear separation problem. The 'fitcsvm' function in MATLAB is used to model the SVM. 'Radial basis function' kernel is used to classify between drowsy and alert classes.

A binary classification tree is a tree-based classification model. The 'fitctree' function is used to model the binary tree classification model in MATLAB.

Naive Bayes method is one of the fast-relative classification algorithms compared to other classifiers. It is based on the Bayes theorem to predict the class of unknown dataset. The classifier assumes that the presence of a particular feature in a category is unrelated to the presence of any other element. The Naive Bayes is especially useful for extensive datasets and multi-classification problems. The 'fitcnb' function in MATLAB is used to model the Naive Bayes classifier for the binary classification between alert and drowsy. The Gaussian method is used for classification.

Discriminant analysis is a classification method. It assumes that different classes generate data based on different Gaussian distributions. The 'fitdiscr' function is used to model the discriminant analysis model in MATLAB. 'quadratic' type is used as a discrimination type.

Classification Ensembles is a predictive model that consists of a weighted combination of multiple classification models. Bagging or bootstrap aggregation, Boosting, and stacking are some of the ensemble classifier methods. The 'fircensemble' function is used to model the ensemble classifier in MATLAB.

V. CLASSIFICATION RESULTS

The band power for the alpha and delta subbands based datasets were trained and tested for several epochs, and the average classification accuracy is considered. The support vector machine classifier takes the maximum computation time while the kNN classifier takes the minimum computation time. Considering the overall results tabulated in Table II, for both the datasets, the kNN classifier produces maximum classification accuracy compared to the other classifiers considered in this research.

Compared to the results from the literature presented in Table III, the proposed drowsiness detection using the DROZY database produces a higher classification accuracy rate.

Table II. Average classification accuracy

Classifiers	**Average class accuracy**	
	Dataset 1	**Dataset 2**
K-Nearest neighbour	**95.20**%	**94.60**%
Support Vector Machine	93.10%	92.50%
Binary classification tree	94.83%	87.66%
Naive Bayes	88.30%	80.00%
Discriminant analysis	91.00%	81.00%
Classification Ensembles	95.00%	90.83%

Table III. Comparison of classification performance from other classifiers

Database	Correa et al. [26]	Belakdhar et al. [24]	Proposed method
Dataset	MIT-BI H	MIT-BIH	DROZY
Classifier	ANN	ANN	kNN
Class Accuracy	81.50% & 83.70%	86.50%	95.20% & 90.83
No. of features	12	9	6
Approach	PSD	FFT	Entropy, Bandpower

VI. DISCUSSION

This study presents a method for classifying the state of vigilance to alert or drowsy states based on an EEG signal. The publicly available DROZY database from ULg was considered for the reason that it contains multimodal signals. The analysis involves the task of detecting the transition from an alert state to the drowsy state. Reyner and Horne [32], [33] state that drivers are aware of feeling sleepy or drowsy for about an average of 45 minutes before the driving event.

Nordbakke and Sagberg [34] Yet, they underestimate the feeling sleepy. Williamson et al. [35] claimed that the driver's ability to assess the degree of their sleepiness is sufficient for them to decide to stop driving. Nazari and his associates [36] conducted a detailed review of the various interventions on the decreasing fatigue and drowsiness during driving.

The EEG signals are measured in microvolts and spread from 0.1 Hz up to 50 Hz. The high-frequency components are not of the interest for this research, and they are removed using a higher order low pass filter with a cut off frequency at 50 Hz. The filtered signal is then segmented into eight sub-bands using a Butterworth bandpass filter. The sub-bands represent the different states of brain activity. Our research interest lies in the delta and alpha subbands. The signal was recorded for 600 seconds (10 minutes). The anomaly in the delta and alpha subbands are extracted using the entropy and band power features. The hypothesis, during this study, is to evaluate the alpha and delta activities. The alpha activity is inversely proportional to the delta activity during drowsiness. Microsleep is a temporary occurrence of sleep or drowsiness which may last from a fraction of a second to two minutes. Microsleeps occur while the person’s eyes are open. It is a straight result of sleep deprivation. Frequent blinking, sudden body jerk, a blank stare, head dropping are the results of microsleep. Also called as daytime drowsiness. During microsleep, there is an increase in theta and alpha waves for more than 3 seconds. [37].

The database considered in this research focuses on the induced drowsiness through the protocol design. The limitation of the protocol is that it lacks the implementation of a driving simulator and may not be compared with other driver drowsiness experiments. However, the reason for drowsiness is sleep deprivation and has been considered during the protocol design.

VII. CONCLUSION

This study performed the detection and classification of drowsiness based on the EEG signal. The five EEG channels are extracted from the publicly available ULg DROZY database. The eight subbands, namely delta, theta, low alpha, high alpha, low beta, mid-beta, high beta and gamma, were separated from the raw EEG signal. The features were extracted based on a frame by frame analysis using a rectangular window with a 50% overlap. The log energy entropy and band power features were computed for all the subbands. The feature sets for the drowsy class was labelled as ‘0’, and the alert was marked as ‘1’. The extracted feature sets were further normalised and tagged as drowsy and alert and then combined to form the final dataset. K-fold cross-validation method is used. The dataset was trained using the six classifier models: discriminant analysis, k-nearest neighbour network, Binary decision tree, ensemble, naive Bayes and support vector machine. The trained models were validated using the test dataset, and the performance of the classifiers on the two datasets was compared. Overall, the k-NN classifier achieves 95.2% and 94.6% by outperforming the other classifiers. The proposed frame-based approach can be used for other classification applications as well. The developed model can be applied for driver drowsiness classification and other drowsiness research.

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