Analysis of Alpha and Theta Band to Detect Driver Drowsiness Using Electroencephalogram (EEG) Signals

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Abstract: *Driver drowsiness is recognized as a leading cause for crashes and road accidents in the present day. This paper presents an analysis of Alpha and Theta band for drowsinesss detection using Electroencephalogram (EEG) signals. The EEG signal of 21 channels is acquired from 10 subjects to detect drowsiness. The Alpha and Theta bands of raw EEG signal are filtered to remove noises and both linear and non-linear features were extracted. The feature Hurst and kurtosis shows the significant difference level (p<0.05) for most of the channels based on Analysis of Variance (ANOVA) test. So, they were used to classify the drowsy and alert states using Quadratic Discriminant Analysis (QDA), Linear Discriminant Analysis (LDA) and K- Nearest Neighbour (KNN) classifiers. In the case of Alpha band, the channels F8 and T6 achieved a maximum accuracy of 92.86% using Hurst and the channel T5 attained 100% accuracy for kurtosis. In the case of Theta band, Hurst achieved 100% accuracy for the channel F8 and Kurtosis obtained a maximum accuracy of 92.85% in the channels FP1, CZ and O1. A comparison between Alpha and Theta band for the various channels using KNN Classifier was done and the results indicate that the selected channels from Alpha and Theta bands can be used to detect drowsiness and alert the driver.*

Keywords: *Electroencephalogram, alpha band, theta band, drowsiness, KNN, ANOVA.*

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1. Introduction

Globally, road in juries are ranked as the 9th leading causes for death and records 2.2% of all deaths [2]. The World Health Organization has noticed that road accidents kills more than 1.25 million peoples and injure about 50 million peoples a year and 90% of such casualties occur in developing countries [15]. In 2017, around 1,306 drivers who were involved in fatal crashes (or almost 3 percent) were reported as being drowsy [7]. Most of the crashes could have been avoided by giving alarm to the drivers at the time of drowsiness with a proper monitoring system.

Drowsiness is defined as a state of transition between alert and sleep, leading to an increase in reaction time as well as a gradual inclination to sleep [17]. The development of drowsiness monitoring system has become a major focus for safe driving. Drowsiness is also influenced by the mental states of the drivers. However, concerning the mental state of drivers, the investigations of the human mind remain difficult; the plentiful and substantial results obtained in the field of cognitive neuroscience have recently provided an opportunity to resolve it [11].

This work intends to detect drowsiness using Electroencephalogram (EEG) signals. The noises, eye artifacts and muscle contraction were removed from the raw signal by appropriate pre-processing. The filtered signal was then segregated into EEG sub bands namely Delta, Alpha, Theta, Beta and Gamma based on the corresponding frequency range. Since drowsiness results better in Alpha and Theta bands the linear and non linear features are extracted from both these bands [20]. The Analysis of Variance (ANOVA) test was performed to know the statistical significance of the extracted features and only the significant features were used to find the accuracy rate of drowsiness using different machine learning algorithms.

The rest of the paper is organized as follows. Section 2 summarizes the related works on similarity search in drowsiness detection. The section 3 provides the system overview and the protocol details of this work. Section 4 shows the results and we provide the conclusion and future work in section 5.

2. Related Works

Researchers have developed many methods to monitor and detect driver's drowsiness. Changes in behaviour of the driver during drowsiness can be monitored by noticing the activities of the drivers such as yawning, position of head [13, 16] or eye blink duration by using optical sensors or cameras [12]. However, it requires a clear view and proper position of the camera for efficient detection. Lighting conditions, movements and speed of the vehicle also hinder the detection of drowsiness using behaviours [5]. Control Area Network (CAN) messages are analysed and is used to determine the driver behaviour and vehicle conditions for alerting in real time [19]. Another approach used by researchers is to use physiological signals of humans such as brain signal (Electroencephalogram) [18], heart beat signal EEG, muscle activity EEG eye blinking and eye gaze (Electro-oculogram) [3, 8, 16] to detect drowsiness. A wearable light weight brain sensing headbands were used to detect the drowsiness with the help of blink pattern yielding an average accuracy of 81% in determining the alert and drowsy state using SVM Classifier [18]. In the work by Picot *et al*. [14], a single channel EEG was used to detect three levels of drowsiness: "awake," "drowsy," and "very drowsy." from 20 different drivers and reached 80.6% correct classifications on three drowsiness levels. A generalized EEG-based Self-organizing Neural Fuzzy system was used in the occipital area to monitor and predict the driver's drowsy states [10]. In the work by Li *et al*. [9], a fully wearable EEG system consisting of a Bluetooth-enabled EEG head band and a commercial smart-watch was used to evaluate the drowsiness in a real-time from 20 subjects using Support Vector Machine (SVM). The Proposed intelligent system will warn the drivers about their speed according to the slope of the bends; thus, the drivers will be able to decide whether to decrease or increase the speed before the bend based on mobile application for decrease accidents [1].

3. Experimental Setup

A near real driving condition was obtained by means of a driving simulator that was setup in Artificial Intelligence Research Lab at Vels Institute of Science Technology and Advanced Studies (VISTAS), Chennai, as shown in Figure 1. The Allengers Polysomnography (PSG) sleep device which has 40 channels is comprised of only 21 EEG and other physiological ECG, Electromyogram (EMG), EOG, SpO2, thoracic and abdomen, limb movement etc) channels. This device is used in collecting various subject information related to their true internal state while driving. The sampling frequency of this data acquisition system is 256 Hz. By using an international 10-20 system arrangements the 21 EEG electrodes are placed on the frontal, central, parietal, occipital regions of the head using a cap. The EEG signals were acquired using FP1, FP2, F7, F3, FZ, F4, F8, T3, C3, CZ, C4, T4, M2, M1, T5, P3, PZ, P4, T6, O1 and O2 electrodes. To feel the drowsy condition a monotonous driving environment was selected using 'speed dreams' game and the vehicle speed was set to be a maximum of 70 km /hr. Ten healthy male participants from VISTAS whose age ranges from 19-32 participated in the experiment. A self report was obtained from each participants to analyse whether they undergone any medical contradictions such as neurological and addictive disorders. In accordance to the circadian rhythm the experiments were conducted on three timings: midnight (12.00 AM to 2.00 AM); early morning (3.00 AM to 5.00 AM) and afternoon (2.00 PM to 4.00 PM). Each experiments lasted for 90-120 minutes, in which first 15 minutes tends for practise to get familiar with the driving simulator game. The subjects also filled a post-questionnaire to help us understand the monotonous driving experience of the subject and evaluate the stages of drowsiness. The overview of the experimental setup was shown in Figure 1.

Figure 1. Driving simulator setup.

3.1. Data Processing

The EEG signals are initially analyzed using the Epoch method by providing the visual stimulus. The EEG signals and the driver behaviour monitoring through video is collected in parallel which is used for data splitting. The split signals are completely based on the video timings and are subject-independent. By using the post-questionnaire and the video analysis, the various instances of drowsy and alert states of the subjects were splitted from the signals and accordingly we get three alert and drowsy signals from each driving sessions. Those splitted raw EEG signal were filtered using Butterworth 6^{th} order Band pass filter (0.5 Hz to 49 Hz) [11, 15] to remove the different noises such as power line interference, movement artifacts etc., Using Fast Fourier Transform (FFT) the signals are decomposed and categorized into sub bands namely, Delta Band (0-4 Hz), Theta Band (4-8 Hz), Alpha Band (8-13 Hz), Beta Band (13-30 Hz) and Gamma Band (30- 44 Hz).

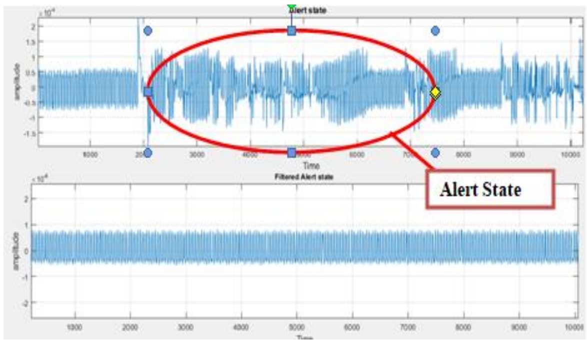
3.2. Feature Extraction

Based on the previous studies there is an indication of drowsiness occurs in the Alpha and Theta bands [18]. So in this study, the Alpha and Theta sub bands are selected and the features were extracted from the Alpha and Theta sub bands. The total of 11 features which were extracted from the sub bands are as follows Mean, Median, Maximum, Minimum, Standard Deviation, Skewness, Kurtosis, Variance, Root Mean Square and Hurst. The features were checked for statistical significance using ANOVA after which it was classified into alert and drowsy states using Linear Discriminate Analysis, Quadratic Discriminate Analysis, and K-nearest neighbour classifiers. Hold out validation method was used with 25% held out and 75% was used as training the classifiers.

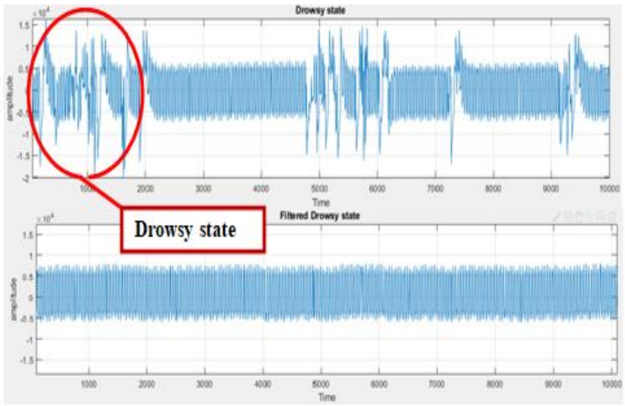
4. Results and Discussion

Figure 2-a) shows the raw and filtered signals of alert state and Figure 2-b) indicates the raw and filtered signals of drowsy state. Theraw EEG signal with artifacts and baseline wandering are filtered by Butterworth 6th order band pass filter in the frequency range of 0.5 Hz to 49 Hz. The pre-processed signals were classified into different sub bands as Alpha, Theta, Beta and Gamma. The various features were extracted from the Alpha and Theta bands. The statistical significance features were selected by applying one way ANOVA. The significant values of the features in Alpha band and Theta band are tabulated in Tables 1 and 2 respectively.

From Table 1, Alpha band indicates the feature Hurst has statistically significant difference in all 21 channels. Similarly, kurtosis feature has the second leading significant difference among 18 channels. So, the feature Hurst and kurtosis in Alpha band are selected for feature classification using various machines learning algorithm. Among 21 EEG channels in Alpha band, the channel C4 is providing maximum of seven features with significance value ($p<0.05$). Likewise, the channels F4, F8, M1 and O2 are providing the next maximum of five features with significant difference value. Hence, the two features Hurst and Kurtosis were considered for classification of drowsiness states. The statistical significance of features derived from Theta band indicated in Table 2, also indicates that the features Hurst and Kurtosis are statistically significant in 13 channels and 12 channels respectively. The other features are significant for some of channels and not significant for the others. Some channels, such as C4, have the significance value ($P < 0.05$) for six features. Likewise, the channels C3, P4 and P3 have the significance difference for five features. Similar to Theta band the features, Hurst and Kurtosis can be chosen for classification of drowsiness using Alpha band.



a) Raw and filtered EEG signals for alert state.



b) Raw and Filtered signals for drowsy state.

Figure 2. Comparison of EEG Alert and Drowsy states.

Table 1. Significance value for Alpha band using one-way ANOVA test.

	Mean	Median	Maximum	Minimum	Standard Deviation	Variance	Skewness	Kurtosis	RMS	Hurst
FP1	.066	.658	.294	.281	.457	.364	.666	**.003**	.457	**.000**
FP2	.649	.068	.623	.628	.096	**.040**	.304	**.030**	.096	**.000**
F7	.128	.208	.341	.261	.065	.075	.897	**.000**	.065	**.003**
F3	.082	**.009**	.604	.643	.177	.125	**.054**	**.050**	.177	**.000**
FZ	.337	.886	.350	.397	.403	.316	.522	**.012**	.403	**.006**
F4	.090	.489	.241	.314	**.020**	**.010**	.615	**.005**	**.020**	**.006**
F8	.685	.195	.902	.970	**.045**	**.030**	.253	**.002**	**.045**	**.001**
T3	.309	.252	**.032**	**.027**	.438	.466	.562	**.042**	.438	**.000**
C3	.134	.088	.287	.265	.222	.075	**.028**	.062	.222	**.000**
CZ	.626	**.054**	**.056**	**.055**	.753	.536	.090	.089	.753	**.001**
C4	**.048**	**.012**	.332	.343	**.036**	**.012**	.760	**.004**	**.036**	**.000**
T4	.469	.147	.253	.327	.564	.503	.687	**.002**	.564	**.002**
M2	.230	**.000**	.150	.106	.095	**.042**	.105	**.017**	.095	**.019**
M1	.131	.963	.423	.429	**.029**	**.018**	.747	**.005**	**.029**	**.000**
T5	.097	.668	.440	.460	**.051**	.089	.633	**.000**	**.051**	**.000**
P3	**.048**	.276	.981	.994	.245	.246	.661	.154	.245	**.001**
PZ	.246	.356	.206	.193	.210	.134	.968	**.012**	.210	**.001**
P4	**.008**	.476	.524	.482	.277	.131	.279	**.014**	.277	**.002**
T6	.683	.066	.070	**.055**	.283	.178	.772	**.018**	.283	**.001**
O1	.372	.821	.359	.422	.266	.140	.093	**.021**	.266	**.002**
O2	**.035**	.071	.165	.146	**.052**	.089	.171	**.000**	**.052**	**.006**

Table 2. Significance value for Theta band using one-way ANOVA test.

	Mean	Median	Maximum	Minimum	Standard Deviation	Variance	Skewness	Kurtosis	Root Mean Square	Hurst
FP1	.088	.991	.121	.088	.539	.525	.853	**.000**	.539	.120
FP2	.097	.890	.911	.952	**.044**	**.021**	.796	.268	**.044**	.099
F7	.172	.080	.195	.107	.290	.161	.096	**.026**	.290	**.009**
F3	**.013**	.183	.525	.509	.138	**.053**	.251	**.013**	.138	**.002**
FZ	**.049**	.882	.239	.371	.221	.103	.605	.577	.221	.751
F4	.709	.607	.249	.206	**.014**	**.013**	.168	**.035**	**.014**	.475
F8	.275	.365	.996	.999	.095	.070	.161	.102	.095	.523
T3	.214	.548	.289	.222	.076	**.026**	.237	.203	.076	**.029**
C3	.170	.364	.794	.776	**.041**	**.022**	.943	**.018**	**.041**	**.001**
CZ	.177	.248	**.047**	.060	.244	.112	.661	**.021**	.244	**.036**
C4	**.037**	.376	.574	.559	**.023**	**.014**	.940	**.001**	**.023**	**.010**
T4	**.021**	.361	.469	.541	.31	.114	.708	.062	.341	.080
M2	.086	.711	.579	.666	.061	.065	.496	**.017**	.061	.163
M1	.255	**.007**	.829	.809	.064	.093	.170	**.003**	.064	**.001**
T5	**.037**	.422	.435	.728	.103	.115	.387	**.010**	.103	**.001**
P3	**.037**	.098	.984	.988	**.024**	**.010**	.774	.579	**.024**	**.044**
PZ	**.025**	.894	.759	.528	.122	.087	.880	.089	.122	**.005**
P4	.152	.178	.996	1.000	**.047**	**.023**	.591	**.041**	**.047**	**.035**
T6	.077	.727	.111	.111	.238	.103	.755	.144	.238	**.008**
O1	.071	.093	.762	.762	.168	**.049**	.452	.633	.168	.076
O2	**.018**	.116	.314	.321	**.080**	.091	.331	**.000**	.080	**.000**

4.1. Classification of Alert and Drowsy States

In this work, different classifiers such as Quadratic Discriminant Analysis (QDA), KNN and LDA were used to classify the statistically significant features of Theta and Alpha band. The accuracy obtained by the respective channels using different classifiers is mentioned below in the Tables 3 to 6.

Table 3. Classifier accuracy of two states for Alpha band (Hurst)(Alert - Drowsy).

Channels	QDA	KNN	LDA
FP2	85.71	71.42	85.71
FP1	85.71	85.71	71.43
F7	78.57	85.71	78.57
F3	78.57	50	85.71
FZ	85.71	71.43	78.57
F4	85.71	85.71	92.86
F8	92.86	92.86	71.43
T3	78.57	85.71	71.43
C3	71.43	64.29	71.43
CZ	85.71	57.14	85.71
C4	78.57	78.57	78.57
T4	85.71	71.43	92.86
M2	71.43	64.29	64.29
M1	64.29	57.14	57.14
T5	78.57	50	71.43
P3	85.71	64.29	78.57
PZ	78.57	78.57	78.57
P4	78.57	85.71	78.57
T6	85.71	92.86	78.57
O1	71.43	50	85.71
O2	64.29	50	71.43

Table 4. Classifier accuracy of two states for Alpha band (Kurtosis) (Alert - Drowsy).

Channels	QDA	KNN	LDA
FP2	78.57	85.71	71.43
FP1	64.24	78.57	57.14
F7	71.43	64.29	71.43
F3	64.29	78.57	64.29
FZ	64.29	78.57	64.29
F4	64.29	85.71	64.29
F8	57.14	78.57	57.14
T3	64.29	85.71	71.43
C3	64.29	71.43	64.29
CZ	57.14	85.71	64.29
C4	50	78.57	42.86
T4	71.43	85.71	78.57
M2	57.14	78.57	57.14
M1	71.43	85.71	71.43
T5	85.71	100	85.71
P3	71.43	85.71	71.43
PZ	78.57	78.57	78.57
P4	57.14	85.71	71.43
T6	57.14	85.71	57.14
O1	71.43	64.29	71.43
O2	78.57	71.43	78.57

Table 5. Classifier accuracy of two states for Theta band (Hurst) (Alert - Drowsy).

Channels	QDA	KNN	LDA
FP2	85.71	71.42	78.57
FP1	78.57	71.42	78.57
F7	78.57	85.71	78.57
F3	92.85	78.57	85.71
FZ	92.85	78.57	71.42
F4	78.57	78.57	78.57
F8	85.71	78.57	100
T3	71.42	71.42	78.57
C3	78.57	78.57	78.57
CZ	78.57	78.57	71.42
C4	92.85	85.71	92.85
T4	85.71	78.57	78.57
M2	85.71	71.42	78.57
M1	71.42	78.57	71.42
T5	85.71	71.42	85.71
P3	78.57	78.57	78.57
PZ	78.57	85.71	78.57
P4	78.57	78.57	78.57
T6	85.71	78.57	92.85
O1	71.42	85.71	71.42
O2	92.85	78.57	85.71

Table 6. Classifier accuracy of two states for Theta band (Kurtosis) (Alert - Drowsy).

Channels	QDA	KNN	LDA
FP2	71.42	92.85	71.42
FP1	78.57	85.71	78.57
F7	71.42	78.57	71.42
F3	71.42	78.57	78.57
FZ	71.42	78.57	78.57
F4	71.42	85.71	78.57
F8	78.57	78.57	78.57
T3	78.57	85.71	71.42
C3	71.42	85.71	78.57
CZ	78.57	92.85	78.14
C4	85.71	85.71	85.71
T4	78.57	71.42	85.71
M2	85.71	85.71	85.71
M1	85.71	85.71	85.71
T5	78.57	78.57	71.42
P3	85.71	78.57	85.71
PZ	78.57	85.71	78.57
P4	85.71	78.57	85.71
T6	71.42	71.42	78.57
O1	64.28	92.85	71.42
O2	78.57	85.71	78.57

The results indicate that the feature Hurst in Alpha band and Theta band provides better performance for channel F8 (100%) compared to other channels. The overall maximum accuracy of 92.86% is achieved by channels F3, FZ, F4, C4, T4, T6 and O2 for classifying the two states using Hurst feature for the Alpha band and Theta band (Table 3 and Table 5). Similarly, the next leading accuracy of 85.71% is obtained from channels FP2, FP1, F7, F3, FZ, T3, CZ, P3, P4 and O1. Finally the 21 channels are reduced through 8 channels (F3, FZ, F8, F4, C4, T4, T6 and O2) based on its accuracy obtained. The 21 EEG channels performances are analyzed based on their significant features. These channels are not analyzed based on the subjects but on the features.

Tables 4 and 6 indicate the results obtained by Kurtosis feature in Alpha band and Theta band for two classes (Alert and Drowsy). The channel T5 (100%) provides better performance for Kurtosis feature compared to all other channels. The next maximum accuracy of 92.86% is achieved by channels FP2, CZ and O1. This encourages a channel reduction technique to reduce the channels to above mentioned 10 based on its accuracy. Based on the accuracy obtained using different classifiers the four channels (T5, FP2, CZ, and O1) were selected.

The frontal, temporal and occipital regions are needed to be concentrated for alert-drowsy data. From the Tables 3 to 6, we analyzed that out of 21 channels the following 12 channels such as F3, FZ, F8, F4, FP2, T4, T5, T6, C4, CZ, O1, and O2 are found the most common channels in both Alpha and Theta bands which provides a maximum accuracy. Thus for alert-drowsy classification in Alpha and Theta bands with features kurtosis and Hurst, the frontal, temporal and Occipital regions are mainly concentrated which provides the better accuracy on analysis.

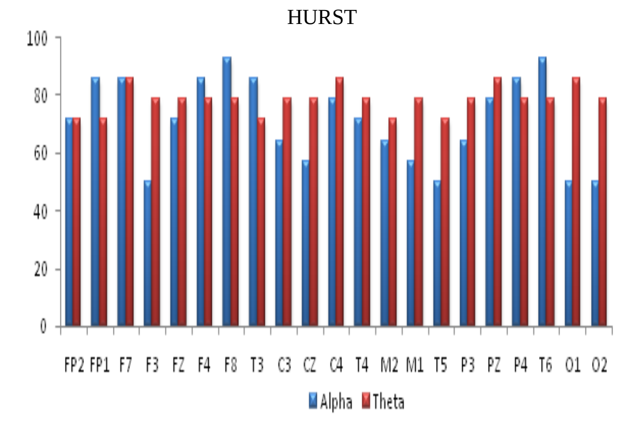


Figure 3. Comparison of alpha and theta band for hurst using KNN classifier.

The comparison on the performance of Hurst and Kurtosis feature for Alpha and Theta bands are as displayed in Figures 3 and 4 respectively. From Figure 3, the channel wise comparison between Alpha and Theta band shows the maximum accuracy of 92.86% is obtained by Alpha band for Hurst feature using KNN classifier, Similarly from Figure 4 the channel wise comparison between Alpha and Theta band shows the maximum accuracy of 100% is obtained by Alpha band for kurtosis feature using KNN classifier. Thus from the result of KNN classifier, the Alpha band provides a better performance for both the features and chosen for driver drowsiness detection.

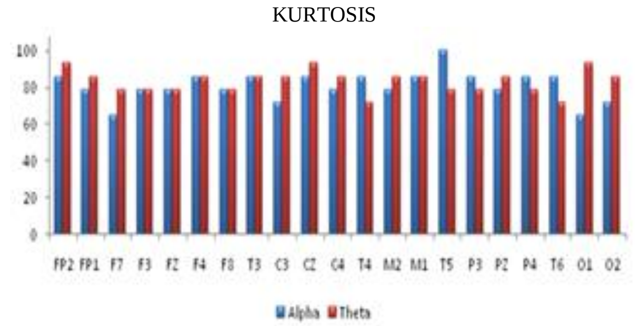


Figure 4. Comparison of Alpha and Theta band for Kurtosis using KNN classifier.

Based on the result from Tables 4 and 6, a comparison was made for kurtosis between the Alpha and Theta bands for the KNN Classifier. From the analysis it is noted that the Theta band has higher accuracy than Alpha band in most of the channels. The channel T5 has the highest accuracy rate of 100% for determining the alert and drowsy states.

In this study, 10 healthy subjects had participated in a VR based driving environment as prescribed in section 2. This system can measure the EEG signals of the drivers using 21 electrodes placed on the head as an EEG cap. Previous studies indicated that there are many physiological signals for predicting the driver's drowsiness such as EEG [8], ECG [2, 4, 10], EOG [11], Electromyogram (EMG) [5] and many more. In this study, we selected the EEG based measures because the central nervous system consists of brain and spinal cord which controls most of the functions of the mind and body [3]. The autonomic nervous system is a control system that acts largely unconscious and regulates body functions such as heart rate [6], pupillary response, and respiratory rate. The first body response occurs on brain, so in this research we preferred EEG other than ECG, EMG and EOG. The driver feels uncomfortable if more electrodes were placed on his/ her head while driving [3, 4]. So channel reduction is the major role to make the driver more comfortable while driving. From the classifiers accuracy result we can find some of the channels are showing highest percentage of predicting drowsiness. FP2, F4, C3, CZ, T4 and PZ channels from Alpha sub band and F3, C3, C4, M2, M1, P4, T6, and O1 from Theta sub band are having the highest accuracy rate in any one of the classifiers. In this study, alert and drowsy data were classified using different classifiers like LDA, QDA, SVM and KNN based on EEG signals.

5. Conclusions

In this paper, the analysis of Alpha and Theta band to detect drowsiness using machine learning algorithms has been proposed. The classification with two class outputs (Alert versus Drowsy) during the simulated driving has been applied with 10 participants. With reference to the results shown in section 4, the channels FP2, F4, C3, CZ, T4, and PZ in Alpha sub-bands and F3, C3, C4, M2, M1, P4, T6, and O1 channels in Theta sub-bands have better accuracy than other channels while comparing with different classifiers. Those channels can be considered for analysis the drowsy states of the drivers. Further research should focus to investigate the efficacy of the driver drowsiness detection system in real time. In future the experiments can be done with more number of participants of wide range of age groups for analysing the results in real time.

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