Driver Drowsiness Detection Using Wearable Brain Sensing Headband and Three-Level Voting Model

Qazal Rezaee [1], Mehdi Delrobaei [2], and Mahdi Aliyari-Shoorehdeli [1]

[1]Affiliation not available
[2]K. N. Toosi University of Technology

October 31, 2023

Abstract

Drowsiness is the leading cause of many fatal accidents and a substantial financial burden for the economy. Efforts have been made to develop techniques to prevent major accidents while remaining practical for everyday use. The most successful approach discovered thus far involves utilizing physiological techniques that rely on EEG signals. Despite their promising performance, the signal collection process has made them unsuitable for practical implementations. However, the emergence of low-cost commercial EEG headsets has enabled tackling this issue. Our study aimed to assess the effectiveness of machine learning models in identifying drowsiness stages using minimal EEG channels. The study was conducted with fifty sleep-deprived participants driving in a simulator. Based on the Observer Rated Drowsiness method, we divided the stages of drowsiness into three categories: alert, drowsy, and sleepy. Various features were extracted from the EEG signals in time, frequency, and time-frequency domains. Three models were trained in each domain using k-nearest neighbors and ensemble bagged tree classifiers. A majority vote among the three models determined data labels, trained using different combinations of channel data features. Three training strategies were utilized: 1) single channel, 2) temporal channels, frontal channels, left-side channels, and right-side channels separately, and 3) all channels. The results of 10-fold cross-validation showed that the frequency features of temporal channels had the highest accuracy. The best results for nearest neighbors were 97.1% (alert-sleepy), 96.6% (drowsy-sleepy), and 96.7% (alert-drowsy). The highest accuracy of ensemble bagged trees was 100% for all three models.

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Faculty of Electrical Engineering, K. N. Toosi University of Technology, Tehran, Iran.

Abstract- Drowsiness is the leading cause of many fatal accidents and a sub-stantial financial burden for the economy. Efforts have been made to develop techniques to prevent major accidents while remaining practical for everyday use. The most successful approach discovered thus far in-volves utilizing physiological techniques that rely on EEG signals. Despite their promising performance, the signal collection process has made them unsuitable for practical implementations. However, the emergence of low-cost commercial EEG headsets has enabled tackling this issue. Our study aimed to assess the effectiveness of machine learning models in identi-fying drowsiness stages using minimal EEG channels. The study was conducted with fifty sleep-deprived participants driving in a simulator. Based on the Observer Rated Drowsiness method, we divided the stages of drowsiness into three categories: alert, drowsy, and sleepy. Various features were extracted from the EEG signals in time, frequency, and time-frequency domains. Three models were trained in each domain us-ing k-nearest neighbors and ensemble bagged tree classifiers. A majority vote among the three models determined data labels, trained using different combinations of channel data features. Three training strategies were utilized: 1) single channel, 2) temporal channels, frontal channels, left-side channels, and right-side channels separately, and 3) all channels. The results of 10-fold cross-validation showed that the frequency features of temporal channels had the highest accuracy. The best results for k-nearest neighbors were 97.1% (alert-sleepy), 96.6% (drowsy-sleepy), and 96.7% (alert-drowsy). The highest accuracy of ensemble bagged trees was 100% for all three models.

Index Terms: Biomechatronic systems, electroencephalogram (EEG), driving simulator, driver alertness, machine learning.

1 Introduction

Every year, nearly 1.3 million people lose their lives in road accidents worldwide, and about 50 million are injured. Such accidents cause serious public health issues and substantial yearly financial losses [1, 2]. About 100,000 accidents occur due to driver drowsiness, resulting in more than 1500 deaths and 70,000 injuries [1]. A driver is more likely to become drowsy when driving for extended periods in monotonous environments such as highways [3]. Drowsiness decreases the driver's reaction time and attention. As a result, they lose their ability to recognize risky situations and control the vehicle accordingly [4, 5].

The primary reasons for driver drowsiness are insufficient sleep and poor physical condition [6]. Sleep deprivation can be due to work overload resulting in prolonged waking time using caffeine or other stimulants. The human brain considers some hours of the day as sleeping time, mainly from 2:00 to 6:00 in the morning. Drivers are more likely to become drowsy during such hours. Obesity, physical weakness, or emotional stress can also cause drowsiness. Hence, drowsiness detection techniques have gained significant attention recently [6].

Driver drowsiness detection techniques are divided into four main categories: (1) physiological methods, (2) vehicle-based methods, (3) behavioral methods, and (4) subjective measures [7, 8].

Vehicle-based techniques employ features such as steering wheel angle and steering wheel velocity obtained by sensors embedded in the car [7, 8]. Despite their non-intrusive nature and easy recording process, vehicle-based measures suffer from the following drawbacks: (1) they rely on external factors such as road markings, lighting, and weather conditions; (2) they are relatively expensive and yield comparatively false-positive detection rates, making them ineffective in actual driving conditions [8].

Behavioral techniques involve analyzing the driver's behavior, including yawn-ing, closing the eyes, blinking, and head position [7]. While behavioral detection methods are non-intrusive, their accuracy decreases drastically in conditions such as low light and driving with eyeglasses. Furthermore, the symptoms of sleepiness can vary significantly from person to person. As a result, methods that rely on detecting these symptoms may not be accurate enough for detecting driver drowsiness in all individuals [8].

Subjective techniques gather data from the driver in a simulated environment to detect the level of sleepiness [8]. These measures are impractical and directly relate to the individual's assessment of their tiredness, making them unsuitable to use in actual driving conditions [9].

Physiological techniques are based on features extracted from the drivers' bio-signals, such as electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), and electrooculogram (EOG) [7]. These techniques allow the detection of driver drowsiness at an early stage. Despite resulting in high accuracies, physiological measures are generally intrusive. Thus, using them in actual driving conditions is challenging [8]. Therefore, small and lightweight physiologically based devices that are less intrusive are a solution to tackle this issue [8, 9]. Recent studies show that commercial EEG headbands have the potential to record the changes in the brain signal caused by drowsiness [10, 11, 4].

In this work, we aim to train models to detect the stages of drowsiness using minimal EEG channels in real-time using commercial EEG headsets from sleep-deprived participants while driving in a simulator.

This paper is organized as follows. Section II surveys related work, and Section III explains the study design, the experimental setup, and signal processing steps. In Section IV, evaluation results and further discussions are proposed, followed by the conclusions in Section V.

2 Related Work

In this section, we investigate the previous studies on driver drowsiness detection systems using wireless EEG headbands. We discuss the results obtained with self-made EEG devices as well as studies involving commercial headsets, including Muse, Emotiv Epoch, Neurosky, and Open BCI headsets.

2.1 Self-made EEG Devices

Arnin *et al.* developed a wireless three-channel headband using EEG and EOG signals. Three subjects were asked to drive in a car racing game and immediately press a button when feeling drowsy for manual identification to compare with the device's auto-detection algorithm. They reported an accuracy of 81% [12]. Chae designed a four-channel EEG recording device and a signal processing algorithm on a PC. The three subjects were requested to drive in an open-source driving-simulation program. The results indicated that their method was feasible [13].

Lin *et al.* presented a 17-probe EEG-based system (Mindo) to monitor the drivers' vigilance status and link driving performance fluctuation with changes in brain activities. A case study with 15 subjects in an immersive virtual driving environment demonstrated the reliability of their proposed system [14]. Hsieh *et al.* proposed a 2-electrode brain signal system. Their simulation results demonstrated that the developed system was feasible [15]. Li *et al.* presented a system with an SVM-based posterior probabilistic model and a smartwatch-based wearable EEG device. Twenty subjects participated in a driving simulation experiment resulting in an accuracy of 91.25% (alert), 83.78% (early-warning), and 91.92% (full-warning) [16]. Li and Chung designed a BMI system. Seventeen subjects participated in a driving simulation experiment resulting in a 93.67% five-level overall accuracy, a 96.15% two-level (alert-slightly drowsy) accuracy, and maximum 16 to 23 min wakefulness maintenance [17].

Lin *et al.* developed a four-channel BCI system to investigate drivers cognitive state changes in a VR-based driving task with five subjects. The practical testing demonstrated the feasibility of the proposed system in real-time processing, automatic analysis, and online warning feedback in real-world operation and living environments [18]. Lin *et al.* presented an EEG-based system that included a wireless physiological signal-acquisition module and an embedded signal-processing module. The average positive predictive value and sensitivity were 76.9% and 88.7%, respectively, obtained from ten subjects in a VR-based driving experiment [19]. Li-Wei Ko *et al.* proposed a single-channel EEG device to detect driver's fatigue levels on mobile devices that resulted in 90% fatigue detection obtained from 15 subjects driving in a VR driving simulator [20]. Ha and Yoo presented an EEG near-infrared spectroscopy (NIRS) ear-module SoC, obtaining over 60% accuracy from a single subject without a driving simulator [21]. Kartsch *et al.* developed a wearable system capable of detecting drowsiness with an accuracy of 85% using seven subjects without a driving simulator [22]. Tsai *et al.* constructed a six-channel EEG-based system that obtained an accuracy of 79.1% for alertness and 90.91% for drowsiness with wavelet features [23]. Zhang *et al.* presented a vehicle active safety model using eight EEG sensors and an accuracy of up to 93% from ten drivers in a simulated environment [24].

2.2 Muse

Almogbel *et al.* achieved the highest accuracy of 95.3% from a single subject in a simulated driving task [40]. Mehreen *et al.*'s result was 92% from 50 subjects without using a simulated environment [41]. Gilbert and Lewis used Muse on 25 subjects in a simulated driving task. Their results with spectral band power features indicated that self-reported measures were consistent with EEG changes [42].

Foong *et al.* assessed the correlation of EEG log band power against reaction time in 31 subjects during a driving simulation experiment. They found out that log delta band power has a significant positive correlation, log theta and alpha band powers had a significant negative correlation [43]. Foong *et al.* proposed an iterative negative-unlabeled (NU) learning algorithm for cross-subject detection of passive fatigue from labeled and unlabeled alert-driving EEG data of 29 subjects. They reported an average accuracy of 93.77% ±8.15% [44].

Rohit *et al.*'s experiment on 23 subjects driving in an in-lab driving simulator reported an accuracy of 81% per subject level and 74% in cross-subject validation. Using a temporal aggregation strategy, they improved the cross-subject validation accuracy to 87% [45].

2.3 Emotiv Epoc

Thuy *et al.* reported an accuracy of 70% from a single subject during a racing game [25]. Pasariu *et al.* achieved the highest accuracy of 84.5% from ten subjects while driving in a simulator [26]. Poorna *et al.* employed an Emotiv Epoc device on 18 subjects in a virtual driving environment. K-nearest neighbor

(KNN) and artificial neural network (ANN) reported an accuracy of 80% and 85%, and sensitivity of 33.35% and 58.21%, respectively [27].

2.4 Neurosky MindWave

Patel *et al.* evaluated the single-electrode Neurosky MindWave performance using a driving simulator on 7 subjects. The results indicated no statistically significant differences between epochs of each class [28]. Salimuddin *et al.* obtained 90% true and 10% false detection rates [29]. Giovanni *et al.* developed a DrowTion application implemented with Mindwave headset to minimize false alarms and give multiple alarms. They achieved 68.11% accuracy [30]. Lim *et al.*'s results indicated that their algorithm has a detection rate of 31% per second, a negligible false alarm rate of 0.5%, and a minimum latency of 2 seconds [31].
Lin *et al.* developed a real-time drowsiness warning system which consists of an embedded system, RF system, and NeuroSky. The proposed system validated the promising ability of the headset integrated with the embedded system [32]. Purnamasari *et al.* proposed a drowsiness detection system named Drowsiver with an accuracy of 95.24% [33]. Ogino and Mitsukuraused achieved an accuracy of 72.7% from 29 subjects without testing in a driving simulator [34]. Abdel-Rahman *et al.*'s system reached an average accuracy of 97.6% from 60 subjects while driving [35].

2.5 Open BCI

Arif *et al.* used a passive BCI with a 16-channel OpenBCI Ultracortex during a simulated driving experiment on five participants. Average classification accuracies were 95.8% for KNN and 93.8% for SVM [36]. Mohamed *et al.* evaluated driver's vigilance level reporting average accuracy of 96.7% and 85.0% for training and testing, respectively, from twenty datasets [37]. Arif *et al.* developed a passive BCI scheme using a 16-channel OpenBCI Ultracortex with 85.6% accuracy [38]. Zhu *et al.* developed a method using an eight-channel Open BCI head cap on 12 subjects during driving tasks. They reached a 95.59% accuracy [39].

3 Materials and Methods

A drowsiness detection test is generally designed to collect data on alertness and various stages of drowsiness. For this purpose, collecting the data at a time and in a situation that fully represents the mentioned situations is necessary. This study proposes a drowsiness detection method using commercial EEG headsets and a driving simulator while collecting drivers' brain signals. The test protocols were designed to make the driver more likely to become drowsy. After analyzing the EEG signals, we applied machine learning methods to distinguish states of alertness and drowsiness.

3.1 Study Design

3.1.1 Test Schedule

The tests were scheduled from 13:00 to 17:00, as this was when fatigue and sleepiness were most likely to affect the participants in this study. All the data collection and monitoring tools were calibrated before starting the tests. The participants first drove the simulator for 15 minutes to acclimate to it and reduce the physiological and psychological effects of using it for the first time. The duration of the experiment varied depending on each participant's performance. The experiment ended if any of the following conditions were met: (1) 75 minutes had passed since the start of the test, (2) the driver lost control of the vehicle for any reason, (3) three cycles of transitioning from alert to sleepy state were achieved, (4) the driver became restless or requested to stop the test for other reasons.

3.1.2 Environment

Drivers' drowsiness can be influenced by the environmental conditions they are exposed to. For example, an environment that is too hot or too cold can have a detrimental effect on their alertness and comfort. Similarly, an environment that is too quiet can make them more sleepy and less attentive. The tests were performed in a room with a balanced temperature (25° C) and relative humidity (30%). The ambient noises were minimized as much as possible, and the sound of the simulated car was adjusted to a level that would not interfere with the sleep onset of the drivers but would still simulate realistic driving conditions. The room was also darkened to increase the likelihood of drowsiness.

3.1.3 Test Participants

To be eligible for participation, volunteers should have met the following inclusion criteria: (1) Age: Based on the literature [6], individuals aged 21 to 57 who drive may be more susceptible to feeling drowsy. However, for those whose job involves driving, this age range may extend from the beginning of their employment to their retirement. In this study, the target age range for the examinees was considered from 20 to 50 years. (2) Driving Experience: It was required to have a valid driver's license and a minimum of two years of driving experience to participate in this study. The study excluded individuals who met any of the following criteria:

- Body Mass Index (BMI): People with a BMI over 40 were not included in the study.
- Sleep disorders or motion sickness: Participants with mental illnesses, significant head injuries, neurological disorders, or severe sleep disorders were also excluded from the study.

The participants were initially asked to complete three questionnaires: (1) a general information form requesting details such as age, height, weight, driving experience, and medical history, (2) the Pittsburgh Sleep Quality Index (PSQI) to assess sleep quality, (3) the Epworth Sleepiness Scale (ESS) to evaluate the likelihood of dozing off in different situations. The participants were encouraged to reduce their sleep duration by only half of their regular night's sleep before the experiment. In order to prioritize their safety, the participants were advised to utilize a ride-hailing service, and their transportation expenses were covered for the test day. They were also asked to refrain from drinking coffee or other caffeinated substances on the test day. They were also given a heavy meal before the test to induce drowsiness.

3.1.4 Labeling

The study employed an Observer Rating of Drowsiness (ORD) method to assess drowsiness and label the recorded signals. The drowsiness state of each individual was determined by analyzing video recordings of their face and neck throughout the experiment. Three observers evaluated the driver's facial expressions and behaviors in the video, such as eye-lid closure rate, staring, yawning, stretching, and head dropping. The observers were assigned a drowsiness level rating from 1 (not drowsy) to 5 (extremely drowsy) every 30 seconds using the ORD checklist shown in Table. 1. The final label was determined based on a voting process among the three observers. For clarity, we will use the following terms in this paper: "alert" for drowsiness levels 1 and 2, "drowsy" for level 3, and "sleepy" for levels 4 and 5.

3.2 Experimental Setup

The experimental setup was designed to induce drowsiness in the participants. The components of the setup are listed below.

3.2.1 Driving Simulator

We used a fixed driving simulator (Nasir driving simulator) to simulate the motion of an actual vehicle [47]. Three large LCD screens were positioned in front of the windshield, covering most of the driver's field of vision (Fig. 1). These screens provided virtual front and side mirrors to simulate a realistic road view. The selected simulated road was known for its high fatality rate in accidents due to its lack of visual attractions. Participants were instructed to drive in the automatic gearbox mode, keep their speed between 70-80 km/h, and move on the right side of the road to minimize distractions that could interfere with the drowsiness process. The simulator generated a preprocessed log containing various sensor data sampled at 30 Hz.

3.2.2 EEG Headsets

We employed two commercial headsets, Muse 2 and Muse S (InteraXon Inc., Toronto, ON, Canada), for recording the brain signals (Fig. 2). These EEG headsets are versatile, accessible tools for neuroscience research and personal

Table 1: The ORD checklist, including the descriptions of progressive drowsiness levels.

Not Drowsy: A driver who is not drowsy while driving will exhibit behaviors such that the appearance of alertness will be present. For example, normal facial tone, normal fast eye blinks, and short ordinary glances may be observed. Occasional body movements and gestures may occur.
Slightly Drowsy: A driver who is slightly drowsy while driving may not look as sharp or alert as a driver who is not drowsy. Glances may be a little longer and eye blinks may not be as fast. Nevertheless, the driver is still sufficiently alert to be able to drive.
Moderately Drowsy: As a driver becomes moderately drowsy, various behaviors may be exhibited. These behaviors, called mannerisms, may include rubbing the face or eyes, scratching, facial contortions, and moving restlessly in the seat, among others. These actions can be thought of as countermeasures to drowsiness. They occur during the intermediate stages of drowsiness. Not all individuals exhibit mannerisms during intermediate stages. Some individuals appear more subdued, they may have slower closures, their facial tone may decrease, they may have a glassy-eyed appearance, and they may stare at a fixed position.
Very Drowsy: As a driver becomes very drowsy, eyelid closures of 2 to 3 seconds or longer usually occur. This is often accompanied by a rolling upward or sideways movement of the eyes themselves. The individual may also appear not to be focusing the eyes properly or may exhibit a cross-eyed (lack of proper vergence) look. Facial tone will probably have decreased. Very drowsy drivers may also exhibit a lack of apparent activity, and there may be large isolated (or punctuating) movements, such as providing a large correction to steering or reorienting the head from a leaning or tilted position.
Extremely Drowsy: Drivers who are extremely drowsy are falling asleep and usually exhibit prolonged eyelid closures (4 seconds or more) and similar prolonged periods of lack of activity. There may be large punctuated movements as they transition in and out of intervals of dozing.

use, offering a non-invasive and affordable way to measure brain activity, already used in sleep, meditation, and mental health studies [46]. Both headsets had Bluetooth connectivity and could be used with multiple platforms (PCs or smartphones). Both devices had similar specifications, featuring four dry electrodes (AF7, AF8, TP9, and TP10) positioned according to the 10-20 system. In the 10-20 system, electrodes AF7 and AF8 are located above the eyes, while electrodes TP9 and TP10 are near the ears. The headsets were designed to fit around the head, with the electrodes embedded in the fabric headband close to the eyes and ears. The middle electrode served as the reference electrode, similar to FpZ in the 10-20 system. Along with EEG electrodes, both devices were equipped with gyroscopes, accelerometers, and PPG sensors, providing four data types. The sampling frequency rate for the data collection was 256 Hz.

Muse electrodes were placed based on the 10-20 system, where AF7 and AF8 electrodes are positioned above the eyes, and TP9 and TP10 electrodes are near the ears. The reference electrode, FpZ, is placed in the middle of the forehead.

3.2.3 Camera

A camera was used during the experiments to record the participant's face for assessing drowsiness and labeling the data. The camera was situated on the left side of the steering wheel, capturing the driver's face and neck without obstructing their view of the screen (Fig. 1).

3.3 Signal Processing

Machine learning methods were carried out to distinguish the three stages of drowsiness. The preprocessing of the EEG signals included (1) filtering with low and high-pass FIR filters with 0.1 and 40 Hz cut-off frequencies, (2) epoching into 30-second sections consistent with the ORD labeling intervals, (3) denoising using the threshold range of each channel (mean ±3std) and removing epochs containing more than 30% outliers, and (4) splitting the data into three parts of alert, drowsy, and sleepy based on the ORD labels. Epochs with ORD labels 1-2 were considered alert, epochs with label 3 were drowsy, and the rest (labels 4-5) were categorized as sleepy.

Features were selected based on the literature [48]. Shannon entropy, log energy entropy, absolute power, relative power, skewness, and kurtosis were the six features extracted from EEG bands (delta: 0.1-4 Hz, theta: 4-8 Hz, alpha: 8-13 Hz, beta: 13-30 Hz, and gamma: 30-40 Hz) of each epoch. Hence, 30 features were extracted from each channel of the epoch.

We used wavelet entropy (WE), which is calculated with the expression for Shannon's entropy based on the coefficients of the wavelet decomposition of the given time series [48]. Shannon entropy is calculated according to

$$-\sum_{i} P(x_i) \ln(x_i) \tag{1}$$

where $P(x_i)$ is the probability distribution of the data.

Log energy entropy is similar to wavelet entropy, but only uses the summation of logarithms of the probabilities [48].

Absolute power is calculated as

$$\lim_{N\to\infty} \frac{1}{2N+1} \sum_{n=-N}^{N} |x[n]|^2 \tag{2}$$

where N is the length of the signal (number of data points) and $\mid x[n] \mid$ its magnitude.

Relative power is the ratio of the power of a specific frequency range to absolute power. Here, frequency ranges were the EEG bands [48].

Skewness is a measure of the asymmetry of the data around its mean. If negative, the data spreads out more to the left of the mean, and if positive, the data spreads out more to the right. Skewness is defined as

$$\frac{E(x-\mu)^3}{\sigma^3} \tag{3}$$

where x represents the data points, μ is the mean of x, σ is the standard deviation of x, and E(.) represents the expected value [48].

Kurtosis is a measure of how much a distribution is prone to outliers. The kurtosis of the normal distribution is 3. If the distribution has a kurtosis greater than 3, it is more outlier-prone than the normal distribution. If its kurtosis is less than 3, it is less outlier-prone than the normal distribution. Kurtosis is defined as

$$\frac{E(x-\mu)^4}{\sigma^4} \tag{4}$$

where x represents the data points, μ is the mean of x, σ is the standard deviation of x, and E(.) represents the expected value [48].

Three models were trained to classify stages of alert, drowsy, and sleepy based on effective features. A final classification was determined using a voting model that involved all three classifiers.

4 Results and Discussion

4.1 Participants

We recorded the EEG signals of fifty participants using Muse 2 (12 female and 13 male) and Muse S (10 female and 15 male) headsets, who drove in a simulated environment. The participants had an average sleep duration of 4.5 hours the night before. The experiment was fully explained to the participants, who gave their written consent before participation.

4.2 Signal Processing

4.2.1 Preprocessing

After filtering and epoching the raw EEG signals, the threshold range for the denoising process (mean ± 3std of each channel data) was calculated to determine the outlier data points. The threshold range of channels TP9 and TP10 was $\pm$ 135, channel AF7 $\pm$ 153, and channel AF8 $\pm$ 159. The epochs containing more than 30% outliers were considered noisy and therefore cast aside. Then the data was labeled into three parts: alert, drowsy, and sleepy, based on the predetermined criteria.

4.2.2 Feature Extraction

Features were extracted in three domains: time, frequency, and time-frequency (Wavelet transform). In the time domain, features were extracted from the time series of the epoch's five frequency bands. The frequency domain was similar to the time domain, but the epochs were converted to the frequency domain by a fast Fourier transform, and then the features were calculated for each band. In the time-frequency domain, epochs were resampled to 240 Hz so that the wavelet coefficients would have the same frequency as the EEG bands. Here, features were extracted from the coefficients.

4.2.3 Feature Selection

The marginal significance level between the two stages was used to determine features indicating a meaningful separation. The p-values were obtained from the data features, once for drowsy and alert data, once for alert and sleepy data, and once for drowsy and sleepy data. A p-value less than 0.05 was considered to be statistically significant.

4.2.4 Classification

During this phase, separate machine learning models were trained for each pair of data classes (alert and drowsy, alert and sleepy, and drowsy and sleepy), with the features of each domain being considered separately. Three models were trained for each domain for each combination of channel features. The aim was to determine the domain with the highest accuracy while minimizing the number of channels used. The combinations were as follows: Single channel data features, temporal channels data features, frontal channels data features, left-side channels data features, right-side channels data features, and all channels data features.

Two classifiers were used for training the models: weighted k-nearest neighbors (KNN) and ensemble bagged trees. In the case of KNN, the value of k was set to 10. The class labels were then determined using the majority vote principle, considering the distance weightings.

Table 2: The frequency domain accuracies with KNN

Channel	Alert-Sleepy	Drowsy-Sleepy	Alert-Drowsy
AF7	69.4%	70.4%	69.4%
AF8	69.7%	72.1%	69%
TP9	73.3%	73%	69.4%
TP10	74.8%	72.9%	66.9%
AF7-AF8	73.9%	73.9%	72%
TP9-TP10	**97.1%**	**96.6%**	**96.7%**
AF7-TP9	78.9%	73.9%	72.8%
AF8-TP10	78.4%	75.7%	72.4%
All Channels	80.4%	76.9%	74.8%

4.2.5 Validation

The k-fold cross-validation method was used to estimate the models' performance. This method splits the data into k sections (folds). The accuracy of the models is calculated in k rounds. In each round, one fold is considered the test data, and the model is trained with the rest. The mean of the k folds' accuracies is the models' final accuracy. In this paper, k was set to 10.

4.3 Evaluation

In each domain, the classification was carried out three times between each of the two categories using the combinations above.

4.3.1 Frequency Domain

Tables 2 and 3 indicate the results of frequency domain classification with the KNN and bagged trees classifiers, respectively.

Table 2, showcases the best result of each frequency domain classification with KNN classifier obtained via the combination of channel TP9 and TP10 features. For alert-sleepy classification, the best result is 97.1%, with 95.1% sensitivity (alert) and 98.7% specificity (sleepy). The maximum accuracy obtained in drowsy-sleepy is 96.6%, with 89.6% sensitivity (drowsy) and 99.9% specificity (sleepy). The best result in alert-drowsy classification is 96.7%, with 91.2% sensitivity (alert) and 99.5% specificity (drowsy).

Table 3 indicates that the best result of each classification in the frequency domain with bagged trees classifier is 100% via the combination of channel TP9 & TP10 features.

4.3.2 Time Domain

Tables 4 and 5 indicate the results of time domain classification with KNN and bagged trees classifiers, respectively.

Table 3: The frequency domain accuracies with bagged trees

Channel	Alert-Sleepy	Drowsy-Sleepy	Alert-Drowsy
AF7	70.5%	72.4%	70.6%
AF8	71.9%	73.4%	69.3%
TP9	74.3%	74.7%	69.3%
TP10	75.4%	73.2%	67.4%
AF7-AF8	75%	74.8%	71.7%
TP9-TP10	**100%**	**100%**	**100%**
AF7-TP9	78.4%	75.4%	73.3%
AF8-TP10	78.4%	75.6%	71.8%
All Channels	81.2%	77.4%	75.3%

Table 4: The time domain accuracies with KNN

Channel	Alert-Sleepy	Drowsy-Sleepy	Alert-Drowsy
AF7	69.5%	71%	69.2%
AF8	70%	72.3%	69%
TP9	72%	72.5%	68.6%
TP10	70.5%	72.1%	69.7%
AF7-AF8	71.6%	73.8%	70.6%
TP9-TP10	77.9%	**78.3%**	**76.4%**
AF7-TP9	75.2%	74.4%	73.3%
AF8-TP10	75.9%	74.4%	71.2%
All Channels	**78.8%**	75.7%	74.3%

Table 5: The time domain accuracies with bagged trees

Channel	Alert-Sleepy	Drowsy-Sleepy	Alert-Drowsy
AF7	70.9%	73.2%	69.9%
AF8	70.9%	73.2%	68.8%
TP9	75.1%	74.6%	69.5%
TP10	75%	74.2%	68.8%
AF7-AF8	76%	75.1%	72.1%
TP9-TP10	**84.6%**	**87.7%**	**82.9%**
AF7-TP9	78.3%	75.9%	73.5%
AF8-TP10	78.9%	75.4%	73.2%
All Channels	80.5%	76.3%	75%

As showcased in Table 4, the best result of classification in the time domain with KNN classifier for alert-sleepy classification was obtained via the combination of all channel features (78.8% accuracy, with 80.2% sensitivity (alert) and 77.2% specificity (sleepy)). In the drowsy-sleepy classification, the maximum accuracy obtained is 78.3%, with 98.2% sensitivity (drowsy) and 34% specificity (sleepy) using the combination of TP9-TP10 channel features. In alert-drowsy classification, the best result is 76.4%, with 39.3% sensitivity (alert) and 95.9% specificity (drowsy), which is also obtained with the combination of TP9-TP10 channel features.

As indicated in Table 5, the best classification result in the time domain with the bagged trees classifier was obtained via the combination of TP9-TP10 channel features. For alert-sleepy classification, the best result is 84.6%, with 87.8% sensitivity (alert) and 80.8% specificity (sleepy)). In the drowsy-sleepy classification, the maximum accuracy obtained is 87.7%, with 68.8% sensitivity (drowsy) and 96.2% specificity (sleepy). In alert-drowsy classification, the best result is 82.9%, with 77.2% sensitivity (alert) and 95.4% specificity (drowsy).

4.3.3 Time-Frequency Domain

Tables 6 and 7 indicate the results of the time-frequency domain classification with KNN and bagged trees classifiers, respectively.

As showcased in Table 6, the best result of alert-sleepy classification in the time-frequency domain with KNN classifier was obtained via the combination of all channel features (74.7% accuracy, with 74.1% sensitivity (alert) and 75.3% specificity (sleepy). The maximum accuracy obtained in drowsy-sleepy classification is 77.8%, with 95% sensitivity (drowsy) and 39.3% specificity (sleepy) using TP9-TP10 channel features. In alert-drowsy classification, the best result is 74.9%, with 65.38% sensitivity (alert) and 79.87% specificity (drowsy), also using TP9-TP10 channel features.

As indicated in Table 7, the best result of each classification in the time-frequency domain with the bagged trees classifier was obtained via the combination of TP9-TP10 channel features. For alert-sleepy classification, the maximum

Table 6: The time-frequency domain accuracies with KNN

Channel	Alert-Sleepy	Drowsy-Sleepy	Alert-Drowsy
AF7	65.2%	70.2%	68.5%
AF8	66.5%	70.5%	67.5%
TP9	66.8%	69.9%	67.4%
TP10	69.4%	70.1%	69%
AF7-AF8	71.8%	73.2%	70.4%
TP9-TP10	74%	**77.8%**	**74.9%**
AF7-TP9	72.9%	74.3%	69.8%
AF8-TP10	73.4%	74%	70.8%
All Channels	**74.7%**	75.1%	72.4%

Table 7: The time-frequency domain accuracies with bagged trees

Channel	Alert-Sleepy	Drowsy-Sleepy	Alert-Drowsy
AF7	68%	70.1%	68%
AF8	67.8%	70.7%	67%
TP9	67.4%	69.7%	69.2%
TP10	68.7%	71.3%	69.2%
AF7-AF8	74.1%	73.1%	69.3%
TP9-TP10	**80.9%**	**87%**	**86%**
AF7-TP9	73.2%	73%	71.1%
AF8-TP10	73.8%	74%	70.2%
All Channels	75.2%	74.5%	71.8%

accuracy is 80.9%, with 81.9% sensitivity (alert) and 79.6% specificity (sleepy). In drowsy-sleepy classification, the best result is 87%, with 66.8% sensitivity (drowsy) and 96% specificity (sleepy). In alert-drowsy classification, the best result is 86%, with 68.8% sensitivity (alert) and 95% specificity (drowsy).

Hence, the highest accuracy was 100% for all three models obtained using frequency features of TP9-TP10 channels with a bagged tree classifier.

5 Conclusion

Detecting drowsiness is crucial in preventing accidents. Although EEG signals are the most accurate method, their complicated signal collection prevents mass production. However, recent advancements in low-cost wireless EEG headbands show promise. In this study, off-the-shelf headbands were tested on fifty sleep-deprived drivers. Machine learning was then used to distinguish between alert, drowsy, and sleepy states. Features were extracted from the signals in time, frequency, and time-frequency domains. K-nearest neighbors and ensemble bagged tree classifiers were used to distinguish the three classes. Three different strategies were used to train the models, and the majority vote was used to indicate the data's label for each strategy. Results showed that frequency features provided the highest accuracy. The temporal region channels were the most effective in detecting drowsiness levels among the channels. Both classifiers performed well, with the ensemble bagged tree providing better results. The best results with frequency features of temporal channels for K-nearest neighbors were 97.1% (alert-sleepy), 96.6% (drowsy-sleepy), and 96.7% (alert-drowsy). The highest accuracy of ensemble bagged trees was 100% for all three models. These findings suggest that wireless EEG headbands can effectively detect drowsiness.

Acknowledgment

The authors thank the volunteers, Frequency Innovation Center at Bonda Group, and Virtual Reality Laboratory at K. N. Toosi University of Technology for their support during the experiments.

References

[1] S. Saleem, *Risk assessment of road traffic accidents related to sleepiness during driving: a systematic review,* Eastern Mediterranean Health Journal, vol. 28, no. 9, p. 695-700, Sep. 2022.

[2] A. Hossan, F. B. Kashem, M. M. Hasan, S. Naher and M. I. Rahman, *"A smart system for driver's fatigue detection, remote notification and semi-automatic parking of vehicles to prevent road accidents,"* 2016 International Conference on Medical Engineering, Health Informatics and Technology (MediTec), Dhaka, Bangladesh, p. 1–6, 2016.

[3] G. Li and W.-Y. Chung, *A Context-Aware EEG Headset System for Early Detection of Driver Drowsiness,* Sensors, vol. 15, no. 8, p. 20873-20893, Aug. 2015.

[4] J. LaRocco, M. D. Le, and D.-G. Paeng, *A Systemic Review of Available Low-Cost EEG Headsets Used for Drowsiness Detection,* Frontiers in Neuroinformatics, vol. 14, Oct. 2020.

[5] S. Soares, T. Monteiro, A. Lobo, A. Couto, L. Cunha, and S. Ferreira, *Analyzing Driver Drowsiness: From Causes to Effects,* Sustainability, vol. 12, no. 5,pp. 1971, Mar. 2020.

[6] N. Sheibani Asl, G. Baghdadi, S. Ebrahimian, and S. J. Haghighi, *Toward Applicable EEG-Based Drowsiness Detection Systems: A Review,* Frontiers in Biomedical Technologies, Aug. 2022.

[7] S. S. Jasim and A. K. Abdul Hassan, *Modern drowsiness detection techniques: a review,* International Journal of Electrical and Computer Engineering (IJECE), vol. 12, no. 3, p. 2986, Jun. 2022.

[8] J. S. Bajaj, N. Kumar, R. K. Kaushal, H. L. Gururaj, F. Flammini, and R. Natarajan, *System and Method for Driver Drowsiness Detection Using Behavioral and Sensor-Based Physiological Measures,* Sensors, vol. 23, no. 3, p. 1292, Jan. 2023.

[9] Q. Rezaee, M. Delrobaei, A. Giveki, N. Dayarian and S. J. Haghighi, *"Driver Drowsiness Detection with Commercial EEG Headsets,"* 2022 10th RSI International Conference on Robotics and Mechatronics (ICRoM), Tehran, Iran, p. 546–550, 2022.

[10] O. E. Krigolson, C. C. Williams, A. Norton, C. D. Hassall, and F. L. Colino, *Choosing MUSE: Validation of a Low-Cost, Portable EEG System for ERP Research,* Frontiers in Neuroscience, vol. 11, Mar. 2017.

[11] A. Wexler and R. Thibault, *Mind-Reading or Misleading? Assessing Direct-to-Consumer Electroencephalography (EEG) Devices Marketed for Wellness and Their Ethical and Regulatory Implications,* Journal of Cognitive Enhancement, vol. 3, no. 1, p. 131-137, Sep. 2018.

[12] J. Arnin et al., *"Wireless-based portable EEG-EOG monitoring for real time drowsiness detection,"* 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Osaka, Japan, p. 4977–4980, 2013.

[13] M. S. Chae, *"Portable, wireless drowsiness-detection system,"* 2012 IEEE 55th International Midwest Symposium on Circuits and Systems (MWSCAS), Boise, ID, USA, p. 762–765, 2012.

[14] C. -T. Lin et al., *"Wireless and Wearable EEG System for Evaluating Driver Vigilance,"* in IEEE Transactions on Biomedical Circuits and Systems, vol. 8, no. 2, p. 165–176, April 2014.

[15] H. -Y. Hsieh, S. -F. Liang, L. -W. Ko, M. Lin and C. -T. Lin, *"Development of a Real-Time Wireless Embedded Brain Signal Acquisition/Processing System and its Application on Driver's Drowsiness Estimation,"* 2006 IEEE International Conference on Systems, Man and Cybernetics, Taipei, Taiwan, p. 4374–4379, 2006.

[16] G. Li, B. -L. Lee and W. -Y. Chung, *"Smartwatch-Based Wearable EEG System for Driver Drowsiness Detection,"* in IEEE Sensors Journal, vol. 15, no. 12, p. 7169–7180, Dec. 2015.

[17] G. Li and W. -Y. Chung, *"Combined EEG-Gyroscope-tDCS Brain Machine Interface System for Early Management of Driver Drowsiness,"* in IEEE Transactions on Human-Machine Systems, vol. 48, no. 1, p. 50–62, Feb. 2018.

[18] C. -T. Lin et al., *"Development of Wireless Brain Computer Interface With Embedded Multitask Scheduling and its Application on Real-Time Driver's Drowsiness Detection and Warning,"* in IEEE Transactions on Biomedical Engineering, vol. 55, no. 5, p. 1582–1591, May 2008.

[19] C. -T. Lin, C. -J. Chang, B. -S. Lin, S. -H. Hung, C. -F. Chao and I. -J. Wang, *A Real-Time Wireless BrainComputer Interface System for Drowsiness Detection,* in IEEE Transactions on Biomedical Circuits and Systems, vol. 4, no. 4, p. 214–222, Aug. 2010.

[20] Li-Wei Ko et al., *"Single channel wireless EEG device for real-time fatigue level detection,"* 2015 International Joint Conference on Neural Networks (IJCNN), Killarney, p. 1–5, 2015.

[21] U. Ha and H. -J. Yoo, *"An EEG-NIRS ear-module SoC for wearable drowsiness monitoring system,"* 2016 IEEE Asian Solid-State Circuits Conference (A-SSCC), Toyama, Japan, p. 193–196, 2016.

[22] V. Kartsch, S. Benatti, D. Rossi and L. Benini, *"A wearable EEG-based drowsiness detection system with blink duration and alpha waves analysis,"* 2017 8th International IEEE/EMBS Conference on Neural Engineering (NER), Shanghai, China, p. 251–254, 2017.

[23] P. -Y. Tsai, W. Hu, T. B. J. Kuo and L. -Y. Shyu, *"A portable device for real time drowsiness detection using novel active dry electrode system,"* 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Minneapolis, MN, USA, p. 3775–3778, 2009.

[24] Z. Zhang et al., *A Vehicle Active Safety Model: Vehicle Speed Control Based on Driver Vigilance Detection Using Wearable EEG and Sparse Representation,* Sensors, vol. 16, no. 2, p. 242, Feb. 2016.

[25] T. Thuy, Thi, Q. V. Le, and Quang Linh Huynh, *Application of Portable EEG Device in Detection and Classification Drowsiness by Support Vector Machine,* p. 521-526, Jun. 2019.

[26] N. T. Br. Pasaribu, T. Halim, R. Ratnadewi, and A. Prijono, *EEG signal classification for drowsiness detection using wavelet transform and support vector machine,* IAES International Journal of Artificial Intelligence (IJ-AI), vol. 10, no. 2, p. 501, Jun. 2021.

[27] S. S. Poorna, Vikri Arsha, P. T. A. Aparna, P. Gopal, and G. J. Nair, *Drowsiness Detection for Safe Driving Using PCA EEG Signals,* p. 419-428, Jan. 2018.

[28] K. Patel, H. Shah, M. Dcosta, and D. Shastri, *Evaluating NeuroSkys Single-Channel EEG Sensor for Drowsiness Detection,* p. 243-250, Jul. 2017.

[29] M. K. Salimuddin, Ramarao and S. Panbude, *"Driver Drowsiness Monitoring System Using Fusion of Facial Features & EEG,"* 2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, p. 1506–1510, 2018.

[30] Giovanni, T. Suprihadi and K. Karyono, *"DROWTION: Driver drowsiness detection software using MINDWAVE,"* 2014 International Conference on Industrial Automation, Information and Communications Technology, Bali, Indonesia, p. 141–144, 2014.

[31] C. -K. A. Lim, Wai Chong Chia and Siew Wen Chin, *"A mobile driver safety system: Analysis of single-channel EEG on drowsiness detection,"* 2014 International Conference on Computational Science and Technology (ICCST), Kota Kinabalu, p. 1–5, 2014.

[32] C. -J. Lin, C. -H. Ding, C. -C. Liu and Y. -L. Liu, *"Development of a real-time drowsiness warning system based on an embedded system,"* 2015 International Conference on Advanced Robotics and Intelligent Systems (ARIS), Taipei, Taiwan, p. 1–4, 2015.

[33] P. D. Purnamasari, P. Yustiana, A. A. Putri Ratna and D. Sudiana, *"Mobile EEG Based Drowsiness Detection using K-Nearest Neighbor,"* 2019 IEEE 10th International Conference on Awareness Science and Technology (iCAST), Morioka, Japan, p. 1–5, 2019.

[34] M. Ogino and Y. Mitsukura, *Portable Drowsiness Detection through Use of a Prefrontal Single-Channel Electroencephalogram,* Sensors, vol. 18, no. 12, p. 4477, Dec. 2018.

[35] A. S. Abdel-Rahman, A. F. Seddik and D. M. Shawky, *"An affordable approach for detecting drivers' drowsiness using EEG signal analysis,"* 2015 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Kochi, India, p. 1326–1332, 2015.

[36] S. Arif, M. Arif, S. Munawar, Y. Ayaz, M. J. Khan and N. Naseer, *"EEG Spectral Comparison Between Occipital and Prefrontal Cortices for Early Detection of Driver Drowsiness,"* 2021 International Conference on Artificial Intelligence and Mechatronics Systems (AIMS), Bandung, Indonesia, p. 1–6, 2021.

[37] F. Mohamed, S. F. Ahmed, Z. Ibrahim and S. Yaacob, *"Comparison of Features Based on Spectral Estimation for the Analysis of EEG Signals in Driver Behavior,"* 2018 International Conference on Computational Approach in Smart Systems Design and Applications (ICASSDA), Kuching, Malaysia, p. 1–7, 2018.

[38] S. Arif, S. Munawar, and H. Ali, *Driving drowsiness detection using spectral signatures of EEG-based neurophysiology,* Frontiers in Physiology, vol. 14, Mar. 2023.

[39] M. Zhu et al., *"Heavy Truck Driver's Drowsiness Detection Method Using Wearable EEG Based on Convolution Neural Network,"* 2020 IEEE Intelligent Vehicles Symposium (IV), Las Vegas, NV, USA, p. 195–201, 2020.

[40] M. A. Almogbel, A. H. Dang and W. Kameyama, *"EEG-signals based cognitive workload detection of vehicle driver using deep learning,"* 2018 20th International Conference on Advanced Communication Technology (ICACT), Chuncheon, Korea (South), p. 256–259, 2018.

[41] A. Mehreen, S. M. Anwar, M. Haseeb, M. Majid and M. O. Ullah, *"A Hybrid Scheme for Drowsiness Detection Using Wearable Sensors,"* in IEEE Sensors Journal, vol. 19, no. 13, p. 5119–5126, 1 July, 2019.

[42] J. Dunbar, J. E. Gilbert, and B. Lewis, *Exploring differences between self-report and electrophysiological indices of drowsy driving: A usability examination of a personal brain-computer interface device,* vol. 74, p. 27-34, Sep. 2020.

[43] R. Foong, K. K. Ang and C. Quek, *"Correlation of reaction time and EEG log bandpower from dry frontal electrodes in a passive fatigue driving simulation experiment,"* 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Jeju, Korea (South), p. 2482–2485, 2017.

[44] R. Foong, Kai Keng Ang, Z. Zhang, and C. Quek, *An iterative cross-subject negative-unlabeled learning algorithm for quantifying passive fatigue,* vol. 16, no. 5, p. 056013-056013, Aug. 2019.

[45] F. Rohit, V. Kulathumani, R. Kavi, I. Elwarfalli, V. Kecojevic, and A. Nimbarte, *Real-time drowsiness detection using wearable, lightweight brain sensing headbands,* IET Intelligent Transport Systems, vol. 11, no. 5, p. 255-263, Mar. 2017.

[46] A. Arsalan, M. Majid, A. R. Butt and S. M. Anwar, *"Classification of Perceived Mental Stress Using A Commercially Available EEG Headband,"* in IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 6, p. 2257–2264, Nov. 2019.

[47] M. Mahmoodi and A. Nahvi, *Driver drowsiness detection based on classification of surface electromyography features in a driving simulator,* Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine, vol. 233, no. 4, p. 395-406, Mar. 2019.

[48] I. Stancin, M. Cifrek, and A. Jovic, *A Review of EEG Signal Features and Their Application in Driver Drowsiness Detection Systems,* Sensors, vol. 21, no. 11, p. 3786, May 2021.

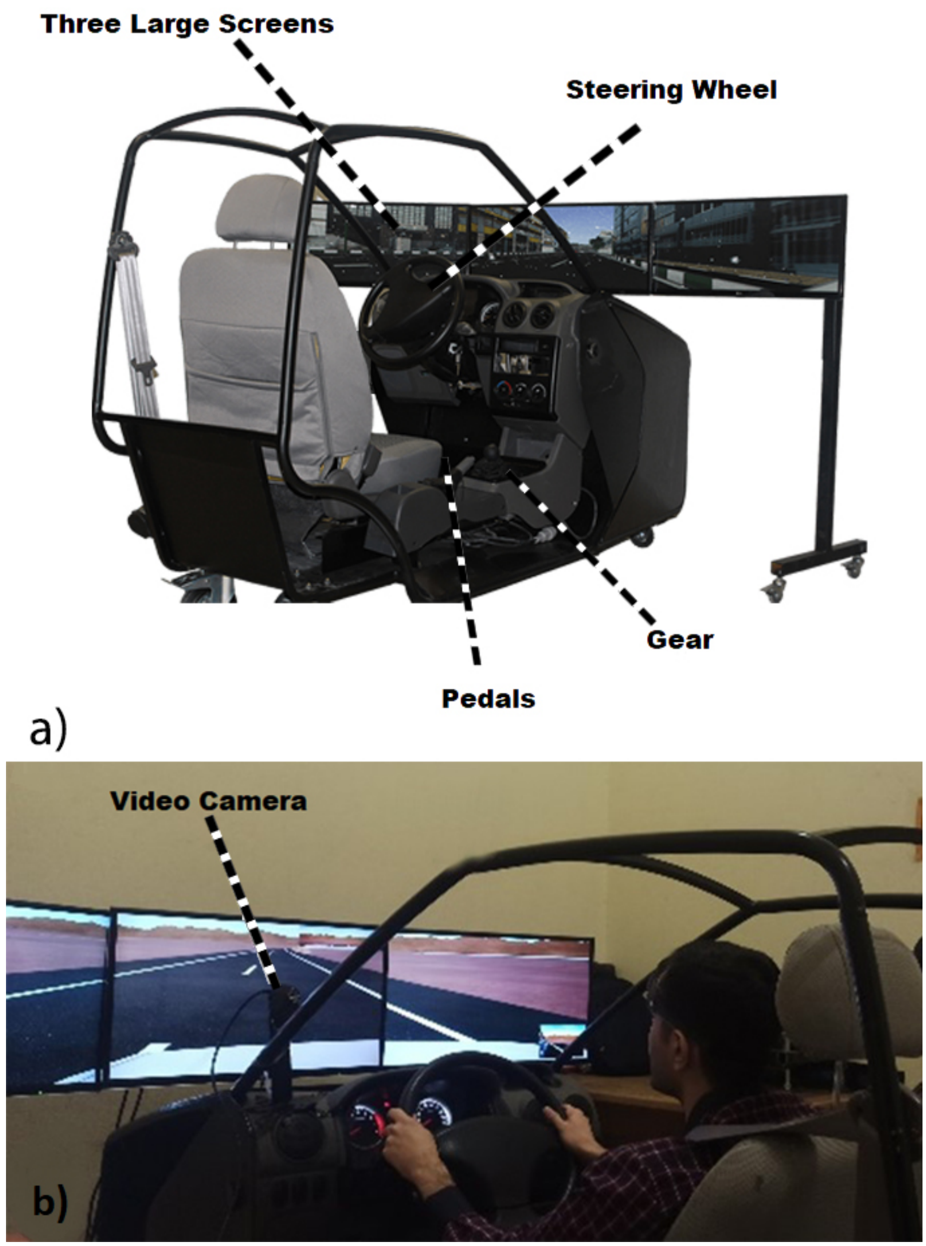

Figure 1: a) Nasir driving simulator; The driver could control the simulator with a steering wheel and pedals and see a virtual road on a big screen on the dashboard. b) The simulator consisted of a video camera to record the face of the driver.

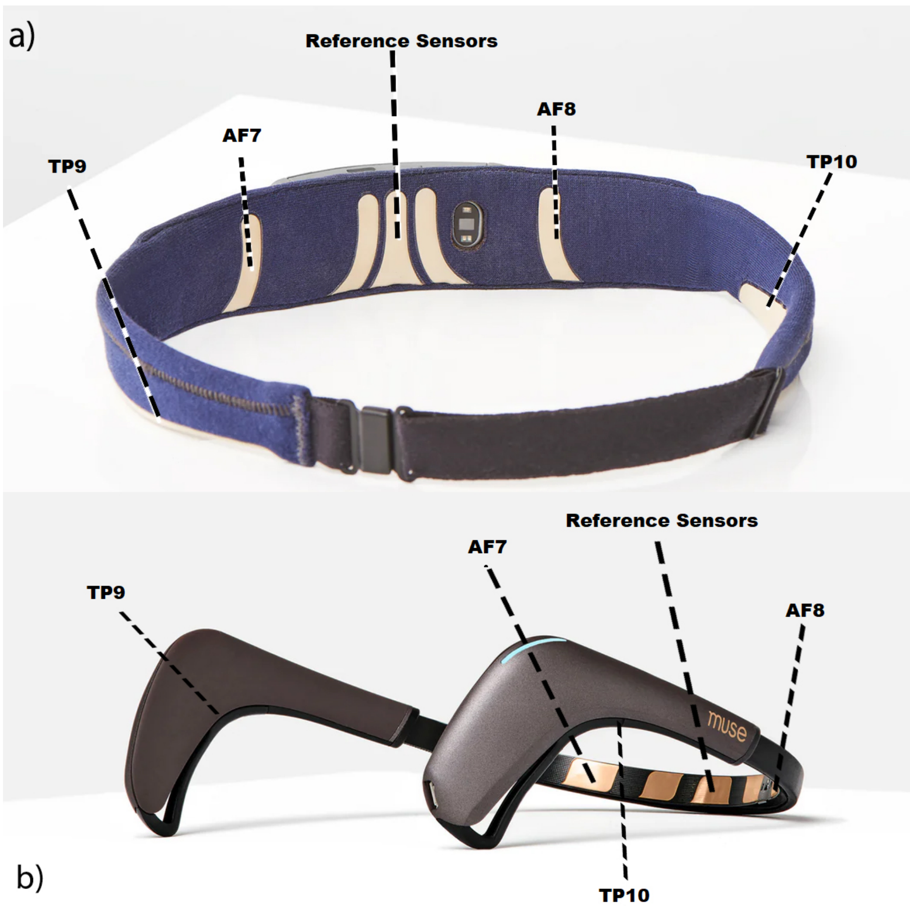

Figure 2: The commercial headsets used in this study; (a) Muse 2; (b) Muse S