

# Toward Applicable EEG-Based Drowsiness Detection Systems: A Review

Nasrin Sheibani Asl<sup>1,2</sup>, Golnaz Baghdadi<sup>1</sup>, Serajeddin Ebrahimian<sup>3\*</sup> , Sahar Javaher Haghghi<sup>1</sup>

<sup>1</sup> Frequency (frequency.com), Tehran, Iran

<sup>2</sup> Department of Electrical Engineering, Sharif University of Technology, Tehran, Iran

<sup>3</sup> Virtual Reality Laboratory, K.N. Toosi University of Technology, Tehran, Iran

\*Corresponding Author: Serajeddin Ebrahimian  
Email: [sebrahimian@mail.kntu.ac.ir](mailto:sebrahimian@mail.kntu.ac.ir)

Received: 21 March 2021 / Accepted: 06 September 2021

## Abstract

**Purpose:** Drowsy driving accounts for many accidents and has attracted substantial research attention in recent years. Electroencephalography (EEG) signals are shown to be a reliable measure for the early detection of drowsiness. Unfortunately, there is no comprehensive study showing the applicability of drowsiness detection systems with EEG signals. In this research, we targeted the studies under the category of drowsiness detection, which adopted an EEG-based approach, to inspect the applicability of these systems from different aspects.

**Materials and Methods:** We included documented studies that utilized clinical devices and consumer-grade EEG headsets for detection of drowsiness and investigated the selected studies from different aspects such as the number of EEG channels, sampling frequency, extracted features, type of classifiers, and accuracy of detection. Among available headsets, we focused on the most popular ones, namely Muse, NeuroSky, and EMOTIV brands.

**Results:** Considerable number of studies have used EEG headsets, and their reports showed that the highest average accuracy belongs to EMOTIV, and the highest maximum detection accuracy, 98.8%, was achieved by the Muse headset. Spectral features extracted from short periods of 1, 2, or 10 secs are the most popular features, and the support vector machine is the most commonly used classifier in drowsiness detection systems. Therefore, implementing a reliable detection system does not necessarily include complicated features and classifiers.

**Conclusion:** It is shown that, despite their few electrodes, commercial headsets have gained decent detection accuracy. This study sheds light on the current status of drowsiness detection systems and paves the way for future industrial designs of such systems.

**Keywords:** Drowsiness Detection; Fatigue; Electroencephalography Features; Commercial Electroencephalography Headsets; Hybrid Systems.

## 1. Introduction

Alertness is crucial in many duties, such as driving, shift working, press shop jobs, night-time security guarding, pilotage, and construction works. The drowsiness of drivers is the primary reason for accidents all over the world. Drowsy driving can occur in any driving vehicle scenario but is more common in long-distance transportation. According to the statistical analysis of the US National Highway Traffic Safety Administration (NHTSA), 91,000 reported crashes involved drowsy drivers in 2017. These crashes led to an estimated 50,000 people being injured and nearly 800 deaths [1,2]. Studies have shown that the rate of accidents due to fatigue in Iran is approximately 20 to 40% of total annual accidents, much higher than the average rate in other countries, which is 8 to 17% [2].

Several factors affect accidents caused by fatigue and drowsiness. Factors like the type of vehicle, time of occurrence, the mental-physical condition of the driver before the trip, the length of the journey, driving history, the amount of sleep the driver had before the trip, the weather condition, and uniformity of the road are reported to be involved in drowsiness related crashes. According to the reports, the most involved vehicles in such fatigue-based accidents are passenger vehicles and, then, trucks. Most of the accidents happened from 6 a.m. to noon. The average age of the drivers involved in the accident was 34, ranging from 21 to 57. The longest driving history was 29 years, the minimum was less than one year, and the average was eight years [2].

Alerting the driver before the onset of drowsiness is one way to prevent crashes caused by drowsy driving. Car industries have spent significant resources on developing new devices to detect and preferably predict driver drowsiness. More than 28 car companies (including Nissan, Renault, Tesla, Ford, etc.) have offered different drowsiness detection systems as assistive driver technologies. These built-in solutions measure a variety of vehicle-based indices to detect fatigue, micro-sleep, or the onset of drowsiness. In addition to the car companies, several independent businesses have developed numerous drowsiness detection systems not integrated into the vehicle that work regardless of the vehicle's brand and model. Progress in developing drowsiness detection systems indicates that this market will grow and become profitable. A variety of methods have been investigated to detect drivers' drowsiness so far. The most famous ones can be classified as follows.

### •Vehicle-Based Measures

- lateral or longitudinal position deviation
- time to lane crossing
- steering wheel movement/angle pattern
- acceleration pedal pressure pattern

### •Behavioral Measures

- percentage of eyelid closure over the pupil
- eyeblink duration and frequency
- head movement patterns
- eye fixation pattern
- face temperature
- driving performance measures (other than lateral position)

### •physiological Measures

- Electroencephalography (EEG)
- Electrocardiography (ECG)
- Electromyography (EMG)
- Electrooculography (EOG)
- Photoplethysmography (PPG)
- Electrodermal Response or conductivity (EDR)

Vehicle-based assistive technologies utilize different sensors, such as steering-angle sensors, Global Positioning System (GPS), ultrasonic sensors, or pedal pressure sensors, embedded in the cars to reflect the driver's performance. The unobtrusiveness and contactless nature of these methods are considered as their positive points. However, these technologies suffer from the following issues [3, 4].

- Sometimes driver fatigue does not affect his performance.
- Some interfering factors, such as strong wind, rutted road surfaces, and paying attention to road-side signs may increase false alarm in these available technologies.
- Most of these technologies need to be designed based on the characteristics of each car brand. Therefore, it is not easy to adapt them to other cars.
- Since they are primarily embedded in the cars, and their installation and maintenance procedures depend on the cars' features and the companies' regulations, it is not easy to estimate the expenses.
- Technologies developed based on these techniques cannot easily be used in other duties such as shift working, night-time security guarding, pilotage, etc.

Behavioral measures that are usually extracted from the facial behavior of the driver include eye closure, eye blinking, head pose, yawning, face components' temperature, etc. These measures are monitored through a camera, and the driver is alerted if any of these indices indicate symptoms of drowsiness. Non-intrusiveness is the main advantage of behavior-based detection devices. However, these methods have the following disadvantages.

- There are concerns over being monitored in one's private space.
- The screen size for monitoring is limited, and, in some applications, it is hard to find an appropriate place to mount the device; hence it is almost not applicable with non-desk jobs.
- Wearing glasses may disrupt the accurate performance of the device [5].
- An actual moving vehicle introduces new challenges such as variable lighting, changing background, and vibrations that can degrade the performance of camera-based detection systems [6].
- The Cost-inefficiency of thermal cameras for drowsiness detection makes them impractical despite their robustness to lighting conditions and good accuracies [7–10].

Most of the available commercial tools work based on vehicle-based or behavioral indices. Although such indices have benefits, the mentioned drawbacks and the fact that they detect drowsiness rather than predicting it are not negligible. Physiological indices have been introduced to overcome the mentioned issue (i.e., the inability to predict the onset of drowsiness). Among all methods of drowsiness detection, EEG shows the strongest relation with drowsiness and is capable of detecting drowsiness promptly with high accuracy [4, 11, 12]. EEG is widely considered a reliable measure for drowsiness, fatigue, and performance evaluation [11–16].

The wireless devices that have been developed in recent years, some of which are available in the [8] market as consumer-grade headsets, are considered as a solution to deal with the relatively intrusive nature of measuring EEG signals [17]. Developing less intrusive methods for data collection has undoubtedly a positive effect on their real-life applicability. Processing and monitoring algorithms are performed in various ways, such as using smartphones [17]. While there are concerns about the quality of data acquired by the consumer-grade headsets, comparative studies on the performance of wireless and clinical devices

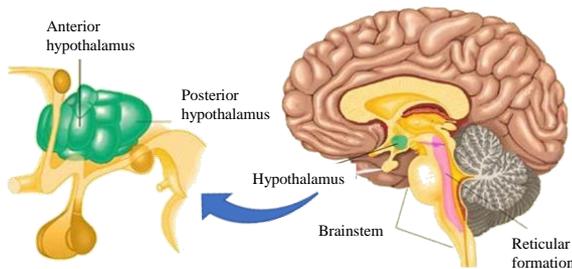
demonstrate the acceptable performance of these new wireless technologies [3, 18–22]. Another approach to improving the accuracy of wireless recording in drowsiness detection is combining their outcomes with other biological signals, behavioral or vehicle-based measures. The suggested combination can be easily implemented since many wireless devices provide auxiliary sensors for recording other signals (e.g., PPG, gyroscope signal, heart rate variation, etc.) besides EEG.

In this paper, we review the studies that investigated the capabilities of EEG biomarkers in drowsiness detection. Data acquisition, preprocessing, feature extraction, and classification are the main stages of a typical EEG-based drowsiness detection system. After defining drowsiness and its causes and effects in [section 1.1](#), we discuss the essential stages in drowsiness detection studies in [section 2](#), materials and methods. [Section 2.1](#) provides details about the data acquisition stage, including the general considerations in conducting a drowsiness detection study, typical devices used for recording, and the common labeling methods. Since drowsiness detection is a real-time procedure, fast and simple techniques are usually used in the preprocessing stage, described in [section 2.2](#). After preprocessing, the cleaned data is given to the feature extraction stage. More commonly investigated features in drowsiness detection systems are introduced in [section 2.3](#). Extracted features are fed to a classifier to distinguish drowsy periods from the alert ones. An assortment of classifiers used in drowsiness detection studies is introduced in [section 2.4](#). Results of studies with an EEG-based approach are presented and discussed in [section 3](#), followed by a conclusion in [section 4](#).

### 1.1. Drowsiness-Definition, Causes, and Effects

Drowsiness is defined as a transition of the psychophysiological state from alertness towards sleep, causing degradation in concentration, thereby increasing the response time [23]. Fatigue, and in a few cases, sleepiness and tiredness, are used in drowsiness detection literature, as well. Physiologically, fatigue and drowsiness are not the same, but the desire to sleep or need to rest may accompany both of them.

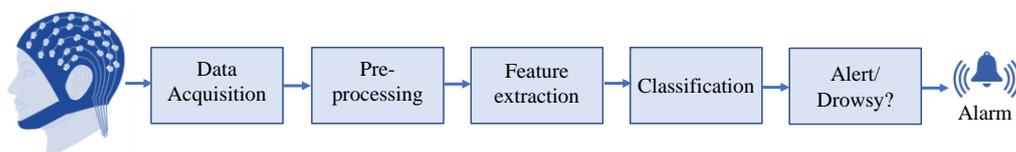
The main brain structures that have an essential role in controlling wakefulness/sleep are the posterior hypothalamus, anterior hypothalamus, the upper part of the midbrain, reticular formation of the brainstem, and hypothalamus ([Figure 1](#)). It is shown that interactions between the thalamus and the cortex are involved in sleep [24, 25].



**Figure 1.** Main brain regions involved in wakefulness /sleep control

A variety of factors, such as heavy meals during the day, lack of enough sleep, mental states, taking medications, or special medical conditions, can cause drowsiness. However, several other influential factors should be taken into account while referring to the causes of drowsiness. For instance, age shows a considerable impact on the progression of drowsiness. Due to their ongoing cognitive and physical development, young adults have higher sleep needs and get drowsy faster [26, 27]. Gender is another factor influencing drowsiness development. A faster increase of homeostatic pressure to sleep in women necessitates more sleep demands [28]. Another factor that can bias the results of studies on drowsiness is smoking addiction. Although evidence shows poor sleep patterns in cigarette smokers, studies on driver drowsiness showed that smokers were more alert. This result can be justified by attributing the lower levels of drowsiness to the smoker's anxiety and impulsiveness that increases because they were not allowed to smoke during the driving experiments [26]. Body Mass Index (BMI) also affects alertness; however, there are contradicting reports on the correlation of BMI and drowsiness progression [26].

Regardless of what causes drowsiness and what influencing factors are involved, feeling drowsy can lead to a state of reduced alertness, usually accompanied by performance degradation and psychophysiological changes, which may result in loss of vigilance or clear thinking [3]. Such changes and declines in cognitive functions and behavioral patterns are due to the alternations in our neural systems' activities that can be measured and quantified using bio-potential recording systems and mathematical processing described in the following sections.



**Figure 2.** EEG-based drowsiness detection system

## 2. Materials and Methods

Figure 2 shows the common methodology used in EEG-based drowsiness detection studies. Each block of this system is described in the following subsections in detail.

### 2.1. Data Acquisition

#### 2.1.1. Considerations in a Drowsiness Experiment

Driver drowsiness experiments are usually conducted in driving simulators due to the risks of drowsy driving on real roads. Driving on real roads is prone to fatal accidents and can be disturbed by unexpected events. Furthermore, in real road drowsiness tests, another person must be present in the vehicle in the front seat to control the car in a drowsy situation. The second person's presence would affect the progression of drowsiness, yet the chances of crashes from human errors are still not negligible. On the other hand, driving simulators will provide a safe and controllable condition to repeat a specific driving scenario without any risks. Recent studies have shown that the signs and progression of sleepiness over time are generally similar in the simulator and on the real road, though the drowsiness level is higher in the simulator [29].

Driving simulators are designed to mimic the conditions in real driving. They are usually equipped with a steering wheel, gear, pedals, and a display to present the driving environment. Some of the simulators also include a real cockpit. The desired driving course can be constructed with virtual reality software packages. Driving in the alert condition is usually performed in metropolitan areas which are crowded and are full of stimuli and distractors such as cars and people. On the contrary, data recordings in drowsy conditions need to take place in monotonous roads with very few or no stimuli on the road.

Another factor that influences the driving performance is circadian rhythm, i.e., the process which controls the sleep/wake alternation during the day [30]. Pack and colleagues [31] found that most of the drowsiness-related car accidents occurred in the peaks of sleep need, namely during early mornings (2-6 a.m.) and in the early afternoons (2-4 p.m.) post-lunch.

Studies have used different strategies in order to induce fatigue and drowsiness. A list of common strategies is provided below.

- Subjects should not have an adequate amount of sleep during the night before the test [32].
- They should avoid anti-fatigue and caffeinated drinks for a certain time before the test [32].
- Experiments are conducted during a time of the day when subjects usually feel drowsy, such as dawn, early afternoons and after lunch, and midnights [15, 33].
- Test durations are set to be lengthy, varying from 30 minutes to more than 2 hours [15, 33].
- Monotonous driving roads are chosen with little or no stimuli on the road [34].

### 2.1.2. EEG Recording Systems

EEG recording systems are generally categorized into conventional clinical recording systems and wireless portable EEG headsets. The former records signals using wired electrodes, and most of them have direct-wired connections to a computer or a processor for data storage and analysis. These systems are commonly used in clinics by trained and qualified operators who know how to identify and prepare electrode sites, inject an appropriate amount of

conductive gel, fixate electrodes position, be cautious about electrode impedance, and other issues that affect clean data recording. The cumbersome nature of conventional clinical EEG recording systems, their high cost, their relatively long installation time, and the need for an expert operator make considerable barriers to their usage in different applications, such as Brain-Computer Interface (BCI) and assistive technologies. The developments in wireless technologies and advancements in conductive materials led to considerable progress in manufacturing EEG headsets. A variety of headset models have been produced so far for different purposes. Muse, NeuroSky, and EMOTIV are three consumer-grade EEG headsets commonly used in drowsiness detection research and market. Table 1 shows some characteristics of these three EEG headsets.

Although using wireless technology diminished the mentioned issues with conventional clinical recording systems, researchers were concerned about the quality of the signals recorded by the EEG headsets. Several studies have been conducted to show the validity of these devices [18, 19, 35–38]. These comparative studies revealed that although the signal quality of these headsets is not as good as clinical devices, their performance is acceptable and even promising in some applications, especially for drowsiness detection purposes.

**Table 1.** Characteristics of EEG headsets commonly used in drowsiness detection research and market

Name	Features	Electrodes	Platforms	Other provided signals
NeuroSky MindWave	Weight: 90g / Sampling frequency: 512 Hz / Battery life: 8 hours	Passive-dry / Num. of Channels: 1 / Electrode site: FP1 / Ref: ear	Windows (XP/7/8/10), Mac (OSX 10.8 or later), iOS (iOS 8 or later), and Android (Android 2.3 or later)	---
Muse 2	Weight: 51g / Sampling frequency: (2021 version) 256 Hz / Battery life: 5 hours	Gold electrode / Active-dry / Num. of Channels: 4 / Electrode sites: AF7, AF8, TP9, and TP10 / Ref: Fpz	Muse App Compatibility (iOS 11.2 or later, Android 5.0 or later)	PPG, SpO2, Accelerometer, Gyroscope signals
Muse S	Weight: 41g / Sampling frequency: (2021 version) 256 Hz / Battery life: 10 hours	Silver electrode / Active-dry / Num. of Channels: 4 / Electrode sites: AF7, AF8, TP9, and TP10 / Ref: Fpz	Muse App Compatibility (iOS 11.2 or later, Android 5.0 or later)	PPG, SpO2, Accelerometer, Gyroscope signals
EMOTIV Insight 5	Lightweight / Sampling frequency: 128 Hz / Battery life: up to 8 hours using USB receiver, up to 4 hours using Bluetooth Low Energy	Hydrophilic semi-dry polymer electrode / Num. of Channels: 5 / Electrode sites: AF3, AF4, T7, T8, Pz / Ref: CMS/DRL references on the left mastoid process	Windows 7,8,10; macOS 10.11 or above; iOS 9 or later; iPhone 5+, iPod Touch 6, iPad 3+, iPad mini; Android: 4.43+ (excluding 5.0); a device with Bluetooth Low Energy	Accelerometer, Gyroscope, and Magnetometer signals
EMOTIV EPOC x	Weight: 170g / Sampling frequency: 2048 internally down-sampled to 128 Hz or 256 Hz (user configurable) / Battery life: up to 12 hours using USB receiver, up to 6 hours using Bluetooth Low Energy	Saline soaked felt pads / Num. of Channels: 14 / Electrode sites: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 / Ref: CMS/DRL references at P3/P4; left/right mastoid process	Not mentioned	Accelerometer, Gyroscope, and Magnetometer signals

### 2.1.3. Labeling Methods

We review seven main labeling methods, in two categories of subjective and objective, which were used in the previous drowsiness detection studies in this section. Labeling refers to the process of tagging short sequences of the data acquired from the participants based on the level of alertness or drowsiness to prepare them for later analysis, such as classification or statistical tests.

#### • Subjective Methods

In subjective methods, the levels of drowsiness are evaluated by the driver’s self-declaration or the scores given by trained raters.

**Karolinska’s Sleepiness Scale (KSS)**, a nine-point scale, is among the most common evaluation scales. In this method, participants determine which scale best describes their psycho-physical state in the last 5 minutes. Reporting moments are announced by displaying a text on the screen or by playing a sound. The inter-report periods are usually set to be relatively large (around 5 minutes each) since the process of asking may reduce drowsiness [12]. [Table 2](#) describes these levels.

**Table 2.** Karolinska’s Sleepiness Scale [12]

Ratings	Verbal descriptions
1	Extremely alert
2	Very alert
3	Alert
4	Rather alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy, but no effort to keep awake
8	Sleepy, some effort to keep awake
9	Very sleepy, great effort to keep awake, fighting sleep

**Stanford Sleepiness Scale (SSS)** has been frequently used to measure one’s perception of how drowsy one feels. It is quite similar to KSS in being a subjective and momentary assessment, but it includes seven levels. [Table 3](#) shows the descriptors for each level [39].

**Borg’s CR10 scale** is usually jointly used with Lee’s subjective fatigue scale in drowsiness detection studies. The Borg CR10 Scale is a general method for quantifying most perceptions and experiences, including pain and perceived exertion. Compared to other subjective methods of drowsiness labeling, this is not a recommended fatigue

**Table 3.** Stanford Sleepiness Scale [39]

Ratings	Degrees of sleepiness
1	Feeling active, vital, alert, or wide awake
2	Functioning at high levels, but not at peak; able to concentrate
3	Awake, but relaxed; responsive but not fully alert
4	Somewhat foggy, let down
5	Foggy; losing interest in remaining awake; slowed down
6	Sleepy, woozy, fighting sleep, prefer to lie down
7	No longer fighting sleep, sleep onset soon; having dream-like thoughts
x	Asleep

assessment method since it is not specifically designed for drowsiness and fatigue assessment. [Table 4](#) features Borg’s Scale [40].

**Observer Rating of Drowsiness (ORD)** is another subjective method. In this method, videos of the driver’s face and body are captured, and then facial tone, behavior, and mannerism of the driver (such as slow eye-lid closure, staring, yawning, stretching, head drooping, etc.) are assessed by three observers. Using the ORD behavior and mannerism checklist presented in [41], the observers keep track of what they observe and score the driver’s drowsiness level from 1 (Not drowsy) to 5 (extremely drowsy) on a regular basis of each 60 seconds or so [42].

[Table 5](#) describes these progressive drowsiness levels. A checklist of facial descriptors can also be found in [41].

**Table 4.** Borg’s CR10 Scale [40]

Ratings	Descriptions
0	Nothing at all
0.5	Extremely weak (just noticeable)
1	Very weak
2	Weak (light)
3	Moderate
4	Somewhat strong
5	Strong (heavy)
6	
7	Very strong
8	
9	
10	Extremely strong (almost max)
•	Maximal

**Table 5.** progressive drowsiness levels [41]

Drowsiness Levels	Description
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 largely 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.

### • Objective Methods

Objective labeling methods refer to the techniques that use physiological or behavioral signals or indices recorded from an individual under the study. They are typically independent of the self-interpretations of individuals.

**Reaction time** In this method, the driver is labeled as drowsy or awake based on his/her performance (reaction time) in fulfilling a requested task. There are different ways to check one's performance based on his reaction time in drowsiness-related research: 1) At predetermined and fixed intervals, the vehicle deviates from the cruising lane, and the driver must steer the car back to the center of the lane. 2) based on an audio or video announcement, the driver must press a key. The reaction time is defined as the time between stimulus onset (deviation or announcement) and response onset. Previous studies have shown that baseline EEG activity is correlated with changes in reaction time [43, 44]. However, determining a suitable threshold for distinguishing between alert and drowsy states is challenging and not well defined in the previous studies.

The advantages of this method over other subjective labeling methods are its strict rules for scoring and voting among the opinions of three trained raters, leading to more reliable results.

**Facial features** Driver's drowsiness/fatigue level can be evaluated by analyzing typical visual cues on a human face. These visual signs include Eye blinking frequency, percentage of eyelid closure, yawning frequency, facial expressions, and head movements [45]. Percentage of eyelid closure over the pupil, "PERCLOS," is introduced as a relevant indicator of drowsiness in several studies [46]. PERCLOS is assessed as the percentage of time the eyes are 80% closed [42]. Eye-related features can be detected through EOG signals or eye-tracking devices. Normal cameras and infrared illuminators are also used to detect facial features. However, the performance of the cameras is limited by the lighting condition, posture, and skin color. However, they often have a limited field of view to capture eye blinks [6].

**EEG-based** In the EEG-based labeling method, a feature from time or frequency domain EEG is selected, and based on the changes of this index, the EEG signal is annotated. An example of such annotation can be found in [47], where they have made use of alpha-theta waves to mark drowsy and alert periods. In another method, at least two well-trained technicians manually score the EEG signals according to the 1968 Rechtschaffen and Kales manual [48]. Then, the sequences of disagreement between the technicians are excluded from the evaluation.

Manual inspection of continuous brain signals is an arduous and difficult work even for trained neurologists since EEG signals are easily contaminated by artifacts, and there are significant differences between brain signals of different individuals [49]. This labeling method is called ‘manual labeling’ in this paper and can be considered a semi-subjective method.

## 2.2. Preprocessing

EEG signals recorded during driving suffer from various types of unwanted patterns categorized as physiological or non-physiological artifacts. The former refers to unwanted signals originating from electrical activities of different parts of our body. The latter relates to the electromagnetic activities of devices and machines in the recording environment or electrode movements [50, 51]. EEG signals are noise-sensitive in nature, and data recording in specific conditions may exacerbate this problem. During driving, electrode movement artifacts are more likely to happen due to the constant vibrations of the vehicle. Moreover, in the case of recording with commercial headsets, the electrodes are more prone to noise. These artifacts are difficult to remove, especially in drowsiness detection applications where fast and real-time processing is highly important. Followings are some information on physiological and non-physiological artifacts and the methods for their elimination in the preprocessing phase.

**Eye movements and blink artifacts** are one of the main sources of EEG artifacts. The amplitude of EOG varies from 100 to 3500  $\mu\text{V}$ , and its frequency is between 0.1 to 20 Hz. Blink artifacts, which are impossible or very difficult to avoid during data recording, are associated with the conductance changes due to the eyelid and cornea contact. The duration of each eye blink is about 200 to 400 ms, and its magnitude is more than ten times that of cortical signals. The majority of eye movements and blink artifacts mostly appear on channels that are close to the eye. However, due to their large amplitude, sometimes both ocular artifacts can even reach the occipital electrodes.

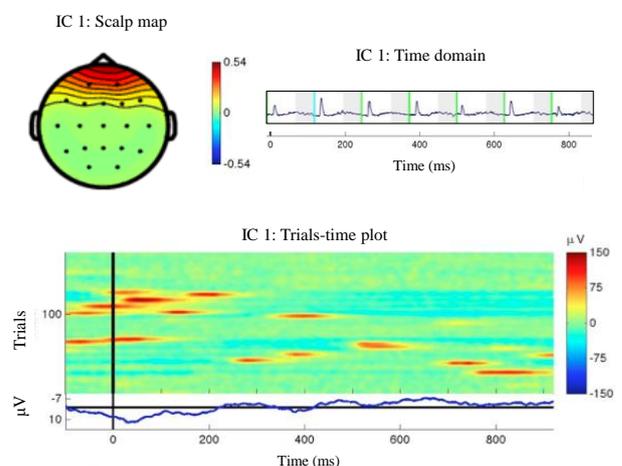
As shown in Figure 3, since ocular artifacts are considerably larger than the cortical activities, thresholding is used to detect and remove them. That is, epochs of EEG signals containing amplitudes outside a specified range (e.g., between  $\pm 70 \mu\text{V}$ ) are excluded in the preprocessing stage. Another popular method used for ocular artifacts removal is Independent Component Analysis (ICA) [52, 53]. Using ICA, the signals are decomposed into their

components. Considering some visual inspection criteria, such as ICs’ shape in the time domain, frequency of their repetition in the time-trial map, and ICs’ power distribution over prefrontal regions in topoplots (Figure 4), ocular components are recognized and removed.

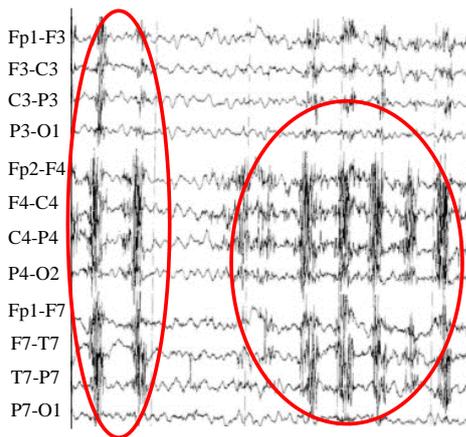


**Figure 3.** A sample of ocular artifacts (adapted from [54])

**Muscle artifacts** are generated due to the head, neck, or chin movements, wrinkling of the brow, teeth clenching, talking or chewing. The frequency range of these artifacts is between 20 to 300 Hz that overlaps entirely with the high-frequency bands of EEG signal, especially the gamma band. The amplitude of muscle artifacts can increase up to about 100  $\mu\text{V}$  [55]. Figure 5 shows a sample of EEG signals contaminated by muscle artifacts. Manual rejection of epochs contaminated by muscle artifacts is one possible method to eliminate this type of artifact. Since muscle artifacts have no specific source, their detection through ICA needs more precise inspection compared to the ocular artifacts.



**Figure 4.** A sample of eye blink artifacts



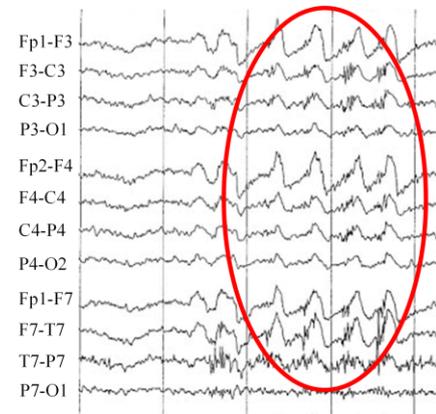
**Figure 5.** A sample of muscle artifacts related to chewing (adapted from [54])

An increase in the power of the higher frequency bands or a distinct activity in the power distribution of ICs over the brain's temporal regions is usually considered a possible sign of muscle artifacts. These two methods (i.e., visual inspection and ICA) are not fully automated, which limits their usage for real-time applications. Low-pass filtering is a common method to reduce the effect of muscle artifacts, especially in higher frequencies [56]. Since muscle artifacts are not thoroughly removed by applying low-pass filters, further studies need to be done to develop better methods for muscle artifact rejections.

The advantage of ICA over the thresholding method is that less data will be lost. However, due to the time-consuming nature of ICA and the need for visual inspection to accurately detect ocular components, this method needs more improvements before it can be used in real-time and fully automatic processes, such as drowsiness detection.

**Glossokinetic Potential (GKP)** is another possible artifact of EEG signals generated from tongue movements. The tongue tip has a negative charge with respect to its base. The movement of the tongue alters the steady charge and produces GKP. Talking, swallowing food and drink, or even saliva or sucking alter the steady charge and produce GKP. This artifact can be observed spatially from frontal

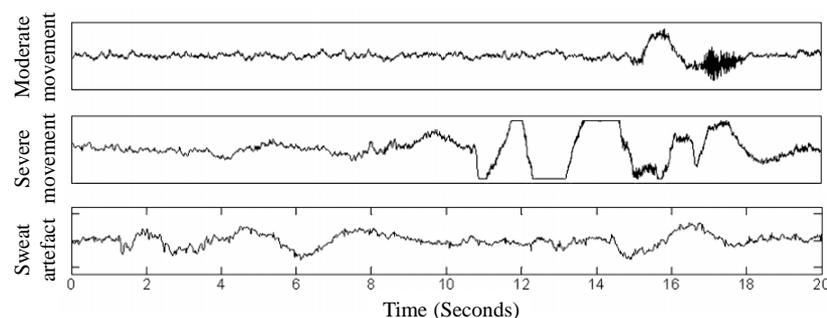
to occipital channels. Its temporal shape is similar to the ocular artifacts but is less steep, as shown in Figure 6. The frequency of GKPs is variable, but it is dominantly in the delta band [57]. Similar to ocular artifacts, visual inspection or thresholding are common methods used for GKP artifacts removal.



**Figure 6.** A sample of Glossokinetic potential (adapted from [54])

**ECG artifact** produced by cardiac muscle depolarization. The common methods for the rejection of this artifact are ICA, adaptive filtering, and ensemble averaging that are time-consuming or need an additional ECG channel as a reference [58]. The detection of this artifact is one of the current fields of study since such methods are not applicable in real-time applications. In addition to physiological /biological artifacts, EEG signals can be contaminated by other potential sources of interferences such as the ones discussed below.

**Electrode artifacts** are commonly observed by the alteration of electrode impedance. It is suggested to keep the electrodes' impedance less than about 5 K $\Omega$  during recording [59]. However, drying of the conductive gel under the electrode or displacement of the electrodes due to the individuals' movement can increase or change this impedance and create artifacts on EEG signals (Figure 7). Dry electrodes, which are commonly used in wireless



**Figure 7.** Three kinds of electrodes artifacts [50]

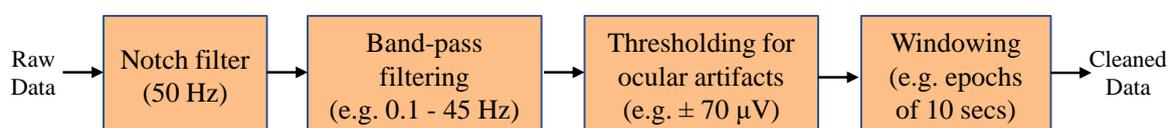
headsets, are especially prone to electrode displacement. The creation of a salt bridge and short connection between electrodes due to the excessive use of conductive gels or sweating are other possible causes of electrode artifacts.

**Power line noise** at 50 or 60 Hz, depending on local standards, is the most common non-biological noise that interferes with EEG signals recorded via devices connected to the source of high voltage power by wire. Suppression of this noise is done using a notch filter or ICA. Although detection and suppression of this noise are more straightforward than other potential noises and artifacts, its removal may affect the gamma-band energy. When gamma is one of the target bands, electromagnetic shields or wireless recording systems can be used to reduce the interference of power-line or other electromagnetic noises using.

Since drowsiness detection systems need real-time processing and timely feedback plays a vital role in these systems, preprocessing steps must be performed as fast as possible. Therefore, in most of the proposed systems, preprocessing steps are limited to notch filtering (power line noise removal), band-pass filtering (drift removal and muscle artifacts suppression), and thresholding (ocular artifacts removal).

Although such fast-preprocessing steps are appropriate for real-time drowsiness detection, these steps cannot remove or suppress the effects of all potential noises and artifacts completely. Incomplete noise removal can lead to incorrect drowsiness detection and increase the false positive or false negative rates. Therefore, one open field for future research is developing novel fast and accurate preprocessing methods.

One step after noise and artifact removal is storing the cleaned signals as short windows called epochs. These epochs are separately used for further processing and feature extraction steps. Since switching between wakefulness and drowsiness does not occur very fast, the duration of the epochs is usually set between 1 to 30 seconds. Figure 8 demonstrates a summary of common preprocessing steps in drowsiness detection systems.



**Figure 8.** A block diagram of common preprocessing steps in drowsiness detection systems

## 2.3. Feature Extraction

A review of the drowsiness detection studies reveals that some features have been used more frequently than others. Statistical features, spectral features, especially the power of different frequency bands, power ratios, and entropy measures, have been widely used in previous studies [12, 13, 60–63]. In the following, these common features are introduced.

### • Statistical features

Statistical features are among the least complicated features that can be extracted from EEG signals. Nevertheless, they have proved to be quite discriminative in drowsiness detection studies, especially when they are fused with other features [60, 63]. These statistical features include mean, standard deviation, variance, median, skewness, kurtosis, etc., that can be applied to the time or frequency domain characteristics such as amplitude.

### • Spectral features

Power Spectral Density (PSD) shows the distribution of the signal power over frequency [64]. Spectral features are the most commonly used feature in drowsiness detection studies. Previous studies have shown that the power of the EEG wavebands changes based on subjects' alertness level, and this relative change in the power of brain waves can be used in performance analysis and drowsiness detection [65, 66]. A review of the PSD estimation methods is presented below.

**Non-parametric methods** Non-parametric PSD estimation techniques are based on the computation of the Discrete Fourier Transformation (DFT). Conventional periodogram, Welch, Bartlett, Blackman, and Tukey methods are well-known non-parametric PSD estimation methods [67]. The advantage of non-parametric methods over parametric ones is mainly their robustness [68], meaning that the estimated PSDs do not contain spurious frequency peaks. Further, there is no need for any previous knowledge or assumption on the data distribution as opposed to the parametric methods. The key limitation with the non-parametric method is the windowing length; choosing an appropriate data length that satisfies the stationarity

condition and brings about enough frequency domain resolution remains a challenging compromise in this method. Once the PSDs are calculated, one might seek to define more features from them by summing the PSD values over frequency bins to yield energy estimates of different frequency bands or computing statistical features such as maximum, minimum, mean, etc. Alternatively, it may also be of interest to compute spectral entropy, which measures the uniformity of signal energy distribution in the frequency domain [69].

**Parametric methods** In contrast to non-parametric methods, parametric methods do not use data windowing. Instead, they rely on parametric models of a time series, such as Autoregressive (AR), Moving Average (MA), and autoregressive moving average (ARMA) models. Therefore, to estimate the PSD of a time series, one must build an appropriate model that best reflects the behavior of the system that produces the time series. If the model parameters and the order are estimated correctly, parametric methods allow for accurate calculation of the PSDs for relatively short signal lengths [50]. However, in the case of a wrong model, spurious frequency peaks emerge in the PSD.

#### • Entropy features

Entropy is a statistical measure that evaluates the uncertainty of a signal. Shannon first introduced it in information theory to measure the uncertainty and randomness in a time series [70]. Since EEG is a complex and nonlinear signal [71–73], entropy has extensively been used to analyze it. Several types of entropies, such as log energy entropy, spectral entropy, approximate entropy, sample entropy, fuzzy entropy, etc., are devised for EEG analysis. As reported in [74, 75], normal state and fatigue state brain signals show significantly different uncertainty degrees. Previous studies have used a single measure or a combination of different entropies in their research. Wang *et al.* tested two common entropy measures: Spectral Entropy ( $S_{En}$ ) and Wavelet Entropy ( $W_{En}$ ). They showed that the wavelet entropy outperforms spectral entropy in its recognition rate of drowsiness [76]. Approximate Entropy ( $Ap_{En}$ ), which is developed to quantify regularity and complexity, has also shown potential for various applications in physiological signals analysis [77]. Low values of  $Ap_{En}$  reflect that the system contains repeated patterns and is predictive, while high values mean that more irregularity and randomness exist within the data [78]. However, due to the time-consuming calculation of this feature, it is more suitable for shorter-length data segments [62]. Sample entropy ( $Samp_{En}$ ),

a statistic proposed by Richman and colleagues, is an alternative regularity statistics to  $Ap_{En}$  [79]. Sample entropy is less sensitive to the changes in the data length [78], but similar to  $Ap_{En}$ ; it is computationally time-consuming. Fuzzy entropy is similar to sample entropy, but instead of Heaviside Function, it uses a fuzzy membership function [80]. Fusion of multiple entropies, i.e., spectral entropy, approximate entropy, sample entropy, and fuzzy entropy, is applied in Min *et al.*'s work; and they have reported these features as significant factors in inferring the fatigue state of the driver [62]. In another study, Min *et al.* have demonstrated that wavelet log energy surpasses other entropy indices in fatigue state recognition rate and computational efficacy [81].

#### • Wavelet-based features

Wavelet decomposition is a well-established mathematical theory that takes into account the non-stationary nature of the EEG signals [49, 60, 82, 83]. A Discrete Wavelet Transform (DWT) decomposes a given signal into several sets, where each set is a time series of coefficients describing the time evolution of the signal in the corresponding frequency band [84]. Subasi *et al.* investigated the effect of mother wavelet on drowsy/alert classification accuracy by examining a set of mother wavelets including db2, db4, db8, sym10, and Coiflet of order 4 (coif4) and reported that Daubechies wavelet, especially db2, offer better efficiency in EEG signals [60]. Statistical features of wavelet coefficients, power of each sub-band, and power ratios derived from the coefficients are the most used wavelet-related features in previous drowsiness detection studies [49, 60, 82].

#### 2.3.1. Auxiliary Signals

Utilizing other biological signals, referred to as auxiliary signals, can improve detection accuracy in EEG-based systems. This can be especially beneficial when EEG acquisition is performed with few channels. Luckily, some of the consumer-grade EEG headsets provide these signals along with the recording of brain signals. Below is a list of common biological signals used for drowsiness detection and the common features extracted from them.

**ECG** is a non-invasive signal that indicates the electrical activity of the heart. Heart Rate (HR) and Heart Rate Variability (HRV), which are derived from ECG, are commonly used in drowsiness detection studies. HR is considered as the number of heart beats in the ECG signal, and HRV is the variations in the time intervals between

each two successive heart beats. HRV is highly resistant to noise and is proved to be an indicator of the psychophysical state of the driver [85]. Jo *et al.* investigated the changes in the Heart rate while driving in drowsy conditions and showed that the HR significantly decreased compared to normal driving conditions [86]. Consistent with previous results, Jing *et al.* showed a negative correlation between HR and driving time, meaning HR decreases as fatigue increases with driving [87]. HR and HRV can be measured using less intrusive sensors attached to the steering wheel [88] or worn on the driver's wrist [89]. However, less intrusive sensors produce less accuracy and are more prone to movement artifacts [12].

**EOG** is used by some researchers to identify driver drowsiness through eye movements. EOG is an electrical signal generated by the polarization of the eyeball and can be measured on the skin around the eyes [90]. By taking the derivation of horizontal and vertical EOG signals, Thumchiachieh has obtained the speed of eyeball movements and has proposed a method to distinguish drowsiness from alertness [90]. Among all oculomotor parameters, blink duration and frequency remain the best indicators of drowsiness [91]. It is known that drowsiness is accompanied by increased blink frequency and blink duration [92]. However, there are considerable inter-individual differences in blinking frequency. For example, Schleicher *et al.* reported that several subjects began to stare during severe sleepiness and showed almost no blinks or saccades after an initial increase in blinks [91].

**PPG** measures the oxygen saturation of blood, producing a photo-plethysmograph. Drivers' fatigue and drowsiness are associated with blood oxygen reduction. Some previous studies reported a negative correlation between drowsiness and blood oxygen level [93, 94]. However, Jing *et al.* reported no obvious trend for oxygen level as the fatigue was deepened [88]. Therefore, they claimed that blood oxygen saturation could not be used as an independent indicator of fatigue, only as an auxiliary indicator to determine whether the driver is experiencing fatigue. In general, we failed to find any solid evidence in the literature on the strong correlation of PPG and drowsiness, which could be easily noticed.

**EMG** is a non-invasive index of the level of muscle activation [95]. In some drowsiness studies, EMG of the muscles involved in the gripping of the steering wheel is measured to investigate its relation with drowsiness. Previous research has indicated a fall in the magnitude of the EMG signal as the driver drowsiness level increases

[96–98]. Frequency domain parameters such as mean power, mean and median frequency are other commonly used indices for drowsiness detection.

**EDR** is a measurement of electrical conductance between two points on the skin and is used in some drowsiness detection studies [94, 99]. Electrodermal response or conductivity (EDR) reflects the activity of the autonomous nervous system [100]. Several parameters of the EDR, including skin conductance level and the number of spontaneous fluctuations, show potential for revealing information about the driver state [101].

## 2.4. Classification

Classification groups the segments of EEG signal into wakeful and drowsy. Extracted EEG features (or EEG samples) are fed into a classifier, and the classifier recognizes the class (i.e., drowsy or wakeful). Several types of classifiers have been used so far for drowsiness detection. Their differences are in the structure and the techniques used for the input categorization. Generally, classifiers can be grouped into shallow and deep models [102, 103]. These two types of classifiers and their characteristics are described in the following sections.

### 2.4.1. Shallow Models

Shallow models have simpler architecture compared to deep models and therefore impose a less computational cost and are more robust to overfitting when the sample size is small [102]. Some of the most famous examples of shallow models that are used in drowsiness detection systems are Linear Discriminant Analysis (LDA), support vector machine (SVM), K-Nearest Neighborhood (KNN), tree classifiers, fuzzy-classifiers, and Artificial Neural Network (ANN).

**LDA** is suitable when classes are linearly separable. This classifier uses a linear combination of features that can make the most distinction between classes. Therefore, it is sometimes used as a preprocessing stage in pattern recognition for feature dimension reduction [104].

**SVM** is the most commonly used classifier in drowsiness detection. In this technique, features are fed as inputs, and outputs are decision boundaries that make the highest separation between classes or space margins around the boundaries. These boundaries can be linear or non-linear. When the boundaries between classes are not linear, non-linear kernels (e.g., Gaussian) are used. Computing the

best boundaries amounts to minimizing a predefined cost function [34, 105].

**KNN** is a non-parametric method. This algorithm assumes that the sample points of each class in the feature space are close to each other. The first step is calculating the distance between the input data and the existing data. Then, the input data is classified by a plurality vote of its K-nearest neighbors [106].

**Tree classifier** is another non-parametric method that uses a series of conditional statements to partition training data into subsets. These series shape a hierarchical structure consisting of a root node (with no incoming edges), internal nodes (one input edge and two or more output edges), and directed edges used to split nodes. Each successive split adds some complexity to the model. To boost the performance of tree-structured classifiers, ensemble methods that get votes among several tree classifiers with different levels of complexity are suggested. Although these classifiers are simple to interpret and can be used in ensemble methods, they are not robust against small changes in the data [107]. Tree classifiers have been used in a few studies on drowsiness detection and are not popular in this field.

**Fuzzy-classifiers** use predefined rules on continuous or categorical features. Experts define these rules based on how features alter in different conditions (e.g., by the occurrence of drowsiness). Rule-based classifiers have a fuzzy inference engine that decides about the label of input based on a combination of all rules' results. In these classifiers, there is no specific boundary between classes. That is, each input may belong to different classes with different levels of probability. The main advantages of fuzzy classifiers are 1) suitable for real data where boundaries between classes might not be well defined, 2) using the existing knowledge and evidence, and 3) the principle behind fuzzy-classifiers is close to the mechanisms of human decision making [108]. Although fuzzy classifiers have significant benefits, their main limitations are the requirement for enough knowledge, an experienced expert, and an appropriate definition of fuzzification/defuzzification functions and inference methods.

**Shallow models of ANNs** consist of an input and an output layer and one or two hidden layers in between. Layers are connected via different weights and their optimum values are calculated through learning mechanisms. These classifiers can deal with classes that are

both linearly or non-linearly separable. However, determining an appropriate structure (i.e., number of neurons, number of hidden layers, the activation function of neurons) is challenging, and finding optimal weights in the training phase is usually computationally intensive [109].

## 2.4.2. Deep Models

Unlike shallow ANNs, deep neural networks (DNNs) have more than two or three hidden layers, often of various types. The key advantage of DNNs is that we do not need to extract features from the signals manually since these networks learn to extract features while training. Several structures of DNNs have been suggested and used for drowsiness detection systems. The following items are examples of some common types of layers used for filter application and feature extraction [47].

- **Convolutional layers:** These layers are mainly used for filtering and feature extraction from raw data. The convolution operation can be represented by Equation 1.

$$Y_i = b_i + \sum_n W_{in} * X_n \quad (1)$$

In this Equation, the convolution operation is shown by \*, the feature map extracted by the layer presented by  $Y_i$ ,  $b_i$  is the bias term,  $W_{in}$  is the sub-kernel of the channel, and  $X_n$  is the input signal.

- **Batch Normalization layers:** These layers are used to speed up the learning process by allowing each layer of the network to be trained more independently. It normalizes the output of the previous layers by subtracting the average and dividing it by the standard deviation.

- **Dropout layer:** This layer is used to prevent a model from overfitting by inactivating randomly selected neurons in the hidden layers at each update of the training phase.

- **Max-Pooling 1D layer:** Max pooling is an operation used for dimension reduction by selecting the maximum element from the region of the feature map.

- **Flatten layer:** The output of some layers is multidimensional that is not suitable for the next steps. Flattening layers convert data into a 1-dimensional array for using in the next layer.

- **Dense layers:** Dense layers are simple, fully connected ANNs, meaning that each neuron in this layer receives input from all neurons of its previous layer and

provides one output to the next layer. Dense layers are mainly placed in the final classification steps.

DNNs have been used in different studies on drowsiness detection. Although the possibility of using raw EEG signals as input is one of the important advantages of DNNs, these methods are significantly costly in terms of time and implementation. To use them in real applications, such as drowsiness detection systems, researchers are trying to boost the speed of these methods and attenuate their cost.

### 3. Results and Discussion

In this research, we targeted the studies under the category of drowsiness detection, which adopted an EEG-based approach or its combination with other signals. We investigated the selected studies from different aspects, such

as recording device, number of EEG channels, sampling frequency, epoch length, labeling method, number of subjects, extracted features, type of classifiers, and accuracy of detection. Table 6 shows the general characteristics of EEG-based drowsiness detection studies.

According to the second column of Table 6, a considerable number of studies have used EEG headsets instead of clinical recording devices. The number of channels in consumer-grade headsets is lower than clinical devices, Figure 9a, reducing the costs of electrode monitoring and maintenance. The accuracy of drowsiness detection using consumer-grade headsets is also promising, Figure 9b. The line graph in Figure 9c indicates that increasing the number of channels does not necessarily accompany a significant rise in detection accuracy; therefore, EEG headsets are worth being considered as

**Table 6.** General characteristics of EEG-based drowsiness detection studies

Ref.	Recording Device	No. Channels	Fs (Hz)	Epoch Time (EEG)	Labeling Method	No. of Subjects	Extracted Features	Classifier	Accuracy
[110]	Clinical	32	1000	1s	KSS	8	Entropy	LDA	~90%
[111]	Clinical	13	256	8s	SSS	Varied	Entropy	---	---
[62]	Clinical	32	1000	1s	ORD, Driver performance, Lee's subjective fatigue scale	12	Entropy	Shallow ANN	98.3%
[112]	---	1 (Fz)	100	30s	---	---	Wavelet coefficients in each sub-band	Thresholding	Precision 98.65% Sensitivity 84.98%
[76]	Clinical	32	1000	---	Lee's subjective fatigue scale and Borg's CR10 scale	20	Entropy	SVM	90.7%
[33]	Clinical	32	500	3s	Reaction time	10	PSD	SVM	83.3%
[113]	Clinical	32	500	10s	ORD	6	---	Deep networks	95%
[114]	Clinical	32	500	30s	Reaction time	16	PSD	---	---
[115]	Clinical	2 (Fp1,Fp2)	1000	1s	Lee's subjective fatigue scale and Borg's CR10 scale	16	Entropy	SVM	95.37%
[116]	Clinical	1 (Fpz-Cz)	---	5s	---	20	Complexity measures	Ensemble of shallow models (KNN,SVM, Bayes, Fisher)	94.45%
[117]	Clinical	32	256	10s	EOG, EEG	20	PSD	SVM	99.3%
[118]	Clinical	40	1000	1s	KSS	11	---	complex network	~100%

Ref.	Recording Device	No. Channels	Fs (Hz)	Epoch Time (EEG)	Labeling Method	No. of Subjects	Extracted Features	Classifier	Accuracy
[119]	---	---	200	1s	Manual	20	PSD, Entropy	ANOVA	---
[82]	---	2 (Fpz-Cz and Pz-Oz)	100	30s	---	---	statistical moments of wavelet coefficients in each sub-band	Unsupervised K-means clustering	---
[120]	Clinical	2 (Fp1, Fp2)	1000	---	Lee's subjective fatigue scale and Borg's CR10 scale	13	Entropy	SVM	85%
[16]	Clinical	2 (Fp1, O1)	200	60s	---	20	PSD	regression model	92.2%
[121]	---	32	1000	10s	Eye tracker	6	PSD	KNN, SVM, ELM, H-ELM, PSO-H-ELM	83.12%
[122]	Clinical	32	2000	2s	ORD, EOG, SSS	43	PSD	Bayesian neural network	88.2%
[85]	Clinical	9	256	8s	Manual	16	Wavelet coefficients, entropy, RQA	ELM-RBF, ELM-sig, SVM	95.6%
[60]	Clinical	8	150	5s	Manual	30	Wavelet Coefficients statistics in each sub-band	ANN	93%
[123]	Clinical	16	256	0.5s	ECG, EOG	10	---	CNN	92.68%
[124]	Clinical	16	512	2s	Reaction time	10	PSD, entropy, complexity	Shallow ANN	83.3%
[125]	Clinical	32	500	30s	---	13	AR model	SVM	81.64%
[126]	Clinical	5	512	2s	Reaction time	14	PSD	SVM, KNN	96.1%
[43]	Clinical	32	250	1s	Reaction time	8	PSD	CNN	78.39%
[61]	Headset (Unknown brand)	24	250	10s, 2s	Reaction time	10	PSD, Entropy	SVM, shallow ANN	97.8%
[127]	Headset (NeuroSky)	1	512	10s	KSS	29	PSD, Entropy	SVM	72.7%
[44]	Headset (Unknown brand)	3	512	180s	---	15	PSD	Thresholding	Precision 76.9% Sensitivity 88.7%
[128]	Headset (Muse)	7	220	1s	---	23	PSD	SVM	87%
[129]	Headset (Muse)	4	256	1s	---	1	---	Deep network	95.76%

Ref.	Recording Device	No. Channels	Fs (Hz)	Epoch Time (EEG)	Labeling Method	No. of Subjects	Extracted Features	Classifier	Accuracy
[130]	Headset (NeuroSky)	1	512	---	---	6	PSD	Thresholding	68.11%
[131]	Headset (NeuroSky)	1	512	10s, 60s	---	60	PSD, statistical	Shallow ANN	97.6 %
[132]	Headset (NeuroSky)	1	512	---	---	3	PSD	Thresholding	81%
[133]	Headset (NeuroSky)	1	512	---	---	10	PSD	SVM	81.9%
[134]	Headset (EMOTIV)	14	128	10s	---	---	PSD	ANOVA	---
[135]	Headset (EMOTIV)	14	128	---	---	---	PSD	---	---
[136]	Headset (Muse)	4	250	---	---	28	PSD	KNN, SVM, shallow ANN	86%
[137]	Headset (EMOTIV)	14	128	2s	---	3	Entropy	Shallow ANN	98%
[138]	Headset (EMOTIV)	14	128	5s	KSS	16	PSD	SVM	94.4%
[139]	Headset (EMOTIV)	14	128	3min	KSS	30	Statistical, PSD	KNN, SVM	96%
[140]	Headset (EMOTIV)	14	128	2s	---	50	PSD	ANOVA	---
[141]	Headset (EMOTIV)	14	128	10s	---	---	PSD	SVM	70%
[142]	Headset (EMOTIV)	14	128	10s	---	18	PSD, blink features	KNN, shallow ANN	85%
[143]	Headset (EMOTIV)	14	128	---	---	2	PSD	Novel classifier	93.75%
[144]	Headset (EMOTIV)	14	128	---	---	5	PSD	KNN, SVM	70%
[145]	Headset (Muse)	4	256	2s	---	3	PSD	SVM, LDA	73.8%
[146]	Headset (EMOTIV)	14	128	---	Self-reported fatigue level	15	PSD, entropy	---	---
[147]	Headset (EMOTIV)	14	128	---	---	13	PSD	KNN	96.8%
[148]	Headset (Muse)	4	256	---	---	48	Entropy	Naive Bayes, shallow ANN, SVM, KNN, Decision Tree	77.5%
[47]	Headset (EMOTIV)	14	128	3.75s	EEG	14	---	Deep network	90.42%
[149]	Headset (EMOTIV Insight)	5	128	---	KSS	25	PSD	---	---
[150]	Headset (Muse)	4	256	2s	Novel proposed algorithm	29	PSD	negative-unlabeled learning algorithm	93.77%

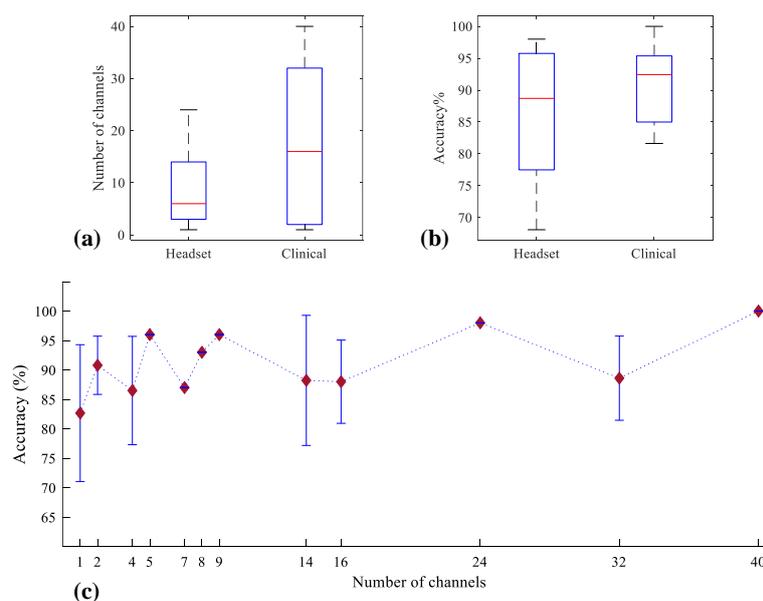
Ref.	Recording Device	No. Channels	Fs (Hz)	Epoch Time (EEG)	Labeling Method	No. of Subjects	Extracted Features	Classifier	Accuracy
[151]	Headset (Muse)	4	256	1s	KSS	50	PSD, blink features	SVM	92%
[152]	Headset (NeuroSky)	1	512	2s	---	5	PSD	---	---
[153]	Headset (NeuroSky)	1	512	60s	---	1	PSD, Statistical measures	Thresholding	---

RQA: recurrence quantification analysis; RBF: radial basis function; ELM: extreme learning machine; H-ELM: hierarchical extreme learning machine, PSO-H-ELM: hierarchical extreme learning machine algorithm with particle swarm optimization; sig: sigmoid activation function.

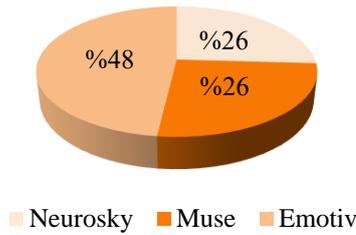
a substitute for clinical devices in drowsiness detection applications. Among several available consumer-grade EEG headsets, Neurosky, Muse, and Emotiv are three brands that have been frequently used in studies on EEG-based drowsiness detection. The percentage of usage of these three brands is shown in Figure 10. This figure shows that the prevalence of EMOTIV headsets is relatively twice as much as Muse or Neurosky headsets. However, by a more detailed look at the studies, which used Emotiv Headsets, it becomes clear that the 14-channel EMOTIV Headset, which is called EMOTIV EPOC, has been much more prevalent in comparison to the other headsets of this brand. This prevalence could be because this type of headset provides more flexibility in channels' location in contrast to the other headsets. Moreover, the greater number of electrodes can lead to higher detection accuracy since it covers more brain

regions and presents more comprehensive data. It should also be noted that although this headset can bring about better detection accuracy, a considerable increase in the set-up time makes it improper for real-life applications. However, the Muse family (i.e., Muse 2 and Muse S), EMOTIV Insight Headset, and NuroSky MindWave Headset do not suffer from such an issue and show potentials for real driving scenarios.

Figure 11 shows that the highest average accuracy belongs to EMOTIV. However, the highest maximum detection accuracy, 98.8%, was achieved by the Muse headset. Again, it should be noted that the accuracy gained by EMOTIV headsets is impacted by the high number of electrodes (14 channels) in EMOTIV EPOC headset, while in Muse and NuroSky headsets, only 4 and 1 electrodes are available, respectively.



**Figure 9.** A comparison between headsets and clinical devices in terms of (a) detection accuracy and (b) number of channels (according to Table 6); (c) shows the detection accuracy versus the number of channels (red diamonds and error bars represent the average and the standard deviation of detection accuracies reported in Table 6, respectively)

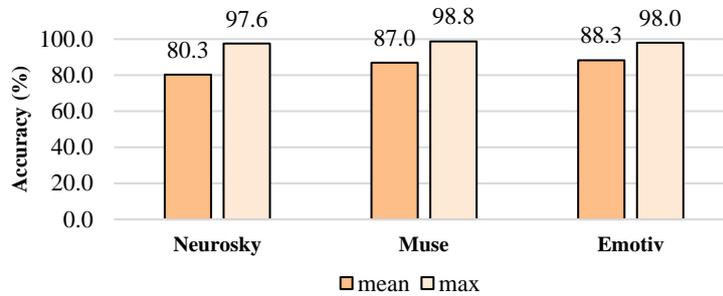


**Figure 10.** Percentage of frequency of use of three popular headsets in previous studies (according to Table 6)

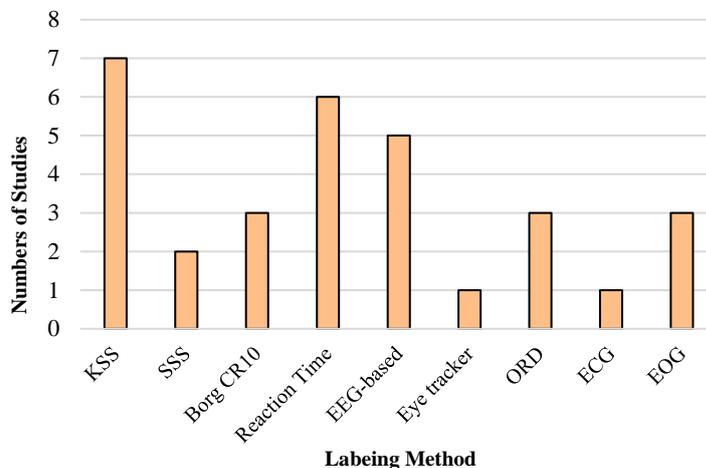
As mentioned before, labeling EEG signals with drowsy/wakeful states is one of the essential parts of drowsiness detection systems design. Figure 12 shows how frequently different labeling methods were used in the studies reported in Table 6. Among all methods, KSS is used more frequently. Although KSS is a subjective method and therefore affected by individuals’ feelings and interpretations, ease of implementation and the momentary nature of its assessment have made it popular. After KSS, reaction time, EEG-based labeling, and ORD were the most popular labeling methods. Labeling with reaction time necessitates designing a specific driving scenario with repeated events, which requires the driver’s on-time reaction.

These events may cause distraction and discomfort to the driver. Moreover, there is no general rule to determine the threshold for separating the reaction times during drowsiness and alertness, making reaction time a less reliable method for labeling.

There are two main approaches to EEG-based labeling. In the first approach, trained practitioners score segments of EEG signals by visual inspection. This labeling method is an arduous and challenging task because of the individual differences in the brain signals of different people and the presence of large-amplitude artifacts that can contaminate the signals and change their appearance. In the second approach, an index like the power of a specific frequency band or a power ratio is targeted, and the epochs are labeled according to a threshold for that index. Determining a suitable index and threshold is a challenging task and requires previous knowledge about the effects of drowsiness on the signals. Moreover, in EEG-based systems, the classification is done by the features extracted from EEG signals; and it does not have logical justification to utilize a single metric both for labeling and classification. Despite the moderate popularity of ORD, it is a reliable labeling technique due to its strict rules for determining the



**Figure 11.** A comparison of performance among three EEG headsets (according to Table 6)



**Figure 12.** Distribution of usage frequency of labeling methods used in different studies on EEG-based drowsiness detection (according to Table 6)

drowsiness level. The scoring can be done offline by checking the videos recorded from the face of the driver. The main challenge of this method is the need for three observers to watch and score the driving session.

Figure 13 demonstrates that most of the surveyed studies used spectral features rather than other features such as entropy. It is repeatedly reported that drowsiness is associated with an increase in low-frequency bands power, particularly theta and alpha bands, and a decrease in high-frequency bands, especially beta band; hence these measures are widely used for drowsiness detection [13, 154–156]. Four ratios of  $(\alpha+\theta)/\beta$ ,  $\alpha/\beta$ ,  $(\alpha+\theta)/(\alpha+\beta)$ , and  $\theta/\beta$  were also frequently used for drowsiness detection. Among these ratios,  $(\alpha+\theta)/\beta$  is proved to be highly useful [156–158]. Its high values indicate an increase in low-frequency and a decrease in high-frequency bands power.

Although there is no consensus on the most effective brain regions for drowsiness detection, previous studies reported the association of some brain frequency bands with some specific regions of the brain during the drowsy state. For instance, the alpha band is more associated with the posterior brain regions [158, 159]. For detailed information on the relation of frequency bands, brain regions, and drowsiness, refer to [13]. Since drowsiness detection is a real-time procedure, features are not

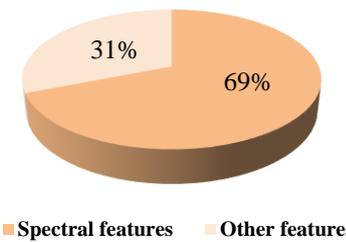


Figure 13. Distribution of feature extraction methods used in different studies on EEG-based drowsiness detection (according to Table 6)

extracted from the whole length data. Instead, features are extracted from short time windows of EEG signals.

Figure 14 shows epoch size variations in different studies on EEG-based drowsiness detection. Small windows have the advantage of being closer to real-time detection, while longer windows can help to estimate the features more accurately and reduce the false alarm rate. According to Figure 14, 1-s, 2-s, and 10-s windows have more repeatedly been used in the previous studies.

Extracted features are then fed into a classifier to distinguish between drowsy and alert periods. In practical applications, simpler classifiers that are fast and easy to implement are superior to other classifiers. Figure 15 shows the popularity of shallow classifiers (e.g., SVM, KNN, and shallow ANN), which are simple and easy to implement,

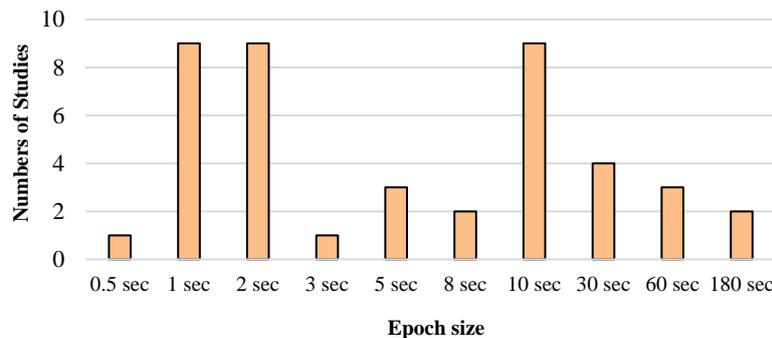


Figure 14. Epoch size variations in different studies on EEG-based drowsiness detection (according to Table 6)

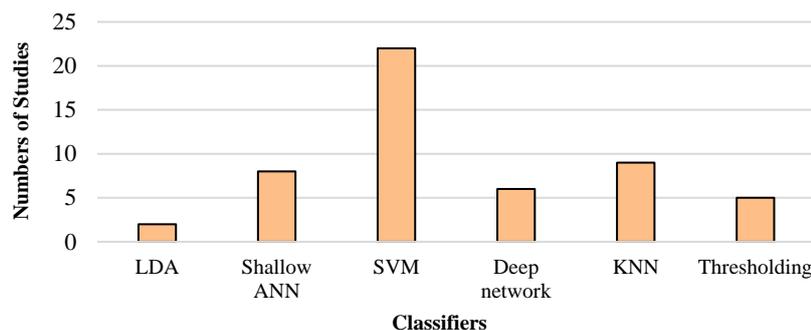


Figure 15. Distribution of classification methods used in different studies on EEG-based drowsiness detection (according to Table 6)

versus deep models. Among shallow classifiers, SVM is more popular than the other ones.

Changing the recording device, features' type and quantity, or the classifier's type are some options for increasing the accuracy of drowsiness detection. Although changing the recording device from headsets to clinical devices can increase the accuracy of drowsiness detection, it increases the cumbersomeness of EEG recording and prevents the practical usage of the designed system. Moreover, increasing the number of EEG-based features, using more complex features/classifiers can increase the

computational complexity and the cost of time and may not be practical. As mentioned before, another feasible and practical option for boosting the accuracy of EEG-based detection systems is to combine them with other biological signals to make use of their discriminative characteristic. Table 7 shows the results of several studies on such hybrid systems. According to this Table, EOG and ECG are among the most popular biological signals used for this intention. The highest accuracy, 99.1%, is obtained by a combination of EEG- and EOG-based indices.

**Table 7.** Results of hybrid-based drowsiness detection studies

Published Work	Signals	No. Channels	Accuracy
[160]	EEG and EMG	2-ch EEG, 2-ch EMG	99%
[63]	EEG and ECG	1-ch EEG, 1-ch ECG	80%
[161]	EEG and Gyroscope	1-ch EEG, 3-ch gyroscope	96.24%
[34]	EEG, ECG, and vehicle measures	16-ch EEG, 1-ch ECG	82.4%
[66]	EEG and EOG	30-ch EEG/EOG	--- (ANOVA)
[155]	EEG, EOG, EMG and EDA	8-ch EEG, 2-ch EDA, 4-ch EOG, 3-ch EMG	Precision 76%
[162]	EEG, ECG	5-ch EEG, 1-c ECG	97.2%
[163]	EEG, EOG	18-ch EEG, 4-ch EOG	correlation coefficient/ RMSE 0.85/0.09
[164]	EEG, EOG	6-ch EEG, 4-ch EOG	99.1%
[165]	EEG, EOG, and contextual information	30-ch EEG, 4-ch EOG	93%
[166]	EEG, EOG	19-ch EEG, 4-ch EOG	--- (ANOVA)
[167]	EEG, EOG	2-ch EEG, 4-ch EOG	98%
[32]	EEG, EOG	30-ch EEG, 4-ch EOG	97.37%
[168]	EEG, EOG	14-h EEG, 4-ch EOG	94.37%
[169]	EEG, EOG	12-ch EEG, 7-ch EOG	correlation coefficient / RMSE 0.8 /0.07
[170]	EEG, EOG	16-ch EEG, 2-ch EOG	--- (t-test)
[171]	EEG, respiration	8-ch EEG, 1-ch respiration	98.6%
[172]	EEG, ECG, EOG	3-ch EEG, 1-ch EOG, 1-ch ECG	97%
[173]	EEG, EOG, ECG, fNIRS	64-ch EEG, 2-ch EOG, 2-ch ECG, 1-ch fNIRS	75.9%
[174]	EEG, EOG, ECG	33-ch EEG/EOG, 2-ch ECG	84.6%
[151]	EEG, Gyroscope	4-ch EEG, 1-ch gyroscope	92%
[155]	EEG, EOG, EMG, EDA	4-ch EEG/EOG/EMG, 4-ch EDA	Precision, Sensitivity, Specificity 88%, 89%, 96%

Although EOG has been quite popular to accompany EEG signals for better drowsiness detection, if they are recorded by separate electrodes attached to the eyes' region, they can disturb the driver and therefore are inappropriate for practical uses. Nonetheless, this signal is also extractable from EEG signals, and we can get help from the derived eye-related features that can discriminate between alert and drowsy states. On the other hand, ECG features such as HR and HRV have the potential for being recorded non-obtrusively. They can either be achieved through wrist bands or by some EEG headsets such as Muse 2 and Muse S, which provide PPG signals. Motion data recorded by gyroscope and accelerometer have also shown great potential for drowsiness detection, whether used alone [175, 176] or in combination with EEG signals [151, 161]. Fortunately, these motion signals are provided in Muse and EMOTIV Headsets.

#### 4. Conclusion

Based on the survey of the previous studies, it can be said that there is a tendency to reduce the cumbersomeness of EEG-based detection systems. Earlier studies were mainly intended to investigate the feasibility of EEG-based drowsiness detection using clinical EEG devices. In contrast, a significant number of recent studies have used consumer-grade EEG headsets. Wireless headsets increase the applicability of EEG-based systems and have shown comparable efficiency in comparison to clinical devices.

A possible solution to improve EEG-based detection accuracy is integrating EEG data with other easily accessible physiological signals such as ECG, EOG, PPG, EMG, and EDR. Luckily, some of these signals can be recorded with the sensors embedded in the commercial EEG headsets.

Spectral EEG features, the most frequently used features in EEG-based drowsiness detection studies, provide better interpretability and impose a less computational burden. Among the examined classifiers, shallow models, especially SVM, outnumbered other types of classifiers and showed acceptable detection accuracy. Most studies have approached drowsiness detection as a binary classification problem, i.e., discriminating two classes of drowsy and wakeful. However, the transition from wakefulness to drowsiness is a gradual process that can be divided into several levels. Detection of these levels necessitates a multi-level classification, which allows drowsiness detection in mild or earlier stages. To achieve this, we must have distinct

definitions for each level to tailor the labeling methods accordingly.

In summary, using less intrusive EEG headsets, along with the use of features and classifiers, which reduce computational complexity, promises practical implementation of driver drowsiness detection systems.

#### References

- 1- M. Zhu *et al.*, "Heavy Truck Driver's Drowsiness Detection Method Using Wearable EEG Based on Convolution Neural Network." in *2020 IEEE Intelligent Vehicles Symposium (IV)*, (2020), pp. 195-201.
- 2- Masoud Ghasemi Noghabi, Saber Nasser Alavi Seyed, and Mahdiah Ghasemi Noghabi, "Statistical report of accidents caused by fatigue and drowsiness of vehicle drivers using police report at the scene of the accident." in *The first national conference on traffic, safety and executive strategies to improve it*, ed, (2010).
- 3- Aleksandar Čolić, Oge Marques, and Borko Furht, "Driver drowsiness detection: Systems and solutions." (2014).
- 4- Albert Kircher, Marcus Uddman, and Jesper Sandin, "Vehicle control and drowsiness." (2002).
- 5- Bagus G. Pratama, Igi Ardiyanto, and Teguh B. Adji, "A review on driver drowsiness based on image, bio-signal, and driver behavior." *Proceeding - 2017 3rd International Conference on Science and Technology-Computer, ICST 2017*, pp. 70-75, (2017).
- 6- L M Bergasa, J Nuevo, M A Sotelo, R Barea, and M E Lopez, "Real-Time System for Monitoring Driver Vigilance." *Trans. Intell. Transport. Sys.*, Vol. 7pp. 63-77, (2006).
- 7- Masoumeh Tashakori, Ali Nahvi, and Serajeddin Ebrahimian, "Driver drowsiness detection using facial thermal imaging in a driving simulator." *Journal of engineering in medicine*, pp. 1-13, (2021).
- 8- Serajeddin Ebrahimian Hadi Kiashari, Ali Nahvi, Amirhossein Homayounfard, and Hamidreza Bakhoda, "Monitoring the Variation in Driver Respiration Rate from Wakefulness to Drowsiness: A Non-Intrusive Method for Drowsiness Detection Using Thermal Imaging." *Journal of Sleep Sciences*, Vol. 3pp. 1-9, (2018).
- 9- Serajeddin Ebrahimian Hadi Kiashari, Ali Nahvi, Hamidreza Bakhoda, Amirhossein Homayounfard, and Masoumeh Tashakori, "Evaluation of driver drowsiness using respiration analysis by thermal imaging on a driving simulator." *Multimedia Tools and Applications*, Vol. 79pp. 17793-815, (2020).
- 10- Masoumeh Tashakori, Ali Nahvi, Azadeh Shahiidian, Serajeddin Ebrahimian Hadi Kiashari, and Hamidreza

- Bakhoda, "Estimation of driver drowsiness using blood perfusion analysis of facial thermal images in a driving simulator." *Journal of Sleep Sciences*, Vol. 3pp. 45-52, (2018).
- 11- Rami N Khushaba, Sarath Kodagoda, Sara Lal, and Gamini Dissanayake, "Driver Drowsiness Classification Using Fuzzy Wavelet-Packet-Based Feature-Extraction Algorithm." *IEEE Transactions on Biomedical Engineering*, Vol. 58pp. 121-31, (2011).
- 12- Arun Sahayadhas, Kenneth Sundaraj, and Murugappan Murugappan, "Detecting driver drowsiness based on sensors: A review." *Sensors (Switzerland)*, Vol. 12pp. 16937-53, (2012).
- 13- Shubha Majumder, Bijay Guragain, Chunwu Wang, and Nicholas Wilson, "On-board drowsiness detection using EEG: Current status and future prospects." *IEEE International Conference on Electro Information Technology*, Vol. 2019-Maypp. 483-90, (2019).
- 14- Saroj K L Lal and Ashley Craig, "Driver fatigue: electroencephalography and psychological assessment." (in eng), *Psychophysiology*, Vol. 39pp. 313-21, (2002).
- 15- Chin-Teng Lin *et al.*, "Wireless and Wearable EEG System for Evaluating Driver Vigilance." *IEEE Transactions on Biomedical Circuits and Systems*, Vol. 8pp. 165-76, (2014).
- 16- Wei Li, Qi Chang He, Xiu Min Fan, and Zhi Min Fei, "Evaluation of driver fatigue on two channels of EEG data." *Neuroscience Letters*, Vol. 506pp. 235-39, (2012).
- 17- Boon-Giin Lee and Wan-Young Chung, "Multi-classifier for highly reliable driver drowsiness detection in Android platform." *Biomedical Engineering: Applications, Basis and Communications*, Vol. 24pp. 147-54, (2012).
- 18- Sarah N Wyckoff, Leslie H Sherlin, Noel Larson Ford, and Dale Dalke, "Validation of a wireless dry electrode system for electroencephalography." *Journal of neuroengineering and rehabilitation*, Vol. 12pp. 1-9, (2015).
- 19- Héctor Rieiro *et al.*, "Validation of electroencephalographic recordings obtained with a consumer-grade, single dry electrode, low-cost device: A comparative study." *Sensors*, Vol. 19p. 2808, (2019).
- 20- Elena Ratti, Shani Waninger, Chris Berka, Giulio Ruffini, and Ajay Verma, "Comparison of medical and consumer wireless EEG systems for use in clinical trials." *Frontiers in Human Neuroscience*, Vol. 11pp. 1-7, (2017).
- 21- Hyun Jae Baek, Gih Sung Chung, Ko Keun Kim, and Kwang Suk Park, "A smart health monitoring chair for nonintrusive measurement of biological signals." *IEEE transactions on Information Technology in Biomedicine*, Vol. 16pp. 150-58, (2011).
- 22- Joan Gomez-Clapers and Ramon Casanella, "A fast and easy-to-use ECG acquisition and heart rate monitoring system using a wireless steering wheel." *IEEE Sensors Journal*, Vol. 12pp. 610-16, (2011).
- 23- Dong Qian *et al.*, "Drowsiness Detection by Bayesian-Copula Discriminant Classifier Based on EEG Signals During Daytime Short Nap." *IEEE Transactions on Biomedical Engineering*, Vol. 64pp. 743-54, (2017).
- 24- Jonathan R L Schwartz and Thomas Roth, "Neurophysiology of sleep and wakefulness: basic science and clinical implications." (in eng), *Current neuropharmacology*, Vol. 6pp. 367-78, (2008).
- 25- Ritchie E Brown, Radhika Basheer, James T McKenna, Robert E Strecker, and Robert W McCarley, "Control of sleep and wakefulness." (in eng), *Physiological reviews*, Vol. 92pp. 1087-187, (2012).
- 26- Sónia Soares, Tiago Monteiro, António Lobo, António Couto, Liliana Cunha, and Sara Ferreira, "Analyzing driver drowsiness: From causes to effects." *Sustainability*, Vol. 12p. 1971, (2020).
- 27- Ronald E Dahl, "Biological, developmental, and neurobehavioral factors relevant to adolescent driving risks." *American journal of preventive medicine*, Vol. 35pp. S278-S84, (2008).
- 28- Roseanne Armitage, "Sex differences in slow-wave activity in response to sleep deprivation." *Sleep Res Online*, Vol. 4pp. 33-41, (2001).
- 29- Carina Fors, Christer Ahlstrom, and Anna Anund, "A comparison of driver sleepiness in the simulator and on the real road." *Journal of Transportation Safety & Security*, Vol. 10pp. 72-87, (2018).
- 30- Riccardo Rossia, Massimiliano Gastaldia, and Gregorio Gecchelea, "Analysis of driver task-related fatigue using driving simulator experiments." *Procedia - Social and Behavioral Sciences*, Vol. 20pp. 666-75, (2011).
- 31- A I Pack, A M Pack, E Rodgman, A Cucchiara, D F Dinges, and C W Schwab, "Characteristics of crashes attributed to the driver having fallen asleep." (in eng), *Accident; analysis and prevention*, Vol. 27pp. 769-75, (1995).
- 32- Zhongke Gao *et al.*, "Relative Wavelet Entropy Complex Network for Improving EEG-Based Fatigue Driving Classification." *IEEE Transactions on Instrumentation and Measurement*, Vol. 68pp. 2491-97, (2019).
- 33- Chun Shu Wei, Yu Te Wang, Chin Teng Lin, and Tzyy Ping Jung, "Toward Drowsiness Detection Using Non-hair-Bearing EEG-Based Brain-Computer Interfaces." *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 26pp. 400-06, (2018).
- 34- Jongseong Gwak, Akinari Hirao, and Motoki Shino, "An investigation of early detection of driver drowsiness using ensemble machine learning based on hybrid sensing." *Applied Sciences (Switzerland)*, Vol. 10(2020).

- 35- John LaRocco, Minh Dong Le, and Dong Guk Paeng, "A Systemic Review of Available Low-Cost EEG Headsets Used for Drowsiness Detection." *Frontiers in Neuroinformatics*, Vol. 14pp. 1-14, (2020).
- 36- Anna Wexler and Robert 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. 3pp. 131-37, (2019).
- 37- Ali Hashemi et al., "Characterizing population EEG dynamics throughout adulthood." *ENeuro*, Vol. 3(2016).
- 38- Olave E Krigolson, Chad C Williams, Angela Norton, Cameron D Hassall, and Francisco L Colino, "Choosing MUSE: Validation of a low-cost, portable EEG system for ERP research." *Frontiers in neuroscience*, Vol. 11p. 109, (2017).
- 39- Azmeh Shahid, Kate Wilkinson, Shai Marcu, and Colin M Shapiro, "Stanford Sleepiness Scale (SSS) BT - STOP, THAT and One Hundred Other Sleep Scales." Azmeh Shahid, Kate Wilkinson, Shai Marcu, and Colin M Shapiro, Eds., ed. New York: *Springer New York*, (2012), pp. 369-70.
- 40- Asha Hareendran, Nancy K. Leidy, Brigitta U. Monz, Randall Winnette, Karin Becker, and Donald A. Mahler, "Proposing a standardized method for evaluating patient report of the intensity of dyspnea during exercise testing in COPD." *International journal of chronic obstructive pulmonary disease*, Vol. 7pp. 345-55, (2012).
- 41- Douglas M Wiegand, J. McClafferty, Sharon E. McDonald, and Richard J Hanowski, "Development and evaluation of a naturalistic Observer Rating of Drowsiness protocol." *Vtechworks.Lib.Vt.Edu*, pp. 1-52, (2009).
- 42- Walter W. Wierwille and Lynne A. Ellsworth, "Evaluation of driver drowsiness by trained raters." *Accident Analysis and Prevention*, Vol. 26pp. 571-81, (1994).
- 43- Eric Juwei Cheng, Ku Young Young, and Chin Teng Lin, "Temporal EEG imaging for drowsy driving prediction." *Applied Sciences (Switzerland)*, Vol. 9(2019).
- 44- Chin Teng Lin, Che Jui Chang, Bor Shyh Lin, Shao Hang Hung, Chih Feng Chao, and I. Jan Wang, "A real-time wireless brain-computer interface system for drowsiness detection." *IEEE Transactions on Biomedical Circuits and Systems*, Vol. 4pp. 214-22, (2010).
- 45- T. P. Nguyen, M. T. Chew, and S. Demidenko, "Eye tracking system to detect driver drowsiness." *ICARA 2015 - Proceedings of the 2015 6th International Conference on Automation, Robotics and Applications*, pp. 472-77, (2015).
- 46- David F. Dinges, M. Mallis Mallis, Greg Maislin, and John Walker Powell, "Evaluation of Techniques for Ocular Measurement as an Index of Fatigue and the Basis for Alertness Management." *Security*, (1998).
- 47- Siwar Chaabene, Bassem Bouaziz, Amal Boudaya, Anita Hökelmann, Achraf Ammar, and Lotfi Chaari, "Convolutional neural network for drowsiness detection using eeg signals." *Sensors*, Vol. 21pp. 1-19, (2021).
- 48- Edward A Wolpert, "A Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Subjects." *Archives of General Psychiatry*, Vol. 20pp. 246-47, (1969).
- 49- Lan-lan Chen, Yu Zhao, Jian Zhang, and Jun-zhong Zou, "Automatic detection of alertness/drowsiness from physiological signals using wavelet-based nonlinear features and machine learning." *Expert Systems with Applications*, Vol. 42pp. 7344-55, (2015).
- 50- Shayan Motamedi-Fakhr, Mohamed Moshrefi-Torbati, Martyn Hill, Catherine M Hill, and Paul R White, "Signal processing techniques applied to human sleep EEG signals—A review." *Biomedical Signal Processing and Control*, Vol. 10pp. 21-33, (2014).
- 51- Erik K St Louis et al., "Electroencephalography (EEG): An Introductory Text and Atlas of Normal and Abnormal Findings in Adults." *Children, and Infants*, (2016).
- 52- Balbir Singh and Hiroaki Wagatsuma, "A removal of eye movement and blink artifacts from EEG data using morphological component analysis." *Computational and mathematical methods in medicine*, Vol. 2017(2017).
- 53- Carrie A Joyce, Irina F Gorodnitsky, and Marta Kutas, "Automatic removal of eye movement and blink artifacts from EEG data using blind component separation." *Psychophysiology*, Vol. 41pp. 313-25, (2004).
- 54- J W Britton, "Hopp JLet al., authors; St. Louis EK, Frey LC, editors. *Electroencephalography (EEG): An Introductory Text and Atlas of Normal and Abnormal Findings in Adults, Children, and Infants* [Internet]. Chicago: American Epilepsy Society; 2016." ed.
- 55- Suresh D Muthukumaraswamy, "High-frequency brain activity and muscle artifacts in MEG/EEG: a review and recommendations." (in eng), *Frontiers in Human Neuroscience*, Vol. 7p. 138, (2013).
- 56- Theo Gasser, Jan C Schuller, and Ursula Schreiter Gasser, "Correction of muscle artefacts in the EEG power spectrum." *Clinical Neurophysiology*, Vol. 116pp. 2044-50, (2005).
- 57- Diego Antonio Rielo Selim R Benbadis, "EEG Artifacts." *Medscape*, (2019).
- 58- Joe-Air Jiang, Chih-Feng Chao, Ming-Jang Chiu, Ren-Guey Lee, Chwan-Lu Tseng, and Robert Lin, "An automatic analysis method for detecting and eliminating ECG artifacts in EEG." *Computers in Biology and Medicine*, Vol. 37pp. 1660-71, (2007).
- 59- Joanna Górecka and Przemysław Makiewicz, "The Dependence of Electrode Impedance on the Number of

- Performed EEG Examinations." (in eng), *Sensors (Basel, Switzerland)*, Vol. 19p. 2608, (2019).
- 60- Abdulhamit Subasi, "Automatic recognition of alertness level from EEG by using neural network and wavelet coefficients." *Expert Systems with Applications*, Vol. 28pp. 701-11, (2005).
- 61- Hongtao Wang, Andrei Dragomir, Nida Itrat Abbasi, Junhua Li, Nitish V. Thakor, and Anastasios Bezerianos, "A novel real-time driving fatigue detection system based on wireless dry EEG." *Cognitive Neurodynamics*, Vol. 12pp. 365-76, (2018).
- 62- Jianliang Min, Ping Wang, and Jianfeng Hu, "Driver fatigue detection through multiple entropy fusion analysis in an EEG-based system." *PLoS ONE*, Vol. 12pp. 1-19, (2017).
- 63- Muhammad Awais, Nasreen Badruddin, and Micheal Drieberg, "A hybrid approach to detect driver drowsiness utilizing physiological signals to improve system performance and Wearability." *Sensors (Switzerland)*, Vol. 17pp. 1-16, (2017).
- 64- O Dressler, G Schneider, G Stockmanns, and E F Kochs, "Awareness and the EEG power spectrum: analysis of frequencies." *British Journal of Anaesthesia*, Vol. 93pp. 806-09, (2004).
- 65- Hong J Eoh, Min K Chung, and Seong-Han Kim, "Electroencephalographic study of drowsiness in simulated driving with sleep deprivation." *International Journal of Industrial Ergonomics*, Vol. 35pp. 307-20, (2005).
- 66- Budi Thomas Jap, Sara Lal, Peter Fischer, and Evangelos Bekiaris, "Using EEG spectral components to assess algorithms for detecting fatigue." *Expert Systems with Applications*, Vol. 36pp. 2352-59, (2009).
- 67- Ahmed M. Dessouky, Taha E. Taha, Mohamed M. Dessouky, Ashraf A. Eltholth, Emadeldeen Hassan, and Fathi E. Abd El-Samie, "Non-parametric spectral estimation techniques for DNA sequence analysis and exon region prediction." *Computers and Electrical Engineering*, Vol. 73pp. 334-48, (2019).
- 68- M Aboy, J McNames, O W Marquez, R Hornero, T Thong, and B Goldstein, "Power spectral density estimation and tracking nonstationary pressure signals based on Kalman filtering." in *The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* Vol. 1, ed, (2004), pp. 156-59.
- 69- "Chapter 12 - Detection, Classification, and Estimation in the (t,f) Domain." in *Time-Frequency Signal Analysis and Processing (Second Edition)*, Boualem Boashash, Ed., Second Edi ed. Oxford: *Academic Press*, (2016), pp. 693-743.
- 70- C. E. Shannon, "A Mathematical Theory of Communication." *Bell System Technical Journal*, Vol. 27pp. 623-56, (1948).
- 71- Jose Luis Rodríguez-Sotelo, Alejandro Osorio-Forero, Alejandro Jiménez-Rodríguez, David Cuesta-Frau, Eva Cirugeda-Roldán, and Diego Peluffo, "Automatic sleep stages classification using EEG entropy features and unsupervised pattern analysis techniques." *Entropy*, Vol. 16pp. 6573-89, (2014).
- 72- Sheng-Fu Liang, Chin-En Kuo, Yu-Han Hu, Yu-Hsiang Pan, and Yung-Hung Wang, "Automatic Stage Scoring of Single-Channel Sleep EEG by Using Multiscale Entropy and Autoregressive Models." *IEEE Transactions on Instrumentation and Measurement*, Vol. 61pp. 1649-57, (2012).
- 73- Peter Achermann, "EEG Analysis Applied to Sleep." *Sleep Rochester*, Vol. 26pp. 28-33, (2009).
- 74- Gianluca Borghini, Laura Astolfi, Giovanni Vecchiato, Donatella Mattia, and Fabio Babiloni, "Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness." *Neuroscience and Biobehavioral Reviews*, Vol. 44pp. 58-75, (2014).
- 75- Gang Li *et al.*, "The impact of mental fatigue on brain activity: A comparative study both in resting state and task state using EEG." *BMC Neuroscience*, Vol. 21pp. 1-9, (2020).
- 76- Qingjun Wang, Yibo Li, and Xueping Liu, "Analysis of Feature Fatigue EEG Signals Based on Wavelet Entropy." *International Journal of Pattern Recognition and Artificial Intelligence*, Vol. 32pp. 1-15, (2018).
- 77- S. M. Pincus and A. L. Goldberger, "Physiological time-series analysis: What does regularity quantify?" *American Journal of Physiology - Heart and Circulatory Physiology*, Vol. 266(1994).
- 78- Alfonso Delgado-Bonal and Alexander Marshak, "Approximate entropy and sample entropy: A comprehensive tutorial." *Entropy*, Vol. 21pp. 1-37, (2019).
- 79- J S Richman and J R Moorman, "Physiological time-series analysis using approximate entropy and sample entropy." (in eng), *American journal of physiology. Heart and circulatory physiology*, Vol. 278pp. H2039-49, (2000).
- 80- Weiting Chen, Zhizhong Wang, Hongbo Xie, and Wangxin Yu, "Characterization of Surface EMG Signal Based on Fuzzy Entropy." *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 15pp. 266-72, (2007).
- 81- Jianliang Min, Chen Xiong, Yonggang Zhang, and Ming Cai, "Driver fatigue detection based on prefrontal EEG using multi-entropy measures and hybrid model." *Biomedical Signal Processing and Control*, Vol. 69p. 102857, (2021).
- 82- Nikita Gurudath and H. Bryan Riley, "Drowsy driving detection by EEG analysis using Wavelet Transform and

- K-means clustering." *Procedia Computer Science*, Vol. 34pp. 400-09, (2014).
- 83- Noor Kamal Al-Qazzaz, Sawal Hamid Bin Mohd Ali, Siti Anom Ahmad, Mohd Shabiul Islam, and Javier Escudero, "Selection of Mother Wavelet Functions for Multi-Channel EEG Signal Analysis during a Working Memory Task." *Sensors*, Vol. 15pp. 29015-35, (2015).
- 84- Mehdi Hosseinzadeh, "4 - Robust control applications in biomedical engineering: Control of depth of hypnosis." in *Control Applications for Biomedical Engineering Systems*, Ahmad Taher Azar, Ed., ed: *Academic Press*, (2020), pp. 89-125.
- 85- Suganiya Murugan, Jerritta Selvaraj, and Arun Sahayadhas, "Detection and analysis: driver state with electrocardiogram (ECG)." *Physical and Engineering Sciences in Medicine*, Vol. 43pp. 525-37, (2020).
- 86- Sang-Ho Jo, Jin-Myung Kim, and Dong Kyoo Kim, "Heart Rate Change While Drowsy Driving." (in eng), *Journal of Korean medical science*, Vol. 34pp. e56-e56, (2019).
- 87- Difei Jing, Shuwei Zhang, and Zhongyin Guo, "Fatigue driving detection method for low-voltage and hypoxia plateau area: A physiological characteristic analysis approach." *International Journal of Transportation Science and Technology*, Vol. 9pp. 148-58, (2020).
- 88- Shahina Begum, "Intelligent driver monitoring systems based on physiological sensor signals: A review." in *16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013)*, ed, (2013), pp. 282-89.
- 89- Thomas Kundinger and Andreas Riener, "The Potential of Wrist-Worn Wearables for Driver Drowsiness Detection: A Feasibility Analysis." *UMAP 2020 - Proceedings of the 28th ACM Conference on User Modeling, Adaptation and Personalization*, pp. 117-25, (2020).
- 90- Thum Chia Chieh, Mohd. Marzuki Mustafa, Aini Hussain, Seyed Farshad Hendi, and Burhanuddin Yeop Majlis, "Development of vehicle driver drowsiness detection system using electrooculogram (EOG)." in *2005 1st International Conference on Computers, Communications, Signal Processing with Special Track on Biomedical Engineering*, ed, (2005), pp. 165-68.
- 91- R. Schleicher, N. Galley, S. Briest, and L. Galley, "Blinks and saccades as indicators of fatigue in sleepiness warnings: Looking tired?" *Ergonomics*, Vol. 51pp. 982-1010, (2008).
- 92- Niels Galley, "Blink Parameter as indicator of drivers sleepiness." *Nursing standard (Royal College of Nursing (Great Britain)) : 1987*, Vol. 23pp. 26-7, (2003).
- 93- Eun-Jung Sung, Byung-Chan Min, Seung-Chul Kim, and Chul-Jung Kim, "Effects of oxygen concentrations on driver fatigue during simulated driving." (in eng), *Applied ergonomics*, Vol. 36pp. 25-31, (2005).
- 94- Mahesh M. Bundeale and Rahul Banerjee, "An SVM Classifier for Fatigue-Detection using Skin Conductance for Use in the BITS-Lifeguard Wearable Computing System Mahesh." *Second International Conference on Emerging Trends in Engineering and Technology, ICETET-09*, pp. 934-39, (2009).
- 95- Carlo J De Luca, "Myoelectrical manifestations of localized muscular fatigue in humans." *Critical reviews in biomedical engineering*, Vol. 11pp. 251-79, (1984).
- 96- Afraiz Tariq Satti, Jiyou Kim, Eunsurk Yi, Hwi Young Cho, and Sungbo Cho, "Microneedle array electrode-based wearable emg system for detection of driver drowsiness through steering wheel grip." *Sensors*, Vol. 21pp. 1-14, (2021).
- 97- Anuva Chowdhury, Rajan Shankaran, Manolya Kavakli, and Md. Mokammel Haque, "Sensor Applications and Physiological Features in Drivers' Drowsiness Detection: A Review." *IEEE Sensors Journal*, Vol. 18pp. 3055-67, (2018).
- 98- Mohammad Mahmoodi and Ali 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. 233pp. 395-406, (2019).
- 99- Dong Wang, Peng Shen, Ting Wang, and Zhu Xiao, "Fatigue detection of vehicular driver through skin conductance, pulse oximetry and respiration: A random forest classifier." *2017 9th IEEE International Conference on Communication Software and Networks, ICCSN 2017*, Vol. 2017-Januapp. 1162-66, (2017).
- 100- Wolfram Boucsein, "Electrodermal activity." (2012).
- 101- Johanna Wörle, Barbara Metz, Christian Thiele, and Gert Weller, "Detecting sleep in drivers during highly automated driving: The potential of physiological parameters." *IET Intelligent Transport Systems*, Vol. 13pp. 1241-48, (2019).
- 102- Kitsuchart Pasupa and Wisuwat Sunhem, "A comparison between shallow and deep architecture classifiers on small dataset." in *2016 8th International Conference on Information Technology and Electrical Engineering (ICITEE)*, ed: *IEEE*, (2016), pp. 1-6.
- 103- Xu-Cheng Yin, Chun Yang, Wei-Yi Pei, and Hong-Wei Hao, "Shallow classification or deep learning: An experimental study." in *2014 22nd International Conference on Pattern Recognition*, ed: *IEEE*, (2014), pp. 1904-09.
- 104- Alaa Tharwat, Tarek Gaber, Abdelhameed Ibrahim, and Aboul Ella Hassanien, "Linear discriminant analysis: A detailed tutorial." *AI Communications*, Vol. 30pp. 169-90, (2017).
- 105- D Garrett, D A Peterson, C W Anderson, and M H Thaut, "Comparison of linear, nonlinear, and feature selection methods for EEG signal classification." *IEEE*

- Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 11pp. 141-44, (2003).
- 106- Prima Dewi Purnamasari, Pratiwi Yustiana, Anak Agung Putri Ratna, and Dodi Sudiana, "Mobile EEG Based Drowsiness Detection using K-Nearest Neighbor." *2019 IEEE 10th International Conference on Awareness Science and Technology, iCAST 2019 - Proceedings*, pp. 1-5, (2019).
- 107- Himani Sharma and Sunil Kumar, "A Survey on Decision Tree Algorithms of Classification in Data Mining." *International Journal of Science and Research (IJSR)*, Vol. 5pp. 2094-97, (2016).
- 108- Ludmila Kuncheva, "Fuzzy classifier design." Vol. 49(2000).
- 109- David J Livingstone, "Artificial neural networks: methods and applications." (2008).
- 110- Zhongke Gao *et al.*, "EEG-Based Spatio-Temporal Convolutional Neural Network for Driver Fatigue Evaluation." *IEEE transactions on neural networks and learning systems*, Vol. 30pp. 2755-63, (2019).
- 111- Sibsambhu Kar, Mayank Bhagat, and Aurobinda Routray, "EEG signal analysis for the assessment and quantification of driver's fatigue." *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 13pp. 297-306, (2010).
- 112- Tiago da Silveira, Alice de Jesus Kozakevicius, and Cesar Ramos Rodrigues, "Drowsiness detection for single channel EEG by DWT best m-term approximation." *Revista Brasileira de Engenharia Biomedica*, Vol. 31pp. 107-15, (2015).
- 113- Yuliang Ma *et al.*, "Driving fatigue detection from EEG using a modified PCANet method." *Computational Intelligence and Neuroscience*, Vol. 2019(2019).
- 114- Yuqi Cui, Yifan Xu, and Dongrui Wu, "EEG-Based Driver Drowsiness Estimation Using Feature Weighted Episodic Training." *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 27pp. 2263-73, (2019).
- 115- Haowen Luo, Taorong Qiu, Chao Liu, and Peifan Huang, "Research on fatigue driving detection using forehead EEG based on adaptive multi-scale entropy." *Biomedical Signal Processing and Control*, Vol. 51pp. 50-58, (2019).
- 116- Venkata Phanikrishna B and Suchismitha Chinara, "Automatic classification methods for detecting drowsiness using wavelet packet transform extracted time-domain features from single-channel EEG signal." *Journal of Neuroscience Methods*, Vol. 347p. 108927, (2021).
- 117- Mervyn V.M. Yeo, Xiaoping Li, Kaiquan Shen, and Einar P.V. Wilder-Smith, "Can SVM be used for automatic EEG detection of drowsiness during car driving?" *Safety Science*, Vol. 47pp. 115-24, (2009).
- 118- Yuxuan Yang, Zhongke Gao, Yanli Li, Qing Cai, Norbert Marwan, and Jurgen Kurths, "A Complex Network-Based Broad Learning System for Detecting Driver Fatigue From EEG Signals." *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, pp. 1-9, (2019).
- 119- Christos Papadelis *et al.*, "Indicators of Sleepiness in an ambulatory EEG study of night driving." *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, pp. 6201-04, (2006).
- 120- Zhendong Mu, Jianfeng Hu, and Jinghai Yin, "Driving Fatigue Detecting Based on EEG Signals of Forehead Area." *International Journal of Pattern Recognition and Artificial Intelligence*, Vol. 31pp. 1-12, (2017).
- 121- Yuliang Ma *et al.*, "Driving drowsiness detection with EEG using a modified hierarchical extreme learning machine algorithm with particle swarm optimization: A pilot study." *Electronics (Switzerland)*, Vol. 9(2020).
- 122- Rifai Chai *et al.*, "Driver Fatigue Classification with Independent Component by Entropy Rate Bound Minimization Analysis in an EEG-Based System." *IEEE Journal of Biomedical and Health Informatics*, Vol. 21pp. 715-24, (2017).
- 123- Hong Zeng, Chen Yang, Guojun Dai, Feiwei Qin, Jianhai Zhang, and Wanzeng Kong, "EEG classification of driver mental states by deep learning." *Cognitive Neurodynamics*, Vol. 12pp. 597-606, (2018).
- 124- Zahra Mardi, Seyedeh Naghmeh Ashtiani, and Mohammad Mikaili, "EEG-based drowsiness detection for safe driving using chaotic features and statistical tests." *Journal of Medical Signals and Sensors*, Vol. 1pp. 130-37, (2011).
- 125- Chunlin Zhao, Chongxun Zheng, Min Zhao, Yaling Tu, and Jianping Liu, "Multivariate autoregressive models and kernel learning algorithms for classifying driving mental fatigue based on electroencephalographic." *Expert Systems with Applications*, Vol. 38pp. 1859-65, (2011).
- 126- Pranesh Krishnan, Mohamed Rizon, Sazali Yaacob, and Annapoorni Pranesh Krishnan, "EEG based drowsiness detection using relative band power and short time fourier transform." *Proceedings of International Conference on Artificial Life and Robotics*, Vol. 2020pp. 323-27, (2020).
- 127- Mikito Ogino and Yasue Mitsukura, "Portable drowsiness detection through use of a prefrontal single-channel electroencephalogram." *Sensors (Switzerland)*, Vol. 18pp. 1-19, (2018).
- 128- Fnu Rohit, Vinod Kulathumani, Rahul Kavi, Ibrahim Elwarfalli, Vlad Kecojevic, and Ashish Nimbarte, "Real-time drowsiness detection using wearable, lightweight brain sensing headbands." *IET Intelligent Transport Systems*, Vol. 11pp. 255-63, (2017).
- 129- Mohammad A. Almogbel, Anh H. Dang, and Wataru Kameyama, "Cognitive Workload Detection from Raw

- EEG-Signals of Vehicle Driver using Deep Learning." *International Conference on Advanced Communication Technology, ICACT*, Vol. 2019-Februpp. 1167-72, (2019).
- 130- Topo Suprihadi and Kanisius Karyono, "DROWTION: Driver drowsiness detection software using MINDWAVE." in *2014 International Conference on Industrial Automation, Information and Communications Technology*, ed: *IEEE*, (2014), pp. 141-44.
- 131- 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 2015*, pp. 1326-32, (2015).
- 132- Bryan Van Hal, Samhita Rhodes, Bruce Dunne, and Robert Bossemeyer, "Low-cost EEG-based sleep detection." in *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, ed: *IEEE*, (2014), pp. 4571-74.
- 133- Prabha C Nissimagoudar and Anilkumar V Nandi, "Precision enhancement of driver assistant system using eeg based driver consciousness analysis & classification." in *Computational Network Application Tools for Performance Management*, ed: *Springer*, (2020), pp. 247-57.
- 134- A Pomer-Escher, R Tello, J Castillo, and T Bastos-Filho, "Analysis of mental fatigue in motor imagery and emotional stimulation based on EEG." in *XXIV Congresso Brasileiro de Engenharia Biomedica-CBEB*, ed, (2014).
- 135- Mejdi Ben Dkhil, Ali Wali, and Adel M Alimi, "Drowsy driver detection by EEG analysis using Fast Fourier Transform." in *2015 15th International Conference on Intelligent Systems Design and Applications (ISDA)*, ed: *IEEE*, (2015), pp. 313-18.
- 136- Vipin Bakshi, "Towards Practical Driver Cognitive Workload Monitoring via Electroencephalography." ed, (2018).
- 137- Fei Wang, Ji Lin, Wenzhe Wang, and Haiming Wang, "EEG-based mental fatigue assessment during driving by using sample entropy and rhythm energy." *2015 IEEE International Conference on Cyber Technology in Automation, Control and Intelligent Systems, IEEE-CYBER 2015*, pp. 1906-11, (2015).
- 138- Jichi Chen, Hong Wang, Qiaoxiu Wang, and Chengcheng Hua, "Exploring the fatigue affecting electroencephalography based functional brain networks during real driving in young males." *Neuropsychologia*, Vol. 129pp. 200-11, (2019).
- 139- Brilian T. Nugraha, Riyanarto Sarno, Dimas Anton Asfani, Tomohiko Igasaki, and M. Nadzeri Munawar, "Classification of driver fatigue state based on EEG using Emotiv EPOC+." *Journal of Theoretical and Applied Information Technology*, Vol. 86pp. 347-59, (2016).
- 140- Dariusz Sawicki, Agnieszka Wolska, Przemysław Rosłon, and Szymon Ordysiński, "New EEG measure of the alertness analyzed by Emotiv EPOC in a real working environment." *NEUROTECHNIX 2016 - Proceedings of the 4th International Congress on Neurotechnology, Electronics and Informatics*, pp. 35-42, (2016).
- 141- Thi Tram Anh Pham, Thi Diem Hang Nguyen, Quoc Khai Le, and Quang Linh Huynh, "Application of portable EEG device in detection and classification drowsiness by support vector machine." in *International Conference on the Development of Biomedical Engineering in Vietnam*, ed: *Springer*, (2018), pp. 521-26.
- 142- S S Poorna, V V Arsha, P T A Aparna, Parvathy Gopal, and G J Nair, "Drowsiness detection for safe driving using PCA EEG signals." in *Progress in computing, analytics and networking*, ed: *Springer*, (2018), pp. 419-28.
- 143- Osmalina Nur Rahma and Akif Rahmatillah, "Drowsiness analysis using common spatial pattern and extreme learning machine based on electroencephalogram signal." *Journal of medical signals and sensors*, Vol. 9p. 130, (2019).
- 144- Theerat Saichoo and Poonpong Boonbrahm, "Brain Computer Interface for Real-Time Driver Drowsiness Detection." *Thai Journal of Physics*, Vol. 36pp. 1-8, (2019).
- 145- Beatriz Campos Raposo Medeiros Araújo, "Drowsiness Detection Using a Headband and Artificial Neural Networks." ed: *Universidade de Coimbra*, (2019).
- 146- Heng Li, Di Wang, Jiayu Chen, Xiaochun Luo, Jue Li, and Xuejiao Xing, "Pre-service fatigue screening for construction workers through wearable EEG-based signal spectral analysis." *Automation in Construction*, Vol. 106p. 102851, (2019).
- 147- Asim Javed, Muhammad Umair Arshad, Ehtesham Saeed, and Noman Naseer, "Real-time Drowsiness Detection and Emergency Parking using EEG." (2021).
- 148- Muhammad Azam, Derek Jacoby, and Yvonne Coady, "Classification of Fatigue in Consumer-grade EEG Using Entropies as Features."
- 149- Jerone Dunbar, Juan E Gilbert, and Ben Lewis, "Exploring differences between self-report and electrophysiological indices of drowsy driving: A usability examination of a personal brain-computer interface device." *Journal of Safety Research*, Vol. 74pp. 27-34, (2020).
- 150- Ruyi Foong, Kai Keng Ang, Zhuo Zhang, and Chai Quek, "An iterative cross-subject negative-unlabeled learning algorithm for quantifying passive fatigue." *Journal of neural engineering*, Vol. 16p. 56013, (2019).
- 151- Aqsa Mehreen, Syed Muhammad Anwar, Muhammad Haseeb, Muhammad Majid, and Muhammad Obaid Ullah, "A hybrid scheme for drowsiness detection using wearable sensors." *IEEE Sensors Journal*, Vol. 19pp. 5119-26, (2019).
- 152- Chee-Keong Alfred Lim, Wai Chong Chia, and Siew Wen Chin, "A mobile driver safety system: Analysis of single-channel EEG on drowsiness detection." in *2014*

- International Conference on Computational Science and Technology (ICCST)*, ed, (2014), pp. 1-5.
- 153- Hamzah S. Alzu'Bi, Waleed Al-Nuaimy, and Nayel S. Al-Zubi, "EEG-based driver fatigue detection." *Proceedings - 2013 6th International Conference on Developments in eSystems Engineering, DeSE 2013*, pp. 111-14, (2013).
- 154- Thien Nguyen, Sangtae Ahn, Hyojung Jang, Sung Chan Jun, and Jae Gwan Kim, "Utilization of a combined EEG/NIRS system to predict driver drowsiness." *Scientific Reports*, Vol. 7pp. 1-10, (2017).
- 155- Nhat Pham *et al.*, "WAKE: A behind-the-ear wearable system for microsleep detection." *MobiSys 2020 - Proceedings of the 18th International Conference on Mobile Systems, Applications, and Services*, pp. 404-18, (2020).
- 156- M Jagannath and Venkatesh Balasubramanian, "Assessment of early onset of driver fatigue using multimodal fatigue measures in a static simulator." *Applied ergonomics*, Vol. 45pp. 1140-47, (2014).
- 157- Chunxiao Chen, Kun Li, Qiuyi Wu, Haowen Wang, Zhiyu Qian, and Gail Sudlow, "EEG-based detection and evaluation of fatigue caused by watching 3DTV." *Displays*, Vol. 34pp. 81-88, (2013).
- 158- Michael Simon *et al.*, "Eeg alpha spindle measures as indicators of driver fatigue under real traffic conditions." *Clinical Neurophysiology*, Vol. 122pp. 1168-78, (2011).
- 159- Malik T.R. Peiris, Paul R. Davidson, Philip J. Bones, and Richard D. Jones, "Detection of lapses in responsiveness from the EEG." *Journal of Neural Engineering*, Vol. 8(2011).
- 160- Mehmet Akin, Muhammed B Kurt, Necmettin Sezgin, and Muhittin Bayram, "Estimating vigilance level by using EEG and EMG signals." *Neural Computing and Applications*, Vol. 17pp. 227-36, (2008).
- 161- Gang Li and Wan Young Chung, "A context-aware EEG headset system for early detection of driver drowsiness." *Sensors (Switzerland)*, Vol. 15pp. 20873-93, (2015).
- 162- Sazali Yaacob, Nur Afrina Izzati Affandi, Pranesh Krishnan, Amir Rasyadan, Muhyi Yaakop, and Firdaus Mohamed, "Drowsiness detection using EEG and ECG signals." *IEEE International Conference on Artificial Intelligence in Engineering and Technology, IICAIET 2020*, pp. 2-6, (2020).
- 163- Wei Long Zheng and Bao Liang Lu, "A multimodal approach to estimating vigilance using EEG and forehead EOG." *Journal of Neural Engineering*, Vol. 14(2017).
- 164- Hongtao Wang, Cong Wu, Ting Li, Yuebang He, Peng Chen, and Anastasios Bezerianos, "Driving Fatigue Classification Based on Fusion Entropy Analysis Combining EOG and EEG." *IEEE Access*, Vol. 7pp. 61975-86, (2019).
- 165- Shaibal Barua, Mobyen Uddin Ahmed, Christer Ahlström, and Shahina Begum, "Automatic driver sleepiness detection using EEG, EOG and contextual information." *Expert Systems with Applications*, Vol. 115pp. 121-35, (2019).
- 166- Saroj K.L. Lal, Ashley Craig, Peter Boord, Les Kirkup, and Hung Nguyen, "Development of an algorithm for an EEG-based driver fatigue countermeasure." *Journal of Safety Research*, Vol. 34pp. 321-28, (2003).
- 167- Yingying Jiao, Yini Deng, Yun Luo, and Bao Liang Lu, "Driver sleepiness detection from EEG and EOG signals using GAN and LSTM networks." *Neurocomputing*, Vol. 408pp. 100-11, (2020).
- 168- Aleksandra Vuckovic, Vlada Radivojevic, Andrew C.N. Chen, and Dejan Popovic, "Automatic recognition of alertness and drowsiness from EEG by an artificial neural network." *Medical Engineering and Physics*, Vol. 24pp. 349-60, (2002).
- 169- Xue Qin Huo, Wei Long Zheng, and Bao Liang Lu, "Driving fatigue detection with fusion of EEG and forehead EOG." *Proceedings of the International Joint Conference on Neural Networks*, Vol. 2016-Octoberpp. 897-904, (2016).
- 170- Faramarz Gharagozlou *et al.*, "Detecting driver mental fatigue based on EEG alpha power changes during simulated driving." *Iranian Journal of Public Health*, Vol. 44pp. 1693-700, (2015).
- 171- Boon Giin Lee, Boon Leng Lee, and Wan Young Chung, "Mobile healthcare for automatic driving sleep-onset detection using wavelet-based EEG and respiration signals." *Sensors (Switzerland)*, Vol. 14pp. 17915-36, (2014).
- 172- Kushaba, "Driver Drowsiness Classification Using Fuzzy Wavelet Packet Based Feature Extraction Algorithm." (2011).
- 173- Sangtae Ahn, Thien Nguyen, Hyojung Jang, Jae G. Kim, and Sung C. Jun, "Exploring neuro-physiological correlates of drivers' mental fatigue caused by sleep deprivation using simultaneous EEG, ECG, and fNIRS data." *Frontiers in Human Neuroscience*, Vol. 10pp. 1-14, (2016).
- 174- Chin Teng Lin, Ruei Cheng Wu, Tzyy Ping Jung, Sheng Fu Liang, and Teng Yi Huang, "Estimating driving performance based on EEG spectrum analysis." *Eurasip Journal on Applied Signal Processing*, Vol. 2005pp. 3165-74, (2005).
- 175- Boon Leng Lee, Boon Giin Lee, and Wan Young Chung, "Standalone Wearable Driver Drowsiness Detection System in a Smartwatch." *IEEE Sensors Journal*, Vol. 16pp. 5444-51, (2016).
- 176- Fajar Manghayu Nuswantoro, Amang Sudarsono, and Tri Budi Santoso, "Abnormal driving detection based on accelerometer and gyroscope sensor on smartphone using artificial neural network (ann) algorithm." *IES 2020 - International Electronics Symposium: The Role of Autonomous and Intelligent Systems for Human Life and Comfort*, pp. 356-63, (2020).