A systematic review on detection and prediction of driver drowsiness

Md. Ebrahim Shaik

Department of Civil Engineering, Bangabandhu Sheikh Mujibur Rahman Science & Technology University, Gopalganj-8100, Dhaka, Bangladesh

ABSTRACT

Driver drowsiness has emerged as one of the key factors in recent times' traffic accidents, which can result in fatalities, serious physical losses, large monetary losses, and significant property damage. Drowsiness in a driver can be brought on by long hours behind the wheel, drowsiness, fatigue, medicine, difficulty sleeping, and medical illnesses. A dependable technology that can identify driver drowsiness and warn the driver before an accident occurs is needed, according to statistics from several research. Many studies have been conducted in the previous to develop a reliable driver drowsiness detection and prediction system that uses a variety of parameters to gauge the driver's level of drowsiness. In this study, we analyzed the numerous measurements made by researchers, which were classified as physiological, vehicle-based, subjective, and behavioral measures. This article presenting a study of the fundamental problems with various sleepiness detection systems and how they are used to detect fatigue while driving. In order to warn a driver before a collision, this analysis will concentrate on what happens while driving and the advancement of technological methods that are intended to detect and, ideally, forecast driver drowsiness. For upcoming researchers to do baseline assessment in the particular field, this thorough review will provide a better understanding.

1. Introduction

Substantial efforts are needed to reduce the consequences of drowsiness since it plays a significant role in road crash fatalities and injuries. Road accidents cause an estimated 1.35 million fatalities and 20–50 million injuries annually, or an average of 27.5 fatalities per 100,000 people worldwide (Shaik et al., 2021). Driving while drowsy poses a severe risk to road safety. According to the National Highway Traffic Safety Administration (NHTSA), 4121 fatal crashes and 3662 injuries were reportedly caused by drowsy driving between 2011 and 2015. This amounts to 2.4% of all fatal crashes and 2.5% of all crash fatalities reported in the USA during the same time period (Bakheet and Al-Hamadi, 2021). Due to the prevalence of drowsy driving accidents on high-speed expressways, they are generally more serious than other accidents. A driver will become tired and obsessed after a long period of driving, which could result in fatal crashes. However, sleepy driving can also be attributed to car drivers who get inadequate sleep on the majority at nights (Zhu et al., 2021). The data above demonstrate the severe damage that sleepy driving triggers and this is one of the main reasons for traffic accidents. With the ability to warn drivers of their drowsy state before accidents, advances in technology have the possibility of significantly reduce the number of deaths and injuries related to traffic accidents (Bakheet and Al-Hamadi, 2021). The security and safety of

drivers, passengers, and pedestrians are jeopardized by driver drowsiness, which is challenging to identify and avoid. Because of this, it's critical to conduct research on techniques for reliably identifying and forecasting drowsy driving in order to increase transportation safety.

There are many different features in driver drowsiness detection systems that the majority of researchers can exploit. Generally, Using behavioral information, physiological parameters, and information gathered from the vehicle, detection can be accomplished (Dua et al., 2021). Eye, face, and head movements that have been recorded are included in behavioral data. Electrocardiograms (ECG), Electroencephalograms (EEG), Electrooculography (EOG), and heart rate are examples of physiological measures. The steering wheel movement, vehicle speed, braking style, and lane position variation are used to obtain vehicle-based data. Using questionnaires and electro physical information, the majority of measured data can be collected.

The majority of studies demonstrate that driver drowsiness continues to be a significant safety issue and a leading contributing element in fatal crashes while driving. The process of developing more effective methods to measure it has moved steadily. The improvement of driver drowsiness comprehension and identification is significantly hampered by this (Lenné and Jacobs, 2016). A key step in lowering the cost of traffic accidents to society is the accurate detection of drowsiness. There have been several studies that have been published that have attempted to

address the issue of driver drowsiness detection. Their fundamental details, accuracy, benefits, and drawbacks are given in Table 1, Table 2, Table 3, Table 4, and Section 3.4. This study also reviews the researches on developing technologies that are intended to identify and, forecast driver drowsiness while focusing on what occurs while driving.

It is appropriate to evaluate how this issue has evolved given the significance of driving while drowsy as a problem for transport safety and the growing interest in continuous surveillance across several transport industries. To evaluate the progress made in predicting sleepiness-related incidents in research investigations and to determine how close researchers have come to being able to measure drowsiness in the field with reliability. The lack of a thorough grasp of behavior in the field has historically impeded driver behavior model development. To achieve a solid theoretical foundation, it is essential to develop new techniques and measurements for studying drowsy driving. It is also getting more important to forecast driver behaviors. Governments, international organizations, the research belonging, and automakers have all made several attempts over the years to address the problem of driver drowsiness and its negative impacts. The purpose of this review is to determine if it is possible to accurately detect or forecast drowsiness on roadways using both vehicle-based data and other measurements obtained in-vehicle, given the present state of research. In order to develop and improve technology interventions, it is essential question that researchers have a theoretical understanding of the actions of drowsy drivers and the safety consequences they cause. Although there have been a number of reviews for the detection and prediction of driver tiredness (Josephin et al., 2020; Lenné and Jacobs, 2016; Sahayadhas et al., 2012), this is the first article that particularly emphasizes the four different methods for drowsiness detection with a synopsis of key aspects, to the greatest extent possible. Most of the existing reviews have been conducted around two or three measures for detecting and predicting driver drowsiness. But a detailed review of all potential measures for detecting drowsiness is necessary.

In this study different methods are analyzed for detecting and predicting driver drowsiness that draws on data from numerous studies and a wide range of characteristics to determine the degree of drowsiness. The different measurements taken by several researchers and categorized as physiological, vehicle-based, subjective, and behavioral parameters were examined and collectively reviews in this study. The benefits and drawbacks of each of these approaches have been thoroughly examined. Detection and Prediction of Driver Drowsiness is covered in detail in this article, providing the reader a comprehensive picture.

Here are some highlights of the paper's main contributions.

- The research and academic community is served by this paper, which offers a thorough analysis of the detection and prediction of driver drowsiness.
- The study investigated various techniques for detecting drowsiness including classification method, drowsiness measures, dataset, participants, and accuracy along with a summary of important factors.
- Providing a study of the key deep issues with various drowsiness detection technologies and their application to the detection of drowsiness in driving.
- Finally, ideas and enhancements for potential future study directions are also mentioned.

The following describes how this paper is organized. In section 2, the criteria for collecting and choosing papers are presented. The measures for measuring driver drowsiness are described in Section 3, which also clarifies and summarizes them for appropriate expression. The "discussion and open issues" are represented in Section 4. Lastly, "Conclusions" brings this article to a close.

Table 1
Summary of previous studies on driver drowsiness detection using physiological measures.

Author	Classification Method	Signal	Subjects/ Participants	Performance
Gao et al. (2019) (Gao et al., 2019)	RN-CNN	EEG	10 right-handed healthy students, 8 males, 2 females, average age: 23.3 years	Accuracy = 92.95% SD = 4.39
Cui and Wu, (2017) (Cui and Wu)	CNN	EEG	16 healthy subjects, normal vision	RMSE = 0.2347
Hajinoroozi et al. (2015) (Hajinoroozi et al., 2015)	CCNN, CNN-R	EEG	70 sessions, 37 subjects	Accuracy = 82.94%
Abbas, (2020)(Abbas, 2020)	CNN, DBN	ECG	56 people, 5880 images	Accuracy = 94.50%
Wang et al. (2015) (Wang et al., 2015)	Pulse coupled neural network (PCNN)	EEG	20 healthy male subjects, mean age: 37.5 years	
Chaabene et al. (2021) (Chaabene et al., 2021)	CNN	EEG	14 active electrodes, 2 reference electrodes	Accuracy = 90.42%
Ma et al. (2016) (Ma et al., 2016)	NN, Fuzzy logic, SVM, ARIMA	EOG	0.5-second-ahead EOG signal behavior	0.5 s, Ahead Prediction
Liu et al. (2016) (Eskandarian and Mortazavi, 2017)	RSEFNN	EEG	10 healthy young adults participants, average age: 24.2 ± 3.7 years	RMSE = 0.0840 ± 0.0285
Zhu et al. (2021) (Zhu et al., 2021)	CNN	EEG	69,054 samples, awake period = 33,035; drowsiness period = 36,019	Accuracy = 94.68%
Gao et al. (2019) (Gao et al., 2019)	Spatio–Temporal CNN	EEG	800 undergraduates (5 males, Females, age: 19 to 26	Accuracy = 97.37%
Kim and Shin, (2019) (Kim and Shin, 2019)	SVM, KNN, RF	HRV	37 recordings, 6 subjects, 5 males, 1 female, ages: 25 to 35.	AUC = 0.95
Becerra-Sánchez et al. (2019) (Becerra-Sánchez et al., 2019)	SVM, KNN, LR	EEG		Accuracy = 93.00%
Cui et al. (2019) (Cui et al., 2019)	FWET	EEG	16 healthy subjects, age 24.2 ± 3.7, 10 males, 6 females	RMSE = 0.2332
Fujiwara et al. (2019) (Fujiwara et al., 2019)	Multivariate Statistical Process Control (MSPC)	EEG	34 participants, nonprofessional drivers	Accuracy = 90.00%
Nguyen et al. (2017) (Nguyen et al., 2017)	Time series analysis	EEG	11 healthy subjects, 1 female, age: 24 to 28	Accuracy = 79.2%
Warwick et al. (2015) (Warwick et al., 2015)	Zephyr Technology	ECG	2 REU students, 1 male and 1 female	
Li and Chung (2014) (Li	Linear regression	EEG	30 subjects, 10 male, age	Accuracy = 87.5%

Table 1 (*continued*)

Author	Classification Method	Signal	Subjects/ Participants	Performance
and Chung, 2014)			26.1 ± 1.97 years	MSE = 0.013
Guo et al. (2016) (Guo et al., 2016)	Bayesian Network (BN)	EEG	1000 cases generated, probabilistic logic sampling	Accuracy = 95.50%
De Naurois et al. (2018) (De Naurois et al., 2018)	ANN	EKG, (PPG)	21 participants, mean age 24.09 ± 3.41 years; 11 men, 10 women	Accuracy = 80%
Zhu et al. (2014) (Zhu et al., 2014)	CNN	EOG	22 different subjects, 70 min, 22 sessions	Correlation coefficient = 0.73
Quddus et al. (2021) (Quddus et al., 2021)	LSTM, CNN	EEG	38 subjects, ages 41 ± 9 years	Accuracy = 95%–97%
Huang et al. (2016) (Huang et al., 2016)	WPT, FLFNN	PPG	60 data, PPG signals	
Gwak et al. (2020) (Gwak et al., 2020)	SVM, KNN, RF	EEG, ECG	16 males participants, ages of 24.2 ± 1.8 years	Accuracy = 95.4% F1-Score = 94.90%
Lawoyin et al. (2014) (Lawoyin et al., 2014)	SVM	EEG	4 participants	Accuracy = 43.33% − 100%

2. Selection and collection of paper

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology was used to conduct the literature search for this study, as indicated in Fig. 1. To complete a systematic review, the PRISMA process has the following sequential steps: finding papers that are relevant to the study realm, removing duplicate documents using checking, sorting the remaining articles focused on qualifying requirements, and including the chosen papers in the final list of articles to be evaluated. We considered the peer-reviewed research articles published in reputable worldwide platforms for this review study. A number of sources were used for the research, including Google Scholar, Elsevier, PubMed, IEEE, and Web of Science to find related works. For manual online searches and database searches, we selected the following keywords: "Detection of driver drowsiness", "Prediction of driver drowsiness", "Detection and prediction of driver drowsiness", and "A review of driver drowsiness detection'', and "Driver fatigue detection". Using this keyword to do a Google Scholar search with the minimum and maximum years set to 2008 and 2021, respectively. For the purpose of removing duplicates and ensuring that the chosen articles are appropriate for this review task, we examined the titles and abstracts of the research works that the search results revealed. Some studies were removed from the review as part of the quality evaluation process since they had unrelated study objectives, and this was done by carefully reading each article's title and abstract.

Finally, this review comprised the papers that were most pertinent to the study topic and was reviewed and summarized. All articles have to be written in English and connected to the topic of detecting and predicting drowsy driving in order to meet the broad inclusion criterion. Following a thorough review of the complete texts of the chosen publications, the data and information was taken from them and summarized.

3. Methods for measures driver drowsiness

Different techniques have been employed by researchers to gauge driver drowsiness. The process of detection can be carried out by using behavioral data, physiological characteristics, subjective measurements, and data collected from the vehicle. In addition to these three, researchers have also employed subjective methods, in which drowsy driving is assessed directly or by completing a questionnaire by the driver. The various measurements and the associated parameters are discussed in this section. The brief classification of driver drowsiness measures is displayed in Fig. 2.

3.1. Physiological measures

The driver in this category is monitored for drowsiness using sensors and other electronic gadgets that are attached to their bodies. By focusing on the heart rate, pulse rate, brain activity, body temperature, and other physiological variables, the state of the driver can be evaluated. Three key signals are electroencephalography (EEG), electrooculography (EOG), and electrocardiography (ECG) that are used to identify sleepiness and enhance performance in this area (Barua et al., 2019; Awais et al., 2017). The EEG technique measures brainwaves that are utilized in several applications, such as the diagnosis of epilepsy and the monitoring of sleep problems, by using the electrical activity of the human brain (Taherisadr and Dehzangi, 2019). The electrical activity of the brain during different states of arousal, such as awakeness, drowsiness, and sleep, is also measured using an EEG (Sahayadhas et al., 2012). Due to its excellent accuracy, objective evaluation, and low chance of fraud, the Electroencephalogram (EEG) is the physiological. EOG is a technique for measuring the corneo-retinal standing potential that exists between the front and the back of the human eye and is employed to capture the motion of the eye (Chen et al., 2015). Heart rate, which is produced by bioelectric currents traveling through the heart at different stages of blood flow, can be tracked and evaluated using the ECG technique (Gupta et al., 2017). Additionally, there are substantial differences in heart rate (HR) between alertness and drowsiness and other sleepiness stages.

The results of a study show that the chosen traits performed better in hybrid techniques than in singular approaches, which may have important implications for future investigations (Hasan et al., 2021). The findings from another investigation show that it is possible to identify a driver's mild drowsiness early and accurately utilizing a hybrid approach with non-contact sensors (Gwak et al., 2020). Because driving involves movement, measuring raw physiological information is always subject to noise and distortions. When compared to other technologies, physiological signals-based driver drowsiness detection has a very high consistency and accuracy. Due to movement artifacts and inaccuracies brought on by incorrect electrode contact, the accuracy of a non-intrusive device is significantly lower. A study proposes a wearable electroencephalographic (EEG)-based convolution neural network (CNN) system for the detection of driver drowsiness in vehicles (Zhu et al., 2021). The study's final testing findings demonstrate the suggested method's excellent effectiveness in detecting driver tiredness in moving vehicles. Driver drowsiness detection utilizing physiological parameters has been the subject of past research, which is summarized in Table 1.

3.2. Behavioral measures

There are several facial signals that indicate someone is drowsy, such as rapid and continuous blinking, head movements, and repeated yawning etc. The amount of drowsiness of drivers is frequently assessed using computerized, quasi behavioral procedures by observing their unusual behavior (Josephin et al., 2020). The majority of research that have been published on employing behavioral techniques to assess tiredness concentrate on blinking (Bamidele et al., 2019; Gwak et al.,

Table 2
Summary of previous studies on driver drowsiness detection using behavioral measures.

Authors	Classification Methods	Drowsiness Measures	Dataset	Performance
Guo et al. (2016) (Guo et al., 2016)	Bayesian Network (BN)	Heart rate, pulse rate, eyelid movement, gaze, head movement	21 participants car simulator for 110 min	Accuracy = 79.50%
Bakheet ang Al Hamadi, (2021), (Bakheet and Al-Hamadi, 2021)	Histogram of Oriented Gradient (HOG) features	Driver image, eye pair region	NTHU-DDD dataset	Accuracy = 85.62% F1-Score = 87.84%
Boyraz et al. (2008) (Boyraz et al., 2008)	Fuzzy inference system (FIS) and ANN	Eye closure, pupil area, gaze vector, head motion	Data set of 30 pairs, 1.5 h highway simulation	Accuracy = 98.00%
Park et al. (2017) (Park et al)	Deep Networks	Driver image	NTHU-driver drowsiness detection benchmark video dataset	Accuracy = 73.06%
Huynh et al. (2017) (Huynh et al)	3D CNN	Eye-closing, nodding and yawning	5 different scenarios, Bare Face, Glasses, Night Bare Face, Night Glasses, and Sunglasses cases	Accuracy = 87.46% F1-Score = 87.97%
Weng et al. (2017) (Weng et al., 2017)	Hierarchicaltemporal Deep Belief Network (HTDBN)	Yawning, blink rate, falling asleep	Large dataset, genders, lighting conditions and driving scenarios	Accuracy = 84.82% F1-Score = 85.39%
Bamidele et al. (2019) (Bamidele et al., 2019)	KNN, SVM, Logistic Regression, ANN	Percentage ofeyelid closure (PERCLOS), blink frequency (BF), Maximum Closure Duration (MCD)	Video data, various facial characteristics, different ethnicities, 5 different scenarios	Accuracy = 72.25% Sensitivity = 83.06%
De Naurois et al. (2018) (De Naurois et al., 2018)	ANN	Driving performance, eyelid and head movements	21 participants car simulator for 110 min	Prediction = 40%, Detection = 80%
Vijayan and Sherly, (2019) (Vijayan and Elizabeth, 2019)	CNN	Eye blinking, yawning, head swaying	68 attributes RGB video input of a driver	Accuracy = 78.61%
Chen et al. (2021) (Chen et al., 2021)	LSTM, CNN	Eye, face area	THU-DDD dataset	Accuracy = 93.30%
Zhang et al. (2020) (Zhang et al., 2020)	Mixed-effect ordered logit (MOL) model	Eyelid closure, pupil diameter, blink frequency, blink duration	data from 27 drivers, driving simulator, Karolinska Sleepiness Scale (KSS)	Accuracy = 62.84%
Wang and Xu, (2016) (Wang and Xu, 2016)	Multilevel ordered logit (MOL) model, ordered logit model, ANN	eyelid opening, pupil diameter, eye blink (PERCLOS),	16 male participants, driving simulator 8 h	Accuracy = 88.80%
Ed-Doughmi et al. (2020) (Ed-Doughmi et al)	RNN	Driver image	NTHU-DDD dataset	Accuracy = 92.00% F1-Scrore = 85.00%
Dua et al. (2020) (Dua et al., 2021)	Deep CNN	Hand gestures, facial expressions, head movements	NTHU-DDD dataset	Accuracy = 85.00% F1-Score = 84.09%
Saif and Mahayuddin, (2020)50	DCNN	Head pose estimation, pupil area	iBUG 300 W dataset,	Accuracy = 98.97%
Reddy et al. (2017) (Reddy et al., 2017)	DNN	Facial landmark	11 subjects, NTHU-DDD dataset, video stored 70,000 images	Accuracy = 89.5%
Guo and Markoni, (2018) (Guo and Markoni, 2019)	Hybrid CNN, LSTM	Facial landmark (eye and mouth)	Public drowsy driver dataset	Accuracy = 84.85%
Zhao et al. (2020)(Zhao et al., 2020)	3D CNN	Driver face and facial landmarks	NTHU-DDD dataset	Accuracy = 88.6%
Quddus et al. (2021) (Quddus et al., 2021)	LSTM, CNN	Blinking, eye closure, saccades, fixation	38 participants driving simulator	Accuracy = 95% – 97%
Vu et al. (2019) (Vu et al., 2019)	CNN	Driver's face	NTHU-DDD dataset	Accuracy = 84.81% F1-score = 86.28%
Wijnands et al. (2019) (Wijnands et al., 2020)	3D neural networks	Yawning, nodding, looking aside, talking, laughing, closing eye	DDD dataset	Accuracy = 80.8%
Yu et al. (2018) (Yu et al., 2019)	3D-DCNN	Head, mouth and eye condition	NTHU-DDD dataset	Accuracy = 76.20% F1-score = 76.50%
Siddiqui et al. (2021) (Siddiqui et al., 2021)	SVM, Decision Tree, Logistic regression, MLP	Eye blink, eyeballs movement, respiration, heartbeat	Real-time data,	Accuracy = 87.00% F1-score = 73.00 %
Shih and Hsu, (2017) (Shih and Hsu, 2017)	Multistage Spatial Temporal Network(MSTN)	Yawning, slow blink rate, falling asleep, burst out laughing	NTHU-DDD dataset	Accuracy = 82.61% F1-score = 87.97%
Rajamohana et al. (2021) (Rajamohana et al., 2021)	CNN, BILSTM	Facial image, eye blink, eye closure	Eye data, 1104 images	Accuracy = 96.00%
Liu et al. (2019) (Liu et al., 2019)	multi-task cascaded CNN	Mouth image, eye image	National Tsing HuaUniversity Driver Drowsiness Detection (NTHU-DDD) dataset	Accuracy = 97.06%
Gwak et al. (2020) (Gwak et al., 2020)	SVM, KNN, RF	Eye blink, eye closure	16 male participants, 30 min drive course	Accuracy = 95.4%
Hachisuka, (2013) (Hachisuka, 2013)	ActiveAppearance Model (AAM)	facial image	1 h driving simulator, 9 facial muscles	SD = 0.14 RMSE = 0.91
Vural et al. (2008) (Vural et al., 2009)	Adaboost, multinomial ridge regression	Blink rate, eye closure, and yawning	Video 3 h session, 31 facial actions	Accuracy = 98.0%
Jabbar et al. (2020) (Jabbar et al., 2020)	CNN	Yawning, slow rate blinking, sleepy head movements	NTHU-DDD dataset	Accuracy = 88.00%
Ghourabi et al. (2020) (Ghourabi et al., 2020)	MLP. KNN	Eye closure, yawning	NTHU-DDD benchmark video dataset	Accuracy = 94.31% F1-Score = 79.00%
Dwivedi et al. (2014) (Dwivedi et al., 2014)	CNN	Skin tone, eye size, facial structure, hair fringes, facial hair	30 subjects standard datasets	Accuracy = 88.00%.
Eskandarian and Mortazavi (2017) (Eskandarian and Mortazavi)	ANN	Eye closure	13 truck drivers (subjects), 8 h sleep	Accuracy = 97.00%

Table 2 (*continued*)

Authors	Classification Methods	Drowsiness Measures	Dataset	Performance
Han et al. (2015) (Han et al., 2015)	vision based, feature extraction	PERCLOS and blink rate	Drivers face video data, 8 subjects, 30 min. driving simulator	Accuracy = 90.45% Correlation Coefficient = 0.91
Zhang et al. (2012) (Zhang et al., 2012)	Computer Vision Technology	Eyelid closure, blink frequency, opening and closing velocity of the eyes	06 participants, driving simulator experiments	Accuracy = 86.00%
Flores et al. (2010) (Flores et al., 2010)	Condensation algorithm (CA), NN	Face and eye image	Real-time data, grayscale images	Accuracy = 98.00%

Table 3
Summary of previous studies on driver drowsiness detection using Vehicle based measures.

Authors	Classification Methods	Input Parameters	Data collecting technique	Performance
Guo et al. (2016) (Guo et al., 2016)	Bayesian Network (BN)	Lane deviations, steering movements	PSO-based feature selection approach, driving measurements	Accuracy = 95.50%
Boyraz et al. (2008) (Boyraz et al., 2008)	Fuzzy inference system (FIS) and ANN	Steering wheel angle, vehicle speed	Standard highway simulation for 1.5 h, data set 30 pair	Accuracy = 98.00% F1 score = 98%
Arefnezhad et al. (2020) (Arefnezhad et al., 2020)	CNN, RNN	Lateral deviation and acceleration, steering wheel angle	44 sessions fixed-base driving simulator simulating monotonous night-time highway drives	Accuracy = 96.00%
Zhang et al. (2020) (Zhang et al., 2020)	Mixed-effect ordered logit (MOL) model	Vehicle speed, lateral position, steering wheel movement	Karolinska Sleepiness Scale (KSS)	Accuracy = 62.84%
Wang and Xu, (2016) (Wang and Xu, 2016)	Multilevel ordered logit (MOL) model, ordered logit model, ANN	Vehicle speed, lateral position, steering wheel angle	High fidelity motion based driving simulator	Accuracy = 64.15%-68.40%
Quddus et al. (2021) (Quddus et al., 2021)	Long short-term memory (LSTM), CNN	Vehicle driving dynamics	38 subjects, simulated driving experimen	Accuracy = 95%–97%
Gwak et al. (2020) (Gwak et al., 2020)	Support Vector Machine (SVM), K-Nearest Neighbor(KNN)	Vehicle velocity, longitudinal acceleration, lateral position, steering wheel acceleration	driving simulator and driver monitoring system	Accuracy = 95.4%
Dehzangi and Masilamani (2018) (Dehzangi and Masilamani, 2018)	Decision-Tree algorithms	Acceleration, braking, steering wheel	KSS (Karolinska Sleepiness Scale)	Accuracy = 99.10% RMSE = 0.31 MAE = 0.14
McDonald et al. (2018) (McDonalda et al., 2018)	Dynamic Bayesian Network	Speed and acceleration	72 participants driving the National Advanced Driving Simulator	False positive rates < 15%
Forsman et al. (2013) (Forsman et al., 2013)	principal component analysis (PCA)	Lateral lane position, steering wheel angle, driving speed	Two laboratory-based, high-fidelity driving simulator studies	Correlation r = 0.88

Table 4
Summary of the benefits and drawbacks of the various types of measures.

Measures	Reference	Benefits	Drawbacks
Physiological measures	(Sahayadhas et al., 2012; Lenné and Jacobs, 2016)	Dependable; Precise, High accuracy	Intrusive
Behavioral Measures		Simple towards using; Non-intrusive, efficient	State of the lights Background
Vehicle based measures		Non-intrusive, efficient	Unreliable
Subjective measures		Subjective, Questionnaire	Incapable in instantaneously

2020; Han et al., 2015; Jabbar et al., 2020) and PERCLOS (Eskandarian and Mortazavi, 2017; Ghourabi et al., 2020; Han et al., 2015; Wang and Xu, 2016) (which is the percentage of eyelid closure over the pupil over time). All of these studies aimed to establish a drowsiness identification model that takes into account the variable possible influence of drowsiness on driving productivity. Multiple facial expressions and ocular scans were employed by several studies to identify signs of drowsiness (Bakheet and Al-Hamadi, 2021; Chen et al., 2021; Ed-Doughmi et al., ; Flores et al., 2010). However, numerous researchers have also created studies on how to use other behavioral indicators, like yawning (Ghourabi et al., 2020; Huynh et al., ; Weng et al., 2017; Wijnands et al., 2020) and head or eye position (De Naurois et al., 2018; Dua et al., 2021; Saif and Mahayuddin, 2020) orientation to measure amount of drowsiness.

A study used machine learning models (artificial neural networks) to detect a driver's level of drowsiness or to forecast the beginning of a driving impairment (De Naurois et al., 2018). In order to gather information about spontaneous behavior during actual periods of drowsiness, a study presented a technique for automatically measuring facial expressions (Vural et al., 2009). For the purpose of detecting drowsy driving, two-stream networks, multi-facial characteristics, CNN, and gamma correction was used and this was highly accurate and avoided placing unnecessary equipment on the driver's body (Liu et al., 2016). In order to improve the classification of the alert and drowsy states of drivers, additionally looked into the accuracy of drowsiness detection through algorithm improvement and the use of ensemble machine learning (Gwak et al., 2020). The Multilayer Perceptron (MLP) and the K-Nearest Neighbors (K-NN) as two supervised classification approaches was used to automatically merge the three features in order to detect drowsiness (Ghourabi et al., 2020). A highly difficult video collection that simulates actual driving situations was used to evaluate their suggested technique. To deliver precise and timely alerts to the driver, it is crucial to develop an automated, real-time sleepiness detection mechanism. The majority of drowsiness detection techniques currently in use simply employ one facial characteristic to determine drowsiness condition, omitting the intricate relationship between drowsiness characteristics and the information provided by the timing of those features. In order to address these issues, a model was suggested for estimating
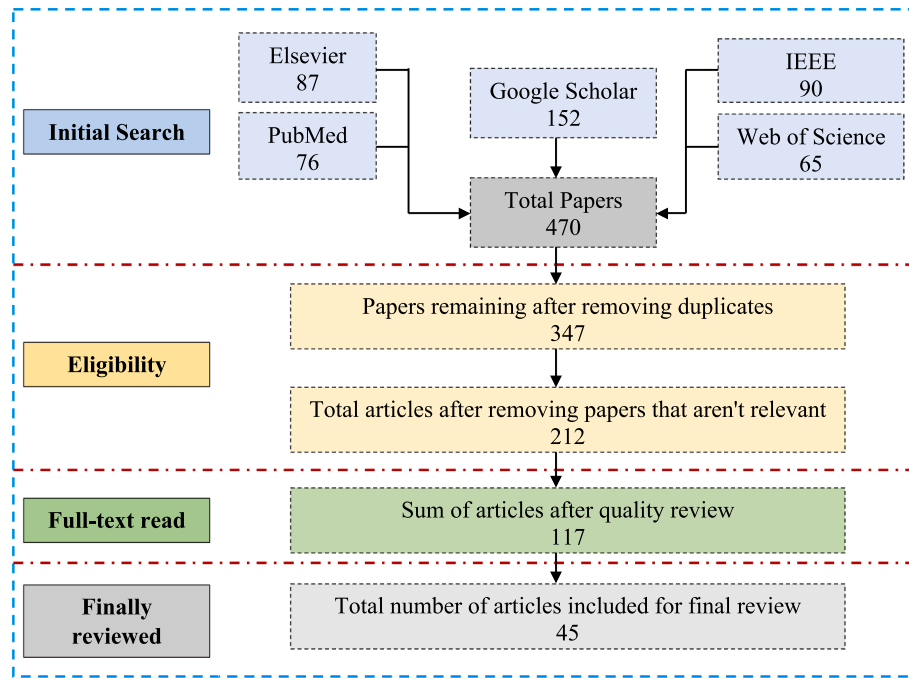
Fig. 1. Flow of the process (PRISMA-based) for choosing articles for the final review.
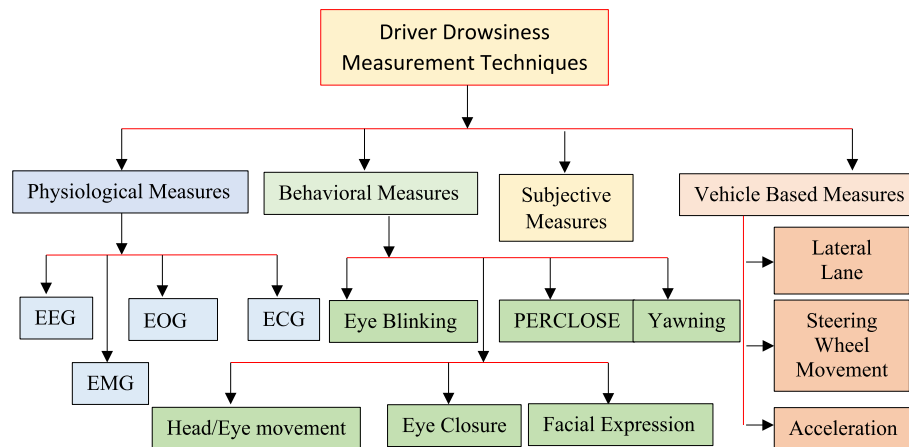

Fig. 2. Brief classification of different driver drowsiness measures.

driver drowsiness based on factorized bilinear feature fusion and a long-short-term recurrent convolutional network (Chen et al., 2021). A drowsiness detection model's performance would be improved if individual differences were taken into account (Wang and Xu, 2016). The identification of driver drowsiness using a transferred deep 3D convolutional network and state probability vector (Zhao et al., 2020). They showed that 3D CNN can pick up spatiotemporal information from irrelevant datasets to increase its effectiveness in classifying driver drowsiness. The learning of spatiotemporal features is better suited to three-dimensional (3D) processes, and most of the algorithms used today for drowsiness detection are frame-based and multistep (Wijnands et al., 2020). A study devised and presented a non-invasive, non-wearable, non-camera based driver drowsiness detection system based on wirelessly extracting respiratory rates (Siddiqui et al., 2021). With the help of this study, UWB (ultra-wideband) technology's effectiveness in detecting driver drowsiness based on respiration can be verified and evaluated. Table 2 provides a summary of previous research on the topic of driver drowsiness detection using behavioral measures.

3.3. Vehicle based measures

The way a drowsy driver operates a vehicle may differ from the way a regular driver operates a vehicle. Any change in these measurements that exceeds a certain threshold denotes a greatly increased likelihood that the driver is sleepy. These metrics include deviations from lane position, steering wheel movement, pressure on the accelerator, etc. (Sahayadhas et al., 2012).

The lateral lane position and steering wheel movement are the two most often utilized vehicle-based measurements. Steering angle sensors are used to assess steering wheel movement, which is a popular vehicle-based method of measuring driver drowsiness (Guo et al., 2016; Boyraz et al., 2008; Arefnezhad et al., 2020; Zhang et al., 2020; Wang and Xu, 2016; Gwak et al., 2020; Dehzangi and Masilamani, 2018). The driver's steering behavior is monitored by an angle sensor that is positioned on the steering column. Another significant indicator of the degree of driver sleepiness is the position of the vehicle in the lateral lane (Wang and Xu, 2016; Zhang et al., 2020; Gwak et al., 2020; Forsman et al., 2013). When conducting field trials, an external camera is used to track the location of

the lane. Numerous studies have shown that drowsiness-related performance error risk is not well predicted by precautions taken while operating a vehicle. Furthermore, drowsiness is not a defined measurement in vehicle-based metrics. A structure was developed to surreptitiously evaluate the driver's level of drowsiness while driving (Dehzangi and Masilamani, 2018). By leveraging the vehicle generated data in an unobtrusive manner, they succeeded in diagnosing the driver's level of drowsiness using vehicle measurements like as acceleration, braking, and steering. In order to detect drowsiness-related lanes, an author develops and tests a contextual and temporal algorithm (McDonalda et al., 2018). The program lowers the proportion of false positives in rural and highway settings, which are normally troublesome for vehicle-based detection techniques. To increase driving safety, it may be utilized in conjunction with all-encompassing mitigation techniques. The previous studies on the subject of detecting driver drowsiness using vehicle-based metrics are summarized in Table 3.

3.4. Subjective measures

Subjective measures that assess the degree of drowsiness are based on the driver's individual assessment. A variety of procedures have been used to convert this evaluation into a measure of driver drowsiness. Most other research used the two most popular drowsiness scales, either the 7-point Stanford Drowsiness Scale (SSS) or the 9-point Karolinska Sleepiness Scale (KSS), where the numerical ratings match to a specific verbal description for the state of drowsiness in question. Examples for the KSS include 1 for extremely alert and 9 for extremely sleepy, requiring significant effort to stay awake (Sahayadhas et al., 2012; Lenné and Jacobs, 2016). The KSS scale is a commonly used subjective sleepiness scale (Åkerstedt et al., 2014) whose results are connected with physiological measurements and the results of the psychomotor vigilance test (PVT) (Kaida et al., 2006). The subjects of these tests are given brief questionnaires, and they are instructed to rate their current state using the provided scale (Mashko, 2017). A sample's members who slept a lot have been identified using KSS scores. In reality, simulator night driving results in greater KSS scores than on-road night driving (Hallvig et al., 2013). Participants who self-rated as more drowsy (KSS > 8) and less sleepy (KSS < 3) were distinguished (Hallvig et al., 2014). A common model for KSS or SSS data analysis is shown in Fig. 3.

The KSS was categorized into three clusters: KSS 1–5 represents alertness; KSS 6–7 represents the onset of drowsiness; and KSS 8–9 represents extreme drowsiness (Anund et al., 2013). Performance

Fig. 3. A typical model for data analysis by KSS or SSS.

variations between people have been observed during insufficient sleep earlier and were predicted (Van Dongen, 2004). Although drowsiness can be detected using subjective assessments in a controlled environment, other metrics may be more appropriate for application in actual settings. It has been shown that the amount of sleepiness as measured by the KSS has, in most situations, a curve-linear relationship to lateral location and blink duration when matched to other driver fatigue measurements (Ingre et al., 2006). Higher subjective drowsiness scores on the KSS scale were associated with slower eye movements (Akerstedt and Gillberg, 1990) and greater visual equivalent drowsiness scores were associated with longer eye blink durations (Caffier et al., 2003). Several instances show that on-road night driving KSS scores are higher than those for daytime driving (Anund et al., 2013; Sandberg et al., 2011). Every five minutes, Shuyan and Gangtie (2009) measured the KSS ratings of drivers and compared them to the gathered EOG signal (Shuyan and Gangtie, 2009). A correlation between the length of the eye blink (Ingre and Åkerstedt, T., Peters, B., Anund, A., Kecklund, G. , 2006), the variation in lane position (Sommer et al., 2010), and the KSS recorded every 5 (Ingre and Åkerstedt, T., Peters, B., Anund, A., Kecklund, G. , 2006) and 2 min (Sommer et al., 2010) during the driving activity has been found by several researches. Table 4 provides a summary of the benefits and drawbacks of the various types of measures.

4. Discussions, open issues, and future trends

A driver loses control of the vehicle if they fall asleep at the wheel, which frequently leads to a collision with some other car or an immovable object. The level of drowsiness of the driver needs to be kept an eye on in order to avoid these fatal collisions. In various research, the link between driver drowsiness and accident probability has been thoroughly examined with the aim of finding and measuring the elevated risk. If a driver who is considered to be drowsy receives an alarm, many accidents on the road may be prevented. The impact of different data sets on adaptation was generally found to vary. Using only behavioral data, the majority of the model performs best at prediction. When a lack of alertness impairs vehicle control or deviates from the path planned, vehicle-based metrics are helpful in assessing drowsiness. The genuine internal state of the driver is revealed by physiological measurements, which are trustworthy and accurate. When employing the entire dataset, including behavioral, physiological, vehicle, personal, and driving time information, the best detection performance is also attained. However, there is no discernible difference between the various dataset combinations in the latter scenario.

On different days, people don't respond and react in precisely the same way, and they don't all have the same propensity to nod off while driving. Forcing a sleepy driver to operate a motor vehicle is not recommended. Understanding the connection between simulated driving behavior and actual driving was one issue raised. As a result, numerous studies have been carried out in simulated circumstances, with the results then undergoing extensive research. In order to design a system that promotes safety and warning features, real-time data collecting and preprocessing are essential. To get this information in actual driving situations without seriously deterring the driver from their main objective is not practical. The accuracy of simulated driving situations has been investigated by several researchers through experiments. The simulated environment should be as accurate a representation of the real environment as feasible when creating a drowsiness detection method. But a hybrid system that combines the advantages of the various techniques would be necessary to create a reliable drowsiness detection system.

The road and weather conditions, the driver's skill level, and the type of vehicle can all have an impact on the accuracy of the majority of approaches. Some researchers suggested deep learning techniques for multi-level classification of drowsiness to increase the accuracy by using a hybrid approach that combines different physiological, behavioral, and driving performance characteristics (Quddus et al., 2021). In order
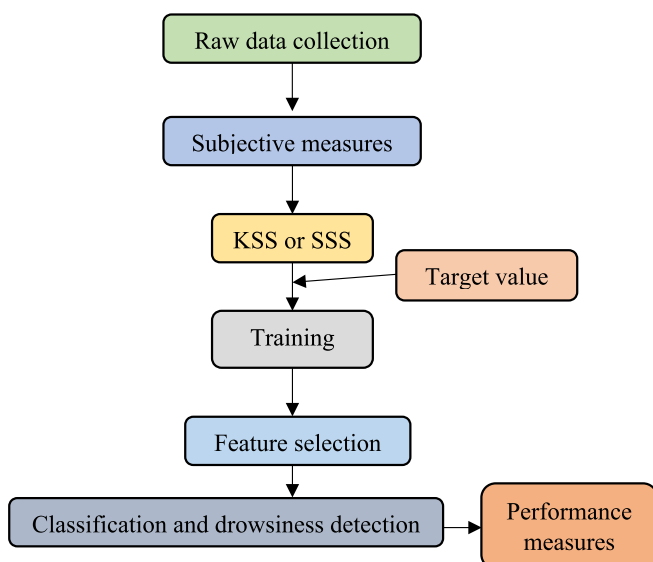
to identify driver drowsiness with high accuracy, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been used.

The majority of research share the same flaw that there weren't enough participants. Finding a generalized model that can be learned is really difficult. Because to inter-individual variability, with a select group of drivers before being applied to more drivers. Numerous studies noted a wide range in how drowsiness impacts general physiological indicators and function. The research demonstrates that initiatives by businesses, academic institutions, and governmental organizations have begun to produce significant advancements in the development of driver drowsiness detection systems.

There are indeed a number of limitations to studying the detection and prediction of driver drowsiness. Most of the studies that have been done so far don't perform well in low light conditions. Since the investigation is also depending on street conditions, light effects, and traffic instances, more trial observations are needed for many countries. The most important thing to remember is that it has become increasingly challenging to be precise as well as comprehensive.

The following aspects need to be evaluated too for future research. This study overviews and summarizes the techniques, participants, performance metrics, and datasets for the physiological, driving-based, subjective, and behavioral drowsiness measures. It is suggested to summarize and analyze all available data regarding driver behavior, psychology, and road conditions in future research, including more feature extraction, preprocessing, and detection algorithms. In addition to considering how future driving conditions with semi-automated and ultimately completely automated driving can affect how driver behaviors like drowsiness will really be represented, it is important to think about new indications that can forecast drowsiness. The development of an appropriate dataset that includes a diverse variety of racial groups will also be a focus of future work in order to make drowsiness assessments more accurate. Any driver sleepiness detection system must take into account practical considerations including pervasiveness, aesthetics, economic viability, and user acceptance. Future research could focus on the significant application of deep learning techniques for more accurate drowsiness detection.

5. Conclusions

The many approaches that can be used to assess a driver's level of drowsiness have been examined in this research. Subjective, driving-based, physiological, and behavioral assessments are among the many tools used to identify drowsiness. These tools were also thoroughly examined, with the benefits and drawbacks of each tool being listed. It takes a lot of time and resources to perform participant-based driver drowsiness investigation, and efforts are still being made to measure drowsiness in on-road investigations. The capacity to perform realistic driving research will be facilitated by the advent of approved and inconspicuous actual surveillance systems. The classification approach, sleepiness measures, dataset, participants, accuracy, and a list of crucial elements have all been highlighted as different methods for detecting drowsiness. Lastly, suggestions and improvements for potential new research directions are also included here. Hopefully, this study will offer academics and researchers who are interested in learning more about the identification and prediction of driver drowsiness a stable foundation on which to do so.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Abbas, Q., 2020. Hybrid fatigue: A real-time driver drowsiness detection using hybrid features and transfer learning. Int. J. Adv. Comput. Sci. Appl. (IJACSA) 11 (1), 585–593.

Åkerstedt, T., Anund, A., Axelsson, J., Kecklund, G., 2014. Subjective sleepiness is a sensitive indicator of insufficient sleep and impaired waking function. J. Sleep Res. 23, 240–252.

Akerstedt, T., Gillberg, M., 1990. Subjective and objective sleepiness in the active individual. Int. J. Neurosci. 52, 29–37.

Anund, A., Fors, C., Hallvig, D., Akerstedt, T., Kecklund, G., 2013. Observer Rated Sleepiness and Real Road Driving: An Explorative Study. PLoS One 8 (5), 1–8.

Arefnezhad, S.; Eichberger, A.; Frühwirth, M.; Kaufmann, C.; Moser, M. (2020). Driver Drowsiness Classification Using Data Fusion of Vehicle-based Measures and ECG Signals. In Proceedings of the 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Toronto, ON, Canada, 451–456.

Awais, M., Badruddin, N., Drieberg, M., 2017. A hybrid approach to detect driver drowsiness utilizing physiological signals to improve system performance and wearability. Sensors 17 (9), 1991.

Bakheet, S., Al-Hamadi, A., 2021. A Framework for Instantaneous Driver Drowsiness Detection Based on Improved HOG Features and Naïve Bayesian Classification. Brain Sci. 11, 240.

Bamidele, A.A., Kamardin, K., Aziz, N.S.N.A., Sam, S.M., Ahmed, I.S., Azizan, A., Bani, N. A., Kaidi, H.M., 2019. Non-intrusive Driver Drowsiness Detection based on Face and Eye Tracking. Int. J. Adv. Comput. Sci. Appl. (IJACSA) 10 (7).

Barua, S., Ahmed, M.U., Ahlström, C., Begum, S., 2019. Automatic driver sleepiness detection using EEG, EOG and contextual information. Expert Syst. Appl. 115, 121–135.

Becerra-Sánchez, E., Reyes, A., Guerrero-Ibañez, J., 2019. Wearable Sensors for Evaluating Driver Drowsiness and High Stress. IEEE Lat. Am. Trans. 17 (3), 418–425.

Boyraz P, Acar M, Kerr D. (2008). Multi-sensor driver drowsiness monitoring. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering. 2008; 222(11):2041-2062.

Caffier, P.P., Erdmann, U., Ullsperger, P., 2003. Experimental evaluation of eye-blink parameters as a drowsiness measure. Eur. J. Appl. Physiol. 89, 319–325.

Chaabene, S., Bouaziz, B., Boudaya, A., Hökelmann, A., Ammar, A., Chaari, L., 2021. Convolutional Neural Network for Drowsiness Detection Using EEG Signals. Sensors 21, 1734.

Chen, S., Wang, Z., Chen, W., 2021. Driver Drowsiness Estimation Based on Factorized Bilinear Feature Fusion and a Long-Short-Term Recurrent Convolutional Network. Information 12, 3.

Chen, L.L., Zhao, Y., Zhang, J., Zou, J.Z., 2015. Automatic detection of alertness/ drowsiness from physiological signals using wavelet-based nonlinear features and machine learning. Expert Syst. Appl. 42 (21), 7344–7355.

Cui, Y., Wu, D. (2017). EEG-Based Driver Drowsiness Estimation Using Convolutional Neural Networks. International Conference on Neural Information Processing. Guangzhou, China, Nov. 2017, pp. 822–832.

Cui, Y., Xu, Y., Wu, D., 2019. EEG-Based Driver Drowsiness Estimation Using Feature Weighted Episodic Training. IEEE Trans. Neural Syst. Rehabil. Eng. 27 (11), 2263–2273.

De Naurois, C.J., Bourdin, C., Bougard, C., Vercher, J.-L., 2018. Adapting artificial neural networks to a specific driver enhances detection and prediction of drowsiness. Accid. Anal. Prev. 121, 118–128.

Dehzangi, O., Masilamani, S., 2018. Unobtrusive Driver Drowsiness Prediction Using Driving Behavior from Vehicular Sensors. In: 24th International Conference on Pattern Recognition (ICPR), pp. 3598–3603.

Dua, M., Shakshi, Singla, R., Raj, S., Jangra, A., 2021. Deep CNN models-based ensemble approach to driver drowsiness detection. Neural Comput. Applic. 33 (8), 3155–3168.

Dwivedi, K., Biswaranjan, K., Sethi, A., 2014. Drowsy driver detection using representation learning. IEEE Int. Adv. Comput. Conf. (IACC) 995–999.

Ed-Doughmi, Y., Idrissi, N., Hbali, Y. (2020). Real-Time System for Driver Fatigue Detection Based on a Recurrent Neuronal Network. Journal of Imaging, 6, 8.

Eskandarian, A., Mortazavi, A., 2017. Evaluation of a Smart Algorithm for Commercial Vehicle Driver Drowsiness Detection. IEEE Intell. Vehicles Sympos. 553–559.

Flores, M.J., Armingol, J.M., Escalera, A., 2010. Real-Time Warning System for Driver Drowsiness Detection Using Visual Information. J. Intell. Rob. Syst. 59 (2), 103–125.

Forsman, P.M., Vila, B.J., Short, R.A., Mott, C.G., Van Dongen, H.P., 2013. Efficient driver drowsiness detection at moderate levels of drowsiness. Accid. Anal. Prev. 50, 341–350.

Fujiwara, K., Abe, E., Kamata, K., Nakayama, C., Suzuki, Y., Yamakawa, T., Hiraoka, T., Kano, M., Sumi, M., Masuda, F., Matsuo, M., Kadotani, H., 2019. Heart Rate Variability-Based Driver Drowsiness Detection and Its Validation with EEG. IEEE Trans. Biomed. Eng. 66 (6), 1769–1778.

Gao, Z.-K., Li, Y.-L., Yang, Y.-X., Ma, C., 2019. A recurrence network-based convolutional neural network for fatigue driving detection from EEG. Chaos: An Interdisciplinary. J. Nonlinear Sci. 29 (11) https://doi.org/10.1063/1.5120538.

Gao, Z., Wang, X., Yang, Y., Mu, C., Cai, Q., Dang, W., Zuo, S., 2019. EEG-based spatio-temporal convolutional neural network for driver fatigue evaluation. IEEE Trans. Neural Networks Learn. Syst. 30 (9), 2755–2763.

Ghourabi, A., Ghazouani, H., Barhoumi, W. (2020). Driver Drowsiness Detection Based on Joint Monitoring of Yawning, Blinking and Nodding. IEEE 16th International Conference on Intelligent Computer Communication and Processing (ICCP), 407-414.s.

Guo, J.-M., Markoni, H., 2019. Driver drowsiness detection using hybrid convolutional neural network and long short-term memory. Multimed. Tools Appl. 78 (20), 29059–29087.

Guo, W., Zhang, B., Xia, L., Shi, S., Zhang, X., She, J., 2016. Driver drowsiness detection model identification with Bayesian network structure learning method. Chin. Control Decision Conf. (CCDC) 2016, 131–136.

Gupta, N., Najeeb, D., Gabrielian, V., & Nahapetian, A. (2017). Mobile ECG-based drowsiness detection. In 2017 14th IEEE Annual Consumer Communications & Networking Conference (CCNC), 29-32.

Gwak, J., Hirao, A., Shino, M., 2020. An Investigation of Early Detection of Driver Drowsiness Using Ensemble Machine Learning Based on Hybrid Sensing. Appl. Sci. 10 (8), 2890.

Hachisuka, S., 2013. Human and Vehicle-Driver Drowsiness Detection by Facial Expression. International Conference on Biometrics and Kansei Engineering 320–326.

Hajinoroozi, M., Mao, Z., Huang, Y., 2015. Prediction of driver's drowsy and alert states from EEG signals with deep learning. In: 2015 IEEE 6th international Workshop on Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP), pp. 493–496.

Hallvig, D., Anund, A., Fors, C., Kecklund, G., Karlsson, J.G., Wahde, M., Akerstedt, T., 2013. Sleepy Driving on the Real Road and in the Simulator - A Comparison. Accid. Anal. Prev. 50, 44–50.

Hallvig, D., Anund, A., Fors, C., Kecklund, G., Akerstedt, T., 2014. Real Driving at Night - Predicting Lane Departures from Physiological and Subjective Sleepiness. Biology Psychology 101, 18–23.

Han, W., Yang, Y., Huang, G., Sourina, O., Klanner, F., Denk, C., 2015. Driver Drowsiness Detection Based on Novel Eye Openness Recognition Method and Unsupervised Feature Learning. IEEE International Conference on Systems, Man, and Cybernetics 1470–1475.

Hasan, M.M., Watling, C.N., Larue, G.S., 2021. Physiological signal-based drowsiness detection using machine learning: singular and hybrid signal approaches. J. Saf. Res. 80 (2022), 215–225.

Huang, Y.-P., Sari, N.N., Lee, T.-T., 2016. In: Early Detection of Driver Drowsiness by WPT and FLFNN Models. and Cybernetics (SMC), Man, pp. 000463–000468.

Huynh X.P., Park, S.M., Kim, Y.G. (2017). Detection of Driver Drowsiness Using 3D Deep Neural Network and Semi-Supervised Gradient Boosting Machine. Asian Conference on Computer Vision, Computer Vision – ACCV 2016 Workshops. 134-145.

Ingre, M., Akerstedt, T., Peters, B., Anund, A., Kecklund, G., 2006. Subjective sleepiness, simulated driving performance and blink duration. J. Sleep Res. 15 (1), 47–53.

Ingre, M., Åkerstedt, T., Peters, B., Anund, A., Kecklund, G., 2006. Subjective sleepiness, simulated driving performance and blink duration: Examining individual differences. J. Sleep Res. 15, 47–53.

Jabbar, R., Shinoy, M., Kharbeche, M., Al-Khalifa, K., Krichen, M., Barkaoui, K. (2020). Driver Drowsiness Detection Model Using Convolutional Neural Networks Techniques for Android Application. ICIoT 2020, Doha, Qatar. Hal-02479367.

Josephin, J. S. F., Lakshmi, C., James, S. J. (2020). A review on the measures and techniques adapted for the detection of driver drowsiness. In: IOP Conference Series: Materials Science and Engineering, 993, 012101.

Kaida, K., Takahashi, M., Åkerstedt, T., Nakata, A., Otsuka, Y., Haratani, T., Fukasawa, K., 2006. Validation of the Karolinska sleepiness scale against performance and EEG variables. Clin. Neurophysiol. 117, 1574–1581.

Kim, J., Shin, M., 2019. Utilizing HRV-Derived Respiration Measures for Driver Drowsiness Detection. Electronics 8, 669.

Lawoyin, S., Liu, X., Fei, D., Bai, O., 2014. In: Detection Methods for a Low-cost Accelerometer-based Approach for Driver Drowsiness Detection. and Cybernetics (SMC), Man, pp. 1636–1641.

Lenné, M.G., Jacobs, E.E., 2016. Predicting drowsiness-related driving events: a review of recent research methods and future opportunities. Theor. Issues Ergon. Sci. 17 (5-6), 533–553.

Lenné, M.G., Jacobs, E.E., 2016. Predicting drowsiness-related driving events: a review of recent research methods and future opportunities. Theor. Issues Ergon. Sci. 17 (5–6), 533–553.

Li, G., Chung, W.-Y., 2014. Estimation of Eye Closure Degree Using EEG Sensors and Its Application in Driver Drowsiness Detection. Sensors 14, 17491–17515.

Liu, Y.-t., Lin, Y.-Y., Wu, S.-L., Chuang, C.-H., Lin, C.-T., 2016. Brain Dynamics in Predicting Driving Fatigue Using a Recurrent Self-Evolving Fuzzy Neural Network. IEEE Trans. Neural Networks Learn. Syst. 27 (2), 347–360.

Liu, W., Qian, J., Yao, Z., Jiao, X., Pan, J., 2019. Convolutional Two-Stream Network Using Multi-Facial Feature Fusion for Driver Fatigue Detection. Future Internet 11, 115.

Ma, Z., Li, B.C., Yan, Z., 2016. Wearable driver drowsiness detection using electrooculography signal. IEEE Topical Conference on Wireless Sensors and Sensor Networks (WiSNet) 41–43.

Mashko, A., 2017. Subjective methods for assessment of driver drowsiness. Acta Polytechnica CTU Proceedings 12, 64–67.

McDonalda, A.D., Leeb, J.D., Schwarzc, C., Brown, T.L., 2018. A contextual and temporal algorithm for driver drowsiness detection. Accid. Anal. Prev. 113, 25–37.

Nguyen, T., Ahn, S., Jang, H., Jun, S.C., Kim, J.G., 2017. Utilization of a combined EEG/ NIRS system to predict driver drowsiness. Sci. Rep. 7, 43933.

Park S., Pan F., Kang S., Yoo C.D. (2017) Driver Drowsiness Detection System Based on Feature Representation Learning Using Various Deep Networks. Asian Conference on Computer Vision. Computer Vision – ACCV 2016 Workshops. 154-164.

Quddus, A., Shahidi Zandi, A., Prest, L., Comeau, F.J.E., 2021. Using long short term memory and convolutional neural networks for driver drowsiness detection. Accid. Anal. Prev. 156, 106107.

Rajamohana, S.P., Radhika, E.G., Priya, S., Sangeetha, S., 2021. Driver drowsiness detection system using hybrid approach of convolutional neural network and bidirectional long short term memory (CNN_BILSTM). Mater. Today:. Proc. 45 (2), 2897–2901.

Reddy, B., Kim, Y.-H., Yun, S., Seo, C., Jang, J., 2017. Real-Time Driver Drowsiness Detection for Embedded System Using Model Compression of Deep Neural Networks. IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW) 438–445.

A. Sahayadhas, K. Sundaraj, M.J.S. Murugappan, (2012). Detecting driver drowsiness based on sensors: a review Sensors, 12 (12) (2012), pp. 16937-16953.

Sahayadhas, A., Sundaraj, K., Murugappan, M., 2012. Detecting Driver Drowsiness Based on Sensors: A Review. Sensors 12, 16937–16953.

Saif, A.F.M.S., Mahayuddin, Z.R., 2020. Robust Drowsiness Detection for Vehicle Driver using Deep Convolutional Neural Network. Int. J. Adv. Comput. Sci. Appl. 11 (10), 343–350.

Sandberg, D., Anund, A., Fors, C., Kecklund, G., Karlsson, J.G., Wahde, M., Akerstedt, T., 2011. The Characteristics of Sleepiness during Real Driving at Night- A Study of Driving Performance. Physiology and Subjective Experience. Sleep. 34 (10), 1317–1325.

Shaik, M.E., Islam, M.M., Hossain, Q.S., 2021. A review on neural network techniques for the prediction of road traffic accident severity. Asian Transp. Stud. 7, 100040.

Shih TH., Hsu CT. (2017) MSTN: Multistage Spatial-Temporal Network for Driver Drowsiness Detection. Asian Conference on Computer Vision, Computer Vision – ACCV 2016, Workshops, 146-153.

Shuyan, H., Gangtie, Z., 2009. Driver drowsiness detection with eyelid related parameters by support vector machine. Expert Syst. Appl. 36, 7651–7658.

Siddiqui, H.U.R., Saleem, A.A., Brown, R., Bademci, B., Lee, E., Rustam, F., Dudley, S., 2021. Non-Invasive Driver Drowsiness Detection System. Non-Invasive Driver Drowsiness Detection System. Sensors 21 (14), 4833.

Sommer, D., Golz, M., Trutschel, U., Edwards, D., 2010. Biosignal based discrimination between slight and strong driver hypovigilance by support-vector machines. Agents and Artificial Intelligence. 67, 177–187.

Taherisadr, M., Dehzangi, O., 2019. EEG-Based Driver Distraction Detection via GameTheoretic-Based Channel Selection. In: Advances In Body Area Networks I. Springer, Cham., pp. 93–105

Van Dongen, H.P.A., 2004. Comparison of mathematical model predictions to experimental data of fatigue and performance. Aviat. Space Environ. Med. 75, A15–A36.

Vijayan, V., Elizabeth, S., 2019. Real time detection system of driver drowsiness based on representation learning using deep neural networks. J. Intell. Fuzzy Syst. 36 (3), 1–9.

Vu, T. H., An, D., Wang, J-C. (2019). A Deep Neural Network for Real-Time Driver Drowsiness Detection, IEICE Transactions on Information and Systems, E102.D, 12, 2637-2641.

Vural, E., Çetin, M., Erçil, A., Littlewort, G., Bartlett, M.S., Movellan, J.R., 2009. Machine Learning Systems for Detecting Driver Drowsiness. 2680827, Corpus ID.

Wang, X., Xu, C., 2016. Driver drowsiness detection based on non-intrusive metrics considering individual specifics. Accid. Anal. Prev. 95, 350–357.

Wang, H., Zhang, C., Shi, T., Wang, F., Ma, S., 2015. Real-Time EEG-Based Detection of Fatigue Driving Danger for Accident Prediction. Int. J. Neural Syst. 25 (2), 1550002.

Warwick, B., Symons, N., Chen, X., Xiong, K., 2015. Detecting Driver Drowsiness Using Wireless Wearables. In: IEEE 12th International Conference on Mobile Ad Hoc and Sensor Systems, pp. 585–588.

Weng CH., Lai YH., Lai SH. (2017) Driver Drowsiness Detection via a Hierarchical Temporal Deep Belief Network. Workshops. ACCV 2016. Asian Conference on Computer Vision, Computer Vision – ACCV 2016 Workshops. 117-133.

Wijnands, J.S., Thompson, J., Nice, K.A., Aschwanden, G.D.P.A., Stevenson, M., 2020. Real-time monitoring of driver drowsiness on mobile platforms using 3D neural networks. Neural Comput. & Applic. 32 (13), 9731–9743.

Yu, J., Park, S., Lee, S., Jeon, M., 2019. Driver Drowsiness Detection Using Condition-Adaptive Representation Learning Framework. IEEE Trans. Intell. Transp. Syst. 20 (11), 4206–4218.

Zhang, W., Cheng, B., Lin, Y., 2012. Driver Drowsiness Recognition Based on Computer Vision Technology. Tsinghua Sci. Technol. 17 (3), 354–362.

Zhang, X., Wang, X., Yang, X., Xu, C., Zhu, X., Wei, J., 2020. Driver Drowsiness Detection Using Mixed-effect Ordered Logit Model Considering Time Cumulative Effect. Analytic Methods in Accident Research. 26, 100114.

Zhao, L., Wang, Z., Zhang, G., Gao, H., 2020. Driver drowsiness recognition via transferred deep 3D convolutional network and state probability vector. Multimed. Tools Appl. 79 (35-36), 26683–26701.

Zhu, M., Chen, J., Li, H., Liang, F., Han, L., Zhang, Z., 2021. Vehicle driver drowsiness detection method using wearable EEG based on convolutional neural network. Neural Comput. Applic. 33, 13965–13980.

Zhu, X., Zheng, W., Lu, B., Chen, X., Chen, S., Wang, C., 2014. EOG-based drowsiness detection using convolutional neural networks. Int. Joint Conf. Neural Netw. (IJCNN) 128–134.