Review Paper

A systematic review of physiological signals based driver drowsiness detection systems

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Abstract

Driving a vehicle is a complex, multidimensional, and potentially risky activity demanding full mobilization and utilization of physiological and cognitive abilities. Drowsiness, often caused by stress, fatigue, and illness declines cognitive capabilities that affect drivers' capability and cause many accidents. Drowsiness-related road accidents are associated with trauma, physical injuries, and fatalities, and often accompany economic loss. Drowsy-related crashes are most common in young people and night shift workers. Real-time and accurate driver drowsiness detection is necessary to bring down the drowsy driving accident rate. Many researchers endeavored for systems to detect drowsiness using different features related to vehicles, and drivers' behavior, as well as, physiological measures. Keeping in view the rising trend in the use of physiological measures, this study presents a comprehensive and systematic review of the recent techniques to detect driver drowsiness using physiological signals. Different sensors augmented with machine learning are utilized which subsequently yield better results. These techniques are analyzed with respect to several aspects such as data collection sensor, environment consideration like controlled or dynamic, experimental set up like real traffic or driving simulators, etc. Similarly, by investigating the type of sensors involved in experiments, this study discusses the advantages and disadvantages of existing studies and points out the research gaps. Perceptions and conceptions are made to provide future research directions for drowsiness detection techniques based on physiological signals.

Keywords

Driver drowsiness detection
Heart rate
Respiration rate
Eye movement
Respiration rate
Muscle response
Brain function
Physiological signals

Introduction

Vigilance, mobilized physiological and cognitive resources and active cognitive performance are the needed traits while driving a vehicle. Driving a vehicle is a complex, multidimensional, and potentially risky activity that demands prudence on the driver's part. Safety is the main factor that should be considered during driving. The drivers should play their part to keep the road secure for others and themselves while driving a motorized vehicle. They should maintain concentration on the road to avoid accidents. With the advancement of technologies, many motorized vehicle manufacturing companies have started to work on driver's safety while driving, especially regarding drowsiness. Drowsiness refers to a state of impaired awareness where the driver is inclined toward sleep than wakefulness (Slater 2008). Often, fatigue and drowsiness are used interchangeably however fatigue is one of the factors that cause drowsiness. Drowsiness leads to impairments such as reduced vigilance, slow reflexes, lack of decision-making capability, slow reaction time, etc. (Ashraf et al. 2019; Khushaba et al. 2010). Several approaches focus only on fatigue detection using the image, physiological signals, and behavioral features (Liu 2021; Yang et al. 2021; Du et al. 2020; Gjoreski 2020).

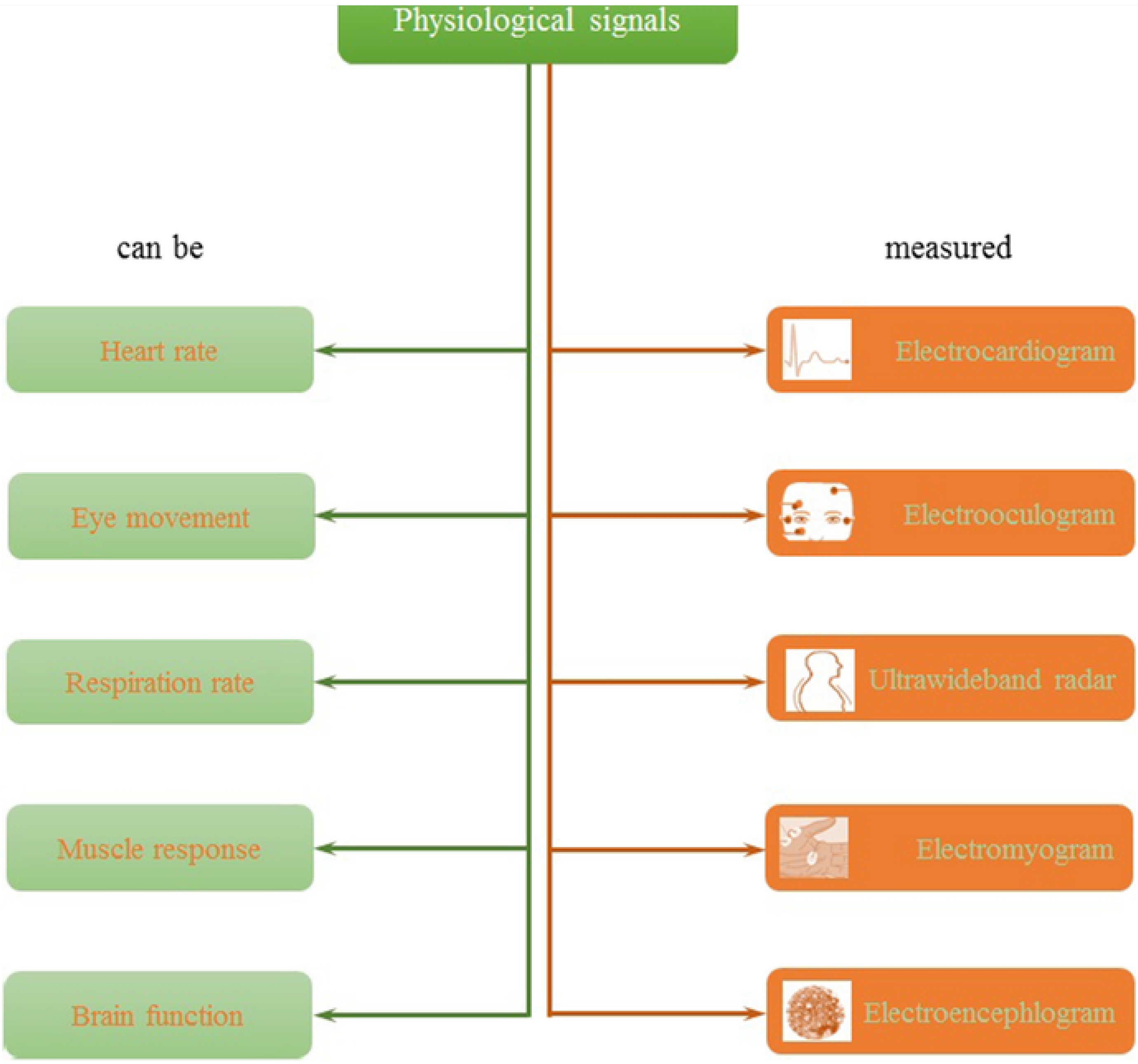
Driver drowsiness is associated with an increased number of accidents (Josephin et al. 2020). While driving on highways, a vehicle covers a distance equal to a football field in 3 to 4 s which indicates that seconds of inattention can lead to severe outcomes (National Security Council 2020). Drowsiness declines cognitive performance that affects drivers' capability and causes many accidents. Driving without sleep for more than twenty hours has an impact similar to having a 0.08% (US legal limit) blood-alcohol concentration level (National Security Council 2020). According to the World Health Organization (WHO) report, deaths related to road accidents exceed one million (World Health Organization et al. 2018). Recent studies show that 30% of fatal accidents take place due to drivers' fatigue or drowsiness (Martiniuk 2013). There are three times higher chances of road accidents if the driver is fatigued (National Security Council 2020). Similarly, a study conducted by the American automobile association (AAA), a foundation for traffic safety, estimated 328,000 drowsy driving crashes which caused a financial loss of $109 billion, not to mention the human loss (National Security Council 2020). National highway safety traffic administration (NHSTA) states that 4111 people died while another 50,000 were injured in the US due to drowsiness between 2013 and 2017 alone (National Highway Traffic Safety Administration 2017). The reports reveal that the night shift male workers of 16 to 29 years of age and the highest risk of drowsiness is associated with people suffering from sleep apnea syndrome (National Center on Sleep Disorders Research 2013).

Increased road accidents associated with drowsiness necessitated the design of drowsiness detection techniques and systems and recent years have witnessed many systems to monitor and alert drivers drowsiness. Driver drowsiness detection system helps in timely fatigue and drowsiness detection that can help decrease the number of accident rates, and financial loss and save lives. Driver drowsiness approaches can be categorized with respect to several parameters. For example, considering the drowsiness detection technique, it can be grouped into image-based, EEG-based, vehicle behavior-based, artificial intelligence-based techniques, etc. The more general categorization, however, is regarding the features used for drowsiness detection which puts all the techniques under three groups (Sahayadhas et al. 2013)

- Behavioral features,
- Vehicular features, and
- Physiological features

Fig. 1

Physiological features and sensors that can be used for drowsiness detection



Vehicular features, also called environmental features, continuously monitor the vehicle movement patterns over time, detect abnormal features like rapid line change, abrupt increase or decrease in the speed, etc. and attribute them to different causing factors (Sałapatek et al. 2017). Behavioral features represent the physical cues/features from the driver mostly detected through visual tools such as camera and detect symptoms related to drowsiness like yawning, fatigue, eye movement, etc. (Saini and Saini 2014). Physiological features, on the other hand, focus on signal measures using different devices like electrocardiogram (ECG), EEG, heart rate measurement, etc. for drowsiness detection (Awais et al. 2017). An illustration of physiological features and the sensors to obtain such features is provided in Fig. 1.

Comparison with previous reviews

LaRocco et al. (2020) conducted a systematic review analysis on low-cost, consumer EEG-based drowsiness detection systems. The authors analyze the reliability of EEG headsets for drowsiness detection. A total of 47 articles are included in the systematic review and conclude that spectral features are more significant for drowsiness detection. Similarly, Nemcová et al. (2020) present a comprehensive review of multimodal features for detecting driving fatigue and stress. In this regard, the test datasets, testing environments, and stress and fatigue detection methods are discussed. However, as pointed out before, drowsiness is different from fatigue, and fatigue is just an indicator of drowsiness. The neuroimaging-based driver behavior detection methods are reviewed by Haghani et al. (2021). The EEG, fMRI (functional magnetic resonance imaging), fNIR (near-infrared) spectroscopy, and MEG (Magnetoencephalography) based methods are reviewed for driver fatigue, distraction, intoxication, and decision-making capability tasks where the initial two methods are found to be the most commonly adopted methods for this purpose. A systematic review of behavioral features-based approaches for drowsiness detection is provided by Caryn and Rahadianti (2021). The study analyzes the use of various machine learning and deep learning models and feature extractions approaches in this regard.

Tian et al. (2021) performs a systematic literature review using 80 articles on EOG signals. Especially the multi-feature fusion techniques are studied with respect to their performance for fatigue and drowsiness detection. In addition, an analytical overview of the classification technique is provided. A review of approaches covering the influence of age on driving performance is presented by Scarpelli et al. (2021). The study includes a systematic review of 10 studies including studies using self-reported measures, behavioral tasks, and objective measures with ECG signals. A review of different multi-sensors, smartphone-based, and cloud-based platforms for driver fatigue and drowsiness detection approaches is done by Abbas et al. (2021). The problems related to machine learning and deep learning techniques are also covered. Specifically, the models and architectures following multimodal features of the driver are discussed. Similarly, Doudou et al. (2020) provide a review of commercial products available to detect drowsiness based on vehicle features, driver behavior, and driver physiological signals. Different technologies are discussed regarding the methods and type of features along with their advantages and disadvantages. Intrusive and non-intrusive techniques are discussed separately regarding their accuracy, intrinsic limitations, and challenges.

Insights on existing woks and research gaps

Discussion of the existing works given in Table 1 reveals several important points. First, not all the reviews specifically focus on different sensors, rather focus only on one kind of sensor. For example, LaRocco et al. (2020) study the use of EEG signals from the influence of age on drowsiness, and Doudou et al. (2020) analyze commercial products available for driver drowsiness detection. Also, Haghani et al. (2021) follows the studies that leverage neuroimaging-based methods. Second, while analyzing these sensors and approaches, inherent limitations and practical hindrances are overlooked or not very well described. Certain authors specifically focus on the feature aspect of drowsiness detection models. For example, Nemcová et al. (2020) focus on those studies that make use of multi-modal features while Caryn et al. (2021) consider those studies that analyze behavioral features like yawning, eye blink, etc. The current study, on the other hand, analyzes approaches that utilize physiological signals like EEG, ECG, heart beat rate, respiration rate, etc. By analyzing such recent works, the study provides a more comprehensive overview of recent works which have been missed by previous studies. Also, a wide range of physiological signal sensors is covered in a single study which fills the research gaps in existing reviews.

Table 1

A comparative analysis of existing reviews/surveys on drowsiness detection

References	Articles	Covered topics	Scope	Findings
LaRocco et al. (2020)	47	Consumer EEG	Review of low cost consumer EEG headsets	Necessity of algorithmic optimization.
				Approaches lack standard calibration and direct comparison is difficult.
				Spectral features are robust and more accurate.
				Low-cost consumer devices have reliability issues.
Nemcová et al. (2020)	120	Multimodal features	Review of test datasets, stress, and fatigue	Predominantly, experiments use simulation environments.
				Data fusion increases the stress and fatigue classification.
				Time pressure, work requirements, shift restrictions, long travel, etc. push drivers to continue driving even while fatigued.
	86	Neuroimaging methods	Covers the approaches based on neuroimaging technology like EEG and MEG, etc.	EEG and fNIRS use mobile equipment, fMRI and MEG need fixed scanners.
				Often, young and healthy drivers are used for experiments.
				Driver with brain impairments is studied very less.
Caryn et al. (2021)	41	Behavioral features	Approaches based on driver behavioral features like yawning, eye lid close, etc.	For the most part, machine learning models are used with behavioral features.
				For highly accurate classification, large datasets and training time are required.
				Lack of behavioral features based on publicly available datasets.
Tian et al. (2021)	80	EOG approaches	Analyzes EOG approaches including single and multimodal features	Multi-feature-based techniques using EOG signals perform better
				EOG approaches are low cost, low power, and low intrusion
				EOG applications are limited regarding driver drowsiness
Scarpelli et al. (2021)	10	Age impact on driver performance	Age based analysis for driver performance	Older drivers are less prone to sleep loss
				The influence of sleepiness-related impairment is high for the younger driver.
				Older people avoid risky scenarios by self-regulating their driving
Abbas et al. (2021)	146	Smartphone-based hypervigilance	The study covers multimodal features based mobile and edge computing architectures	Smartphone and edge-based hypervigilance systems provide low-cost solutions.
				Majority of the solutions utilize vision approaches.
				Use of 5G can increase the efficiency of image-based approaches for edge-based solutions.
Doudou et al. (2020)	138	Market products for drowsiness detection	The study covers commercial solutions based on driver, vehicle, and behavioral features	Several approaches can not distinguish between the drowsiness and band driving attitude
				Using multiple physiological signals is expensive and difficult to implement for real-time scenarios.
				Physiological signals are difficult to get and are prone to many challenges.

Major contributions

Many researchers presented driver drowsiness detection systems that utilize different features related to subjective ratings, vehicle characteristics, and driver behavior, in addition to physiological measures. Despite a large body of published material on physiological signals-based drowsiness detection, a systematic review of physiological signals-based techniques is scarce. In this study, recent diverse solutions to driver physiological signal-based drowsiness detection systems are explored and presented. Aiming to efficiently review the recent progress in the said domain to make an understanding of physiological signal-based driver drowsiness detection for the readers, the study provides insights on the recent developments in physiological signal-based driver drowsiness detection. This study presents a survey in this regard and fills the gap by making the following contributions

- A comprehensive systematic literature review of the recent techniques to detect driver drowsiness using physiological sensors is presented.
- Various physiological data collection techniques are analyzed with respect to several aspects such as data collection sensor, environment consideration like controlled or dynamic, experimental set up like real traffic or driving simulators, etc.

- Respiration rate-based approaches are analyzed separately regarding their advantages and limitations for driver drowsiness detection.
- Sensors used for experiments are discussed regarding the advantages and disadvantages and research gaps are discussed. Perceptions and conceptions are made to provide future research directions for drowsiness detection techniques based on physiological signals.

Table 2

List of acronyms used in this study

Acronym	Details	Acronym	Details
1D-TDCNN	1D-temporal deep dilated CNN	AAA	American automobile association
ADB	Alarm test driving database	ANOVA	Analysis of variance
ARTL	Adaption regularization based transfer learning	BCI	Brain–computer interaction
BVP	Blood volume pulse	CNBSL	Complex network-based broad learning system
CNN	Convolutional neural network	CSDF	Class separation and domain fusion
CT	Complex tree	CW	Continuous wave
CWGAN	Conditional wasserstein GAN	DBN	Deep-belief network
DFA	Detrended fluctuation analysis	DFT	Discrete Fourier transform
DL	Deep learning	D-LSTM	Deep LSTM
DNN	Deep neural network	DOD	Degree of drowsiness
DQN	Deep Q networks	ECG	Electrocardiogram
EDA	Electro-dermal activity	EEG	Electroenchyphlogram
ELM	Extreme learning machine	EMG	Electromyography
EOG	Electrooculography	ESS	Epworth Sleepiness Scale
fMRI	Functional magnetic resonance imaging	fNIR	Functional near-infrared
FFBPNN	Feed-forward backpropagation neural network	FFT	Fast Fourier transform
FIR	Far infrared	GAN	Generative adersarial network
H-ELM	Hierarchal ELM	HF	High frequency
HFD	Higuchi fractal dimension	HHT	Hilbert–Huang transform
HOG	Histogram of oriented gradients	HRV	Heart rate variability
IBI	Inter-beat interval	ICA	Independent components analysis
I/E	Inspiration and expiration	IMF	Intrinsic mode function
IoT	Internet of Things	IR-UWB	Impulse radio ultrawideband
KNN	K nearest neighbor	KSS	Karolinska Sleepiness Scale
LBP	Local binary patterns	LCD	Liquid crystal display
LDA	Least discriminant analysis	LF	Low frequency
LR	Logistic regression	LSTM	Long short term memory
MEG	Magnetoencephalography	MI	Magnetic induction
ML	Machine learning	MLP	Multi-layer perceptron
MME	MiniMax entropy	MMSE	Modified Multi-Scale Entropy
MS	Microsleep	MWRN	Ultivariate weighted recurrence networks
NHSTA	National highway safety traffic administration	NN	Neural networks
OP	Oximetry pulse	P+	Positive predictive value
PCA	Principal component analysis	PCB	Printed circuit board
PERCLOS	Percentage closure of eyes	PPG	Photo plethysmo graphy
PPG-PRS	PPG pattern recognition system	PSD	Power spectral density
PSO	Particle swarm optimization	PSO-H-ELM	Particle swarm optimization H-ELM
PSQI	Pittsburgh Sleep Quality Index	PVT	Psychomotor vigilance task
RBFNN	Radial basis function-neural network	RRI	R-wave Interval
PRISMA	Preferred reporting items for systematic reviews and meta-analyses	RDB	Real driving database
RF	Random forest	RGB-D	Red green blue-depth
RRV	Respiration rate variability	RRS	Respiratory rate slope
RSA	Respiratory sinus arrhythmia	SC	Skin conductance
SD	Standard deviation	SDB	Simulated driving database
SDLP	Standard deviation of lateral position	SEED-VIG	Simulated virtual driving drivers
Se	Sensitivity	SFFS	Sequential forward floating selection
SIFT	Scale invariant feature transform	SFFT	Short FFT

Acronym	Details	Acronym	Details
Sp	Specificity	SVM	Support vector machine
SWA	Steering wheel acceleration	TEDD	Thoracic effort derived drowsiness
THW	Time headway	TLC	Time to lane crossing
VMD	Variational mode decomposition	WHO	World Health Organization
WoS	Web of science	WT	Wavelet transform

Table 2 provides the acronyms used in this study.

Organization of paper

The rest of this study is divided into nine sections. Section 2 presents the research methodology used in this study, followed by the discussion of respiration-based drowsiness detection methods in Sect. 3. Sections 4 and 5 presents the approaches based on the ECG and EEG sensors. Various machine learning and deep learning models are discussed along with the commonly used features dir drowsiness detection. Analysis of techniques related to GSR is given in Sect. 6. Thermal camera-related approaches are presented in Sect. 7 while the multimodal approaches are discussed in Sect. 8. Section 9 provides the discussions and future directions. In the end, the study is concluded in Sect. 10.

Research methodology

The most important step for a systematic literature review is to devise the search strategy for selecting the most appropriate research papers. For this paper, most relevant, as well as, most recent research papers should be considered. This study selects two important and prominent research databases/engines for this purpose and executes the search query on WoS and Google scholar. Google Scholar is a free service that compiles results from throughout the Internet. As a result, it has gained a great deal of attention as a tool for searching the literature, especially in searches for grey literature, as needed by systematic reviews. Shultz et al. (2007) discovered that Google Scholar offered free access to nearly three times as many articles than PubMed. PubMed and WoS are human-generated databases which provides accurate retrieval indicating that search results are reproducible and reportable. On the contrary, Google Scholar is a search engine of the whole internet and can narrow down the results to 'scholarly' articles based on machine automated criteria (Kendall 2019). Since this review aims at analyzing the studies using the physiological signals only, the search query contains the physiological signals utilized for driver drowsiness detection. The search query is executed on the Google scholar and WOS core collection that contains over 82 million records and covers 21,894 journals, in addition to books and conferences. The WOS covers citation index for science, social sciences, arts and humanities, conference proceedings, book citation, emerging sources, Chemicus, and current chemical reactions (Clariavate 2021). The study follows the recommendations provided by PRISMA. A systematic review aims at providing an understanding of a specific research area by discussing the current tools and techniques and their associated pros and cons (Alamoodi 2021). It also provides the research gaps in the current literature and discusses comprehensive future directions (Dani et al. 2019).

Papers searching strategy

Research studies for this review are searched with the aim to obtain the relevant papers. To extract the papers, an efficient search query is defined by considering the keywords found in the papers related to driver drowsiness. The following query is prepared

(TS=drows) AND ((TS=physiological signals) OR (TS=ECG) OR (TS=EEG) OR(TS=UWB) OR (TS=machine learning) OR (TS=deep learning) OR (TS=data analysis))*

Papers inclusion criteria

We defined inclusion criteria to include a research paper in the review if it meets the following conditions.

- Research papers that utilize statistical tools and techniques for drowsiness detection.
- Studies that use machine learning and deep learning algorithms.
- Studies that evaluated drowsiness detection techniques using the physiological signals only such as ECG, EEG, EOG, respiration rate, etc.

Exclusion criteria

In addition to an inclusion criterion, the following exclusion criterion is used to exclude irrelevant studies.

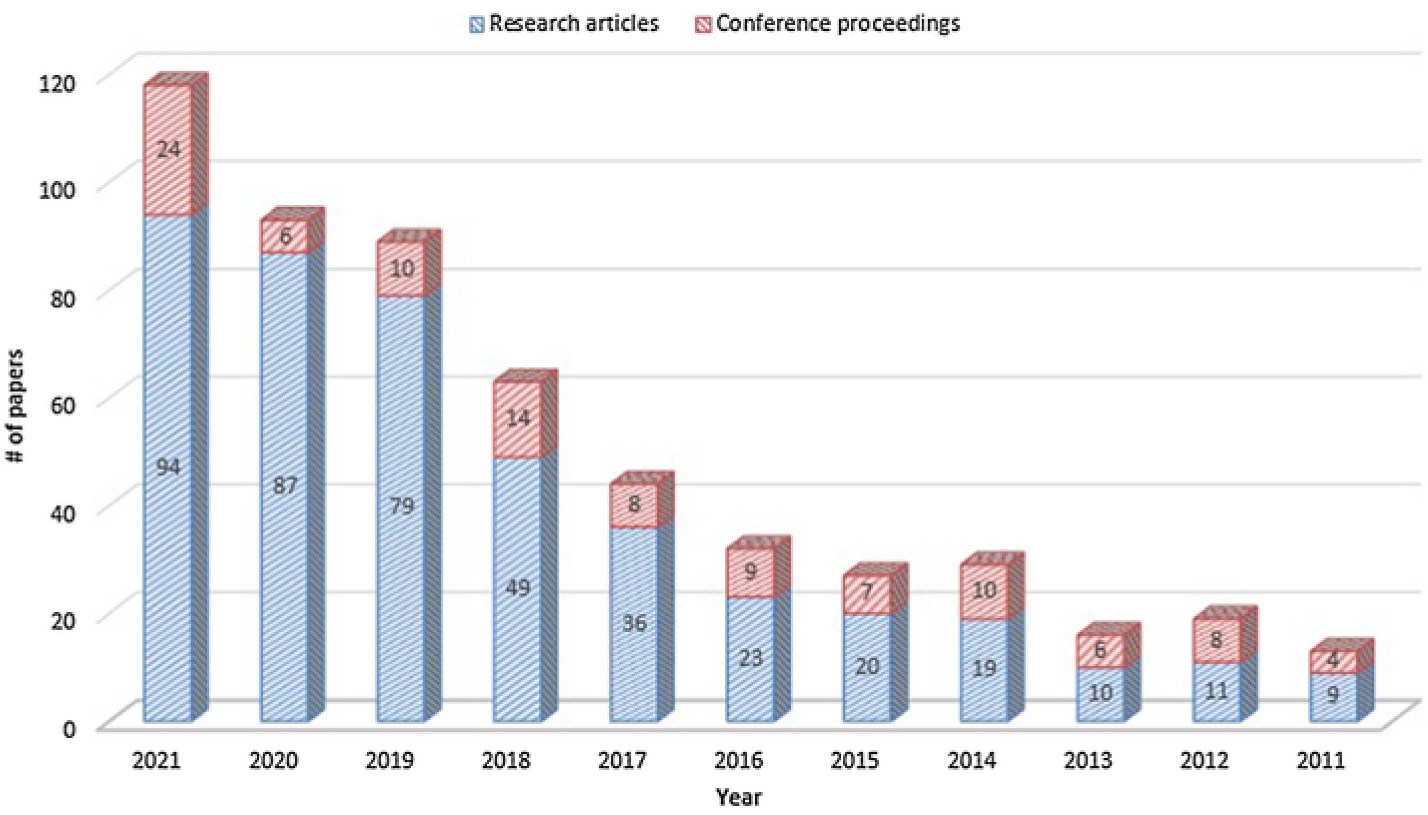
- Studies focusing on problems that are not directly related to drowsiness detection. It is used to ensure that only the most relevant studies are selected. Several studies focus on investigating the driver behavior while driving the vehicle and drowsiness detection is not included in those objectives. Such studies are removed from the selection.
- Studies using subjective measures or behavioral features for drowsiness detection. Subjective measures include answering questionnaires from the drivers or monitoring the drivers by external observers that use intensity ratings for driving drowsiness. Such studies are excluded from the selected articles.
- Survey or review studies. A rich variety of survey papers are also available for driver behavior monitoring including drowsiness detection. The surveys are not part of the analysis carried out in this study.

Papers selection

Search query results into 502 articles containing articles, conference proceedings, review articles, etc.; a distribution of retrieved papers are presented in Fig. 2. 8 research papers are excluded including 4 papers in Russian, 3 in Chinese, and 1 in the French language. Next, the papers published from 2011 to 2021 are considered only, making it 161 papers. These papers are manually examined by reading their abstracts to check their relevance to the topic under study. Several papers are found unrelated and removed. For example, papers covering feature extraction approaches for image-based drowsiness detection are removed. Similarly, many conference proceedings with minor contributions are not included in this study.

Fig. 2

Year-wise and paper type-wise distribution of the articles



Research questions

Research questions help in determining the starting point of a systematic literature review and define the scope of the study. This review defines the following research questions

- *RQ1* What kind of physiological signals have been used for driver drowsiness detection?
- *RQ2* What are the approaches used for different kinds of physiological signals-based methods?
- *RQ3* What are the traditional machine learning and deep learning models used for physiological signal-based drowsiness detection?
- *RQ4* What kind of experimental setup is used for validating the approaches?
- *RQ5* What kind of environment/scenarios are used for experiments?
- *RQ6* What kind of features are used for physiological signals-based approaches?
- *RQ7* Which type of physiological signals provide high accuracy for driver drowsiness detection?
- *RQ8* Which factors affect the performance of physiological signals-based drowsiness detection approaches?
- *RQ9* What are the limitations of existing approaches?

Respiration based drowsiness detection

This section contains the discussion of the research works that utilize respiration signals for driver drowsiness. Besides the discussion of works that use respiration data, a few works that use heart rate in addition to the respiration data are also discussed. Since such works use the data from a single and the same sensors for both respiration and heart rate measurement, they are discussed as single model approaches. Respiration rate is one of the factors correlated to drowsiness as the respiratory system exhibit different patterns during drowsiness and wakefulness. Several studies have analyzed the changes in the respiration rate for sleep and wakefulness (Helakari et al. 2020; Rodríguez-Ibáñez et al. 2014). Additionally, significant changes are observed in the inhaling to exhaling ratio (Cai et al. 2020). Such features make the respiration rate a suitable candidate for drowsiness detection. Consequently, a wide range of works can be found on approaches that leverage respiration rate for driver drowsiness detection.

For example, a system is proposed by Sharma et al. (2015) to detect drowsiness using respiration signals. Respiration signals of the one-hundred-fifty drivers are acquired for pre and post-driving states for three to five minutes in a real environment. The features from pre and post-driving states are used to analyze the difference in the respiration signals. For this purpose, different feature sets are utilized where feature set 1 has fifty-six features of DMeyer wavelet at level four decomposition, and feature set 2 includes thirty-seven features extracted versions implemented. K-means algorithm in three different versions is used for classification. Here, the fundamental notion of classifying data based on the smallest distance between clusters was applied. In version 1, each column of the feature matrix was considered a separate input to the K-means algorithm. In version 2, the variance of each dataset column was computed and utilized as an input for the K-means algorithm. Version 3 processed data rows as object arrays rather than individual columns. The classification accuracy is obtained at specific decomposition levels of the implemented filter. Experiments reveal that Daubechies wavelet can obtain a 100% accuracy when decomposed at level 3. Similarly, when decomposed at level 4, the DMeyer wavelet can also provide 100% accuracy. The selected features can be used for the fatigue classification.

Similarly, Guede-Fernandez et al. (2019) propose a system that uses a plethysmography belt to get the respiration rate for drowsiness detection. Respiration signals of twenty healthy subjects (ten males and ten females) of ages ranging between 20 to 60 years are recorded on two different days in a driving simulator. The simulator consists of a front screen and a car body that is equipped with the steering wheel, pedals, and automatic transmission. Experiments are conducted at room temperature with low light and highway sounds. A video camera is used to record the video of the experiment to validate the drowsiness signals by external observers. The noise from the respiration signal is removed by using a 0.5 Hz cutoff frequency with a low-pass filter while the baseline signal is cleaned with a high pass filter on a 0.05 Hz cutoff frequency. The RRV is obtained from the respiration signal. The ratings generated by the external observer are used to validate the system. The TEDD index is used for the classification of the collected dataset that achieves a sensitivity of 90% and specificity of 96.6%.

Respiration rate has also been used with the heart rate to increase the drowsiness detection efficiency, as by Leicht et al. (2017) which uses a safety belt to monitor heart rate and respiration for driver state recognition. The belt is equipped with two types of sensors including an optical sensor and an MI system. The former emits infrared light towards the body of the driver and the heart rate is detected by the reflection of the infrared light while the latter comprises an oscillator and a coil embraided on the safety belt. The orientation of the driver's body changes concerning coil while breathing causes a change in the frequency. That change in the frequency can be used to detect respirate. Keeping in mind regulatory and safety considerations, a textile cover comprising these sensors is made that can be positioned on the safety belt using Velcro tape. Respiration and heart rate signals are sampled equipped with a seat belt having an MI sensor is used for data acquisition. To validate the system, these ECGs and a piezoelectric sensor heart rate signal are processed using an FIR sensor of order twelve. The comparison of safety belt and validation sensors shows that a better respiration rate can be obtained using the MI system but it produces high-frequency noise in the signal which makes heart rate monitoring difficult.

The use of radar has been observed during recent endeavors for respiration-based drowsiness detection. An IR-UWB radar is used by Leem et al. in Leem et al. (2017) for vital signs and mobile usage detection of the driving to prevent accidents. Vital signs like respiration and heart rate are monitored in both moving and stationary drivers. The FFT is used to find respiration and heartbeat rate. The metals used in mobile phone manufacturing make it easy to detect the mobile phone using radar. The short movements while driving which are not dangerous for the driver should be ignored by any algorithm. For this dual-mode background subtraction method algorithm is used. When a cell phone is detected, the background is removed before updating the signal to detect minimal movement of the cellphone. An alarm is kept on beeping when the cellphone is detected. The clutter can be removed using a loopback filter. A sinusoidal fitting algorithm is used to detect the sinusoidal motion caused by respiration and heart pumping. R value can find the fit where the signals having low R square values are discarded. The radar is set up in the car and the detection region is divided into two parts—mobile detection and vital sign detection. Experimental results show that this proposed system detects mobile phones perfectly in most cases.

Gu et al. (2018) use a CW Doppler radar for fatigue detection. A CW radar placed on the car dashboard is used to acquire the respiration and heart rate of the driver. The experiment is performed on the heart and respiration signals collected from three healthy subjects in normal and fatigued states. Subjects face the digital Doppler radar placed 0.625 m away from the subjects. Data of normal state is gathered in the morning when the subjects feel fresh and fatigued data is collected in the afternoon because that causes the subjects to get fatigued easily Miao et al. (2017). The subjects have to sit in front of the radar for ten minutes. During the data collection, the status of the subject is asked every five minutes that is recorded as a reference. A decision tree is used for classification due to its capability to process non-linear characteristics and it shows an accuracy of 82.5% Lavanya et al. (2017).

The respiration signals can also be obtained from ECG signals. For example, the system proposed in Tateno et al. (2018) by Tateno et al. used respiration rates derived from ECG signals. Two experiments are performed. In the first experiment, the accuracy of the respiration rate is verified by calculating the respiration rate from the heart rate signal and by observing the actual respirations of four healthy subjects. The study uses a fingertip pulse wave sensor for acceleration pulse data at a sampling rate of 50 Hz. The time interval between neighboring peaks is calculated to form an RRI. Cubic spline interpolation is used to equal the sampling point intervals. The RSA information is extracted from interpolated RRI data using DFT that maps the complex $f(x)$ to the complex $f(t)$. RSA includes the HF component of HRV (0.15–0.4 Hz) so, a bandpass filter is used to remove the useless signal. An inverse DFT is applied to calculate RSA from the processed signal. The second experiment is performed to detect drowsiness in the driver. In this experiment heart rate data of four healthy subjects along with their facial expressions monitored using portrait recognition based on the android system is acquired. The heart rate signal is sampled at 50 Hz with a constant temperature of 25 degrees. The RRS of the linear regression equation is calculated by the least square method at a specific time. The DOD is associated with a pre-defined threshold (which is 3.0 in this case). The portrait recognition program detected drowsiness eleven-time and gave an accuracy of 72.7% while the accuracy achieved by Tateno et al. (2018) is 64.4%.

In addition to using the radar and different physical sensors placed around the arm, a vision camera and optimal camera have potential applications for acquiring the respiration rate. For example, Solaz et al. (2016) use two dynamic cameras to obtain videos that are processed for breathing rate. Two experiments are performed for data collection. First, the experiment is carried out to validate Kinect for a non-invasive breathing rate detector. Second, the experiment is performed to find the best position of the cameras for better results. Each camera is equipped with a microcontroller that is responsible for video signal transmission. Data collected from these cameras are then processed using a custom algorithm OCTAVE to find the breathing rate. The breathing rate is then compared with the results obtained from a Plethysmography band, an off-the-shelf chest band for respiration rate detection. Respiration signals of five males with ages 18 to 38 for normal sleep and deprived sleep are used for experiments in a driving simulator. Noise filter and image stabilization are leveraged to mitigate the impact of motion. Differential techniques are used to quantify motion levels. The solution Solaz (2016) is advantageous for driver fatigue detection as a non-invasively based on respiration signal.

In a similar fashion, Tayibnapis et al. (2016) employ an optical imaging technique to collect brainwave, cardiac and respiration data. A dashboard-installed IR camera is used to get facial images. From these captured images, fatigue is detected by visual behavior like eye, mouth and head poses. The use of PPG is made to obtain physiological signals heart rate, HRV, etc. in Poh et al. (2010). PPG obtains plethysmogram that can detect changes in blood volume. Viola-Jones algorithm is used to detect face region Viola and Jones (2001) while SIFT key points are extracted from facial images and stored in a database Lowe (2004). These extracted facial features are used to detect eye blinking, yawning, and head-nodding which helps in driver drowsiness detection. PPG extracts BVP from a sequence of facial images Allen (2007). HRV is acquired from BVP while respiration rate is obtained from the center of frequency of HF that varies between 0.15 and 0.4 Hz of HRV. A multi-class SVM is trained with the extracted facial and physiological features to obtain drowsiness results.

A drowsiness detection system based on respiration rate acquired using UWB radar is presented in Siddiqui (2021) by Siddiqui et al. Chest movement of 40 subjects is collected in pre (before driving) and post (after driving) driving states for five minutes using UWB radar. The area under the curve is used to obtain noisy respiration signals from the chest movement. A low pass Butterworth filter with order 10 and cutoff frequency of 0.04 is applied to obtain a respiration signal and subsequently, respiration per minute is obtained. The respiration rate obtained from the respiration signal is verified by the commercially available device Pulse Oximeter. A structured dataset is maintained comprising respiration per minute, age, and classes (drowsy/non-drowsy). Various ML classifiers are used for drowsiness detection including SVM, LR, DT, GBM, ETC, and MLP. SVM shows superior performance as compared to other models with an accuracy of 87% (Tables 3, 4, 5, 6, 7, and 8).

Table 3

A comparative summary of respiration based drowsiness detection approaches

References	Sub.	Sensor	Approach	Pros	Cons
Sharma et al. (2015)	150	–	K means	Achieved 100% accuracy using signals acquired in real-time environment	No explanation about signal acquisition. Also, the signals are only acquired before and after driving, not during the driving
Guede-Fernandez et al. (2019)	20	Plethysmography belt	–	Sensitivity of 90% is achieved by system	Virtual environment is used for signal acquisition. Invasive belt is used for signal acquisition
Leicht et al. (2017)	–	Optical sensor & MI coil	–	A cover for seat belt is made for signal acquisition that can be adjusted or removed by Velcro tape. Non-invasive signal acquisition is proposed	Data is collected in a controlled virtual environment. Heart rate is not monitored correctly due to high noise during inspiration
Leem et al. (2017)	–	IR-UWB	–	Signals acquired in real environment when driver is stationary or moving. Mobile usage is detected	The acquired Signals are used for classification purposes. Mobile usage is detected in a specific region
Gu et al. (2018)	3	CW Doppler radar	Decision tree	Decision tree achieves an accuracy of 82.5%. A non-invasive method for signal acquisition	Data collected in a controlled environment. The number of subjects used in experiments is too low
Tateno et al. (2018)	4	Fingertip wave pulse	–	Threshold system is designed that gives an accuracy of 64.4%. Respiration signals are acquired from ECG signals	Attachable sensor is used for signal acquisition. Time and resource usage while extracting respiration signals from ECG. Signals acquired in a controlled environment
Solaz et al. (2016)	5	PAC16 and FRCAM	–	Non-invasive method for acquisition of respiration signal is proposed	A virtual controlled environment is used for signal acquisition. Camera results can be affected by environmental factors in a real environment. Signals acquired but not used for classification or model training
Tayibnapis et al. (2016)	–	Infrared camera	SVM	Non-invasive method for acquisition of respiration signal is proposed and PPG is used for physiological signal calculation from images	Camera's result can be affected by environmental factors in a real environment. SVM is used for classification, but results are not mentioned. There is no explanation about how many subjects are used in the experiment
Siddiqui et al. (2021)	40	UWB	SVM	Non intrusive drowsiness detection without physical contact	The obtained accuracy is low as compared to other respiration based approaches. Data is gathered in a controlled environment

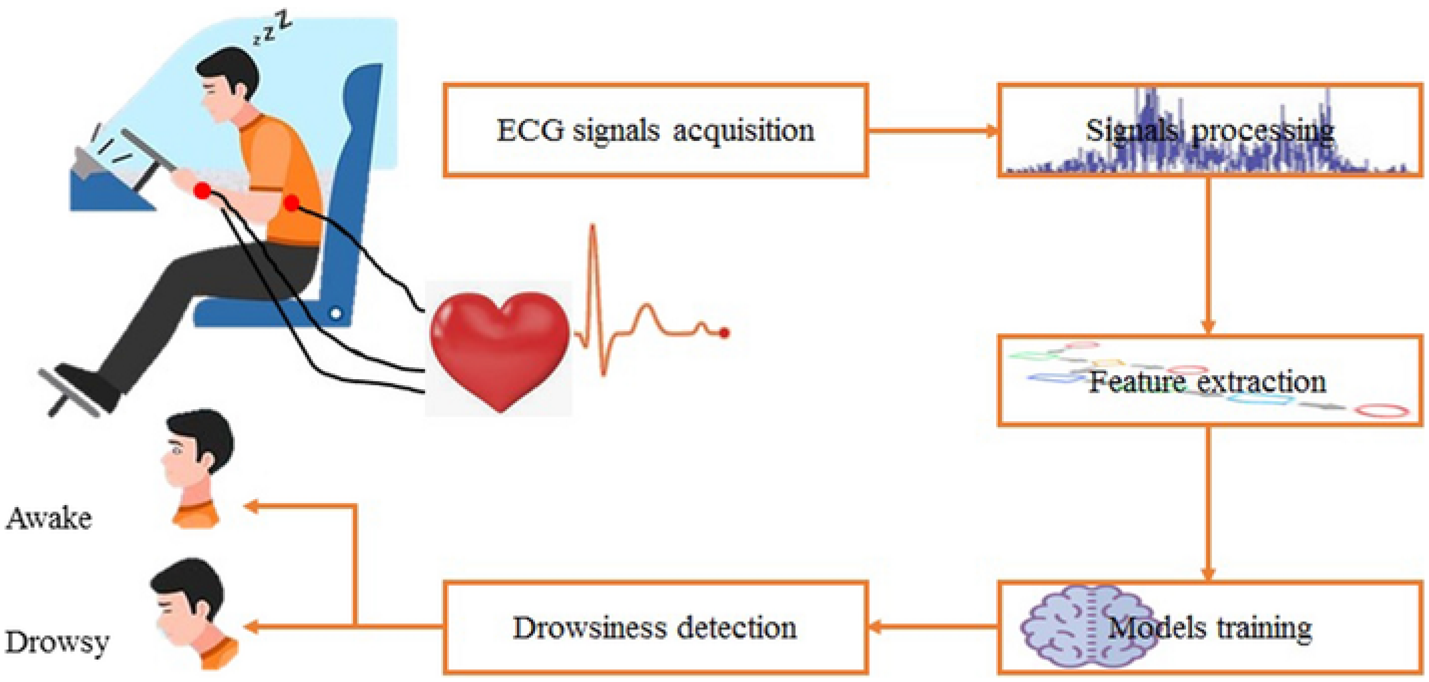
The studies that utilized the respiration rate make use of several sensors for determining the respiration rate. Such sensors are utilized with respect to the quality of provided data, nature of experiment portfolio, preference of features available for the data, and the desired accuracy. For example, plethysmography data using the plethysmography belt provides higher accuracy than using the UWB radar data. For the most part, the research is moving from contact-required approaches to contactless approaches where remote monitoring can be done using IR-UWB radar, vision cameras, and Doppler radar. Such sensors do not require to place electrodes, as required for ECG approaches, and can record the respiration rate and heart rate with moderate accuracy. DMeyer wavelet features at level 4 decomposition, FFT and DFT are often used for radar-acquired data. The use of multiple-vision cameras is another development in this regard, however, it is a computationally expensive approach and prone to error with small changes in the driver movement and is affected by lighting conditions. Predominantly, the research works leverage radar data for contactless driver drowsiness detection and invasive and contact-required approaches for higher accuracy.

Drowsiness detection using ECG signals

ECG-based drowsiness approaches fall under the banner of non-invasive technology. Comparatively ECG signals are less intrusive and can easily be captured. Different internal states and pathological conditions can be obtained from the ECG signals to detect driver drowsiness, among which is HRV which shows high resistance against noise. An illustrative process of ECG-based drowsiness detection is presented in Fig. 3.

Fig. 3

A flow of typical ECG based driver drowsiness detection approach



Two different methods are proposed for drowsiness detection based on HRV signals by Vicente et al. (2016). The study uses three different datasets including SDB, ADB, and RDB. SDB consists of ECG signals of nine volunteers and ADB consists of ECG recordings of eleven volunteers. RDB consists of ECG signals of ten volunteers. HRV signal is acquired from ECG signal, the QRS complex is detected and artifacts are identified to tune the dataset. The integral pulse frequency model and Wigner–Ville distribution are used for HRV signal estimation and smoothness, respectively. To measure the performance of the system, Se, P+, and Sp are estimated. Seven features are extracted from each minute of driving in the first method called drowsiness episode detector. The proposed method gives 0.96, 0.59, and 0.98 of P+, Se, and Sp, respectively. In the second method, sleep deprivation is estimated from the first three minutes of HRV data. This method gives 0.80, 0.62, and 0.88 P+, Se, and Sp, respectively.

Along the same direction, Gupta et al. (2017) detect drowsiness using ECG signals acquired by a wearable computing system. The system comprises a Zephyr BioHarness device and an Android application. Zephyr BioHarness is a device with a chest strap and BioHarness module that is used to acquire and transmit ECG signals. ECG signals are transmitted to the Android application after establishing a Bluetooth connection to determine the state of the subject (awake/sleepy). The actual sleep and awake driving dataset taken from PhysioBank datasets is used to test the system. The dataset contains physiological signals of actual sleep and awake drivers. The application is used to monitor the current activity of the driver and warning system. The system uses two algorithms. First, the algorithm is used to set a threshold value based on the average heart rate of the awake dataset of the driver. If the heart drops below the threshold, the algorithm categorizes it as drowsiness and an alert is generated for the user by the android application in the form of audio and vibration alerts. While the second algorithm finds a ratio of low to high frequency from the ECG signal used to set the threshold instead of average heart rate.

Driver fatigue detection based on ECG signals using deep learning and machine learning models is proposed by Bhardwaj et al. (2018). This study is based on two datasets. The first dataset is acquired on driving simulation and the other is acquired in a real environment with sleep deprivation and no sleep deprivation, respectively. In the dataset, ECG signals are collected from ten subjects of ages ranging from 22 to 31 years. The experiment is conducted on a driving simulator that comprises a steering wheel, feed pedals, gear shift lever, and LCD. ECG signals are acquired with the silver/silver chloride electrodes at a sampling rate of 150 Hz from the subject's chest and processed in MATLAB. A fourth-order bandpass Butterworth filter with a cutoff frequency of 0.5–40 Hz is applied to the ECG signals to remove noise. The time domain, frequency domain, and nonlinear HRV features are extracted for classification to ensure a high detection rate and accuracy. For classification, different machine learning models such as SVM, KNN, LR, CT, ensemble (subspace KNN), and ensemble (bagging trees) deep learning models such as stacked autoencoders are used. The study shows that deep learning models perform better than machine learning models. For machine learning models, the highest accuracy is achieved by KNN which is 95% while the deep learning model autoencoder achieved 96.6% accuracy which is better than ML models.

An accuracy of 91.4% and sensitivity of 91.5% is achieved by extracting new features from HRV signals to classify drivers' state of sleep by Babaeian et al. (2018). For this purpose, an annotated dataset of the driver's actual sleep from 'Physio.net' is used. Cyclic alternating pattern sleep data is used to generate this dataset. A threshold of 45% of the maximum of the signal is used to detect R-waves. RR intervals (time elapsed between two successive R waves) are extracted from these R-waves and time-domain features like standard deviation, NN50 (number of pairs of successive RR intervals after 50ms), PNN50 (proportion of NN50 divided by total RR intervals), root mean square, standard error and standard deviation of difference are then extracted for RR intervals. The geometric features like density distribution, triangular interpolation, and frequency domain features like resampling of linear interpolation, PSD, and frequency of PSD are used to calculate the magnitude and phase of each point and to create new signals using a Poincare plot. A total of 66 features are extracted from RR intervals and from new signals created using the Poincare plot. The T-test is used to reduce the number of features to 18. An MLP neural network is used for classification.

Correspondingly, Babaeian et al. (2019) present an innovative technique based on machine learning that uses biomedical signal analysis (HRV signals that are measured from ECG) to detect drowsiness in drivers. The dataset is collected for eight hours using three electrodes in both awake and sleep states of twenty-five subjects (eleven females and fourteen males of ages ranging between 20 and 60 years). An adaptive filter is applied to the acquired ECG signals for noise removal. Two machine learning algorithms KNN and SVM are applied to two different feature sets extracted using WT and SFFT. SVM and KNN achieved an accuracy of higher than 80%. An accuracy of 85.5% and 81.4% respectively for males and females is observed by KNN based on SFFT features. While on WT features, the accuracy of 88.3%

and 85.7% is achieved respectively for males and females. SVM obtained an accuracy of 83.9% for males and 81.1% for females on STFT features. While on WT features, the accuracy of 87.6% is observed for males and 82.5% for females. Results show that KNN performs better than SVM in drowsiness detection.

A microcontroller-based driver drowsiness detection based on HRV signal analysis is proposed by Hendra et al. (2019). ECG signals are recorded during driving simulation. The system comprises an AD8232 ECG module, HC-05 Bluetooth, microcontroller Arduino Nano, and an Android smartphone. Eight ECG signals are acquired from four participants using the AD8232 ECG module. The acquired signals are processed in a microcontroller Arduino nano and then sent to a smartphone via HC-05 Bluetooth. HRV features from the time and frequency domain are extracted in Android smartphones from ECG signals. RR intervals are segmented into 30, 20, and 10-s segments. To classify drowsy and normal states, the RBF-NN is used. Features extracted from 30 sec RR interval segments performed better and achieved an accuracy of 79.26%.

The system presented by Gromer et al. (2019) includes both software development and hardware design for drowsiness detection. The PCB, an extension shield of Arduino, is used for hardware implementation. PCB contains a low pass filtering, double inverted ECG channel, and two analog outputs for Arduino. Electrodes are attached to the body of the driver. Preprocessing of the signal is done before QRS complex detection by discarding signals of 50 Hz or low. The QRS complex is used to drive HR and HRV. This makes it possible to detect the fatigue of drivers using a machine learning algorithm.

A system using HRV-derived respiration measures to detect driver drowsiness is presented in Kim and Shin (2019). Euro Truck simulator and FANATEC virtual hardware setup are used to create a virtual environment for drivers to collect datasets. A wearable ECG device is used to detect RR intervals. Data is gathered from six individuals giving thirty-seven recordings from which 1% poorly monitored values are excluded. Some constraints have been used to collect the dataset e.g. the participant should not have caffeine intake four hours before the experiment and have to drive for one hour in the same virtual environment They are advised to keep the speed at about 80–90 km/h and keep a steady lane. PolarH7 device is used to collect HRV data. The average running time of each recording is about 67 min. Two cameras are used in the experiment setup video of the upper body of the driver and the screen. New RR interval data is acquired by performing the cubic interpolation. Three different machine learning models are used including RF, KNN, and SVM to verify the performance of the drowsiness detection. SVM shows better accuracy among these three models.

By the same token, driver drowsiness is detected by using ECG data by Murugan et al. (2020). Experiments are performed using a driving simulator by putting ECG electrodes on both left and right wrists of the driver. A continuous two-hour driving session is carried out to collect ECG data. First fifteen minutes the driver has to drive quietly without talking and then the driver has to respond to three SMS for visual distraction and again drive quietly for the next fifteen minutes. Then while driving, the driver has to respond to mathematical questions and after that, the subject is allowed to drive till s/he falls asleep or cannot control his/her sleep. To remove false R peak values, the ECG signal reconstruction algorithm is used. FFT is used to decrease the complexity of the R-value. Sixth order Butterworth filter is used with a cutoff frequency of 0.5 Hz for high-frequency cutoff. HRV information calculated by R-R interval difference is used for feature extraction. Mean, mode, median, root mean square, second quartile, SD first quartile, third quartile, interquartile range, harmonic mean, variance, skewness, kurtosis, energy, approximate entropy, maximum, Hurst, minimum, and power are the features extracted from the signal. The PCA (Principal Component Analysis) is used for feature reduction and classified using SVM, ensemble, and KNN algorithms. Ensemble gives better accuracy of 56.9% than the other two while classifying five different states of the driver.

HRV extracted from ECG signal to detect drowsiness is presented by Chang et al. (2021). ECG signals of twenty-one participants are acquired using a chest belt in the morning and early evening for ninety minutes. A smart mobile device with low-powered Bluetooth receives HR and RR intervals from the chest belt. Time domain, frequency domain, and nonlinear analysis are used to extract features from the HRV analysis. KNN, NB, neural network, and DT are trained and evaluated on this data. Neural network and NB achieved an accuracy of 98.65% outperforming other models.

Kundinger et al. (2020) worked on driver drowsiness detection using the wrist-worn sensors with a machine learning approach. The study performed a comparison of the proposed approach with medical equipment ECG for drowsiness detection. Many machine learning models are trained on wrist-worn sensors that collected data for drowsiness detection. KNN model achieved the highest 92% accuracy score. The authors designed a smart steering wheel for drowsiness monitoring and inconspicuous health by Babusiak et al. (2021). The parameters used for detecting drowsiness are heart rate, heart rate variability, and blood oxygenation for health and drowsiness detection. The study uses ECG and oximeter integrated with the steering wheel.

ECG data has been reported to produce driver drowsiness detection with an accuracy of higher than 95%. Although it requires placing the electrodes on the driver's body, its efficiency is high as compared to contactless approaches. Studies utilizing the ECG signals primarily focus on three different aspects to obtain high performance. First, data is cleaned by removing the noise through a high-order bandpass filter which helps in better training of the models. The cutoff frequency is different; however, it is used between 0.5 and 40 Hz on the ECG signals. Second, the use of features is multifarious where time and frequency domain and geometric features are acquired from the ECG data. Time-domain features including standard deviation, NN50, PNN50, root mean square, standard error, and standard deviation of difference are taken from RR intervals. Resampling of linear interpolation, PSD, and frequency of PSD are used from the frequency domain. Similarly, geometric features like density distribution, triangular interpolation, mean, mode, median, root mean square, second quartile, SD first quartile, third quartile, interquartile range, harmonic mean, variance, skewness, kurtosis, energy, approximate entropy, maximum, Hurst, minimum, and power are used. Thirdly, feature reduction techniques like PCA are applied to reduce the dimensions of the features to obtain better results. Deep learning approaches are reported to have better results using the ECG signals.

Table 4

A summary of ECG signals based approaches

References	Sub.	Sensor	Approach	Pros	Cons

References	Sub.	Sensor	Approach	Pros	Cons
Vicente et al. (2016)	30	ECG electrodes	–	Signals are collected to make three datasets one in real environment and two in virtual environment. Achieved a 96% and 80% positive predicted value	Invasive electrodes are used for signal acquisition that makes driver uncomfortable
Gupta et al. (2017)	–	Zephyr BioHarness	–	Standard dataset from PhysioBank website is used. A threshold-based system is designed. The system alerts the driver by an alarm	Invasive chest strap is used for signal acquisition that makes the driver uncomfortable. A threshold is set on the average of ECG signals when the driver is awake
Bhardwaj et al. (2018)	10	Electrodes	ML, DL	KNN achieves an accuracy of 95% while an autoencoder achieved 96.6% accuracy. Data acquired in a real-time environment with no sleep deprivation	Invasive electrodes are used for signal acquisition that makes the driver uncomfortable. Signal acquired in a virtual environment with sleep deprivation
Attarodi et al. (2018)	–	–	MLP	MLP achieves an accuracy of 91.4% with standard data set from 'Physio.net'	Dataset is used only to train MLP. No information about subject sensors
Babaeian et al. (2019)	25	Three electrodes	KNN	KNN achieves accuracy above 80%	Signals acquired in controlled virtual environment. Electrodes are attached to body for signal acquisition
Hendra et al. (2019)	4	AD8232 ECG module	RBF-NN	HRV features from the time and frequency domain were used to classify between drowsy and fresh states. RBF-NN achieves an accuracy of 79.26%	Data is collected in simulation controlled environment
Gromer et al. (2019)	–	Electrodes	–	Hardware is design using Arduino and electrodes to acquire ECG signal. Software is designed to detect HR and HRV from ECG signals	Does not describe details about data collection and experiments. Attachable electrodes are used
Kim et al. (2019)	6	Polar H7	SVM	Uses both signals and their combination and achieved an accuracy of above 90% with SVM	Wearable strap used. Respiration signals are calculated from ECG signals. A Virtual controlled environment is used
Murugan et al. (2020)	–	Electrodes	–	Data is acquired in real environment	Electrodes are placed at the backside of the shirt for data acquisition which makes the driver uncomfortable
Chang et al. (2021)	21	Chest belt	NN	Achieved an accuracy of 98.65 with neural network and NB. A smart mobile device was used to receive the signal from the belt	Physical contact using the belt causes discomfort and introduces noise
Kundinger et al. (2020)	30	Empatica E4	KNN	Non-intrusive wrist watch usage	Simulator data, noisy data is not considered
Babusiak et al. (2021)	–	Electrocardiograph	–	Unobtrusive monitoring	No information about subjects, no reported accuracy

Driver drowsiness detection using EEG signals

EEG is an objective method that can be used to evaluate the function of the brain. Although often used in auxiliary diagnosis, it has many applications like illness detection, mental state detection, etc. A large body of work use EEG signals for driver drowsiness detection (Hu 2017; Nguyen et al. 2017; Awais et al. 2014). EEG electrodes are placed on the scalp, as shown in Fig. 4, to record the electrical activity of the brain. The recorded and processed signals can be divided into different frequency bands like alpha, beta, delta, etc. Papadelis (2007); Lin (2005). Further analysis is performed on these frequency bands to detect driver drowsiness.

Fig. 4

An experimental set up to detect drowsiness using EEG signals (left), placement of electrodes as per international 10-20 system standard (right) (Hu 2017)

Spectral and band power features extracted from EEG signals are used to detect drowsiness by Krishnan et al. (2020). ULg DROZY a publicly available dataset comprised of EEG, EOG, ECG, and EMG signals is used in this research. All these signals are recorded at a sampling rate of 512 Hz for a total of 14 subjects. Three trials of the test are carried out in a controlled environment. The individuals are requested to have a decent sleep pattern for the previous week before the first session. The individuals are instructed to execute an action while seeing the screen in the first trial. Following the first experiment, the subjects are advised to stay up for 36–38 h in order to maintain their sleep deprivation. The volunteers repeated the prior experiment in the second and third trials. Following the last test, the individuals are instructed to get a good night's sleep before driving home. The raw EEG signals are recorded for 10 min for two states drowsy and non-drowsy. Signals are split into 2 s epochs to extract features. KNN and SVM are trained and tested on the dataset with an accuracy of 96.1%.

EEG signals are used to detect driver drowsiness by Sarabi et al. (2020). The EEG signal of 600 people is gathered continuously for 117 s considered classes. Perceptron and radial base neural networks are used to classify between closed and open eyes that achieved the highest classification rate of 99.45% and 100%, respectively. A genetic algorithm is used to find the value of unknown coefficients and values of the fitness function. Values of coefficients are then multiplied by the features matrix and a new matrix are obtained that are fed to perceptron neural networks for clustering that achieved a classification rate of 98.38%. Optimized data with a Genetic algorithm is considered to reduce computational complexity.

Yang et al. (2019) proposed the CNBLS to detect drowsiness from an EEG signal from eleven (seven males and four females) students of Tianjin university. Subjects are advised to have proper rest of 7 h before data collection. EEG data is collected while subjects are driving for ninety minutes on a driving simulator wearing a 40-channel recording cap. The 9-point KSS is applied and the driver's state is classified as 'alert', 'mild fatigue', and 'fatigue state'. The acquired raw EEG signal is filtered into 1–50 Hz by a bandpass FIR filter. ICA is applied to remove artifacts from the signal and the signal is down-sampled to 200 Hz to reduce the computational burden. The first 20 min are considered alert and the last 20 min are considered fatigued data. The data of both categories are split into 1 s making a sample total of 2400 for each subject and 1200 from each category. The MWRN is used to transform EEG data into a network matrix-like image representation. CNBLS model is constructed and generalized on the data subsequently achieving an accuracy of 99.58%.

EEG signal of six healthy subjects in wakefulness and drowsy state is collected by Ma et al. (2020) to detect drowsiness. EEG device Brain Products GmbH is used to acquire EEG signals of the subjects for twenty minutes while driving in a driving simulation. Subjects had to sleep for at least 8 h before wakefulness data collection and 4 h (sleep deprivation) to collect drowsiness data. EEG data is collected from 32 electrodes positioned at the head of the subject at a sampling rate of 1 kHz. Raw EEG data is down-sampled to 200 Hz and a bandpass filter with a cutoff frequency of 0.1–45 Hz is applied to reduce the artifacts. EEG signal is then filtered into five traditional frequency bands that include Alpha (8–13 Hz), Delta (0.1–4 Hz), Beta (13–20 Hz), Theta (4–8 Hz), and Gamma (20–45 Hz). Filtered data is segmented into 10-s frames making 240 samples for each subject and 1440 samples in total. Out of these 1440 samples 240 are kept for testing and 1200 for training. A total of 160 PSD features are extracted from these segmented EEG frames. KNN, SVM, ELM, H-ELM, and PSO-H-ELM are trained and evaluated on the collected data. PSO-H-ELM achieved an accuracy of 83.12% outperforming other classifiers.

Multi-channel EEG signals are acquired to detect drowsiness by Zhang et al. (2020). A total of sixteen subjects of ages ranging from 24 to 28 years take part in data collection. A 40-channel Neuroscan EEG acquisition device is used to acquire EEG signals at a sampling rate of 1 kHz while subjects are driving in a driving simulator. Subjects have to perform two driving tasks Task A (driving on a 2-lane road) and Task B (on a foggy road) for 20 min. Task A and B are considered favorable and non-favorable for driving, respectively. A bandpass FIR filter with a cutoff frequency from 0.01 to 70 Hz to reduce artifacts, subsequently, signals are split into 1-s frames making a total of 800 frames for each class. Sample entropy is used to extract features from all channel data. PCA is applied to automatically select the optimal feature set. Various ML classifiers that include SVM, LR, KNN, and DT are trained and evaluated with SVM with the cubic kernel. The achieved accuracy scores for PCA and KNN are 97.25% and 92.19%, respectively.

A technique to detect drowsiness from alpha spindles of an EEG signal is presented by Houshmand et al. (2021). Nineteen male subjects ages ranging between 26 and 52 years took part in the data collection process. Prior to experiments, a wakefulness test of the subject is performed to measure the ability to stay awake without any activity. EEG data is collected from seven monopolar electrodes while subjects were driving in a simulator. Three experts evaluated the predefined drowsiness level scale where 1 indicates the mean alertness and 5 indicates extreme drowsiness. Grabs outlier detection method is used to remove outliers from the raw EEG data. A Butterworth bandpass filter with a cutoff frequency of 0.1–31 Hz is used. Alpha spindles are detected using the Morlet mother wavelet. Each signal is split into 30-s frames and each frame is analyzed by continuous wavelet transform to determine the intensity using frequency and time domains. Neighborhood component analysis is used to detect channels with the highest potential of detecting drowsiness. CNN achieved an accuracy of 94% while trained and evaluated on data of 14 and 3 subjects. Similarly, the alpha and theta band of EEG signals are analyzed to detect driver drowsiness by Sivakumar et al. (2021). From 10 subjects, EEG signals are acquired with 21 channels to detect drowsiness. The authors use the KNN for drowsiness detection using Alpha and Theta bands. KNN achieves 100% accuracy using the Theta band.

Zhu et al. (2021) present a drowsiness detection method based on EEG signal obtained by the wearable device. The EEG cap consists of eight Ag-CL electrodes that collect data at a sampling rate of 256 Hz. EEG data of twenty-two subjects of age ranging from 22 to 42 years is collected in a sleep-deprived state from 2 a.m. to 5 a.m. and after a normal night's sleep at 10 a.m. on different days. A fatigue warning system MR688 is used to verify and assist the fatigue state of subjects. The data is collected for 1 h in each state. Low and high-frequency unwanted components are removed from a raw EEG signal using a 3rd order Butterworth bandpass filter with a cutoff frequency of 1–60 Hz. Another Butterworth filter with a cutoff frequency of 50 Hz is used to remove the power frequency interface. Fast ICA is used to remove the artifacts from the signal. Neural network with inception module achieved an accuracy of 95.59% and modified AlexNet achieved an accuracy of 94.68%.

Single-channel EEG-BCI (EEG-bBrain computer interface) system coupled with deep learning is presented by Balam et al. (2021). For classification in drowsy and non-drowsy states of drivers, SEED-VIG and PSAED data sets are used. SEED-VIG data set has data of twenty-three subjects that is collected using 18 electrodes. PSAED data set comprises EEG signal of twenty-three subjects collected using two electrodes. The EEG signals of both datasets are split into 1-sec epochs. Seven direct domain features are extracted from raw EEG signal HFD Hjorth parameters such as mobility and complexity, DFA, energy, exponential energy, and log energy. A simple deep neural network is trained and evaluated on the datasets that achieved an accuracy of 96.80% and 74.89% on PSAED and SEED-VIG datasets, respectively.

Paulo et al. (2021) used two approaches for drowsiness detection; one using the EEG signal and one is EEG encoding signals as spatiotemporal images. The dataset used in the study records the reactions-times of participants to different events that are related to drowsiness. A CNN model is used for the classification in both approaches. Experiments are done on 27 subjects' publicly available datasets and CNN shows good performance with up to 75.87% accuracy with both approaches.

Similarly, Chen et al. (2021) proposed an approach for drowsiness detection using EEG signals and a deep learning model. The authors proposed a deep CNN model with 12 layers that automatically extract significant features from ECG signals. A 4 s segment of ECG signals are used to train and test the proposed CNN model for drowsiness detection which reports a 97.02% accuracy on test data. A method to detect drowsiness from single-channel EEG signal using wavelet packet transform to extract time-domain features was presented by Chinara et al. (2021). Physionet dataset and dataset virtually recorded by Zheng et al. (2017) was used. 50 Hz notch filter and 0.1–45 Hz band pass filter were used to remove artifacts from the EEG signal. Different ML and deep learning classifiers were trained and evaluated on these datasets extra tree outperforming others with an accuracy of 94% and 85.36% on Physionet and (Zheng and Lu 2017) dataset respectively.

A BCI is used for drowsiness detection by Dunbar et al. (2020). A total of 26 participants drove in a controlled simulated environment with a BCI device mounted on the head. Both BCI and KSS data were gathered for experiments. Neither KSS nor BCI data differed between individuals who show drowsiness. A CNN-based drowsiness detection method using a single-channel EEG signal was proposed by Balam et al. (2021). A prerecorded EEG signals dataset acquired from Physionet was used. By manually verifying each epoch (i.e. 1 s timestamp window) data, hardware artifacts were eliminated. The 50 Hz notch filter and 0.15–45 bandpass filter were used to remove resonance noise and eye blink artifacts. Subject-wise, cross-subject-wise, and combined-subjects-wise validations were used to enhance the performance of the suggested technique, yielding accuracy of 93%, 89%, and 94%, respectively. The MMSE approach is applied by Wang et al. (2021) for driver drowsiness detection. Initially, the EEG signals are decomposed using VMD. Later, the best IMF and scale factors are selected with the help of LSM (the least square method). The VMD-MMSE method is combined with a questionnaire where the driver performance is reported under normal driving and auditory stimulation mode. Results indicate that VMD-MMSE can classify the driver state efficiently.

Besides several medical applications like illness detection, mental state detection, etc. EEG data has been used for driver behavior analysis as well. Data is recorded at high frequency, so the data for a second or two is enough to predict the driver's state. EEG data for closed and open eyes have different features and neural networks and machine learning models can be used to differentiate. Accuracy can further be enhanced using noise filtering, and bandpass FIR filtering. Similarly, downsampling is also used to reduce the artifacts. Butterworth filter and bandpass FIR are the most commonly used filters for cleaning the EEG signals. Signals can further be transformed into different frequency bands to obtain refined results for driver drowsiness detection. Similarly, a large number of studies focus on using a 40-channel EEG acquisition device for better accuracy. Neighborhood component analysis can be used to detect channels with the highest potential of detecting drowsiness. Predominantly, signal features like DFA, energy, log energy, and exponential energy are used for EEG signals. Studies also follow image processing techniques where the signals are transformed into matrix-like image transformations to obtain higher accuracy. For the most part, the employed approaches are based on deep learning models for their superior performance. However, machine learning models are also utilized. The driver drowsiness prediction is based on the data of 1–2 s frames and accuracy is higher than other sensors.

Table 5

Comparative analysis of EEG based approaches for drowsiness detection

References	Sub.	Sensor	Approach	Pros	Cons
Sarabi et al. (2020)	600	Neuroheadset	Perceptron	Correctly classify between closed and open eyes	No information about data collection. Only CR was considered. An invasive device was used
Yang et al. (2019)	11	–	CNBLS	High classification accuracy using only EEG signals	Invasive device was used, and data was collected in controlled environment
Ma et al. (2020)	6	GmbH	PSO-H-ELM	Performance comparison from multiple machine and deep learning models	Electrodes are placed on the body causing interference during the driving and simulated environment
Krishnan et al. (2020)	14	–	KNN, SVM	Robust and high accuracy	Experiments are performed in a controlled environment
Zhang et al. (2020)	16	Neuroscan	PCA, KNN	Feature selection through PCA to obtain important features	Simulated environment makes the approach less practical for real scenarios
Houshmand et al. (2021)	17	Monopolar electrodes	CNN	Simple and robust model with 94% accuracy	Low number of test samples, results are not generlizable
Zhu et al. (2021)	22	Ag-CL electrodes	NN, AlexNet	Used MR668 fatigue warning system to verify fatigue. Achieved an accuracy of 95.59%	The data is collected in a controlled environment, wearable electrodes are used
Balam et al. (2021)	23	Electrodes	DNN	Statistical method to find best channel was presented. Two datasets PSAED and SEED-VIG were used	Lower accuracy for SEED-VIG dataset, use of electrodes for data collection
Sivakumar et al. (2021)	10	Electrodes	LDA & KNN	High accuracy using theta band of EEG	The data is collected using a simulation setup
Paulo et al. (2021)	27	Scan SynAmps2 express	CNN	Resolves low SNR and cross-subject disparities	Comparatively low accuracy with data from simulated driving
Wang et al. (2021)	15	Emotiv device	MMSE	Drowsiness detection under normal and auditory stimulation modes	Low no. of participants, simulation environment

Galvanic skin response for drowsiness

The GSR-based features have been utilized for driver drowsiness detection as well. GSR sensors record the electrical conductance of the skin. It shows the response of the autonomic nerve which is used as a parameter of the sweat gland (Sharma et al. 2016; Bakker et al. 2021). A GSR is attached to the index and middle fingers and records the change in the electrical conductance while driving. The change in GSR is associated with stimulation, emotional reaction, and actions related to alertness and attention (Khalfallah 2010). A schematic diagram of GSR-based driver drowsiness detection is shown in Fig. 5.

Fig. 5

GSR placement set up (left), experiment set up for driver drowsiness (middle Darzi et al. 2018) and location for placing electrodes (right Sharma et al. 2016)

A real-time driver state detection using a wearable device is presented by Misbhauddin et al. (2019). Galvanic skin response (GSR) and the heart rate of the driver are recorded for analysis. GSR is used for the detection of the relaxation of internal organs. HRV and GSR are measured for a better classification of the driver status in terms of drowsiness and non-drowsiness. E4 wristband is used for the measurement of HRV and GSR data. An android-based application is developed for drowsiness detection. The application includes user management, monitoring, detection, and notification features. E4 link library is used by the application to access the data gathered by the wristband. When the wristband is queried for data by the application, it receives IBI and EDA. EDA is a skin conductance signal value and IBI is the time between two heartbeats. The frequency of forty seconds is set to ascertain the data. Five IBI and ten EDA values have been collected at the completion of each epoch. This data is stored in temporary memory and calculation of HRV and GSR is started. HRV is measured by taking square differences of IBI and the root mean square of these calculated differences. The absolute difference of EDA values is calculated to find the GSR value. There are training and testing phases in the system. In the training phase, the user has to train the system at four different times of the day before using it. The response of the user is recorded on a scale of 1–4. HRV and GSR data are also measured and a threshold value is set. The monitoring phase triggers when the driver is driving the vehicle. In this phase, HRV and GSR data are extracted from the wearable device acquired data. If both HRV and GSR values are less than the threshold, an alarm is generated to alert the user. Testing of this system is conducted in a simulated environment on ten subjects. A total of forty data points, ten from each out of four subjects are gathered at four different times of the day: in the morning, after a heavy meal, being awake for almost 18 h, and before sleeping. HRV and GSR values are gathered and the alert system is checked. The accuracy of the system is computed using the confusion matrix. There were thirty-two true positive out of forty data points which shows the system is accurate about 80% of the time.

Bartolacci et al. (2020) evaluate the role of sleep changes in driving behavior and vigilance levels. For this purpose, 80 healthy subjects are included in the experiment to analyze the sleep quality, sleepiness, and vigilance using the PSQI, KSS, ESS, and PVT. The cognitive abilities of drivers are assessed with the help of the Vienna Test System TRAFFIC. Results using the ANOVA test indicate that less habitual sleep efficiency is associated with worse performances in PVT. Younger subjects report higher self-rated sleepiness while older drivers show lower performance regarding attention and perception tests.

Similarly, Darzi et al. (2018) perform experiments with 21 healthy drivers in a sleep-deprived session. Skin conductance, respiration, and body temperature are used for drowsiness detection. Using three features, the drowsiness detection accuracy is 98.8%, however, the performance is degraded if a single sensor is used.

IoT-based fatigue and drowsiness monitoring system is implemented by Munir et al. (2020) that uses the GSR and heart rate variability. Using the change in the heart rate and GSR when moving from wakefulness to drowsiness, can be used to detect the driver's state.

Choi et al. (2017) designs a wearable device-based driver drowsiness detection. For better accuracy, signal processing and optimal feature selection are performed. A fine-tuned SVM model is used for driver state classification that obtains a 98.43% accuracy.

GSR device records the electrical conductance of the skin which can be used for driver drowsiness detection. It is a contact-requiring approach where the GSR device is attached to the hand of the driver. HRV and GSR are measured for a better classification of the driver status in terms of drowsiness and non-drowsiness. Using features from GSR, heart rate and temperature, the prediction accuracy of higher than 98% is possible which is not possible if a single sensor is used. The response in GSR varies as the driver moves from the state of wakefulness to sleepiness. Both machine learning and deep learning models are used with GSR data for driver behavior prediction.

Table 6

Comparison of EEG-based studies

References	Sub.	Sensor	Approach	Pros	Cons
Misbhauddin et al. (2019)	10	E4 wristband	–	A threshold-based system has presented that set a threshold during the training phase. The system achieves an accuracy of 80%	Data is collected in a controlled environment. User-specific training was required before using the system. The system uses a wrist band to record the data that makes the user uncomfortable
Bartolacci et al. (2020)	80	–	Vienna test system TRAFFIC	Sleep quality, sleepiness, and vigilance of elders and adults is tested	Different devices linked to the test system were used to record the physiological signals. This test was performed before driving

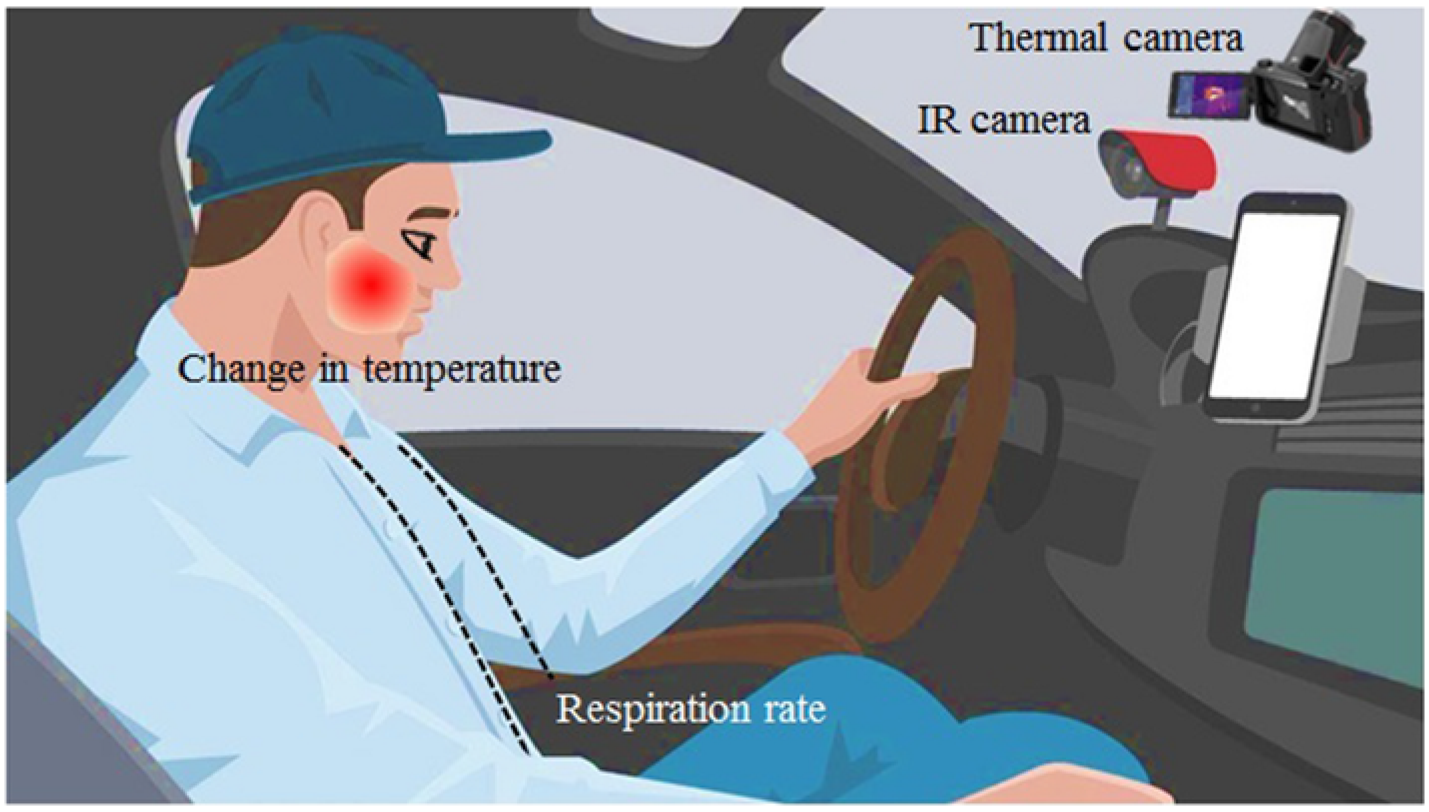
References	Sub.	Sensor	Approach	Pros	Cons
Darzi et al. (2018)	21	Electrodes for ECG, thermistor sensor for respiration, Electrodes attached to glove for GSR	–	ECG, skin conductance, respiration, and GSR are used for drowsiness detection. Using three features, the drowsiness detection accuracy of 98.8% was achieved	Data was collected in a controlled and simulated environment. On-body sensors are used that cannot be used in a real environment
Munir et al. (2020)	1	Electrodes attached to Arduino	–	IoT based low-cost system was presented. The experiment was conducted in a real-time environment	System uses on body sensor for predictions. A threshold-based system is presented
Choi et al. (2017)	28	Wearable device designed by authors	SVM	Wearable device was designed by authors to collect data. System achieves an accuracy of 98.43%	Experiments were conducted in controlled simulation environment. Wearable device was used that makes user uncomfortable

Use of thermal imaging for driver drowsiness detection

Thermal imaging-based driver drowsiness detection approaches follow a non-contact approach. The setup includes a thermal camera, occasionally augmented with visible light or IR camera, as shown in Fig. 6. The thermal camera captures the changes in the temperature of the forehead, nostrils, and cheeks and the change can be associated with the driver's state moving from wakefulness to drowsiness. The use of the thermal camera is advantageous over contact measurement approaches like ECG, and EEG and non-invasive approaches like the visible light camera as it is not affected by illumination conditions.

Fig. 6

A schematic setup of thermal imaging based drowsiness detection



Driver drowsiness is detected using thermal imaging-based respiration in Kiashari et al. (2020). Empirical analysis reveals that a change in nostrils' temperature is observed during drowsiness and wakefulness. Geometrical features can be used to detect the respiration region and frames from a thermal camera can provide the respiration rate. The frequency of respiration of normal humans varies between 12 and 20 breathes per minute (Lindh et al. 2013). The maximum time interval is five seconds between two breaths so, the region of the image with a high variation rate in the first five seconds is located as the respiration region. A canny edge detector is used to separate the respiration region from the image. To get an accurate respiration region, the head of the driver should not move quickly in the first five seconds of the thermal imaging process. A respiration signal can be formed using the respiration region. Environmental features can affect the performance of the thermal imaging process so environmental variables are kept constant during the experiment. Respiration rate, I/E ratio, standard deviation, and mean are the main extracted features from the respiration signal. Fused features are used with SVM and KNN resulting in 90% and 83% accuracy scores by SVM, and KNN, respectively.

Similarly, a thermal image-based approach is adopted by Kiashari et al. (2018) for driver drowsiness detection using the respiration rate. The respiration rate is extracted using the nostrils' movement with physiological characteristics. In addition, the frame-to-frame mean temperatures of the nostril are used. Experiments are performed using 12 subjects within a driving simulation environment. Results show that the respiration rate from the thermal images is non-intrusive and reliable. The observations indicate that the respiration rate is decreased while the standard deviation is increased while the driver moves from wakefulness to drowsiness.

Driver drowsiness is performed using the facial depth map by Forcamanski et al. (2018). The visual data is collected using the RGB-D sensor. Several object detectors are trained like Haar-like features, HOG, and LBP. With face detected, a heuristic approach is applied to estimate the drowsiness level. Using the depth features, the drowsiness analysis can be performed at a low level where the impact of illumination can be minimized. Experiments show promising results with the feasibility of using depth features for drowsiness detection.

Along the same directions, Tashakori et al. (2018) use the thermal images for drowsiness detection. Facial temperature is measured from thermal images and drowsiness level is associated with observer rating. The observations of four facial blood vessels show that facial temperature is decreased from wakefulness to drowsiness. The change in the temperature is observed to be decreasing by 0.54, 0.33, and 0.32 °C for 12 subjects when their state moves from wakefulness to drowsiness and extreme drowsiness, respectively.

Similarly, Moazen et al. (2021) employ a thermal camera for driver state detection using facial images. Facial features are extracted using horizontal and vertical integration, along with projection, contours, etc. Four target areas have been used from the cheeks and forehead. A total of 15 subjects are used for data collection in a driving simulator. Results using the observer rating confirm that the thermal facial images can provide reliable results for driver drowsiness.

The study by Fofrcamanski et al. (2021) determines the driver's state with the help of facial features using the thermal camera. The study specifically utilizes the eyes and mouth state estimation. Using the Haar-like features with the AdaBoost classifier, eyes and moth regions are detected. Gabor filter is used on the detected region and features are used to detect the drowsiness. Analysis reveals that the thermal camera provides reliable results in diverse lighting conditions during day and night time.

The feasibility of thermoregulation features is tested by Gielen et al. (2019), which performs experiments using 19 subjects in a driving simulation. During experiments, nose and writs temperature is recorded and analyzed for wakefulness to drowsiness. The study reports that an initial increase in temperature is observed for drowsy drivers followed by a gradual decrease while no such patterns are observed for non-drowsy drivers. Classification accuracy of 68.4%, 88.9%, and 70.6% can be obtained when using nose temperature, wrist temperature, and heart rate, respectively. Using multimodal features, accuracy of 89.5% is achievable.

Similarly, Kajiwara et al. (2021) establish a driver's condition with the help of eye blinks and yawning frequency. For this purpose, both visible-light cameras and thermal cameras are used. Both vision cameras and thermal cameras are non-contact and the driver is not annoyed and his movements are not hindered. Experiments show that using a visible-light camera, the accuracy of driver state determining is 90% with well-illuminated conditions, however, bad light conditions can substantially decrease the performance. On the other hand, an accuracy of 74% is obtained when a thermal camera is used.

Knapik et al. (2019) presented a system based on yawn detection to decide the drowsiness from thermal images. The proposed approach continuously monitors the driver and initiates an alert when drowsiness is detected. The method is resilient to various light conditions. For detecting yawning, eye corners are used for face alignment and face average temperature is used. Experiments performed in simulated and real environments show promising results.

The authors analyze the changes in temperature of the forehead and cheeks to determine the drivers' state by Tashakori et al. (2022). A driving simulator is used where 30 participants drove the car in two sessions. Driver drowsiness is monitored and annotated at three levels by human observers. The study employs KNN, SVM, and regression trees to classify driver drowsiness using the forehead and cheeks temperatures. Observations show that a decrease in forehead and cheek temperature can be associated with drowsiness like a temperature decrease of 0.46 °C and 0.81 °C for forehead and cheek, respectively. Results indicate that accuracy of 82% can be achieved using the proposed approach. Cardone et al. (2021) used 10 sleep-deprived drivers on the driving simulator for drowsiness detection. Device Alab SmartIr640 thermal camera is used to record the skin temperature along with the vision camera. Several regions of interest are used to record the change in the temperature like nose tip, glabella, etc. Features extracted for 30 s are used with a three-level SVM to determine the driver's state to 'awake', 'fatigue', and 'sleepy'. The average classification accuracy of 0.65 is obtained with the thermal camera.

Thermal camera is a recent application in driver behavior analysis. It is a contactless approach and does not require any sensors to be placed on the driver's organs. Instead, it can remotely record the data, similar to the vision camera, however, the difference is that it records the relative temperature of an item. The use of the thermal camera for driver drowsiness detection is multi-objective involving the use of multiple features in this regard. For example, the change in the temperature of the driver's facial parts is associated with states of wakefulness and sleep. Similarly, the chest movement can be captured using the thermal camera which is later used for respiration rate and heart rate measurement. Last but not least is to measure the breathing patterns by analyzing the change in the nostril positions of the driver using the thermal camera. Also, several facial depth markers can be used for the same purpose. Eyes and mouth state estimation is also possible with the thermal camera which in turn can be used for driver behavior analysis. Eye blinks and yawning are two important facial markers for driver drowsiness detection regarding the thermal camera. Despite its contactless approach and better accuracy for driver drowsiness detection, the thermal camera is sensitive to light and heat conditions. For experiments, the external environment needs to be kept at a relatively constant temperature to get reliable results.

Table 7

Thermal camera-based driver drowsiness detection approaches

References	Sub	Sensor	Approach	Pros	Cons
Kiashari et al. (2020)	–	Thermal camera	SVM, KNN	Thermal camera was used. Environmental factors have no effect on the camera. SVM achieved an accuracy of 90%	Driver has to remain still for five seconds. Head movement affects the result of the system
Kiashari et al. (2018)	12	Thermal camera	–	A non-intrusive method that estimates respiration rate from change in temperature under the nostrils	Head movement affects the results of the system. Not feasible in a real driving environment
Tashakori et al. (2018)	12	Thermal camera	–	Facial temperature decreases from wakefulness to drowsiness. Data was collected in a simulated environment	Head movement affects the results of the system. Not feasible in a real driving environment
Moazen et al. (2021)	15	Thermal camera	–	Four target areas are used from the cheeks and Forehead. Results using the observer rating confirm that the thermal facial images can provide reliable results for driver drowsiness	Data was collected in a simulated environment. Head movement affects the results of the system. Not feasible in a real driving environment
Forczmanski et al. (2021)	19	Thermal camera	–	Haar features were extracted from eyes and moth regions	Data was collected in a simulated environment. Head movement affects the results of the system. Not feasible in a real driving environment
Gielen et al. (2019)	19	VarioCAM infrared thermal camera, Empatica	DT	Classification accuracy of 68.4%, 88.9%, and 70.6% can be obtained when using nose temperature, wrist temperature, and heart rate, respectively. Using multimodal features, and accuracy	Data was collected in a simulated environment. On-body sensors were used. Head movement affects the thermal camera

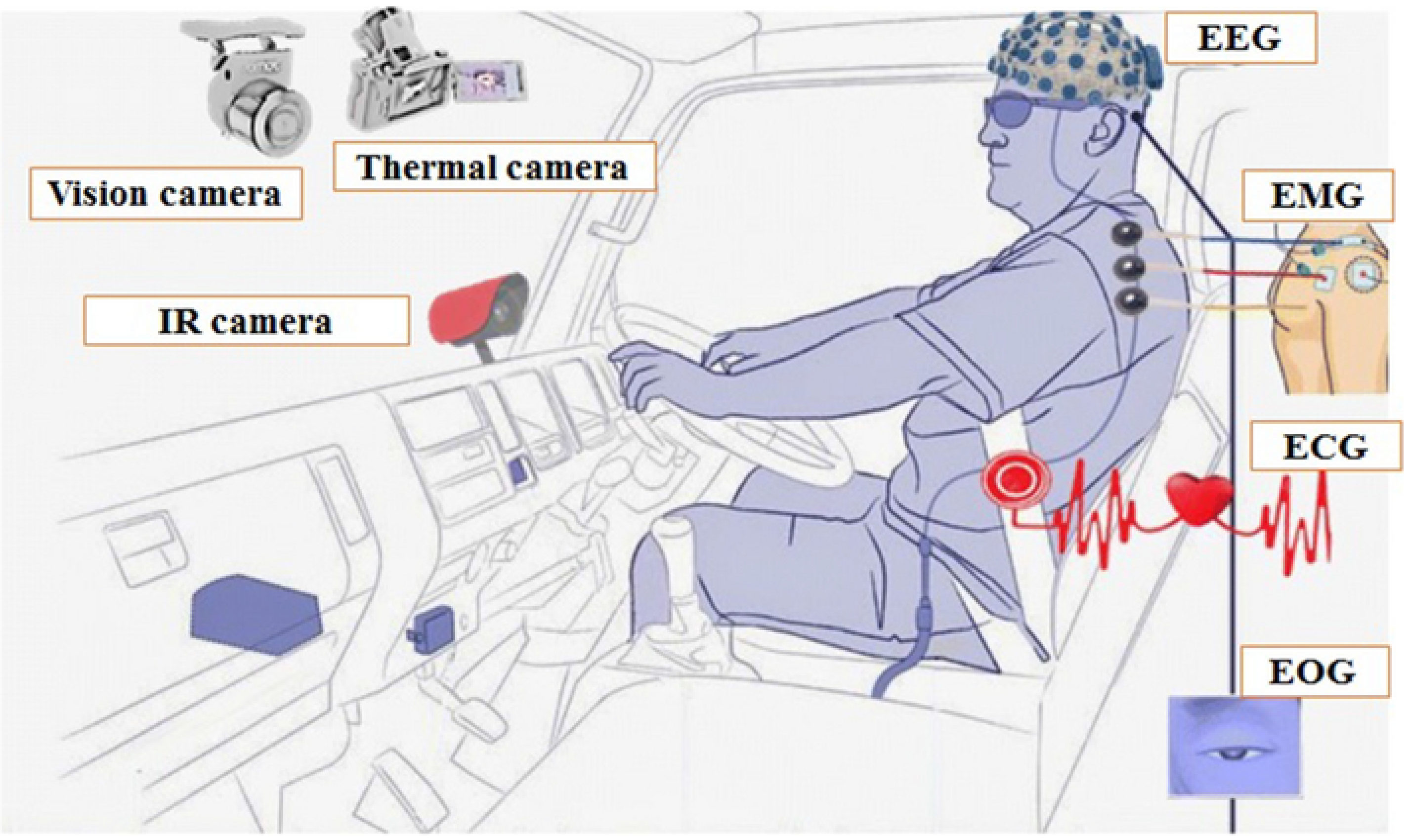
References	Sub	Sensor	Approach	Pros	Cons
Kajiwara et al. (2021)	–	Visible-light cameras and thermal camera	–	Both cameras were used separately. The vision camera achieved an accuracy of 90% in illuminated conditions	Bad lights effects the vision camera results and head movement affects the thermal camera results. No information about subjects
Knapik et al. (2019)	–	Thermal camera	–	System is resilient to change in light. For detecting yawning, eye corners are used for face alignment	Data was collected in a simulated environment. Change in temperature affects thermal camera results
Tashakori et al. (2022)	30	Thermal camera	KNN, SVM	Change in forehead and cheek temperature is observed to detect drowsiness. The system achieved an accuracy of 82%	Data was collected in a simulated environment. The use of a camera is not feasible in a real environment due to head movement during driving
Cardone et al. (2021)	–	Alab SmartIr640 thermal camera	SVM	Change in temperature under the nose tip was collected to respiration rate. A three-level SVM to determine the driver's state of 'awake', 'fatigue', and 'sleepy' which achieves an accuracy of 56%	Data was collected in a simulated environment. The use of the camera is not feasible in a real environment due to head movement during driving

Driver drowsiness systems using multiple sensors

Although predominantly the driver drowsiness systems are based on a single sensor, yet, several research works experiment with multiple sensors to increase the efficacy of detection and decrease the single sensor dependency. The objective of multisensor or multimodal approaches is to combine the signals from multiple sources to overcome the limitations of a single sensor. Figure 7 shows a schematic diagram of a multisensor approach.

Fig. 7

Schematic diagram of an approach that combines data from multiple sensors [adopted from Doudou et al. (2020)]



For example, driver drowsiness is detected from the respiration signals acquired using a wearable clothing sensor by Yuda et al. (2020). Respiration, ECG, and acceleration signals of seven healthy subjects are recorded while driving and wearing a smart shirt biometric sensor (Hexoskin). Hexoskin is made up of a smart garment and data logger in a shirt pocket which is used to monitor respiratory movements. ECG electrodes are placed at the back of the shirt. Respiration, ECG, and 3-axial acceleration signals are sampled at a rate of 128, 256, and 64 Hz, respectively. Respiration signals are analyzed by complex demodulation with amplitude and frequencies ranging from 0.05 to 0.45 Hz. In the previous investigation, drowsiness is accompanied by a typical heart rate pattern named Dip & waves. Changes in respiration signals are compared with the traditional Dip & waves characteristic associated with driver drowsiness. Respiration amplitude and frequency do not show significant changes in the Dip & wave. So, from the experiment, it is observed that the acquired respiration signals can be used for drowsiness detection.

Another similar work that relies on multiple physiological signals by Wang et al. (2017) where OP, SC, and respiration signals are acquired for fatigue detection by tagging respective sensors to the drivers' body. Physiological signals are recorded using a piece of equipment named Nexus-10 designed by B.V. Mind Media. Nexus-10 can record ten types of physiological signals by tagging the respective sensor to the subject's body. The physiological signals of ten drivers are recorded at a sampling rate of 256 Hz for three to five minutes. Baseline drift and noise are removed using median filter and bandpass filter, respectively. The study combines Hilbert–Huang transforms with RF using the GSR and pulse to detect fatigue and drowsiness. RF provides an accuracy of 99% as compared to 93% by the MLP.

The ECG and EEG signals and behavioral data are acquired for driver drowsiness detection by Gwak et al. (2018). ECG and EEG signals of sixteen healthy male subjects ages twenty-four years are acquired using a driving simulator. The driving simulator comprises a display screen, steering wheel, and pedals in a controlled environment having a temperature of 26 degrees. Two experts rated the drowsiness of the drivers based on the recorded video every ten seconds. An infrared camera is used to record eye blink data at a sampling rate of 60.1 Hz. EEG signals are acquired at a sampling rate of 500 Hz using EEG measuring instrument EEG-1200. The eye blinks are counted every ten seconds from the raw data. ECG signals are acquired at a sampling rate of 1 kHz using WEB-7000. A bandpass filter with a cutoff and thirty-two features are extracted. Four machine learning models are used for classification including SVM, KNN, LR, and RF. RF performs better with an accuracy of 81.4% than others that achieved accuracy scores of 72.3%, 78.6%, and 75.3% for LR, SVM, and KNN, respectively.

In the same way, an efficient cross-subject transfer learning system is proposed for the driver's drowsiness detection based on physiological signals by Chen et al. (2019). Two data sets that are recorded in the simulated and real environments are used for validation of the proposed system. Dataset 'A' contains physiological signals of nine healthy subjects in three different driving conditions including rest period (low stress), highway section (medium stress), and city session (high stress). ECG, GSR, and respiration signals are acquired at a sampling rate of 496, 31, and 31 Hz, respectively for thirty minutes. The acquired signals are then segmented into hundred-second segments. Specific thresholds for each signal are set to remove the noise from the original time series. Data set B consists of EEG and EOG signals of twenty-three subjects in a simulated driving environment. The route is designed in such a way that it can easily induce a drowsy state. EEG signals are collected from the posterior, temporal, and forehead at a sampling rate of 1 kHz. EOG signals are captured from the electrodes placed at the forehead. From the recorded twenty-three subject's data, balanced physiological signals of fourteen subjects are selected. After initial signal processing and feature selection, feature evaluation is applied to find the important feature for classification purposes. Cross-subject feature evaluation is performed by both CSDF. After cross-domain feature evaluation and selection, the samples from target and source domains are sent to the classifier. The ARTL is used and compared in Chen et al. (2019). ARTL optimizes structural risk, joint distribution, and manifold consistency. ARTL achieved an accuracy of 94.44% and 88.67% on Dataset A and B, respectively which is better than the seven base classifiers including SVM, ELM, and KNN.

Deploying the machine learning and deep learning techniques has been reported with higher performance. For example, Jiao et al. (2020) proposed an approach for driver sleepiness detection using EEG and EOG signals. They used a conditional CWGAN for data augmentation and used the LSTM model for classification. The dataset size was insufficient to train learning models and this problem is resolved by the CWGAN. LSTM achieved a 0.98 accuracy score after data augmentation.

Seok et al. (2020) proposed an approach of optimal feature search vigilance estimation using a machine learning approach. The deployed reinforcement learning model DQN generated the more optimal features as two from ECG and two from EEG. According to the study, ECG features were more impactful as compared to EEG.

Miao et al. (2017) proposed an approach to detect driver drowsiness using a custom-made device comprising a 2-axis accelerometer. The accelerometer is used to detect neck bends which is a good indicator of driver drowsiness. The approach makes predictions using neck posture and eye blinking duration.

Wali et al. (2020) proposed an approach for drowsiness classification using EMG and wavelet packet transform. EMG signals are decomposed into approximations up to four levels. An FFBPNN model is used for drowsiness classification. An average accuracy of 75% is obtained using a 3 s window. A PPG-PRS is proposed by Rundo et al. (2021) to capture the PPG signal for driver drowsiness detection. It is used to obtain the drivers' blood pressure and is augmented with eye dynamics to enhance detection accuracy. Classification is performed using deep-LSTM and 1D-TDCNN which show a classification accuracy of 88.88%.

Similarly, Barua et al. (2020) used several machine learning models like KNN, SVM, and RF for driver cognitive load classification. The authors used multi-component signals such as physiological measures and vehicular features and extract features using the SFFS method. RF outperforms all models with a 0.80 F1 score.

Another study on the use of ECG signals is by Abbas et al. (2020) that uses hybrid features and a transfer learning approach for drowsiness detection. The hybrid features are the combination of the visual features through PERCLOS measure and non-visual features by heart-beat (ECG) sensors. CNN and DBN models are used for drowsiness detection which shows superior performance with 94.5% accuracy.

Wang et al. (2019) presented a combination of a driver monitoring system with an EOG for the localization of MS occurrences and the study of EEG spectrum behavior during MS events. During the simulated flight, EEG, EOG, and facial behavior data were collected concurrently from 16 commercially qualified pilots. Relative spectral power was measured in frontal, central, temporal, parietal, and occipital brain areas for delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz). The findings show the potential of the EEG delta and alpha spectrum to classify MS occurrences; hence, application toward sleepiness detection through EEG electrodes incorporated in a conventional aviation headset is feasible. A system to detect driver drowsiness based on image data, EEG, and Gyroscope data was presented by Karuppusamy et al. (2020). Five subjects ages ranged between 21 and 30 years took part in the data collection process. The system is made up of multimodal time series data collected from the driving simulator platform's EEG, gyroscope, and image processing modules. The data is analyzed in the EEG module, the gyroscope module, and the vision module for driver drowsiness, head activity, and facial behavior, respectively. These modules' predictions were then fed to DNN which then analyses the data and predicts. The proposed DNN achieved an accuracy of 93.91% in detecting drowsiness.

EEG signal with eye blink data to detect drowsiness was presented by Kondapaneni et al. (2021). Neurosky Mindflex headset was used to acquire brainwave data and the blink sensor linked to the goggles is a TCRT5000 IR module. One Arduino was used to gather data from sensors, while another was used to receive the final output and sound an alert. A 433 MHz RF transceiver pair was utilized to wirelessly transmit data from one Arduino to another to sound an alert. EEG band collects attention and mediation values as the attention values decrease from the mediation value then the system proceeds to the eye state and if the driver's eye state was closed for a longer amount of time than the threshold, the driver was identified as sleepy, and an alarm was raised, and email warning was issued. The system predicts correctly 89% from 500 samples.

Change in alpha waves extracted from EEG and EOG signals was used to detect drowsiness by Jiao et al. (2020). Twelve healthy subjects took part in the data collection process in a controlled simulated driving environment. Features from frequency and time domains were extracted using continuous wavelet transform. A GAN was used to augment the training dataset. LSTM was trained and evaluated on the dataset that achieved an accuracy of 98%.

Vehicle, physiological, and behavioral-based features were used to detect drowsiness by Gwak et al. (2020). Data from sixteen male data from an eye-marked camera. EEG-1200 and WEB-7000 were used to record EEG and ECG data respectively. The hybrid measurements acquired throughout the experiment were used to create a dataset with 10 s segments of data. Various classifiers were trained and evaluated on the dataset, RF outperformed others with an accuracy of 78.7% accuracy.

Multimodal information was combined by Sunagawa et al. (2019) to detect drowsiness. ECG and respiration data from professional 50 drivers were collected using a BIOPAC device in a simulated driving environment. The facial behavior of the subject was captured using a camera. The results showed that posture information enhanced the accuracy of detecting mild sleepiness, and the suggested model integrating the driver's blink and posture information had an F1 score of 53.6%.

The objective of multisensor or multimodal approaches is to combine the signals from multiple sources to overcome the limitations of a single sensor and increase the prediction accuracy of the system. The choice of sensors for fusion is relevant to the availability of sensors, the capability of the fusion framework, the level of fusion like low-level or high-level fusion, and the desired accuracy, among others. Often, ECG and EEG signals are good choices to be used together, along with the heart rate and respiration data to obtain higher accuracy (Gwak et al. 2018; Jiao et al. 2020). Similarly, ECG, GSR, and respiration signals are reported to obtain 94.44% accuracy using the machine learning approach (Chen et al. 2019). Accuracy scores higher than that are reported using EEG and EOG signals. A 98% accuracy is reported for a hybrid system that uses EEG and EOG where both time and frequency domain features are combined for driver drowsiness detection (Jiao et al. 2020). Of all the sensors used for multi-sensor systems, EEG, heart rate and respiration signals are among the most commonly used data.

Table 8

A comparative summary of approaches using multiple sensors

References	Sub.	Sensor	Approach	Pros	Cons
Yuda et al. (2020)	7	Hexoskin	–	Data is acquired in a real environment	Electrodes are placed at the backside of the shirt for data acquisition that makes the driver uncomfortable
Wang et al. (2017)	10	Nexus-10	RF	Data is collected in real-time. RFT gives an accuracy of 99%	Data is collected before or after the driving, not during the driving. An attachable device is used for signal acquisition
Gwak et al. (2018)	16	EEG-1200, WEB-7000	RF	RF shows an accuracy of 81.4%	Signals acquired in a virtual controlled environment. Attachable devices are used for signal acquisition
Chen et al. (2019)	32	Electrodes	–	Accuracy of 94.44% and 88.67% achieve using data sets A and B respectively	Signals in dataset B are acquired in a real environment. Signals in dataset A are acquired in a controlled virtual environment. Attachable electrodes are used for signal acquisition
Jiao et al. (2020)	12	Electrodes	GAN, LSTM	High accuracy with less number of electrodes	Simulated environment is used for data collection, electrodes placement on subjects
Seok et al. (2020)	11	Electrodes	Q learning	Using DQN for analyzing biomarkers to increase classification accuracy	The data is collected in a simulation environment
Wali et al. (2020)	40	Ag-AgCl electrodes	FFBPNN	Using db2 wavelet that require less filter coefficients, low processing time	Low accuracy & data from simulated environment
Rundo et al. (2021)	71	–	D-LSTM & 1D-TDCNN	Study of drivers with higher or lower than average blood pressure	Driving conditions are simulated, accuracy is slightly low
Barua et al. (2020)	–	g.HIamp electrodes	KNN, RF, SVM	Optimal feature selection using SFFS	Use of driving simulator for experiments
Abbas et al. (2020)	14	Pulse Sensor Amped	CNN & DBN	Higher accuracy with less power	Low number of participants, use of electrodes
Wang et al. (2019)	16	Electrodes	–	Alpha, Beta, Delta and Theta waves were retrieved from EEG signal that were helpful in drowsiness detection	On-body sensor was used that makes the user uncomfortable and no ML was used
Karuppusamy et al. (2020)	5	EEG module, the gyroscope module, and vision module	DNN	Time series data was used for classification that achieves an accuracy of 93.91%	Simulation and a controlled environment were used in data collection. On-body sensors and a camera was used that are not feasible in a real environment
Kondapaneni et al. (2021)	500 samples	Neurosky Mindflex headset	–	A threshold-based system was presented that achieved an accuracy of 89%	Systems uses on-body sensor and no information about data collection
Jiao et al. (2020)	12	Electrodes	LSTM	Time and frequency domain features were extracted. GA is used for data augmentation	Data was collected in simulation and controlled environment. The on-body sensor was used
Gwak et al. (2020)	16	EEG-1200 and WEB-7000	RF	ECG, EEG, and eyeblink data were used to make a dataset that was further used for classification. RF achieved an accuracy of 78.7%	On body sensors was used for classification that makes user uncomfortable. Data was collected in a simulated environment
Sunagawa et al. (2019)	50	BIOPAC, Camera	–	Posture information enhanced the accuracy of detecting mild sleepiness	On-body sensors were used. The camera is not feasible to use in a real environment. Data is collected in a simulated environment

Discussions and future directions

The recent investigations to detect driver drowsiness using physiological signals have been reviewed. In these investigations, different sensors augmented with machine learning are presented, which subsequently yield in the driver drowsiness detection system aiming to decrease accident rate, economic loss, and save lives.

RQ1: what kind of physiological signals have been used for driver drowsiness detection?

The systematic review indicates that ECG, EEG, and multimodal sensors are predominantly the most widely deployed sensors in physiological signals-based drowsiness detection. These sensors are deployed in various conditions with both male and female drivers. Often the subjects are sleep-deprived for experiments, however, a few research studies involve long driving sessions to make the subjects tired and fatigued. Predominantly, young and healthy drivers are used for experiments, and age and illness-related aspects are ignored in existing approaches which necessitates the inclusion of drivers from different age groups.

RQ2: what are the approaches used for different kinds of physiological signals-based methods?

Studies utilizing physiological sensors involve traditional approaches where the sensors are placed on the subject's body, head, arms, and hands. Such sensors are annoying and hinder the free movement of the drivers during the experiments. It also leads to subconscious reactions and the driver feels irritated. Non-invasive methods are also investigated, however, the numbers are very low as the majority of physiological signal capturing sensors are intrusive like EEG, ECG, GSR, etc. Similarly, very few studies utilize custom-designed wrist-worn-based devices or smartphone-based approaches for driver drowsiness detection. Owing to the wide proliferation of IoT sensors and smartphones with a large number of embedded sensors, such approaches should be adopted.

RQ3: what are the traditional machine learning and deep learning models used for physiological signal-based drowsiness detection?

Besides using the traditional classification methods, for the most part, driver drowsiness detection approaches utilize machine learning and deep learning models. Often, the machine learning models are augmented with feature reduction and optimal feature selection approaches to enhance the accuracy of drowsiness detection. SVM, LR, RF, and KNN have been widely used with physiological signals for the task at hand. Furthermore, HoG, PCA, LDA, and Haar-like features are used with machine learning models. CNN, LSTM, MLP, and DNN are widely adopted for driver drowsiness detection. Both machine learning and deep learning models produce good results, yet, their wide use is limited by two factors. First, machine learning models require a large dataset and appropriate feature set to provide high accuracy. The problem of feature optimality can be resolved using the deep learning models, however, they are data-hungry and need even larger datasets to learn the complex relationships. Second, both machine learning and deep learning models require higher computational power which limits their application in real-time scenarios. The concepts of distributed learning and transfer learning have not been explored within the context of driver drowsiness detection.

RQ4: what kind of experimental setup is used for validating the approaches?

A critical review of the existing approaches reveals the fact that an ample big part of the approaches utilizes simulated environments. Several different kinds of driving simulators are used for experiments. Although a few research works utilize dynamic driving seats to make the setup realistic, for the most part, a static seat is used for experiments indicating the gap between the simulated and real-world environment. Despite the potential of such approaches to provide high accuracy, the gap in the simulated and real driving circumstance reduce their wide application. To bridge this gap, experiments should be conducted in the real driving setup, although a specific driving area can be utilized.

RQ5: what kind of environment/scenarios are used for experiments?

By and large, experiments involve multiple sessions involving driving conditions similar to the daytime. Despite the potential of physiological sensors being prone to illumination conditions, most works use daytime light conditions. Only a few studies consider multiple scenarios covering both day and nighttime conditions. However, other driving conditions and environments are mostly ignored like rain, fog, and snow conditions. Similarly, studies lack driving behavior and drowsiness in busy traffic, road types, and long dangerous routes. Without investigating such scenarios, the study of human behavior during driving is incomplete and the proposed systems can not provide the reported accuracy in real-time situations. Thermal images utilize the change in temperature of the forehead, cheeks, and nose to determine driver states of wakefulness and drowsiness.

RQ6: what kind of features are used for physiological signals-based approaches?

The analysis of the studies using EEG, ECG, GSR, and the infrared camera shows that the choice of feature depends on the sensors used for drowsiness detection. However, many features are shared by different sensors. For example, respiration rate is widely used for driver drowsiness detection with different sensors including ECG, radar and optical camera, etc. The majority of the ECG-based approaches employ HRV for driver drowsiness detection. For EEG signals-based approaches, alpha and delta frequency bands are utilized to extract features for driver state recognition. The use of multiple features from the single sensors has not been investigated in the existing works. For example, the signals from multiple frequency bands of EEG signals can be investigated in this regard.

RQ7: which type of physiological signals provide high accuracy for driver drowsiness detection?

Although both EEG and ECG signals are advantageous over GSR and thermal cameras to provide high accuracy, they have several limitations as well. Both EEG and ECG sensors are contact measurement approaches and require placing electrodes on the subject. A thermal camera, on the other hand, offers a non-intrusive approach and monitors the subject remotely, however, the internal heat conditions of a car can affect its performance. EEG and ECG signals show resiliency towards environmental conditions and prove to be more accurate. Multimodal approaches that perform sensor fusion tend to show better accuracy, tolerance, and specificity, however, the overall cost of the system is increased. For multimodal systems, the trade-off has to be made between complexity and accuracy.

RQ8: which factors affect the performance of physiological signals-based drowsiness detection approaches?

The choice of feature and classification model for physiological signals-based approaches affects the accuracy. The same data may generate different results when used with different machine learning or deep learning model. Other than that different environmental conditions can affect the performance of such sensors. For example, thermal camera-based approaches use the change in the facial skin temperature that may be affected by the heat or cold in the car. GSR and thermal camera-based approaches often utilize empirically derived threshold values which may not be suitable for different environmental conditions.

RQ9: what are the limitations of existing approaches?

Many investigators collected data in a controlled and virtual environment on driving simulators for driver's safety during experiments, however, simulation conditions are very much different from real scenarios that may affect the efficacy of the proposed approaches. It is observed that many of the investigators used invasive approaches in their investigation that make drivers uncomfortable while driving. Many approaches utilize the publicly available datasets, however, such datasets are limited and do not include enough data to perform exhaustive validations. Also, the small-sized datasets are not appropriate to validate the performance of machine learning and especially deep learning models. Similarly, the datasets lack the data from multiple sensors and multimodal approaches can not be tested properly. Often the generalized machine learning and deep learning models are utilized which indicates the need for custom-built and novel architectures for providing enhanced performance. Q learning and transfer learning-based approaches are not studied within the context of driver drowsiness detection.

Conclusion

Driving is a complex task that requires the full mobilization of physiological and cognitive resources. Driver drowsiness caused by sleep deprivation, stress, and fatigue can lead to reduced cognitive performance that often leads to accidents. Drowsiness has been regarded as one of the main factors for accidents and timely detection of driver drowsiness can save both human and financial losses. Many research works have been presented to detect driver drowsiness using different kinds of features like driver features, car features, and driver-related physiological features. In view of the wide application of physiological signals, this study presents a systematic literature review of recent techniques and technologies for driver drowsiness detection. Literature shows that EEG and ECG sensors are widely used for obtaining physiological signals followed by GSR and thermal cameras. Both machine learning and deep learning models have been deployed for driver drowsiness detection, predominantly in driving simulation conditions. Often using the generalized models, research lacks customized deep learning architecture, as well as, transfer learning. Multimodal approaches show high accuracy, yet are limited by the complexity and real-time application. Predominantly, the existing datasets lack multi-sensor data which makes the validation of multimodal approaches difficult. The use of heterogeneous hardware sensors makes it very difficult to compare the performance at a common standard. It is observed that many of the investigators used invasive sensors in their investigation that make drivers uncomfortable while driving. The research requires novel solutions comprising IoT and mobile devices, non-invasive sensors, transfer learning, and customized deep learning architecture to provide robust, reliable, resilient, and real-time solutions for driver drowsiness detection.

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Data Availability

The data used in this study is available on request.

Declarations

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