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 affects drivers’ capability and causes many accidents. Drowsiness-related road accidents are associated with trauma, physical injuries, 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 accidents 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 point out the research gaps. Perceptions and conceptions are made to provide future research directions for drowsiness detection techniques based on physiological signals.

**Keywords**: Drowsiness detection; heart rate; respiration rate; advanced driver assistance systems; machine learning;

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 towards sleep than wakefulness[1](#_bookmark15). 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.[2](#_bookmark16),[3](#_bookmark17). There are several approaches that focus only on fatigue detection using the image, physiological signals, and behavioral features[4](#_bookmark18)–[7](#_bookmark19)

Driver drowsiness is associated with the increased number of accidents[8](#_bookmark20). While driving on highways, a vehicle covers a distance equal to a football field in 3 to 4 seconds which indicates that seconds of inattention can lead to severe outcomes[9](#_bookmark21). Drowsiness declines the cognitive performance that affects drivers’ capability and causes many accidents. Driving without sleep for more than twenty hours has an impact similar to having 0.08% (US legal limit) blood-alcohol concentration level[9](#_bookmark21). According to the world health organization (WHO) report, deaths related to road accidents exceed one million[10](#_bookmark22). Recent studies show that 30% of fatal accidents take place due to drivers’ fatigue or drowsiness[11](#_bookmark23). There are three times higher chances of road accidents if the driver is fatigued[9](#_bookmark21). 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[9](#_bookmark21). National highway safety traffic administration (NHSTA) states that 4,111 people died while another 50,000 were injured in the US due to drowsiness between 2013 to 2017 alone[12](#_bookmark24). The reports reveal that the night shift male workers of 16 to 29 years of age and a highest risk drowsiness is associated with people suffering from sleep apnea syndrome[13](#_bookmark25).

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, 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 bases, 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[14](#_bookmark26)

* + Behavioral features,
	+ Vehicular features, and
	+ Physiological features



**Figure 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 the abnormal features like rapid line change, abrupt increase or decrease in the speed, etc. and attribute them to different causing factors[15](#_bookmark27). 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.[16](#_bookmark28). Physiological features, on the other hand, focus on signal measures using different devices like electrocardiogram (ECG), electroencephalogram (EEG), heart rate measurement, etc. for drowsiness detection[17](#_bookmark29). An illustration of physiological features and the sensors to obtain such features is provided in Figure [1](#_bookmark0).

## Comparison with Previous Reviews

LaRocco et al. [18](#_bookmark30) 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. [19](#_bookmark31) presents 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. [20](#_bookmark32). 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 et al. [21](#_bookmark33). The study analyzes the use of various machine learning and deep learning models and feature extractions approaches in this regard.

Tian et al. [22](#_bookmark34) 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 Scarpelli et al. [23](#_bookmark35). 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. [24](#_bookmark36). 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. [25](#_bookmark37) provides 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.

**Table 1.** A comparative analysis of existing reviews/surveys on drowsiness detection.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Ref. | Articles | Covered topics | Scope | Findings |
| LaRocco et al. [18](#_bookmark30) | 47 | Consumer EEG | Review of low cost consumerEEG 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. [19](#_bookmark31) | 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 restriction, long travel, etc. push drivers to continue driving even while fatigued. |
| Continued on next page |

## Table 1 – continued from previous page

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Ref. | Articles | Covered topics | Scope | Findings |
| Haghani et al. [20](#_bookmark32) | 86 | Neuroimaging methods | Covers the approaches basedon 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. [21](#_bookmark33) | 41 | Behavioral features | Approaches based on driverbehavioral 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 avail- able datasets. |
| Tian et al. [22](#_bookmark34) | 80 | EOG approaches | Analyzes EOG approachesincluding single and multi- modal features *•**•**•* | Multifeatured based techniques using EOG signals perform betterEOG approaches are low cost, low power and low intrusionEOG applications are limited regarding driver drowsiness |
| Scarpelli et al. [23](#_bookmark35) | 10 | Age impact on driverperformance | Age based analysis for driverperformance*•**•**•* | Older drivers are less prone to sleep lossThe influence of sleepiness related impairment is high for younger driver.Older people avoid risky scenarios by self- regulating their driving |
| Abbas et al. [24](#_bookmark36) | 146 | Smartphone-basedhypervigilance | The study covers multimodalfeatures 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. |
| Continued on next page |

**Table 1 – continued from previous page**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Ref. | Articles | Covered topics | Scope | Findings |
| Doudou et al [25](#_bookmark37) | 138 | Market products fordrowsiness detection | The study covers commercialsolutions based on driver, vehicle, and behavioral features *•**•* | Several approaches cannot distinguish between the drowsiness and band driving attitudeUsing 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 on driver physiological signal-based drowsiness detection systems are explored and presented. The purpose of this paper is to make an insight and the progress in physiological signal-based driver drowsiness detection for the future investigators to investigate challenges, gaps and pave the way forward. 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](#_bookmark2) provides the acronyms used in this study.

## Organization of Paper

The rest of this study is divided into nine sections. Section [2](#_bookmark1) presents the research methodology used in this study, followed by the discussion of respiration-based drowsiness detection methods in Section [3](#_bookmark3). Sections [4](#_bookmark4) and [5](#_bookmark6) 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 drowsiness detection. Analysis of techniques related to GSR is given in Section [6](#_bookmark7). Thermal camera-related approaches are presented in Section [7](#_bookmark9) while the multimodal approaches are discussed in Section [8](#_bookmark11). Section [9](#_bookmark13) provides the discussions and future directions. In the end, the study is concluded in Section [10](#_bookmark14).

# 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 the 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 for literature, especially in searches for grey literature, as needed by systematic reviews. Shariff et al. [] discovered that Google Scholar offered free access to nearly three times as many articles than PubMed. 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[26](#_bookmark38). The study follows the recommendations provided by the PRISMA. A systematic review aims at providing the understanding of a specific research area by discussing the current tools and techniques and their associated pros and cons[27](#_bookmark39). It also provides the research gaps in the current literature and discusses comprehensive future directions[28](#_bookmark40).

**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 andMeta-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 |
| 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 |

## 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,
		- Studies using subjective measures or behavioral features for drowsiness detection, and
		- Survey or review studies

## Papers Selection

Search query results into 502 articles containing articles, conference proceedings, review articles, etc. 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.

## 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

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[29](#_bookmark41),[30](#_bookmark42). Additionally, significant changes are observed for the inhaling to exhaling ratio[31](#_bookmark43). 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. [32](#_bookmark44) to detect drowsiness using the 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 by Daubechies wavelet function of order six and a level three decomposition. 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 as 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 as 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. [33](#_bookmark45) propose a system that use 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 0.5 Hz cutoff frequency with a low-pass filter while baseline signal is cleaned with high pass filter on 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. [34](#_bookmark46) 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 of 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 show that a better respiration rate can be obtained using 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. [35](#_bookmark47) 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. R2 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 or vital sign detection. Experimental results show that this proposed system detects mobile phones perfectly in most cases.

 Similarly, Gu, X. et al. [36](#_bookmark48) uses a CW Doppler radar for fatigue detection. A CW radar placed at 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[37](#_bookmark49). 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%[38](#_bookmark50).

The respiration signals can also be obtained from ECG signals. For example, the system proposed by Tateno et al. [39](#_bookmark51) used respiration rate 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 to 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 in 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 [39](#_bookmark51) 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. [40](#_bookmark52) uses two dynamic cameras to obtain videos that are process 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 from 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 level. The solution[40](#_bookmark52) is advantageous for driver fatigue detection as a non-invasively based on respiration signal.

In a similar fashion, Tayibnapis et al. [41](#_bookmark53) employs 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[42](#_bookmark54). PPG obtains plethysmogram that can detect changes in blood volume. Viola-Jones algorithm is used to detect face region[43](#_bookmark55) while SIFT key points are extracted from facial images and stored in a database[44](#_bookmark56). 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[45](#_bookmark57). HRV is acquired from BVP while respiration rate is obtained from the center of frequency of HF that varies between 0.15 Hz to

* 1. 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 Siddiqui et al. [46](#_bookmark58). 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 of 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%.

**Table 3.** A comparative summary of respiration-based drowsiness detection approaches.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Ref. | Sub. | Sensor | Approach | Pros | Cons |
|  Sharma et al. [32](#_bookmark44) | 150 | - | K means | Achieved 100% accuracy using signals acquired in real- time environment. | No explanation about signalacquisition. Also, the signals are only acquired before and after the driving, not during the driving. |
| Guede-Fernandez et al [33](#_bookmark45) | 20 | Plethysmographybelt | - | Sensitivity of 90% isachieved by system. | Virtual environment is usedfor signal acquisition. On body belt is used for signal acquisition. |
| Leicht et al. [34](#_bookmark46) | - | Optical sensor &MI coil | - | A cover for seat belt ismade for signal acquisition that can be adjusted or re- moved by Velcro tape. Non- invasive signal acquisition is proposed. | Data is collected in a con-trolled virtual environment. Heart rate is not monitored correctly due to high noise during inspiration. |
| Leem et al. [35](#_bookmark47) | - | IR-UWB | - | Signals acquired in real environment when driver is stationary or moving. Mobile usage is detected. | The acquired Signals areused for classification purposes. Mobile usage is detected in a specific region. |
| Gu, X. et al. [36](#_bookmark48) | 3 | CW Dopplerradar | Decision tree | Decision tree achieves an accuracy of 82.5%. A non- invasive method for signal acquisition. | Data collected in a controlledenvironment. The number of subjects used in experiments is too low. |
| Continued on next page |

**Table 3 – continued from previous page**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Ref. | Sub. | Sensor | Approach | Pros | Cons |
| Tateno et al. [39](#_bookmark51) | 4 | Fingertip wavepulse | - | Threshold system is de-signed that gives an accuracy of 64.4%. Respiration signals are acquired from ECG signals. | Attachable sensor is used forsignal acquisition. Time and resource usage while extracting respiration signals from ECG. Signals acquired in a controlled environment. |
| Solaz et al. [40](#_bookmark52) | 5 | PAC16 and FR-CAM | - | 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. [41](#_bookmark53) | - | 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 fac- tors in a real environment. SVM is used for classification, but results are not mentioned. There is no explanation about how many sub jects are used in the experiment. |
| Siddiqui et al.[46](#_bookmark58) | 40 | UWB | SVM | Non-intrusive drowsiness detection without physical con tact. | The obtained accuracy is lowas compared to other respiration-based approaches. Data is gathered in controlled environment. |

# 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 that shows high resistance against noise. An illustrative process of ECG-based drowsiness detection is presented in Figure [2](#_bookmark5).



**Figure 2.** 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. [47](#_bookmark59). 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 directions, Gupta et al. [48](#_bookmark60) detects 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. [49](#_bookmark61). This study is based on two datasets. 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 between 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 to 40 Hz is applied on 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% are achieved by extracting new features from HRV signals to classify drivers’ state of sleep by Attarodi et al. [50](#_bookmark62). For this purpose, an annotated dataset of driver’s actual sleep from ’Physionet’ 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, frequency of PSD are used to calculate the magnitude and phase of each point and to create new signals using Poincare plot. Total 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. [51](#_bookmark63) presents 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 to 60 years). An adaptive filter is applied to the acquired ECG signals for noise removal. Two machine learning algorithms KNN and SVM are applied on 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 STFT 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.

 Similarly, a microcontroller-based driver drowsiness detection based on HRV signal analysis is proposed by Hendra et al. [52](#_bookmark64). 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 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 sec, 20 sec, and 10-sec 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. [53](#_bookmark65) 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 by Kim et al. [54](#_bookmark66). 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 minutes. Two cameras are used in the experiment setup video of the upper body of the driver and the screen. New RR intervals 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. [55](#_bookmark67). 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. [56](#_bookmark68). 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. [57](#_bookmark69) 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 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 Babusiak et al. [58](#_bookmark70). 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.

**Table 4.** A summary of ECG signals-based approaches.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Ref. | Sub. | Sensor | Approach | Pros | Cons |
| Vicente et al [47](#_bookmark59) | 30 | ECG electrodes | - | Signals are collected to makethree datasets one in real environment and two in virtual environment. Achieved a 96% and 80% positive predicted value. | On body electrodes are usedfor signal acquisition that makes driver uncomfortable. |
| Continued on next page |

**Table 4 – continued from previous page**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Ref. | Sub. | Sensor | Approach | Pros | Cons |
| Gupta et al. [48](#_bookmark60) | - | Zephyr BioHarness | - | Standard dataset from PhysioBank website is used. A threshold-based system is de- signed. The system alerts the driver by an alarm. | Chest strap is usedfor 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. [49](#_bookmark61) | 10 | Electrodes | ML, DL | KNN achieves an accuracyof 95% while an autoencoder achieved 96.6% accuracy. Data acquired in a real-time environment with no sleep deprivation. | On body electrodes are usedfor signal acquisition that makes the driver uncomfortable. Signal acquired in a virtual environment with sleep deprivation. |
| Attarodi et al. [50](#_bookmark62) | - | - | MLP | MLP achieves an accuracy of91.4% with standard data set from ’Physio.net’. | Dataset is used only to trainMLP. No information about subjects sensors. |
| Babaeian et al. [51](#_bookmark63) | 25 | Three electrodes | KNN | KNN achieves accuracyabove 80%. | Signals acquired in con-trolled virtual environment. Electrodes are attached to body for signal acquisition. |
| Hendra et al. [52](#_bookmark64) | 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 [53](#_bookmark65) | - | Electrodes | - | Hardware is design using Arduino and electrodes to ac- quire ECG signal. Software is designed to detect HR and HRV from ECG signals. | Does not describe detailsabout data collection and experiments. Attachable electrodes are used. |
| Kim et al. [54](#_bookmark66) | 6 | Polar H7 | SVM | Uses both signals and theircombination 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. [55](#_bookmark67) | - | Electrodes | - | Data is acquired in real environment. | Electrodes are placed at thebackside of the shirt for data acquisition that makes driver uncomfortable. |
| Chang et al. [56](#_bookmark68) | 21 | Chest belt | NN | Achieved an accuracy of98.65 with neural network and NB. A smart mobile de- vice was used to receive the signal from the belt. | Physical contact using thebelt causes discomfort and introduces noise. |
| Kundinger et al. [57](#_bookmark69) | 30 | Empatica E4 | KNN | Non-intrusive wrist watch usage | Simulator data, noisy data isnot considered. |
| Babusiak et al [58](#_bookmark70) | - | Electrocardiograph | - | Unobtrusive monitoring | No information about sub-jects, 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[59](#_bookmark71)–[61](#_bookmark72). EEG electrodes are placed on the scalp, as shown in Figure **3**, 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.[62](#_bookmark73),[63](#_bookmark74). Further analysis is performed on these frequency bands to detect driver drowsiness.

Spectral and band power features extracted from EEG signals are used to detect drowsiness by Krishnan et al.[64](#_bookmark75). ULg DROZY a publicly



**Figure 3.** An experimental set up to detect drowsiness using EEG signals (left), placement of electrodes as per international 10-20 system standard (right)[59](#_bookmark71).

available dataset comprised of EEG, EOG, ECG, EMG signals are used in this research. All these signals are recorded at a sampling rate of 512 Hz of 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 hours 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 minutes for two states drowsy and non-drowsy. Signals are split into 2 seconds 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.[65](#_bookmark76). The EEG signal of 600 people is gathered continuously for 117 sec using a neuroheadset emotive device. A total of fourteen features are received from the brain with leads and open and closed eyes are considered as 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 features matrix and new matrix are obtained that are fed to perceptron neural networks for clustering that achieved classification rate of 98.38%. Optimized data with a Genetic algorithm is considered to reduce computational complexity.

Yang, et al. [66](#_bookmark77) proposed the CNBLS to detect drowsiness from an EEG signal from eleven ( seven males four females) students at Tianjin university. Subjects are advised to have proper rest of 7 hours 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 river’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 minutes are considered as alert and the last 20 minutes are considered as fatigued data. The data of both categorize is split into 1 second making a sample total of 2400 for each subject and 1200 from each category. The MWRN is used to transform EEG data to 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, Y. et al [67](#_bookmark78) 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 hours before wakefulness data collection and 4 hours (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-second 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.[68](#_bookmark79). A total of sixteen subjects of age ranging between 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 minutes. Task A and B are considered as 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 sec frames making a total of 800 frames for each class. Sample entropy is used to extract features from all channels 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.[69](#_bookmark80). Nineteen male subjects of 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 the extreme drowsiness. Grabs outlier detections method is used to remove outliers from the raw EEG data. A Butterworth bandpass filter with a cutoff frequency of 0.1 to 31 Hz is used. Alpha spindles are detected using the Morlet mother wavelet. Each signal is split into 30 sec 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.[70](#_bookmark81). 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, M. et al. [71](#_bookmark82) presents 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 between 22 to 42 years is collected in a sleep-deprived state at 2 a.m. to 5 a.m. and after a normal night 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 hour 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 to 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-Brain Computer Interface) system coupled with deep learning is presented by Balam et al. [72](#_bookmark83). 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. [73](#_bookmark84) used two approaches for the 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 carried out on 27 subjects’ publicly available dataset and CNN shows good performance with up to 75.87% accuracy with both approaches. Similarly, Chen et al. [74](#_bookmark85) 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 is 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. [75](#_bookmark86). Physionet dataset and dataset virtually recorded by Zheng et al.[76](#_bookmark87) was used. 50Hz notch filter and 0.1-45Hz 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[76](#_bookmark87) dataset respectively.

A BCI is used for drowsiness detection by Dunbar et al. [77](#_bookmark88). 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. [78](#_bookmark89). 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. [79](#_bookmark90) 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 (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.

**Table 5.** Comparative analysis of EEG based approaches for drowsiness detection.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Ref. | Sub. | Sensor | Approach | Pros | Cons |
| Sarabi et al. [65](#_bookmark76) | 600 | Neuroheadset | Perceptron | Correctly classify betweenclosed and open eyes. | No information about datacollection. Only CR was considered. A contact measurement device was used. |
| Yang, et al. [66](#_bookmark77) | 11 | - | CNBLS | High classification accuracyusing only EEG signals. | On body device was used,and data was collected in controlled environment. |
| Ma, Y. et al [67](#_bookmark78) | 6 | GmbH | PSO-H-ELM | Performance comparisonfrom multiple machine and deep learning models. | Electrodes are placed on thebody causing interference during the driving and simulated environment. |
| Krishnan et al [64](#_bookmark75) | 14 | - | KNN, SVM | Robust and high accuracy. | Experiments are performedin a controlled environment. |
| Zhang et al. [68](#_bookmark79) | 16 | Neuroscan | PCA, KNN | Feature selection throughPCA to obtain important features. | Simulated environmentmakes the approach less practical for real scenarios. |
| Houshmand et al. [69](#_bookmark80) | 17 | Monopolar electrodes | CNN | Simple and robust modelwith 94% accuracy. | Low number of test samples,results are not generalizable. |
| Zhu, M. et al [71](#_bookmark82) | 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 con-trolled environment, wear- able electrodes are used. |
| Balam et al. [72](#_bookmark83) | 23 | Electrodes | DNN | Statistical method to findbest 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 [70](#_bookmark81) | 10 | Electrodes | LDA & KNN | High accuracy using thetaband of EEG. | The data is collected using asimulation setup. |
| Paulo et al. [73](#_bookmark84) | 27 | Scan SynAmps2Express | CNN | Resolves low SNR and cross-subject disparities | Comparatively low accuracywith data from simulated driving. |
| Wang et al. [79](#_bookmark90) | 15 | Emotiv device | MMSE | Drowsiness detection undernormal 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[80](#_bookmark91),[81](#_bookmark92). 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[82](#_bookmark93). A schematic diagram of GSR based driver drowsiness detection is shown in Figure [4](#_bookmark8).

A real-time driver state detection using a wearable device is presented by Misbhauddin et al. [84](#_bookmark94). 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 on the completion of each epoch. This data is stored in temporary



**Figure 4.** GSR placement set up (left), experiment set up for driver drowsiness (middle[83](#_bookmark95)) and location for placing electrodes (right[80](#_bookmark91)).

memory and calculation of HRV and GSR is started. HRV is measured by taking square differences of IBI and 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 hours, 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. [85](#_bookmark96) evaluates the role of sleep changes to the 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. [83](#_bookmark95) performs experiments with 21 healthy drivers in a sleep-deprived session. Skin conductance, respiration, ECG and GSR recorded with small sensor attached to little finger, thermistor based sensor, electrodes attached to a glove respectively 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. [86](#_bookmark97) 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 driver state.

Choi et al. [87](#_bookmark98) 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. Similarly,[88](#_bookmark99) propose a wearable-based solution to determine driver’s activeness in real-time. The proposed solution monitors the HRR and GSR from the driver and determines the states of wakefulness and drowsiness. Haptic feedback is used to alert the driver if the driver is found drowsing.

Table 6 Comparison of EEG based studies

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Ref. | Sub. | Sensor | Approach | Pros | Cons |
| Misbhauddin et al. [84](#_bookmark94) | 10 | E4 wristband | - | A threshold-based system was presented that set a threshold during training phase. Systems achieves an accuracy of 80%. | Data is collected in controlled environment. User specific training was required before using the system. System uses a wrist band to record the data that makes user uncomfortable. |
| Bartolacci et al. [85](#_bookmark96)  | 80 | - | Vienna Test System TRAFFIC | Sleep quality, Sleepiness, and Vigilance of elders and adults is tested. | Different devices linked to test system were used to record the physiological signals. This test was performed before driving. |
| Darzi et al. [83](#_bookmark95) | 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% achieved. | Data was collected in controlled and simulated environment. On body sensors are used that cannot be used in real environment.  |
| Munir et al. [86](#_bookmark97)  | 1 | Electrodes attached to Arduino | - | IoT based low-cost system was presented. Experiment was conducted in real time environment. | System uses on body sensor for predictions. A threshold-based system is presented.  |
| Choi et al. [87](#_bookmark98)  | 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-intrusive approach. The setup includes a thermal camera, occasionally augmented with visible light or IR camera, as shown in Figure [5](#_bookmark10). 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.

Driver drowsiness is detected using thermal imaging based respiration Kiashari et al. [89](#_bookmark100). Empirical analysis reveal that change in nostrils’ temperature is observed during drowsiness and wakefulness. Geometrical features can be used to detect the respiration region and frames from thermal camera can provided the respiration rate. The frequency of respiration of normal humans varies between 12-20 breathes per minute[90](#_bookmark101). 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. Respiration signal can be formed using the respiration



**Figure 5.** A schematic setup of thermal imaging based drowsiness detection.

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 that results in 90% and 83% accuracy scores by SVM, and KNN, respectively.

Similarly, a thermal image-based approach is adopted by Kiashari et el. [91](#_bookmark102) 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 Forczma´nski et al. [92](#_bookmark103). 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 the 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. [93](#_bookmark104) uses 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 *◦* for 12 subjects when their state moves from wakefulness to drowsiness and extreme drowsiness, respectively.

Similarly, Moazen et al.[94](#_bookmark105) employs 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 are 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.

Forczma´nski et al. [95](#_bookmark106) determines the driver 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 mouth 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. [96](#_bookmark107), 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, an accuracy of 89.5% is achievable.

Similarly, Kajiwara et al. [97](#_bookmark108) establish a driver’s condition with the help of eye blinks and yawning frequency. For this purpose, both visible-light cameras and thermal camera 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, the 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. [98](#_bookmark109) 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 Tashakori et al. analyze the changes in temperature of the forehead and cheeks to determine the drivers’ state in [99](#_bookmark110). 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% was be achieved using the proposed approach.

Cardone et al. [100](#_bookmark111) 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.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Ref. | Sub. | Sensor | Approach | Pros | Cons |
| Kiashari et al. [89](#_bookmark100) | - | Thermal Camera | SVM, KNN | Thermal camera was used. Environmental factors have no effect on camera. SVM achieved and accuracy of 90%. | Driver has to remain still for five seconds. Head movement affects the result of the system.  |
| Kiashari et el. [91](#_bookmark102)  | 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 real driving environment |
| Tashakori et al. [93](#_bookmark104) | 12 | Thermal Camera | - | Facial temperature decreases from wakefulness to drowsiness. | Data was collected in simulated environment. Head movement affects the results of the system. Not feasible in real driving environment. |
| Moazen et al.[94](#_bookmark105)  | 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 simulated environment. Head movement affects the results of the system. Not feasible in real driving environment. |
| Forczma´nski et al. [95](#_bookmark106)  | 19 | Thermal Camera | - | Haar features were extracted from eyes and moth regions. | Data was collected in simulated environment. Head movement affects the results of the system. Not feasible in real driving environment. |
| Gielen et al. [96](#_bookmark107) | 19 | VarioCAM infrared thermal camera, Empatica E4 wristband | 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, an accuracy of 89.5% is achievable. | Data was collected in simulated environment.On Body sensors were used. head movement effects the thermal camera results |
| Kajiwara et al. [97](#_bookmark108)  | - | Visible-light cameras and thermal camera | - | Both cameras were used separately. Vision camera achieved an accuracy of 90% in illuminated conditions | Bad lights effects the vision camera results and head movement effects the thermal camera results. No information about subjects. |
| Knapik et al. [98](#_bookmark109)  | - | Thermal Camera | - | System is resilient to change in light. For detecting yawning, eye corners are used for face alignment | Data was collected in simulated environment. Change in temperature effects thermal camera results. |
| Tashakori et al. 99 | 30 | Thermal Camera | KNN,SVM | Change in forehead and cheek temperature is observed to detect drowsiness. System achieved an accuracy of 82% | Data was collected in simulated environment. Use of camera is not feasible in real environment due to head movement during driving |
| Cardone et al. [100](#_bookmark111)  | - | 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 to ’awake’, ’fatigue’, and ’sleepy’ that achieves an accuracy of 56%. | Data was collected in simulated environment. Use of camera is not feasible in 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 [6](#_bookmark12) shows a schematic diagram of a multisensor approach.



**Figure 6.** Schematic diagram of an approach that combines data from multiple sensors [adopted from[25](#_bookmark37)].

For example, driver drowsiness is detected from the respiration signals acquired using a wearable clothing sensor by YUDA et al. [101](#_bookmark112). 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 Hz 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 than 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 is presented by Wang et al. [102](#_bookmark113) 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. [103](#_bookmark114). 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 frequency of 1-40 Hz is used on EEG signals for noise removal. EEG, ECG, and eye blinking data are segmented into ten-second frames 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. [104](#_bookmark115). 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 Hz, 31 Hz, 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[104](#_bookmark115). 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 have been reported with higher performance. For example, Jiao et al. [105](#_bookmark117) 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 the 0.98 accuracy score after data augmentation.

Seok et al. [106](#_bookmark118) 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.

The authors Wali et al. [107](#_bookmark119) proposed an approach for drowsiness classification using EMG and wavelet packet transform. EMG signals are decomposed into approximations up to four levels. A FFBPNN model is used for drowsiness classification. Average accuracy of 75% is obtained using a 3 s window.

A PPG-PRS is proposed by Rundo et al. [108](#_bookmark120) 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 that show a classification accuracy of 88.88%.

Similarly, Barua et al. [109](#_bookmark121) 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.[110](#_bookmark122) 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. [111](#_bookmark123) presented a combination of 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. [112](#_bookmark124). Five subjects’ ages ranged between 21-30 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 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. [113](#_bookmark125). 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 value as the attention values decrease from 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. [114](#_bookmark126). Twelve healthy subjects took part in the data collection process in a controlled simulated driving environment. Features from frequency and time domain 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.[115](#_bookmark127). Data from sixteen male subjects were collected in a simulated driving environment. The number of eye blinks and the PERCLOS over 10 seconds were estimated using 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-second 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. [116](#_bookmark128) to detect drowsiness. ECG, 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%.

**Table 6.** A comparative summary of approaches using multiple sensors.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Ref. | Sub. | Sensor | Approach | Pros | Cons |
| YUDA et al. [101](#_bookmark112) | 7 | Hexoskin | - | Data is acquired in a real environment. | Electrodes are placed at thebackside of the shirt for data acquisition that makes driver uncomfortable. |
| Wang et al. [102](#_bookmark113) | 10 | Nexus-10 | RF | Data is collected in real-time.RFT gives an accuracy of 99%. | Data is collected before orafter the driving, not during the driving. An attachable de- vice is used for signal acquisition. |
| Gwak et al. [103](#_bookmark114) | 16 | EEG-1200, WEB-7000 | RF | RF shows an accuracy of81.4%. | Signals acquired in virtualcontrolled environment. Attachable devices are used for signal acquisition. |
| Chen et al. [104](#_bookmark115) | 32 | Electrodes | - | Accuracy of 94.44% and88.67% achieve using data sets A and B respectively. | Signals in dataset B are ac-quired in a real environment. Signals in dataset A are ac- quired in a controlled vir- tual environment. Attachable electrodes are used for signal acquisition. |
| Jiao et al. [105](#_bookmark117) | 12 | Electrodes | GAN, LSTM | High accuracy with less num-ber of electrodes. | Simulated environment isused for data collection, elec- trodes placement on subjects. |
| Seok et al. [106](#_bookmark118) | 11 | Electrodes | Q learning | Using DQN for analyzingbiomarkers to increase clas- sification accuracy. | The data is collected in a sim-ulation environment. |
| continued on next page |

**Table 6 – continued from previous page**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Ref. | Sub. | Sensor | Approach | Pros | Cons |
| Wali et al [107](#_bookmark119) | 40 | Ag–AgCl electrodes | FFBPNN | Using db2 wavelet that re-quire less filter coefficients, low processing time | Low accuracy & data fromsimulated environment. |
| Rundo et al. [108](#_bookmark120) | 71 | - | D-LSTM & 1D-TDCNN | Study of drivers with higheror lower than average blood pressure | Driving conditions are simulated, accuracy is slightly low. |
| Barua et al. [109](#_bookmark121) | - | g.HIamp electrodes | KNN, RF, SVM | Optimal feature selection using SFFS | Use of driving simulator forexperiments. |
| Abbas et al [110](#_bookmark122) | 14 | Pulse SensorAmped | CNN & DBN | Higher accuracy with lesspower | Low number of participants,use of electrodes. |
| Wang et al. [111](#_bookmark123) | 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 user uncomfortable and no ML used. |
| Karuppusamy et al. [112](#_bookmark124) | 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 controlled environment were used in data collection. On body sensors and camera was used that are not feasible in real environment. |
| Kondapaneni et al. | 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. [114](#_bookmark126) | 12 | Electrodes | LSTM | Time and frequency domain features were extracted. GA used for data augmentation. | Data was collected in simulation and controlled environment. On body sensor was used. |
| Gwak et al.[115](#_bookmark127) | 16 | EEG-1200 and WEB-7000 | RF | ECG, EEG and eyeblink data was used to make dataset that 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 simulated environment. |
| Sunagawa et al. [116](#_bookmark128)  | 50 | BIOPAC, Camera | - | Posture information enhanced the accuracy of detecting mild sleepiness. | On body sensors were used. Camera is not feasible to use in real environment. Data is collected in 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 decreases 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 with different age groups.

* 1. **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 type, 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.

* 1. **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 ap- proaches?

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 makes 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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The data used in this study is available on request.

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