Machine Learning Approaches for Detecting Driver Drowsiness: A Critical Review

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Abstracts: Driver drowsiness is a serious issue that poses a significant threat to road safety, as it can lead to accidents and injuries. In response to this problem, a thorough review of machine learning techniques for detecting driver drowsiness was conducted. The review examined a range of techniques, including more recent approaches that use machine learning and deep learning algorithms as well as different types of data sources driver behaviours, physiological signals, and vehicle behaviours. The primary objective of this paper was to critically analyse and provide a comprehensive overview of the current state-of-the-art in detecting driver drowsiness, evaluate the effectiveness of each technique in terms of accuracy and reliability, and identify potential areas for future research and improvement. In order to achieve this, a systematic review of relevant research studies was undertaken. The review determined that machine learning-based techniques can improve the accuracy and reliability of driver drowsiness detection systems. However, certain limitations, such as the need for large amounts of data, feature extraction, and model structure, must be addressed. By overcoming these limitations, machine learning-based systems have the potential to enhance road safety and prevent accidents. In conclusion, this paper provides a thorough review of machine learning techniques for driver drowsiness detection, evaluates their effectiveness, identifies potential research directions, and highlights their significance and contribution to road safety. The insights gained from this study can be used to guide the development of more effective driver drowsiness detection systems and improve road safety for the community.

Keywords: Driver Drowsiness, Machine Learning Techniques, Road Safety, Detection Systems and Critical Review.

1. INTRODUCTION

Road traffic accidents are a significant cause of mortality and morbidity worldwide. According to Ministry of Transport Malaysia, each year approximately 1.35 million people die in road crashes, and an average of 3,700 people lose their lives every day on the roads. Not only do these accidents cause devastating personal losses, but they also result in considerable economic losses for individuals, their families, and entire nations. In particular, the value of a human life lost in a car accident can have significant financial implications for governments. Based on the value of statistical life (VSOL) calculation used by the Malaysian Institute of Road Safety Research (MIROS) in 2018, the Malaysian government loses at least 3.12 million for each life lost in a car accident ("Ministry of Transport Malaysia Official Portal,"). The statistics of road accidents and road fatalities of Malaysia road are shown in Fig. 1.

Fig. 1: Malaysia Road Accidents and Fatalities 2010 – 2021("Ministry of Transport Malaysia Official Portal,")

The significant number of deaths suggests that sleepy driving is a serious issue that requires attention in order to lessen its effects. Drowsiness is the term for drowsiness, frequently in unsuitable contexts. ("Drowsiness: MedlinePlus Medical Encyclopedia,") Driving lengthy distances without getting adequate rest or doing so when the driver should be sleeping might make one drowsy. ("Fatigued Driving,"). In thesesituations, the primary issue is the driver's loss of focus, which causes a delayed response to any on-the- road occurrence. ("Drowsy Driving,").

Despite being distinct concepts, several studies equated sleepiness with tiredness because of their comparable effects. An accurate measuring scale for sleepiness levels is required in order to analyse stages of tiredness systematically and to make it easier to design automatic early drowsiness detection systems. Numerous strategies have been put out in that approach. (Wierwille et al., 1994) presented a new scale for evaluating sleepiness. According to their five-level definition of sleepiness as described in Table 1.

Table 1. Proposed drowsiness scale. (Wierwille et al., 1994)

Levels	Verbal Description
1	Not drowsy
2	Slightly drowsy
3	Moderately drowsy
4	Significantly drowsy
5	Extremely drowsy

Fortunately, it is feasible to identify early signs of driving sleepiness and alert the driver to help prevent any potential accidents. Drowsy driving is indicated by a variety of behaviours, such as excessive yawning, frequent eye closing, and continuously veering off the pavement. ("Drowsy Driving,").

In their study (Sharma et al., 2021) discussed about machine learning and deep learning that machine learning is a sub-class of artificial intelligence as shown in figure 2, is self-learning based on algorithms that mean the system learns from its experience. For instance, the type of data given input to the system learns the pattern and responds from its learning at the output. It uses a statistical learning algorithm that automatically learns and improves without human help. On the other side, in a deep learning system, it learns from its experience, but a large database or large information provided at input. Deep is the term that refers to several layers in between the input and output of a neural network, whereas in shallow neural networks maximum of two layers are present in between the input and output neural network. Artificial intelligence is a wide discipline of generating intelligent machines. Mostly artificial intelligence work includes machine learning as intelligent behaviour needs extensive information or knowledge.

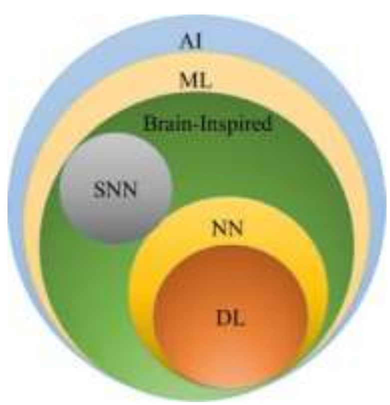

Fig. 2: Illustrates the artificial intelligence, machine learning and deep learning (Shinde & Shah, 2018)

In their work on machine learning models, (Goodfellow et al., 2016) provide the fundamentals of machine learning and deep learning. The researchers emphasize the increasing reliance on intelligent systems that incorporate artificial intelligence capabilities. The authors also discuss the automated analytical model building process in detail as shown in figure 3.

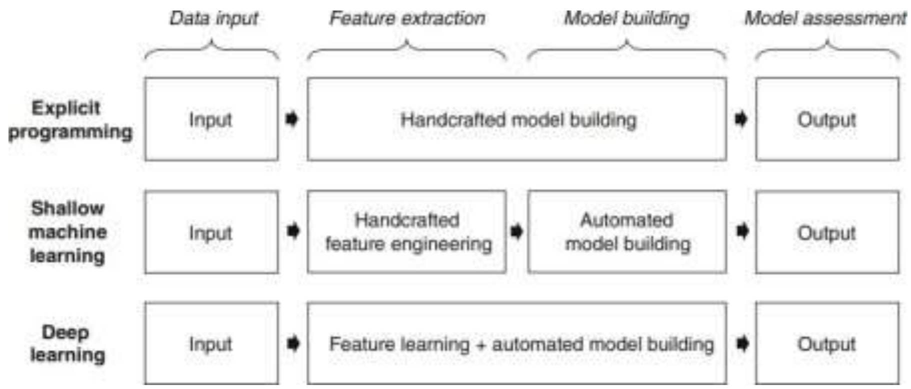

Fig. 3: Details of artificial intelligence model building(Goodfellow et al., 2016).

Many researchers are using machine learning and deep learning techniques to solve complex problems (Umair & Foo, 2022; Umair et al., 2021). Using machine learning and deep learning techniques, researchershave developed systems to detect driver drowsiness and prevent accidents caused by it.

In reality, recent years have seen a lot of study into driver drowsiness detection (DDD) methods. In order to prevent accidents, researchers have suggested a number of ways to identify these sleepiness signalsas soon as feasible. These measurements can be broken down into four main categories: first, image-based measures, which rely on analysing the driver's movements and facial expressions using a camera; second, biological-based measures, which correspond to the driver's by attaching specific bio-signals and data sensors to the driver's body; third, vehicle-based measures, which rely on observing the behaviour and movement of the vehicle; and fourth, hybrid-based measures, which combine two or more of the aforementioned categories. The DDD system is a tool for detecting driver sleepiness since it records specificbehaviours that a motorist demonstrates while driving while drowsy.

There are several types of DDD systems that use various methods to identify drowsy driving. According to (Reddy et al., 2017) there are three categories that may be used to classify the approaches. According to the literature, (Ramzan et al., 2019) gave a thorough study for the current DDD approaches as well as a thorough analysis for the widely utilised categorization methods in this industry. The DDD methodologieswere divided into three groups by Ramzan et al.: behavioural, physiological, and vehicular parameter- based strategies. The best supervised learning methods for detecting sleepiness were then examined. Finally,they conducted a comparison analysis, outlining the advantages and disadvantages of the three DDD.

However, (Sikander & Anwar, 2018) provided a thorough overview of the most current developments in the area of driver tiredness detection. The DDD techniques in this evaluation were divided into five classes based on the retrieved fatigue characteristics, such include observable characteristics, driving characteristics, biological characteristics, subjective reports, and hybrid characteristics. According to a survey on sleepiness detection methods conducted (Arceda et al., 2020) , the researchers' suggested drowsiness detection methods have not been evaluated in real-world driving situations. Testing is done in a synthetic setting that is completely unrepresentative of the circumstances on the actual roads. Many various driving situations might be encountered by the driver, which could influence how aware they are. Besides, The use of contextual information in sleepiness detection has been proposed by (de Naurois et al., 2019). Contextual information is essential since it might affect the driver's attitude while driving, such as vehicle flow and time of day.

Also, in their recent publication (Albadawi et al., 2022) provides a comprehensive analysis of various methods for drowsiness detection. The researchers discuss different types of detection systems, including those that use physiological signals and those that rely on visual and auditory cues as shown in figure 4. They also highlight recent advances in machine learning and AI that have improved the accuracy of these systems. They report current DDD issues and discusses future trends and research directions. Overall, the paper provides valuable insights into this important field of research.

Additionally (Ping & Shie, 2022) conducted a survey to assess the feasibility of encouraging Malaysiandrivers to use the suggested scheme. Authors propose a hybrid approach to tackle driver drowsiness in Malaysia, which combines vehicle diagnostics, physiology, and remote sensing information. Driving an instrumented car on the North-South Motorway at different times of the day allowed the authors to gather training and test data. Also, the authors compare different types of detection systems with their proposed methodology.

By discussing newly deployed DDD systems, particularly those published in the last five years, this review adds to the body of literature. Based on the methods employed to assess sleepiness, our article divides these systems into four groups. From our vantage point, these measurements can be hybrid, physiological, behavioural, and vehicle diagnostic. Along with the datasets, the review also summarises and tabulates the employed parameters, sensors, extracted features, algorithms, and classifiers, as well as quality measures (such as accuracy, sensitivity, and precision). A comparison of the usability and dependability of each of the four DDD categories is also provided. The structure of this paper is as follows:Measures for detecting sleepiness are covered in section 2. Section 3 covers a list of the challenges facing DDD. Section 4 discusses some of the future trends in drowsiness detection systems. Section 5 discuss and suggestion of critical review. Finally, Section 6 concludes the paper.

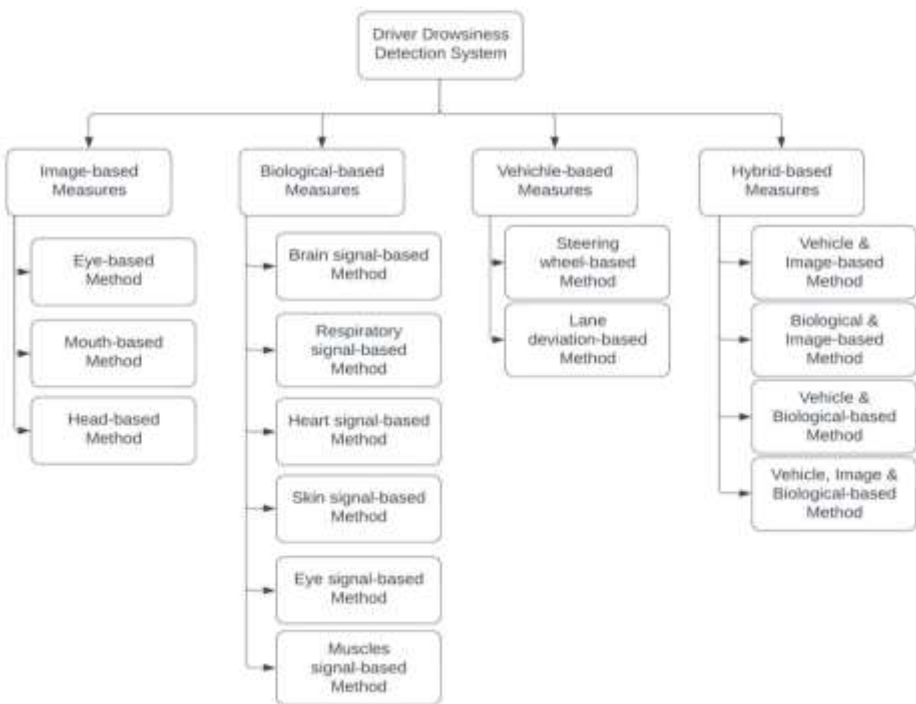

Fig. 4: Different types of detection systems (Albadawi, Takruri, & Awad, 2022)

2. DROWSINESS DETECTION MEASURES

The research focuses on various techniques for detecting driver fatigue, drowsiness, and hazardous driving events. The first technique, Vehicle Diagnostic, involves the use of machine learning and in-vehicle sensordata to detect lateral hazardous events. The second technique, Physiological, involves the use of real-time automated multiplexed sensor systems to monitor vital signs and EEG signals. The third technique, Behavioural Features, involves the use of machine learning and deep learning to analyse driver behaviour and detect signs of fatigue or drowsiness. The research highlights the importance of using on-board sensors,physiological signals, and behavioural features and hybrid of all three to detect and prevent dangerous driving events.

2.1. Vehicle Diagnostic

On-board vehicle sensors are widely used to detect dangerous driving behaviour. Various sensor types such as speed, gyro, steering wheel angle, throttle position, GPS, RPM, and lane/centre of gravity sensors have been utilized. Steering wheel angle sensors have been particularly studied for detecting driver drowsiness and fatigue. Researchers have proposed machine learning and deep learning methods to analyse continuousvehicle data and prevent dangerous driving events. These studies highlight the importance of on-board sensors in preventing road accidents and showcase the effectiveness of their proposed approaches in real- world scenarios.

2.1.1. Speed and Velocity Sensors

In the study conducted by (Harkous & Artail, 2019), 26 persons willingly took part in the tests to gather data about driving. The researchers presented a two-stage machine learning approach to detect drunk driving by analysing the signals from various on-board speed and velocity sensors of the vehicle. The prediction accuracy reaching a maximum of 98%.

(Malik & Nandal, 2021) presents a framework for analysing driving behaviour and patterns using the OBD-II tool, which is a standard diagnostic tool available in most vehicles. The study focuses on leveragingspeed and velocity sensors to analyse driving behaviour. It is worth noting that this particular research does not involve conducting experiments or utilizing a specific dataset, nor does it measure any evaluation matrices.

In their study, (Peppes et al., 2021) presents a study that uses machine and deep learning methods to detect and prevent dangerous driving events. They analysed continuous streams of vehicular data from five vehicles belonging to a major Greek highway operator. The study focused on using the speed sensor to analyse the data. Impressive training accuracy of 99.9% and validation accuracy of 100% were attained bythe RNN-LSTM model.

2.1.2. Global Positioning System (GPS)and Gyro Sensors

(Jeong et al., 2013) conducted a study using data from the in-car gyro sensor to identify lateral risky driving incidents. They equipped a probe vehicle with a customized data collection setup. The proposed algorithm achieved a classification accuracy of more than 85%.

In the study by (Harkous & Artail, 2019) a two-stage machine learning approach was introduced to detect drunk driving from on-board sensors, including gyro sensors. The voluntary collection of driving data by a set of 26 volunteers produced an impressively near-perfect detection accuracy of 98%.

In their study (Peppes et al., 2021) introduce a range of machine and deep learning techniques. These algorithms were applied to a privately collected dataset comprising vehicular data obtained from GPS and various sensors. The aim of their research was to analyse continuous streams of this data to identify and mitigate instances of hazardous driving events. Impressively, their approach achieved an impressive accuracy rate of 99.8%.

In the study (Jeong et al., 2013) conducted research focused on detecting lateral hazardous driving events using in-vehicle gyro sensor data. They employed Support Vector Machine (SVM) in conjunction with gyro sensor and GPS data. The study utilized a private dataset, and their approach achieved an accuracyrate of 85%.

2.1.3. Steering Wheel Angle

In their study (Arefnezhad et al., 2019) presents a study that uses steering wheel data and adaptive neuro-fuzzy feature selection to detect driver drowsiness. And achieved an accuracy of 98.12% on a privately simulated dataset.

In their study, (Z. Li et al., 2017) presents a real-time system for driver fatigue detection using steeringwheel angles. Dynamic Time Warping (DTW) with Steering angle achieved an accuracy of 78.01%, specificity of 29.35%, and sensitivity of 15.15% on a private dataset.

Also, (Chai, 2019) presents a study that uses the status of the steering wheel to monitor driver drowsiness and prevent dangerous driving events. Multilevel Ordered Logit (MOL), Support Vector Machine (SVM), and Back Propagation Neural Network (BP) with Steering angle achieved accuracies of 72.92%, 63.86%, and 62.10% respectively on a private dataset.

(R. Li et al., 2021) This study describes a technique for identifying driver weariness based on an examination of the grip the driver has on the steering wheel. The steering wheel grip sensor signals' energy is used by the authors to suggest a unique feature extraction approach. Linear Regression (LR) with SteeringWheel Grip Force achieved an accuracy of 86.6%, sensitivity of 97.2%, and specificity of 94.4% on aprivate dataset.

(Mutya et al., 2019) This paper explores the potential of image-based steering features for detecting drowsiness on rural roads. The authors analyse the relationships between different image-based features and drowsiness levels and propose a method for detecting drowsiness using these features. VGG 16 and VGG 19 Deep Learning models with Steering angle achieved a true positive rate of 52.3% and a false positive rate of 15.8% on a private dataset.

2.1.4. Throttle Position and RPM

Recently (Harkous & Artail, 2019) presents a two-stage machine learning approach to detect drunk drivingby analysing the signals from various on-board sensors of the vehicle. Hidden Markov Model (HMM) andRecurrent Neural Classification Method achieved an accuracy of 98% using throttle position, and other sensors on a privately collected dataset.

(Malik & Nandal, 2021) presents a framework for analysing driving behaviour and patterns using the OBD-II tool, which is a standard diagnostic tool available in most vehicles. Various methods including NN,SVM, F & NF, DT, k-Means Clustering, GA, Reinforcement Learning, BN, GMM, and HMM were used with throttle position, RPM, and other parameters, but no specific evaluation metrics were provided.

In the study (Peppes et al., 2021), utilized machine and deep learning techniques on a privately collected dataset, mainly comprising vehicular data from RPM measurements, throttle position, and other sensors. Their research aimed to analyse continuous RPM and sensor data to detect and prevent hazardous driving events. Their innovative approach achieved a remarkable accuracy rate of 99.8%.

Multiple studies extensively investigated vehicle parameters to analyse driving behaviour using different classification methods and evaluation metrics. Parameters like Vehicle Speed, Gyro Sensor, GPS, Throttle position, and Steering wheel angle were examined. Techniques like Hidden Markov Model (HMM), Recurrent Neural Networks, and Support Vector Machine (SVM) achieved accuracies ranging from 85% to 98%. Other studies explored RPM, Steering wheel, Velocity, steering angle, and Steering Wheel Grip Force, employing various classification and regression methods with different evaluation metrics and datasets. These studies contribute to understanding driving patterns and identifying hazardous events (see Table 2.

Table 2. Vehicle diagnostic drowsiness detection systems.

Ref	Vehicle Parameters	Classification Method	Evaluation Metric	Dataset
(Harkous &Artail, 2019)	Vehicle Speed, Gyro Sensor, Throttle positionand Steering wheel angle.	Hidden Markov Model (HMM) and Recurrent Neural Network (RNN)	Accuracy 98%	Private collected
(Malik & Nandal, 2021)	Vehicle Speed, Throttle position,and RPM	fuzzy & Neuro Fuzzy, Decision Trees, k-Means Clustering, Genetic Algorithm, and Reinforcement Learning. Gaussian Mixture Model, Bayesian Networks, and HMM	-	-
(Peppes et al., 2021)	Speed, Throttle position, andRPM	Logistic regression, SVM and random forest, recurrent neuralnetworks (RNNs), multiple layer perceptron (MLPs)	Accuracy 99.8%	Private collected
(Jeong, Oh, &Kim, 2013)	Gyro sensor andGPS	Support Vector Machine (SVM)	Accuracy 85%	Private Dataset
(Y. Li, 2020)	Steering wheel	Reviewed Based	-	-
(Ramesh, etal., 2011)	Steering wheel	Not Machine Learning Based	-	-
(Arefnezhadet al., 2019)	Velocity and steering angle	ANFIS	Accuracy of98.12%	Private Simulated Dataset
(Li et al.,2017)	Steering angle	Dynamic Time Warping (DTW)	78.01% accuracy, specificity 29.35%, sensitivity, 15.15%	Private Dataset
(Chai, 2019)	Steering angle	Multilevel Ordered Logit (MOL), Support Vector Machine (SVM) and Back Propagation NeuralNetwork (BP)	Accuracy of MOL, SVM and BP 72.92%, 63.86% and 62.10% respectively	Private Dataset
(R. Li, Chen, & Zhang,2021)	Steering Wheel Grip Force	Linear Regression (LR)	Accuracy of86.6%, sensitivity of 97.2% and specificity of 94.4%	Private Dataset
Mutya, etal., 2019)	Steering angle	VGG 16 and VGG 19	Sensitivity of52.3% and false positive rate of 15.8%	Private Dataset

2.2. Physiological

various physiological signals are discussed for detecting driving fatigue. The use of electroencephalogram (EEG) signals for detecting drowsiness in drivers is explored in several research papers. The potential of wrist-worn wearable sensors and ECG sensors for detecting driver drowsiness is also assessed in research papers. Additionally, the use of Electrooculogram (EOG) signals and Electromyogram (EMG) signals for detecting driving fatigue is reviewed in papers. Overall, these studies show that various physiological signals can be used effectively for detecting driver drowsiness, and machine learning models can be trainedon this data to accurately classify drowsiness levels.

2.2.1. Electroencephalogram (EEG)

(Ma et al., 2019) In this research paper, the authors propose a new method for detecting driving fatigue from EEG signals. The proposed method is based on the PCA-Net algorithm, which is a deep learning algorithm for image classification. The authors used modified PCANet, SVM, and KNN classification methods achieved an accuracy of 95.14% using EEG (Electroencephalogram) on a private dataset.

This research paper (Chinara, 2021) focuses on the use of EEG signals to detect drowsiness in drivers.The authors propose a method based on the Wavelet Packet Transform (WPT) to extract time-domainfeatures from single-channel EEG signals. Various methods were used with EEG as the biological parameter, achieving an accuracy of 94.45%, recall of 95.82%, precision of 96.14%, and F1 score of 95.98% on Physionet and simulated virtual driving driver (SVDD) dataset.

In their research (Rahma & Rahmatillah, 2019) presents a new method for analysing drowsiness usingEEG signals. The authors propose a method based on the Common Spatial Pattern (CSP) algorithm and theExtreme Learning Machine (ELM) algorithm. The results show that the proposed method achieved testing accuracies ranging from 91.67% to 93.75% on a private dataset, making it a promising technique for use in drowsiness detection systems.

2.2.2. Electrocardiogram (ECG)

(Kundinger et al., 2020) - In this research paper, the authors assess the potential of wrist-worn wearable sensors for detecting driver drowsiness. The authors collect physiological data from wrist-worn sensors anduse it to train a machine learning model for drowsiness detection. Various methods were used with ECG (Electrocardiogram), achieving an accuracy of 92.13%, F1 score of 95% (non-drowsy), and F2 score of 83% (drowsy) on a private dataset, making them a promising technology for use in drowsiness detection systems. (Abbas & Alsheddy, 2020) The authors collect physiological data from ECG sensors and use it to train a machine learning model for drowsiness detection, ANN and RF classifiers with ECG achieved accuracies of 96.5% and 94.1% respectively, using publicly available multimodal datasets.

2.2.3. Electrooculogram (EOG) and Electromyogram (EMG)

(Nasri et al., 2022) The authors employed a review-based approach to train a machine learning model for this purpose, utilizing EOG and EMG as the primary biological parameter. However, the study did not provide specific evaluation results regarding the performance of the model.

In their study, (Xiao & bin Abas, 2021) focused on drowsiness detection using EOG and EMG sensors. Machine learning models such as SVM, LSTM, and CNN classifiers were trained using EOG as the biological parameter. It's worth mentioning that the study did not conduct experiments.

Studies have examined various biological parameters to detect drowsiness (see Table 3). One study used EEG signals with different classifiers on private datasets, achieving high accuracies. Another study explored multiple classifiers for EEG analysis, showing promising results on different datasets. EEG signalscombined with Extreme Learning Machine (ELM) achieved satisfactory accuracies on a private dataset. ECG signals were investigated with diverse classifiers, obtaining notable accuracies on private datasets. ANN and RF classifiers yielded high accuracies on publicly available multimodal datasets. EOG and EMGsignals were also explored.

Table 3. Physiological drowsiness detection systems.

Ref	Biological Parameters	Classification Method	Evaluation Metric	Dataset
(Ma et al., 2019)	EEG	Modified PCANet, SVM and KNN	Accuracy 95.14%	Private Dataset
(Chinara, 2021)	EEG	LAD, LR, GNB, QDA, SVM, KNN,DT, BDT, RF, ET, and ANN	Accuracy 94.45%, recall 95.82%, precision 96.14% and F1 score 95.98%	Physionet and simulated virtual driving driver (SVDD) dataset
(Rahma & Rahmatillah, 2019)	EEG	Extreme learning machine (ELM)	accuracy of testing ranges from 91.67% to 93.75%	Private Dataset

(Kundinger, Sofra, & Riener,2020)	ECG	BN, NB, KNN, SVM,RF, RT, DT, DS and MLP	Accuracy of 92.13%,F1 score of 95% (non-drowsy) and F2 score of 83% (drowsy)	Private Dataset
(Abbas & Alsheddy, 2020)	ECG	ANN, and RF	Accuracy of ANN 96.5% and RF 94.1%	Publicly available multimodal datasets
(Nasri et al.,2022)	EOG, EMG	Review-based	Review-based	Review-based
(Xiao & binAbas, 2021)	EOG, EMG	SVM, LSTM and CNN classifiers.	No ExperimentPerformed	Publicly AvailableDatasets

2.3. Behavioural Features

This section is based a review study has been conducted on research papers that utilize visual and behavioural features, specifically focusing on facial expressions such as eye movement, head movement, and face movements. These features are analysed for the purpose of drowsiness detection. The review studyexamines various papers that explore the relationship between these facial expressions and drowsiness. This review study highlights the significance of visual and behavioural features, specifically facial expressions,in the field of drowsiness detection.

2.3.1. Eye Movement, Face Expression and Head Position

The second study, (Ed-Doughmi et al., 2020) proposes a real-time system for detecting driver fatigue basedon frames of behavioural feature i.e., eye movement and head position. The study investigates the use of Recurrent Neural Networks (RNN) to analyses the behaviour of drivers and detect signs of fatigue using behavioural feature. Using behavioural feature achieved an accuracy of 92% and F1 score of 85% on the NTHU-DDD dataset.

The study (Vu et al., 2019), focuses on the use of Deep Neural Networks (DNN) for detecting driver drowsiness in real-time. The researchers propose a DNN model that analyses driver behaviour and identifies indications of drowsiness using eye movement, face expression and head position as a visual behavioural parameter. The model achieved an accuracy of 84.81%. F1 score of 86.28% for drowsiness detection and F1 score of 82.99% for non-drowsiness detection on the NTHU-DDD dataset.

The study (Dua et al., 2021), presents an ensemble approach to driver drowsiness detection based on Deep Convolutional Neural Network (DCNN) models using behavioural feature i.e., face expression and eye movement. The study combines multiple DCNN models to improve the accuracy of drowsiness detection. Models including AlexNet, VGG-FaceNet, FlowImageNet, and ResNet with Camera as the visual behavioural parameter achieved an accuracy of 85%, Precision of 86.3%, Sensitivity of 82%, Specificity of 87%, and F1 score of 84.09% on the NTHU-DDD dataset.

The study (Z. Zhao et al., 2020), explores the use of Convolutional Neural Networks (CNN) for detecting driver fatigue. The study uses behavioural feature i.e., face expression and eye movement and the EM-CNN method to detect driver fatigue. And using AlexNet, VGG-16, GoogLeNet, ResNet-50, and EM-CNN with Video Camera as the visual behavioural parameter achieved accuracies of 89.565%, 25.797%, 91.015%, 92.899%, and 93.623% respectively on the private dataset but can be attained upon request.

Various studies have focused on drowsiness detection by analysing visual behavioural parameters suchas head position, face expression, and eye movement. Neural network models, including CNN and RNN, have been employed to achieve high accuracy and distinguish between drowsiness and non-drowsiness states. These studies highlight the potential of utilizing visual behavioural cues in real-time drowsiness detection systems, emphasizing the importance of eye movement, head position, and face expression as indicators of drowsiness. Overall, these advancements contribute to improving the effectiveness and reliability of drowsiness detection methods as demonstrate in Table 4.

Table 4. Driver Behavioural drowsiness detection systems.

Ref	Visual Behavioural Parameters	Classification Method	Evaluation Metric	Dataset
(Ed-Doughmi et al.,2020)	Head Position, Eye Movement	Recurrent Neural Networks(RNN)	Accuracy of 92% and F1score of 85%.	NTHU-DDD("Driver Drowsiness Detection Dataset,")
(Vu et al., 2019)	Head Position, Face Expression and Eye Movement	Convolutional Neural Network (CNN), Convolutional Control Gate- based Recurrent Neural Network, and a Voting Layer	Accuracy of 84.81%. F1 score of 86.28% for drowsiness detection and F1 score of 82.99% for non-drowsiness detection	NTHU-DDD
Z. Zhao et al.,2020)	Face Expression and Eye Movement	AlexNet, VGG-16, GoogLeNet, ResNet-50 and EM-CNN	Accuracy of models i.e, AlexNet, VGG-16, GoogLeNet, ResNet-50 andEM-CNN are 89.565%, 25.797%, 91.015%, 92.899% and 93.623%	Private dataset can beattained uponrequest
(Dua et al., 2021)	Face Expression and Eye Movement	AlexNet, VGG-FaceNet, FlowImageNet and ResNet	Accuracy 85%, Precision: 86.3%, Sensitivity: 82%, Specificity: 87% and F1 score: 84.09%	NTHU-DDD

2.4. Hybrid

Various techniques for detecting driver fatigue and drowsiness, as well as hazardous driving events. The techniques include Vehicle Diagnostic, Physiological, and Behavioural Features, which use on-board sensors, real-time monitoring of vital signs and EEG signals, and analysis of facial expressions and driving patterns, respectively. The chapter includes both research papers and review papers that propose new models and systems for detecting driver fatigue and drowsiness, as well as providing an overview of the current research and market solutions.

2.4.1. Vehicle Diagnostic and Behavioural Features

(Omerustaoglu et al., 2020) developed a hybrid system for detecting driver distraction using CNN (Transfer Learning) and RNN (LSTM) with Hybrid Parameters from the OBII port (Speed, Throttle Position, Engine Load, Engine RPM, Fuel level, and Temperature) and Mobile phone sensors (Camera, Gyroscope, and Accelerometer). The system achieved an increased driving distracted detection accuracy from 76% to 85% on the State Farm's distracted driver detection dataset and collected dataset.

(X. Li et al., 2019) used multi-feature fusion and semi-supervised active learning in research study that proposes a new model for detecting driver fatigue. The model makes use of multiple features, such as EEG signals, facial expressions, and driving patterns, and fuses them together to make more accurate predictions.The authors proposed a model for detecting driver fatigue using Deep Learning Algorithms and Graph- based Semi-Supervised Learning (GSSL) with Hybrid Parameters including the Steering wheel sensor and camera. The model achieved a precision of 89.43%, recall of 91.04%, F1-score of 90.23%, and accuracy of 86.25% on a private dataset.

(D. Zhao et al., 2022) is a review paper that provides an overview of the various methods for recognizing driving behaviour based on multi-sensor information. They examined systems utilizing in- vehicle sensors (such as speed and acceleration sensors) and external sensors (such as cameras and heart rate monitors). The paper provided an overview of the different methods, analysing their strengths, weaknesses, and suitability for various use cases. However, no specific evaluation metrics or dataset detailswere provided for this review paper.

2.4.2 Vehicle Diagnostic and Physiology

(Meireles et al., 2019) is a review paper that provides an overview of the various methods for recognizing driving behaviour based on multi-sensor information. The authors examine different systems that use a combination of in-vehicle sensors, such as speed and acceleration sensors, and external sensors, such as cameras and heart rate monitors. The paper provides a comprehensive analysis of the strengths and weaknesses of each method, as well as their suitability for different use cases, but no specific evaluation results were provided.

2.4.3. Vehicle Diagnostic, Physiology and Behavioural Features

(Gwak et al., 2020) highlights the use of hybrid sensing, which combines multiple sensing modalities, to detect driver drowsiness. The classification methods employed were Decision Tree and Multi-View classifier. The evaluation metric reported an accuracy of 82.4% for slightly drowsy and 95.4% for moderately drowsy drivers. The study utilized a simulated private dataset.

(Schwarz et al., 2019) presents a driver monitoring system that combines multiple features, such ashead movement, eye closure, and vehicle speed, to detect driver drowsiness in real-time. The classification method used was the Random Forest algorithm with an Over-sampling Technique (SMOTE). The evaluation metric reported was the ROC curve with an AUC of 0.897. The study utilized a private dataset.(Doudou et al., 2020) provides a review of the current research and market solutions for driver drowsiness measurement technologies. The paper highlights the advantages and limitations of various hybrid approaches, including the combination of multiple sensors and the use of artificial neural networks but the study did not provide specific classification methods or evaluation metrics.

2.4.4 Physiology and Behavioural Features

(Abbas & Alsheddy, 2020) conducted a comparative analysis of systems for detecting driver fatigue. They examined systems using various sensors (e.g., EEG, heart rate monitors, cameras) combined with smartphones and cloud-based platforms. Different classification methods (SVM, ANN, CNN, RNN, LSTM) were utilized. The evaluation results showed a sensitivity of 88.3%, specificity of 89.6%, precision of 87%, and accuracy of 88%. Publicly available multimodal datasets were used.

(Abbas, 2020) proposed a real-time system for detecting driver drowsiness. It combined features like EEG signals, facial expressions, and driving patterns using transfer learning to enhance accuracy. The system outperformed existing methods. Pre-trained Convolutional Neural Network (CNN) and Deep BeliefNetwork (DBN) were used for classification. The evaluation showed an accuracy of 94.5% with pre-trained CNN and DBN. The study utilized the Columbia gaze dataset (CAVE-DB), multimodality drowsiness database (DROZY), and closed eye wild dataset (CEW)

Several studies have investigated the development of hybrid systems for driver distraction and drowsiness detection as explained in Table 5. These systems utilize parameters, sensors (e.g., vehicle diagnostics, behaviour, physiology, camera images), and classification methods (e.g., deep learning, decision trees, random forests, support vector machines) for accurate detection. Evaluation metrics include accuracy, precision, recall, F1-score, sensitivity, and specificity. Datasets range from publicly available multimodal datasets to private research-specific datasets. Overall, these studies aim to enhance the effectiveness of driver distraction and drowsiness detection systems by leveraging a combination of different parameters and sensor inputs.

Table 5. Hybrid drowsiness detection systems.

Ref	Hybrid Parameters	Sensors	Classification Method	Evaluation Metric	Dataset
(Omeru staoglu et al.,2020)	Vehicle Diagnostic and Behavioural Features	From OBII port Speed, ThrottlePosition, Engine Load, Engine RPM, Fuel level and Temperature. From Mobile phone Video Recorder Camera, Gyroscope and Accelerometer.	CNN(Transfer Learning), RNN(LST M)	Using sensordata and image data increased the accuracy from 76% to 85%	SFDDD Dataset ("State Farm Distracted Driver Detection,"), and collected dataset
(X. Li etal., 2019)	Vehicle Diagnostic and Behavioural Features	Steering wheel sensor, camera	(ANN, CNN, RNN and DBN), Graph- based Semi-Supervised Learning (GSSL)	the precision is 89.43%, the recall is 91.04%, the F 1-score is 90.23% andthe accuracyis 86.25%.	Private Dataset
(D. Zhao, etal., 2022)	Vehicle Diagnostic and Behavioural Features	OBD sensors such as GPS, Gyroscope, camera, radar, CAN bus.	The Random Forest, SVM, CNN and RNN.	Review based	Reviewed on Base of video/images and time series(sensors data)
(Meirel es, etal., 2019)	Vehicle Diagnosticand Physiology	Head Position Sensor, Vehicle Speed Sensor, Blind SpotSensor.	Not any specified just Proposed	-	-
(Gwak, et al., 2020)	Vehicle Diagnostic, Physiology and Behavioural Features	EEG and ECG. eye blinks, eyeclosure percentage, and seat pressure. vehicle velocity, acceleration, lateral position, steering wheel acceleration, and headway and lane crossing times	Decision Tree, MultiView classifier, Random Forest	Accuracy of slightly drowsy 82.4%, moderately drowsy 95.4%	Simulated private dataset
(Schwar z, et al., 2019)	Vehicle Diagnostic, Physiology and Behavioural Features	SDLP for lateral position variability, Steer for steering wheel angle. Also, eye blink rate and face yaw were measured.	Over-sampling Technique (SMOTE), Random Forest	(ROC) curveof 0.897	Private dataset
(Doudo u, et al.,2020)	Vehicle Diagnostic, Physiology and Behavioural Features	Steering Wheel Movement (SWM), Vehicle Deviation andPosition, Vehicle Acceleration and Speed, Eye Movement, Facial Expression, Head Position, EEG-NIRS, EOG, EMG, ECG, Respiration, Gastrointestinal, EDA, and Core Temperature	Review based	-	-
(Abbas & Alsheddy, 2020)	Physiology and Behavioural Features	EEG,EOG,ECG, Camera, Hand watch	SVM, ANN, CNN, RNN and LSTM	sensitivity, specificity, precision, and accuracy,88.3%, 89.6%, 87%, 88% respectively.	Publicly available multimodal datasets

Abbas, 2020)	Physiology and Behavioural Features	Driver face image Detect Eyes, Face, Head Yawning and from ECG sensor on Steering wheel Detect Heart Rate Fatigue Alert	Pre-trained CNN and Deep Belief Network (DBN)	Accuracy of 94.5% basedon pre-trained CNN and DBN	CAVE-DB ("Columbia Gaze DataSet,"), DROZY ("Multimodalit y Drowsiness Database,") and CEW ("ClosedEyes in The Wild,")

3. Challenges

A thorough literature review revealed that various methods have been implemented for drowsinessdetection to mitigate potential hazards while driving. Moreover, the continuous technological advancements in the field of artificial intelligence have successfully addressed numerous challenges encountered by these systems, significantly enhancing their performance. This section aims to compare the practicality and reliability of drowsiness detection systems, as reported in the literature, and discuss the four aforementioned measures employed for drowsiness detection. System practicality is determined by evaluating the system's efficacy in detecting true drowsiness states, considering factors such as sensor availability, dataset diversity, utilized techniques, and the level of accuracy achieved.

3.1. Vehicle Diagnostic

In the study by (Harkous & Artail, 2019), the sensitivity of prediction to the nature of the track and the limited number of drivers in the data collection pose limitations. (Malik & Nandal, 2021), acknowledge limitations in driver behaviour model needs more detailed and personalized models, integration of GPS andweather updates. (Peppes et al., 2021), suggest additional clustering analysis and a meta-profile engine. (Ramesh et al., 2011), express the need for better accuracy and the system's efficiency could be enhanced by incorporating sensors on the seat belt for improved accuracy. (Arefnezhad et al., 2019), highlight the need for more data, the use of EEG signals, and new machine learning algorithms. (R. Li, Chen, & Zhang, 2021), point out the influence of hand position and steering wheel characteristics.

3.2. Physiology

The research limitations of the papers mentioned are as follows. (Ma et al., 2019), propose an approach for fatigue classification but need validation in an actual driving environment with a larger population and do not address the automatic selection of the best filter number. (Kundinger, Sofra, & Riener, 2020), mention the need for more data and realistic study environments, as well as driver self-ratings. (Rahma & Rahmatillah, 2019), identify subject-dependency and individual calibration/training sessions as limitationsof BCI systems, mentioning the discomfort and fatigue caused by longer training sessions.

3.3. Behavioural Features

The research limitations of the papers mentioned are as follows. (Ed-Doughmi et al., 2020), rely on data from a simulated environment, which may not fully represent real-world scenarios. (Vu et al., 2019), havesuboptimal inference speed due to the implementation of the voting layer. (Z. Zhao et al., 2020), need further testing of the proposed method's performance and robustness and lack implementation on a hardware device. (Dua et al., 2021), use pre-trained models and suggest incorporating vehicle andphysiological measurements.

3.4. Hybrid Features

The research limitations of the papers mentioned are as follows. (Omerustaoglu et al., 2020), have limitations regarding the dataset's size and diversity. (X. Li et al., 2019), mention the accuracy of their model as a limitation. (D. Zhao et al., 2022), identify limitations related to machine learning algorithms used and the need for multiclass models. (Gwak et al., 2020), acknowledge limitations related to participant demographics and subjective evaluation of drowsiness. (Schwarz et al., 2019), mention limitations in differentiating between drowsiness levels and sample size. (Doudou et al., 2020), highlight limitations associated with subjective measures and current technologies. (Abbas & Alsheddy, 2020), identify challenges related to data and communication issues.

4. FUTURE TRENDS IN DROWSINESS DETECTION SYSTEMS

The recommendations and future trends of the mentioned papers are as follows. (Harkous & Artail, 2019) suggest investigating the impact of track characteristics and increasing the number of drivers for more reliable results. (Malik & Nandal, 2021) propose developing personalized models, integrating new technologies, and exploring autonomous vehicle potential.

In the study (Jeong, Oh, & Kim, 2013) propose field experiments and practical applications. (Ramesh et al., 2011) proposes improving accuracy and system efficiency. (R. Li, Chen, & Zhang, 2021) suggest researching hand position effects and enhancing system effectiveness. (Mutya et al., 2019) proposes using a larger dataset and evaluating real-world performance. (Li et al., 2017) recommends combining information sources and improving system accuracy. (Chai, 2019) suggests increasing subject numbers and exploring practical applications. (Kundinger, Sofra, & Riener, 2020) suggest data collection improvements and alternative methods. (Rahma & Rahmatillah, 2019) recommend reducing discomfort and adapting BCI systems. (Ed-Doughmi et al., 2020) propose real-world data validation. (Vu et al., 2019) suggests improving inference speed and exploring hardware options. (Z. Zhao et al., 2020) recommend testing and evaluating the method on hardware.

Also (Omerustaoglu et al., 2020) suggest increasing dataset size and addressing generalization. (X. Li et al., 2019) aim to improve model accuracy and incorporate advanced techniques. (Meireles et al., 2019) aim to advance the prototype and explore additional technologies. (Gwak et al., 2020) suggests larger studies, real vehicle conditions, and advanced methods. (Schwarz et al., 2019) propose increasing sample size, incorporating measures and variables, and leveraging algorithms. (Doudou et al., 2020) focus on efficient sleepiness detection, standard measures, and real road evaluations. (Abbas & Alsheddy, 2020) suggest low-cost environments, real-time detection, datasets, and data aggregation solutions. (Abbas, 2020) aims to integrate mobile apps, multi-camera approaches, and refine the Hybrid Fatigue system.

5. DISCUSSION

When it comes to drowsiness detection systems, there are several challenges that need to be addressed. Researchers have implemented various methods to mitigate potential hazards while driving and advancements in artificial intelligence have significantly improved the performance of these systems. To compare the practicality and reliability of drowsiness detection systems, it is important to evaluate their efficacy in detecting true drowsiness states. Factors such as sensor availability, dataset diversity, utilized techniques, and achieved accuracy play a crucial role in determining the practicality of these systems.

Challenges related to vehicle diagnostics include track limitations and a small driver population, requiring more detailed and personalized driver behaviour models. Integrating GPS and weather updates is necessary, and adding sensors to the seat belt can enhance system efficiency. However, they exhibit accuracies ranges from 62.1% to 99.8%, compared to other methods. On the bright side, they are easy to use, as they do not require any setup or user intervention. However, most datasets used for vehicle-based systems are private and not readily available for research purposes.

Physiological aspects of drowsiness detection require validation in real driving environments with larger populations. Brain-Computer Interface (BCI) systems should address subject-dependency, individual calibration/training sessions, and driver self-ratings while minimizing discomfort and fatigue. Reported accuracies range from 91.67% to 96.5%, showcasing their effectiveness. However, these systems may require some setup, user intervention, or wearing of sensors for data collection. Despite this, they have good availability, with datasets mostly being accessible for research and development purposes.

Behavioural features need consideration beyond simulated environments. Optimizing inference speed and testing proposed methods on real hardware devices ensure performance and robustness. Vehicle and

physiological measurements can offer valuable insights. They have demonstrated accuracies ranging from 25.79% to 93.63% in the literature. Image-based systems are easy to use, as they typically require no setup or user intervention. Publicly available datasets contribute to their widespread adoption and research.

Hybrid features pose challenges like dataset limitations, model accuracy, machine learning algorithms, participant demographics, subjective evaluation of drowsiness, differentiating between drowsiness levels, and sample size. Overcoming these limitations and advancing prototype systems are crucial for improving overall performance. Hybrid-based systems exhibit high accuracies ranging from 85% to 94.5%, but they may require some setup, user intervention, or wearing of sensors. However, they have comparatively less availability in terms of accessible datasets as shown in table 6.

Table 6. DDD Method Comparison: Accuracies, Accessibility, Availability

DDD Features	Reported Performance	Accessibility	Availability of Dataset
Behaviour based	The literature reports accuracies, ranging from 25.79% to 93.63%.	It does not require any setup or user interventionbut using camera can raise privacy concern.	The dataset is publicly available.
Physiological based	The reported accuraciesfor systems range from 91.67% to 96.5%.	It may require some setup, user intervention,or wearing of sensors.	The dataset is mostly available.
Vehicle based	Accuracies ranges from 62.1% to 99.8%.	it is easy to use withoutany setup or user intervention.	The dataset is mostly private.
Hybrid based	systems achieve high accuracies, ranging from 85% to 94.5%.	It may require some setup, user intervention, or wearing of sensors.	The dataset is less available.

Based on the above information the convincing theoretical framework is shown in figure 5

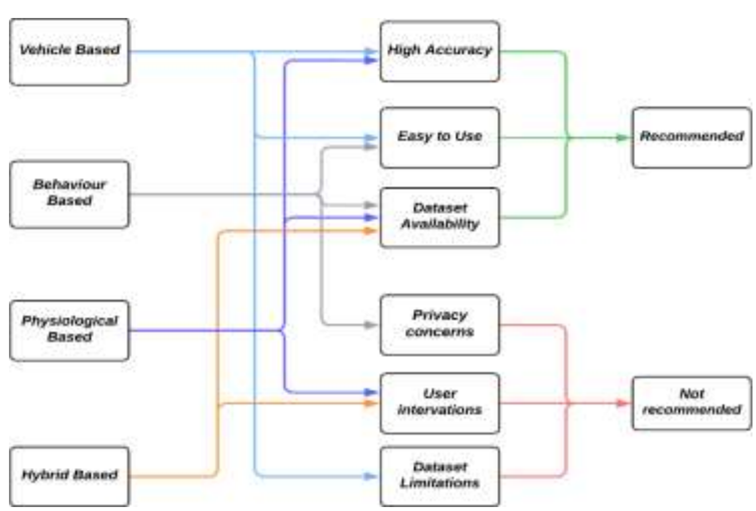

Fig. 5 Convincing theoretical framework for driver drowsiness detection system.

CONCLUSIONS

In conclusion, drowsiness detection systems play a crucial role in ensuring road safety by identifying and mitigating the risks associated with driver fatigue. This literature review has provided a comprehensive overview of the practicality and reliability of various drowsiness detection methods, highlighting their strengths and limitations. It is evident that continuous advancements in artificial intelligence and related technologies have significantly enhanced the performance of these systems.

Overall, the findings of this literature review highlight, the vehicle-based system appears to have several advantages, it is important to acknowledge the challenges associated with the other DDD features. Behaviour-based systems show a wide range of accuracies, but the use of cameras can raise privacy concerns, which may impact their acceptance and adoption. Physiological-based systems offer high accuracies, but they may require setup, user intervention, or wearing of sensors, which can introduce inconvenience for users. Additionally, the availability of datasets for physiological-based systems is mostly limited, potentially hindering further research and development. Hybrid-based systems achieve high accuracies, but similar to physiological-based systems, they may require setup, user intervention, or wearing of sensors. Moreover, the dataset availability for hybrid-based systems is comparatively less. Therefore, while vehicle-based systems present strong performance and ease of use, researchers should also address the challenges associated with behaviour-based, physiological-based, and hybrid-based systems to enhance their overall effectiveness and accessibility in drowsiness detection applications.

AUTHOR CONTRIBUTIONS

All authors contribute integral roles in the reviewed paper. Khubab Ahmad contributed to the conceptualization, methodology, data analysis, and writing. Poh Ping Em conducted the literature review, data analysis, and contributed to manuscript writing. Nor Azlina Ab. Aziz provided guidance, feedback, and assisted with manuscript preparation and final approval. Their collective efforts greatly enriched the research work.

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