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Research Article

State-of-the-Art in Driver's Drowsiness Detection: A Comprehensive Survey

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ABSTRACT

Recent developments in computing technology and advancements in artificial intelligence have led to major improvements in driver monitoring systems. These enhancements are crucial given the substantial risk posed by fatigue or drowsiness on roads, leading to numerous accidents and impacting overall road safety. Timely detection and alert mechanisms for fatigued drivers can prevent many such accidents. Various methods have been formulated to monitor driver drowsiness during operation and alert drivers when their attention wanes. These methods utilize facial expressions like yawning, eye closures and head movements to gauge the level of drowsiness, in addition to analyzing biological markers of fatigue in the driver's body and monitoring vehicle behavior. This study delves into an in-depth analysis of existing driver drowsiness detection methods, focusing on widely used classification techniques. The paper classifies these methods into three primary categories: behavioral, vehicular and physiological based techniques. This study thoroughly investigates advanced methods for detecting driver fatigue, utilizing multiple machine learning and deep learning capabilities and a comparative study of these methods is presented. The research includes a detailed analysis of approaches to detect driver fatigue through facial landmark detection, employing established algorithms rooted in artificial neural networks and computer vision principles. Furthermore, the paper discusses potential advancements in driver fatigue detection technologies, providing valuable guidance for professionals and researchers striving to improve road safety through effective fatigue detection systems.

Keywords: T Driver drowsiness detection, Drowsy driving, Fatigue detection, Machine learning, Computer Vision, Transfer Learning, Deep Learning.

Introduction

Drowsiness is a condition characterized by sleepiness, fatigue or a reduced state of alertness and attentiveness. It is often associated with a decreased ability to sustain attention and focus on tasks, which may raise due to multiple factors for drivers. These factors include inadequate or poor-quality sleep, extended periods of wakefulness, underlying medical conditions, physical weakness or illness, alcohol consumption or environmental influences.

When individuals experience drowsiness, their response times tend to slow down. This diminished level of alertness can pose significant risks, particularly when engaged in activities such as driving or operating heavy machinery that require continuous concentration.

Driver drowsiness represents a significant concern because of its potential to cause accidents and extensive damage on the roads. Drowsy driving is as risky as driving under the influence of alcohol or drugs, affecting performance and safety. Detecting and addressing drowsiness is crucial for enhancing safety and preventing accidents, particularly in tasks that demand constant vigilance and swift reactions.

According to AAA traffic safety foundation, around 17.6% of fatal accidents occurring between 2017 and 2021 were attributed to drowsy drivers. Over this five-year span, it's estimated that 29,834 individuals lost their lives in accidents involving drowsy drivers. Although the proportion of fatal crashes involving drowsy driving remained relatively stable throughout the study period, the yearly count of fatal accidents related to drowsy driving rose notably, primarily due to a substantial uptick in total annual fatal crashes. In terms of percentages, the highest proportion of drowsy drivers involved in fatal crashes belonged to the age group of 16–20 years. However, the most significant number of drowsy drivers in such crashes fell within the age bracket of 21–34 years.

Notably, men are significantly more prone to drowsiness than women, contributing to the majority of drowsy drivers in fatal accidents. Surprisingly, around two-thirds of drowsy drivers in fatal crashes had not consumed any alcohol (blood alcohol concentration, BAC = 0.00), while the remaining one-third had non-zero BAC values. The prevalence of drowsiness was notably higher among drivers who had been drinking than those who hadn't. An estimated 17% of drivers with a BAC of 0.01–0.07 and 20% of drivers with a BAC >=0.08 were found to be drowsy, contrasting with 11% among those who had not consumed alcohol. The highest percentage of drowsy drivers was observed among those involved in crashes on rural collectors and local roads. However, the most fatal drowsy driving crashes were recorded on urban arterials, given that these roads witness the highest proportion of fatal crashes overall, regardless of drowsiness. The peak number of fatal drowsy driving crashes occurred between 11:00 PM and 2:59 AM, while the highest percentage of drowsy drivers was found among those who crashed between 3:00 AM and 6:59 AM [1].

Drowsiness is more than just feeling sleepy; it's a state that can lead to dangerous situations. Even if it lasts for just a short while, its effects can be devastating. Fatigue is often the culprit behind drowsiness, as it lowers our ability to stay alert and focused. Long drives without enough rest or driving during late hours when our body expects to be asleep are common triggers for drowsiness. The real danger lies in the lack of concentration that drowsiness brings. A drowsy driver's reactions to events on the road can be delayed, increasing the risk of accidents. It's crucial to recognize the signs of drowsiness and take breaks or avoid driving during peak drowsiness periods to ensure safety on the road.

This review contributes to the literature by covering the recently implemented DDD systems. The literature survey explores various methods for driver fatigue detection based on computer vision, machine learning and deep learning. Section 2 discusses input feature-based classification techniques for driver fatigue detection systems. Section 3 elaborates on the working mechanisms of driver drowsiness detection systems. Section 4 provides an in-depth review of driver fatigue detection methods, while Section 5 presents the literature survey findings. Observations derived from the survey are detailed in Section 6. Finally, concluding remarks and future directions for research are outlined in Section 7.

2. Input feature-based classification of driver drowsiness detection system

Existing methodologies reveal several path ways for detecting driver’s drowsiness. Major approaches for detecting driver drowsiness are depicted in **FIGURE 1**.

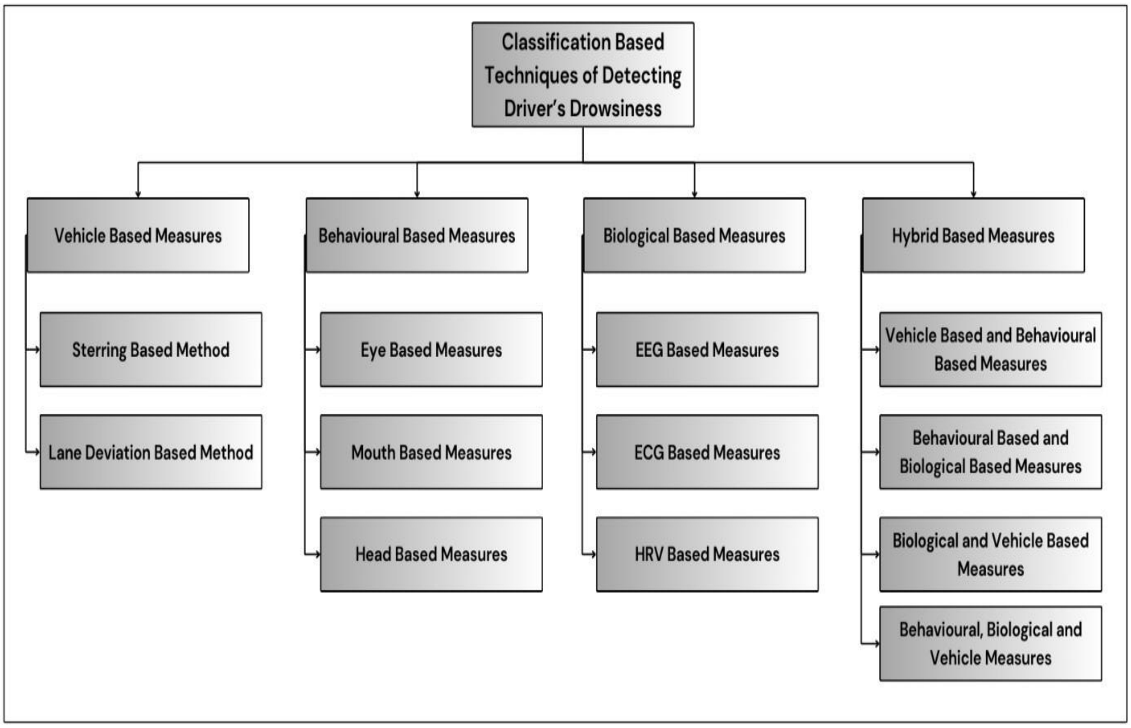

Figure 1 Major approaches for detecting driver's drowsiness

The first method relies on vehicle-based metrics, monitoring parameters associated with the vehicle to detect driver drowsiness. The second method examines behavioural patterns of the driver to assess signs of fatigue. The third approach uses biological indicators, analysing` the driver's physiological state for drowsiness detection. Lastly, the hybrid method combines aspects of the previous approaches, allowing researchers to tailor the detection process based on specific needs.

2.1 Vehicle-Based Measures

Steering-Based: Monitors irregular steering patterns through sensors that detect unusual frequencies (20–60 Hz) or angles (±30°). Alerts are issued when thresholds are exceeded.

Lane Deviation-Based: Tracks Lane alignment using sensors and cameras. Alerts are triggered for lane deviations made without signalling.

2.2 Behavioural-Based Measures

Eye-Based: Tracks blink rate, eye closures and EAR (Eye Aspect Ratio) using infrared cameras to detect drowsiness. Mouth-Based: Analyses yawning patterns using MAR (Mouth Aspect Ratio) to identify fatigue.

Head-Based: Monitors head nodding, posture and facial expressions via cameras and image processing.

2.3 Biological-Based Measures

EEG (Electroencephalogram): Detects brainwave changes (increased theta, decreased alpha) using scalp electrodes. ECG (Electrocardiogram): Monitors heart rate and rhythm changes via chest/wrist electrodes.

HRV (Heart Rate Variability): Analyses reduced variability and increased sympathetic tone for fatigue indicators.

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2.4 Hybrid-Based Measures

Vehicle & Behavioural: Combines vehicle sensors and behavioural data for improved accuracy. Behavioural & Biological: Integrates eye, head and biological indicators for early fatigue detection. Biological & Vehicle: Links biological metrics with vehicle data for reliability.

Thus, by merging different approaches like vehicle, behavioural and biological data a robust system can be created.

These approaches enhance detection accuracy, offering customizable combinations based on specific requirements.

These measures can be applied to enhance system performance and achieve greater accuracy. The choice of model combinations whether vehicle-based, behavioural, or biological can be customized based on individual preferences for accuracy and feasibility, allowing flexibility in selecting the most effective approach.

3 Working Mechanism of Driver Drowsiness Detection System

Feature Extraction:

Let us take input as face; after detecting the face the next step is extracting essential facial features for further analysis. This stage captures specific aspects like eye position, mouth movement and facial contours, which play a crucial role for recognizing drowsiness. By isolating these features, the system simplifies the complexity of each image, targeting elements most associated with drowsiness, such as eyelid movement, mouth openness and head orientation. This serves as a crucial preprocessing step for accurately interpreting drowsiness-related facial cues.

Feature Transformation:

Once features are extracted, a transformation process is applied to optimize them. Techniques such as normalization, scaling or dimensionality reduction (e.g., Principal Component Analysis) help make features more uniform and interpretable. Transforming features aids in differentiating alertness from drowsiness, refining the dataset structure for efficient analysis in later steps. This transformation reduces noise and strengthens the reliability of the feature set, preparing it for selection and detailed analysis.

Feature Selection/Analysis:

The transformed features are then assessed and filtered to retain only the most relevant ones. This involves focusing on parameters such as:

- Eye State: Determines whether the eyes are open, partially closed or fully closed; prolonged eye closure is a strong indicator of drowsiness.
- Head Movement: Monitors head orientation and stability, as frequent tilting or drooping suggests fatigue.
- Blinking Rate: An increase or irregular blinking pattern can be an early sign of drowsiness.
- Yawning Frequency: Observing mouth movements and yawning frequency helps detect deeper levels of fatigue. This focused analysis ensures that the algorithm zeroes in on key indicators of drowsiness, optimizing data for the classification phase.

Classification:

With optimal features selected, the final stage involves categorizing the driver's state, such as alert or drowsy. Choosing an appropriate classifier is crucial, as it must distinguish between varying drowsiness levels based on facial features. Classifiers typically operate in two modes:

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- Training Mode: In this phase, the classifier learns from a labelled dataset, associating specific facial patterns with either alert or drowsy states.
- Testing Mode: After training, the classifier is tested on new data to assess its accuracy and reliability. Common classifiers for drowsiness detection include:
- Deep Neural Network (DNN): DNNs excel at recognizing complex patterns within facial data because their multiple layers, which capture detailed feature hierarchies.
- Convolutional Neural Network (CNN): CNNs are especially effective for image-based tasks, as their convolutional layers capture spatial structures within facial features, enhancing detection accuracy.
- Support Vector Machine (SVM): SVMs are suitable for smaller datasets and binary classification, helping to distinguish between alert and drowsy states. Each classifier type has unique strengths, depending on the system requirements, real-time performance needs, data volume and available processing power. Ultimately, this classification phase enables the detection of drowsiness, triggering alerts to improve driver safety.

Thus, the person is classified whether is drowsy or driving correctly. If drowsy then appropriate actions would be taken. The figure below Figure-2 [26] presents a flowchart illustrating the working process of Driver Drowsiness Systems.

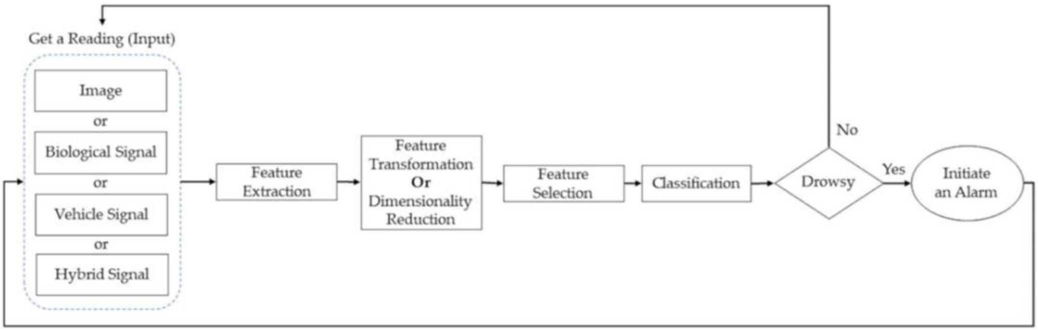

Figure 2 Working Mechanism of Driver Drowsiness Systems

4. Driver Fatigue Detection Methods

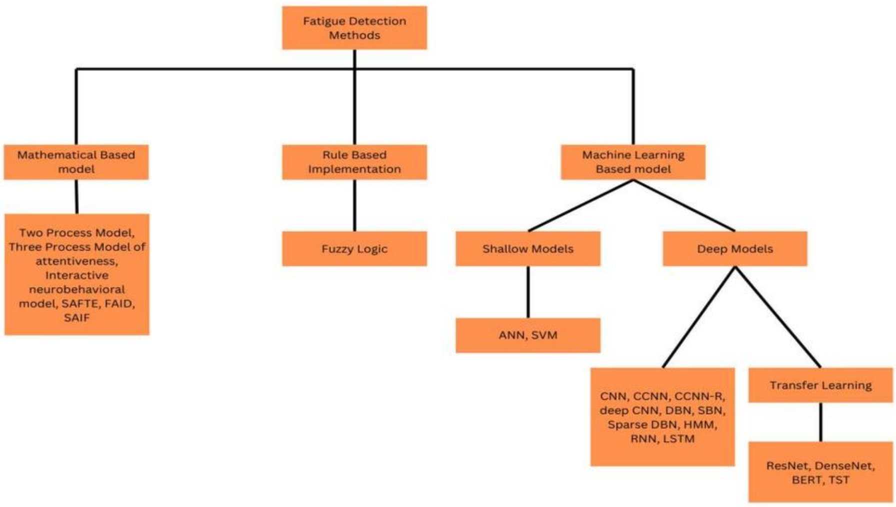

Figure 3 Driver Fatigue Detection Methods

Mathematical model-based implementation

Two-Process Model

The Two-Process Model explains sleep regulation through homeostatic pressure (Process S), which increases with wakefulness, and circadian rhythm (Process C), which follows a 24-hour cycle [27].

For drowsiness detection, this model helps predict when a driver is most likely to feel sleepy, allowing systems to issue alerts based on sleep patterns and time of day.

Three-Process Model of Alertness

This model expands on the Two-Process Model by adding sleep inertia (Process W), which describes the temporary grogginess experienced after waking [28].

It improves drowsiness detection by recognizing short-term impairments in alertness, preventing drivers from resuming driving too soon after sleep.

Interactive Neurobehavioral Model

This model considers sleep history, cognitive demands, and circadian rhythms to dynamically assess fatigue rather than relying on fixed sleep-wake cycles [29].

It enhances drowsiness detection by providing personalized monitoring, adapting to individual variations in fatigue levels.

SAFTE, FAID, SAFE Models

These models analyse sleep data, work schedules, and cognitive effectiveness to predict fatigue risks and performance impairments.

They are useful in driver drowsiness detection for managing workload-based fatigue, helping optimize work schedules to prevent excessive drowsiness.

Rule based implementation

Fuzzy Logic

Fuzzy Logic processes uncertain and imprecise data using degrees of truth instead of binary classifications, making it useful for variable conditions.

In drowsiness detection, it combines multiple factors like blink rate and reaction time, ensuring flexible, real- time decision-making.

Machine Learning based implementation Shallow Models

Artificial Neural Networks (ANN)

ANNs mimic the brain of human by learning patterns from input data such as facial expressions and eye movement.

They help detect drowsiness by classifying fatigue-related features, though they need extensive datasets to train effectively.

Support Vector Machines (SVM)

SVMs are machine learning models used to classify data by distinguishing between different categories using hyperplanes, commonly used for recognizing drowsiness indicators.

For driver monitoring, SVMs provide high accuracy with structured datasets but struggle with complex, unstructured real-time video inputs.

Deep models

Convolutional Neural Networks (CNN)

CNNs are deep learning models designed for image and video processing, making them ideal for detecting facial cues of fatigue.

They enhance real-time drowsiness detection by automatically extracting relevant features, reducing the need for manual feature selection.

Compact Convolutional Neural Networks (CCNN)

CCNNs are a lightweight version of CNNs, designed to perform efficiently on low-power or embedded devices while maintaining high accuracy.

For drowsiness detection, CCNNs allow real-time monitoring in vehicles without requiring high computational power.

Compact Convolutional Neural Networks – Recurrent (CCNN-R)

CCNN-R extends CCNN by incorporating recurrent layers, allowing it to analyze sequential frames for better context understanding.

It improves drowsiness detection by tracking continuous behavioral changes, making fatigue assessment more reliable over time.

Deep Convolutional Neural Networks (Deep CNN)

Deep CNNs are more advanced CNN architectures with multiple layers for capturing complex patterns in facial and physiological data.

In drowsiness detection, they provide higher accuracy but require more computational resources, making them best suited for high-performance systems.

Deep Belief Networks (DBN)

DBNs use layers of Restricted Boltzmann Machines (RBMs) to learn hierarchical features from input data.

They are useful in drowsiness detection for processing physiological signals (EEG, ECG) to detect fatigue even before visible signs appear.

Sparse Belief Networks (SBN)

SBNs are a variation of DBNs that focus on sparse connections between neurons, improving computational efficiency.

They enhance drowsiness detection by reducing unnecessary processing, which makes them well-suited for real- time applications with constrained resources.

Sparse Deep Belief Networks (Sparse DBN)

Sparse DBNs further optimize DBNs by selecting only the most relevant features, reducing computational overhead.

They improve driver fatigue detection by focusing on key fatigue indicators, ensuring faster and more efficient processing.

Hidden Markov Models (HMM)

HMMs are statistical models that analyse time-series data to predict future states based on past observations.

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For drowsiness detection, they help track behavioural changes over time, recognizing gradual shifts from alertness to fatigue.

Recurrent Neural Networks (RNN)

RNNs are a form of neural network designed to process sequential data by maintaining a hidden state that captures temporal dependencies.

They help in driver drowsiness detection by analysing time-series data from physiological signals (EEG, ECG) and behavioural patterns (eye blinks, yawning). RNNs detect changes over time, triggering alerts when fatigue indicators are identified.

Long Short-Term Memory (LSTM)

LSTMs are an advanced type of RNN built to manage long-term dependencies through memory cells and gating mechanisms.

They improve driver drowsiness detection by accurately analysing prolonged patterns in physiological signals (EEG, heart rate) and behavioural cues (eye closure, head movement). LSTMs prevent information loss over time, ensuring more reliable fatigue prediction.

Transfer Learning

Transfer Learning is a machine learning technique where a model trained on one task is used for another related task. Instead of training a model from the beginning, it uses the knowledge gained from a large dataset to improve accuracy and reduce training time.

ResNet (Residual Network)

ResNet is a deep CNN model that uses residual connections to overcome vanishing gradients, enabling very deep networks to train efficiently.

It enhances driver drowsiness detection by extracting hierarchical features from facial images, improving accuracy in detecting subtle fatigue signs like drooping eyelids and head tilts.

DenseNet (Densely Connected Network)

DenseNet connects each layer to all subsequent layers, ensuring better gradient flow and feature reuse.

For driver drowsiness detection, it efficiently learns complex facial and eye movement patterns from video data, improving detection accuracy with fewer parameters.

BERT (Bidirectional Encoder Representations from Transformers)

BERT is a transformer-based NLP model that processes text bidirectionally to understand context better.

It aids driver drowsiness detection by analysing driver speech or text inputs (e.g., reaction delays in voice commands), identifying signs of cognitive fatigue.

TST (Time-Series Transformer)

TST is a transformer-based model optimized for time-series data, capturing long-range dependencies efficiently.

It improves driver drowsiness detection by analysing physiological signals (EEG, heart rate) over time, providing more robust and real-time fatigue predictions.

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5. Literature Survey

1. Vehicle Based Measures:

a. The study [2] investigates drowsy driving impacts introducing a novel approach for detecting drowsiness-related lane departures using steering wheel angle data analysed by random forest algorithm. Traditional detection methods, which rely on complex behavioural and physiological data, tend to be intrusive. By contrast, the proposed approach is minimally invasive, analysing steering angles to identify signs of drowsiness. The model used a ten-fold cross- validation approach to mitigate overfitting and achieved strong performance metrics surpassing the traditional PERCLOS model in accuracy (by 24%) and delivering a higher AUC in ROC analysis. While PERCLOS showed sensitivity at low thresholds, the random forest model maintained reliable predictions across all thresholds, underscoring its robustness. These findings suggest that this approach could be effectively integrated into alert systems to help prevent accidents caused by driver fatigue.

b. In the 2016 Maxima model [3], Nissan introduced a driver attention alert system that observes steering behaviour to detect irregularities. If the driver's steering deviates significantly from their usual pattern, the system triggers an alert, signalling that a break may be advisable. This alert system customizes its response by establishing a baseline for each driver's normal behaviour and constantly analysing steering corrections to detect any shifts. Upon detecting signs of fatigue, a warning icon appears on the console to notify the driver.

c. Volkswagen's Rest Assist system [4] monitors lane tracking, pedal usage and irregular steering movements to assess driver fatigue. When signs of fatigue are identified, the system alerts the driver through (i) a visual message, (ii) an audible signal and (iii) steering wheel vibrations.

2. Biological Based Measures:

a. ECG Based:

i. In the study [5], the driver drowsiness detection system was evaluated using HRV data from both ECG and PPG sensors, analysed through a CNN model with three types of recurrence plots (Bin-RP, Cont-RP and ReLU-RP). The ReLU-RP-based CNN model yielded the highest classification accuracy, achieving 70% accuracy with ECG data and 64% with PPG data. The study also included a comparison with models based on recurrence quantification analysis (RQA) features, including logistic regression (LR), K-nearest neighbour (KNN), support vector machine (SVM) and random forest (RF). The CNN models using ReLU-RP consistently outperformed these conventional models, showing approximately 6-17% better accuracy for ECG and 4-14% for PPG. Additionally, the ReLU-RP model demonstrated superior performance across other metrics, including precision, recall and F-measure, supporting its effectiveness in detecting drowsiness through wearable ECG and PPG sensors.

b. EEG Based:

i. This study [6] introduces a driver drowsiness detection system using EEG signals to differentiate between alertness and drowsiness. Ten volunteers, sleep-deprived for 20 hours, participated in a simulated driving task. EEG data were collected during a virtual driving game as subjects navigated barriers. Key features, such as Higuchi's and Petrosian's fractal dimensions and signal energy, were extracted. Statistical analysis showed significant differences between alert and drowsy states, with a 95% confidence level for most EEG channels. An artificial neural network (ANN) achieved 83.3% accuracy in classifying alert and drowsy states, demonstrating the effectiveness of these features for drowsiness detection.

c. HRV Based:

i. This study [7] introduces a driver drowsiness detection system that leverages respiratory measures derived from heart rate variability (HRV) to identify fatigue signs. Two novel spectral indices—weighted mean (WM) and weighted standard deviation (WSD) of the high-frequency (HF) band within the HRV power spectrum are proposed to improve upon traditional dominant respiration metrics. In a simulated driving setup, HRV data were collected and analysed, revealing that WM and WSD indices effectively captured trends of slower, more regular breathing as drowsiness increased. When used in predictive models alongside standard HRV features, these indices achieved up to 0.95 in area under the curve (AUC), highlighting a substantial accuracy boost over previous drowsiness detection techniques.

3. Behavioral Based Measures:

a. Eye Based:

i. A novel driver fatigue detection system is outlined in [8], where the authors present an approach that combines several algorithms, with a key focus on facial landmark analysis and real-time eye-tracking techniques. By collecting tailored data across various states of drowsiness—such as wakefulness with eyes open, drowsiness with eyes closed, head tilting and yawning—they created a model that accurately gauges fatigue derived from landmark coordinates alone. Moreover, the system enhances real-time detection by integrating eye-gaze landmarks to track blinking frequency using the eye aspect ratio equation. This integration of multiple techniques significantly boosts the system's accuracy in detecting driver fatigue.

ii. Ameen Aliu Bamidele and his team introduced an eye-tracking-based method for detecting driver drowsiness [9], which they describe as both low-cost and non-intrusive. This technique aims to combat driver fatigue using machine learning models, including Support Vector Machine (SVM), Logistic Regression and K-Nearest Neighbours (KNN). In addition, an Artificial Neural Network (ANN) with three hidden layers and a SoftMax activation function was also implemented. The results showed that KNN and ANN provided the most accurate predictions, with KNN achieving an accuracy of 72.25% and ANN following closely at 71.61%. The system was evaluated and validated using a medium-quality driver video dataset.

iii. In [10], Muhammad Tayab Khan and colleagues proposed a system for detecting drivers drowsiness that monitors eye movement behaviour through a classification-based approach. The system introduces a real-time, image- based method for detecting driver sleepiness. It follows a four-step procedure: detecting the face, extracting the eyes, analysing eyelid curvature and classifying the eyes. The system demonstrated an average classification accuracy of 95% on a standard driving video dataset, 70% on a more complex benchmark dataset and over 95% accuracy when applied to real-time driving surveillance footage.

iv. A system [11] designed for eye movement tracking efficiently detects and classifies eye states (open or closed). It utilizes algorithms for facial feature and skin-color segmentation, enabling precise identification of the eye region. The system applies an Extended Kalman filter for continuous tracking, allowing for the measurement of blink frequency and duration. Developed in MATLAB, it operates with near real-time efficiency, achieving success rates of 95.3% for CCD-based videos and 96.3% for CMOS-based videos.

v. A different approach to drowsiness detection is presented in [12], where the system uses eye-tracking and image processing to non-invasively detect driver fatigue. To address challenges such as varying lighting conditions and different driver postures, it incorporates a self-quotient image technique and evaluates six key eye closure metrics: Percentage of Eyelid Closure (PERCLOS), Maximum Close Duration (MCD), Blink Frequency (BF), Average Opening Level (AOL), Opening

Velocity (OV) and Closing Velocity (CV). The system demonstrates an accuracy of over 86% in detecting drowsiness during simulator tests through the use of Fisher's linear discriminant functions. By factoring in individual differences in blink frequency, the system's accuracy improves and incorporating personalized evaluations during the initial stages of driving further enhances detection rates.

b. Mouth Based:

i. Shabnam Abtahi, Behnoosh Hariri and Shervin Shirmohammadi proposed a driver drowsiness detection method cantered on monitoring yawning behaviour [13]. The approach analyses facial features by tracking facial movements, minimizing reliance on facial geometry to enhance robustness. The authors highlight the method's practicality for in-vehicle camera systems, advocating for a simple design that avoids the use of complex algorithms. Based on experimental findings, they support the real-world application of this proposed technique.

ii. A drowsiness detection method proposed by Mohamad-Hoseyn Sigari and colleagues uses an adaptive approach to detect driver fatigue by analysing eye and facial symptoms [14]. The system employs horizontal projection and template matching, achieving high accuracy in extracting symptoms and estimating drowsiness. While it primarily functions in the visible spectrum, it can be modified for use with infrared (IR) technology. However, the face tracking technique employed by the system is computationally intensive and prone to inaccuracies, highlighting the potential for improvement, possibly through adaptive filtering methods such as the Kalman filter.

iii. Sushma Nagdeote, Heenakausar Pendhari, Martina John and Shagun Agrawal introduced a fatigue detection method that uses facial landmark detection to analyse metrics like the mouth aspect ratio and eye aspect ratio [15]. This system is capable of accurately detecting drowsiness, activating an alert to wake the driver and help prevent potential accidents.

c. Head Based:

In their study, Mehreen et al. [16] introduced an innovative method for identifying driver fatigue by extracting both behavioural and biological signals using a lightweight, non-invasive headband, instead of relying on cameras or intrusive sensors. The developed system gathers a combination of data from the headband's accelerometer, gyroscope and EEG electrodes. Data was gathered under both drowsy and alert conditions from 50 volunteers using a driving simulator. To enhance accuracy and robustness, the authors created a feature vector by integrating information from head movement, eye blinking and spectral signals. They then applied backward feature selection across different classifiers. The linear SVM, when provided with the complete feature vector, achieved an accuracy of 86.5% before feature selection, which increased to 92% after the selection process.

4. Fuzzy Logic Based:

i. In [17], Wasin AlKishri and colleagues present a real-time, nonintrusive system that detects driver fatigue using image processing and fuzzy logic. The system employs the Viola–Jones algorithm for detecting and monitoring facial features, including eye blinks and mouth movements in video frames, while a fuzzy controller interprets these cues to assess drowsiness levels and triggers alert signals. Tested on the YaWDD yawning dataset, the system achieved a high accuracy of 94.5% in detecting drowsy states, with offline detection accuracies of 87.9% for eye states and 100% for mouth states. The method addresses challenges such as varying lighting and facial accessories, showing promise for improved road safety. Future enhancements include infrared integration for low-light detection and the use of steering wheel data for more comprehensive monitoring.

ii. In [18], Hamid Shirmohammadi and Farhad Hadadi present a study using fuzzy logic and multinomial logistic regression to predict driver drowsiness based on behavioural measures. The study analyses data such as neck bending angle, back and foot pressure and driver seat pressure

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distribution, finding that the vertical neck bending angle is a significant predictor of drowsiness, with a correlation coefficient of 0.56 and prediction accuracy of 0.73 for drowsy states. The fuzzy logic system is used to evaluate the impact of environmental factors, such as light and weather conditions, on drowsiness risk. Results show that adverse conditions, like rain, significantly increase drowsiness levels compared to clear conditions. The study concludes that combining fuzzy logic with logistic regression improves drowsiness prediction accuracy and can be beneficial for real-time monitoring systems aimed at enhancing driver safety.

5. Machine Learning Based Models:

a. Shallow Models:

i. A regression-based facial landmark detector is used in a dynamic eye blink detection algorithm proposed by researchers in [19]. This technique demonstrates high performance on standard datasets by combining accurate facial feature identification with eye blink detection through Support Vector Machines (SVM). One of the key advantages of this approach is its low computational demand. Additionally, the study introduces an SVM-driven method that analyses the eye aspect ratio over a temporal window, surpassing traditional methods that rely on fixed threshold values for detecting blinks. However, the research highlights a limitation, namely the assumption of a constant blink duration across different individuals.

ii. Another approach to drowsiness detection is outlined in [20], which the authors claim is both cost-effective and reliable for identifying driver fatigue. This method utilizes visual behavioural features and applies several machine learning algorithms, including Fisher's Linear Discriminant Analysis (FLDA), Support Vector Machine (SVM) and a Bayesian classifier. The system analyses indicators such as the Eye Aspect Ratio (EAR), the Mouth Opening Ratio (MAR) and the Nose Length Ratio from webcam video footage, using adaptive thresholding for precise real-time fatigue detection. Among the machine learning models tested, SVM and FLDA provided the best performance, achieving sensitivity values of 0.956 and 0.896, respectively.

iii. A fatigue detection method was introduced by Matthew Sacco and Reuben A. Farrugia, featuring a real-time driver sleepiness detection system. The technique employs several images preprocessing steps, including median filtering and histogram equalization [21]. For facial feature identification, the Viola-Jones object detection algorithm is used, followed by correlation coefficient template matching to evaluate the driver's condition. An SVM classifier is applied, utilizing a blend of three key drowsiness indicators—mouth opening, PERCLOS (percentage of eyelid closure) and the average eye closure interval—to determine the fatigue level. The system processes 15 frames per second at a resolution of 640×480 and demonstrated exceptional performance with an average detection accuracy of 95.2%., achieving an average detection accuracy of 95.2%.

b. Deep Models:

i. A new driver fatigue evaluation system was introduced by Wanghua Deng and Ruoxue Wu, which incorporates both face tracking and facial landmark detection [22]. Their approach features the MC-KCF algorithm, combining CNN with Multi-task Cascaded Convolutional Networks (MTCNN) to improve the kernelized correlation filters technique. This MC-KCF-based DriCare system operates almost in real-time, providing remarkable speed in tracking and analysing eye and mouth movements.

ii. Another approach to drowsiness detection is detailed in [23], where Elena Magan and colleagues propose two deep learning methods for assessing fatigue. Unlike traditional methods that rely on single images, these models analyse a continuous a minute-long video sequence intended to present a more precise evaluation. The first method integrates CNN and RNN, while the second utilizes fuzzy logic to assess fatigue, following data preprocessing through AI and deep learning techniques. Tests conducted on 122 video samples showed relatively low accuracy, with training data achieving about 65% and test data around 60% for both approaches. Nevertheless, the second method effectively reduces false alarm rates, despite its limitations.

iii. A drowsiness detection approach developed by Younes Ed-Doughmi, Najlae Idrissi and Youssef Hbali utilizes deep learning with multi-layer architectures [24]. This method incorporates a combination of Recurrent Neural Networks (RNN) and 3D Convolutional Networks (ConvNets), trained on an extensive video dataset to address ongoing challenges in detecting and preventing drowsiness. The authors designed a 3D ConvNet model that achieved a notable accuracy of almost 97% across various subject sequences, each displaying different postures. Their approach primarily examines changes in driver behaviour and posture over time, but faces challenges in detecting drowsiness when the driver maintains a consistent posture.

iv. A fatigue detection method introduced by Md. Tanvir Ahammed Dipu and colleagues features an advanced drowsiness detection system based on Convolutional Neural Networks (CNN), with a focus on creating a lightweight solution for use in integrated devices [25]. The current system is trained on 250 low-light images, with plans for future development aimed at expanding the dataset to include more low-light images and tackling issues related to poor lighting conditions. Suggestions for improvement include enhancing the dataset by adding yawning data and optimizing the SSD_MOBILENET architecture to enhance the effeciency of drowsiness detection.

6. Observations after the literature survey:

The results obtained from the literature survey highlight that numerous researchers have employed a wide range of techniques for drowsiness detection. A common trend is the use of various classifier approaches, including Support Vector Machine (SVM), K- Nearest Neighbours (KNN) and Convolutional Neural Networks (CNN), among others. Additionally, methods like Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), face mapping and algorithms such as Hidden Markov Models (HMM), Decision Trees (DT) and Long Short-Term Memory (LSTM) networks are frequently integrated to enhance accuracy. The emphasis is on refining the detection systems by integrating these techniques to improve performance and real-time applicability. The following findings were identified:

Lighting Fluctuations: Lighting conditions, whether due to time of day or weather, play a significant role in the system's performance. Variations in lighting can hinder the accuracy of facial feature detection, impacting drowsiness monitoring. Bright sunlight can create glare which can impact facial landmarks detection, while low-light conditions at night may reduce the visibility of critical features such as eyes or mouth. Additionally, artificial lighting inside the vehicle, like dashboard lights, can cause inconsistent illumination on the driver's face. Weather conditions like fog, rain or overcast skies further complicate the system's ability to adapt to dynamic lighting environments effectively.

Dimensionality Reduction for Improved Accuracy: A combination of both high-level and low-level features, processed through dimensionality reduction methods, enhances the accuracy of driver drowsiness detection systems, making them more reliable. High-dimensional data, such as detailed facial landmarks, blink rates, and head movements, can include redundant or irrelevant features that may hinder model performance. By using dimensionality reduction techniques like Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA), the system isolates the most relevant features critical for identifying drowsiness patterns. This reduces noise and computational complexity, enabling faster and more accurate real-time analysis. As a result, the system becomes better equipped to consistently detect drowsiness across various driving conditions and individual variations.

Reflective Surfaces Challenge: The detection accuracy of driver drowsiness systems can be significantly impaired by reflective surfaces behind the driver, leading to challenges in maintaining consistent performance in such conditions. Reflections from windows, mirrors, or glossy interior surfaces can create duplicate or distorted images that confuse the system's algorithms. This interference often disrupts the precise identification of facial features, such as eyes and mouth, which are critical for detecting drowsiness. Additionally, changing angles of sunlight or artificial lights can amplify these reflections, further complicating image analysis. Addressing this issue requires advanced filtering techniques or camera positioning strategies to minimize the impact of reflective surfaces on detection reliability.

Frame Rate Sensitivity: The detection process is highly sensitive to the frame rate of the capturing camera. A lower frame rate may fail to capture subtle facial changes, such as micro-sleeps, gradual eye closures, or minor head movements, which are critical indicators of drowsiness. This can result in missed detections or delayed responses, compromising the system's effectiveness in real-time scenarios. On the other hand, while higher frame rates improve the ability to track rapid changes in facial expressions, they also demand greater computational resources, which may challenge real-time processing capabilities. Balancing frame rate and computational efficiency is essential to ensure accurate and timely drowsiness detection.

Wearables and Eye Tracking: The presence of sunglasses or other eyewear, especially across different lightning enviroments, complicates the detection of eye movement. Sunglasses can obscure the eyes entirely, while reflective or polarized lenses can distort the captured images, making it challenging for the system to identify key indicators of drowsiness, such as blink rate or eyelid closure. Additionally, corrective glasses can introduce glare or reflections that interfere with image clarity. These challenges necessitate the use of advanced camera systems, such as infrared cameras that can penetrate certain types of lenses, and sophisticated image processing algorithms capable of compensating for distortions. Adapting to these factors is essential for maintaining the accuracy and reliability of drowsiness detection in real-world conditions.

Complex Backgrounds and Multi-Objective Classifiers: In complex driving environments, such as during heavy traffic or adverse weather conditions, the accuracy of drowsiness detection systems can be significantly impacted by background noise and dynamic changes in the surroundings. These factors make it difficult for the system to isolate and analyze driver-specific features accurately. Multi-objective machine learning classifiers can address this challenge by simultaneously focusing on multiple data sources, such as facial expressions, head movements, and steering behavior. By integrating and prioritizing these features, the system can maintain high performance even in challenging scenarios. This approach enhances robustness and ensures reliable drowsiness detection across diverse and complex real-world driving conditions.

Dataset Limitations: The lack of standardized datasets across different studies complicates comparisons between machine learning techniques like SVM, CNN, and HMM. Variations in datasets—such as differences in lighting conditions or vehicle environments—introduce inconsistencies that hinder the ability to benchmark and evaluate the performance of these algorithms effectively. This lack of uniformity impedes the generalizability of findings, as models trained on one dataset may not perform well when applied to a different dataset. Additionally, the absence of comprehensive datasets that represent real-world driving scenarios limits the robustness of these techniques. Addressing this gap requires the development of diverse, standardized datasets that can facilitate fair comparisons and improve the reliability of drowsiness detection systems across varied conditions.

Camera Movement and Road Features: Sudden movements of the camera caused by road features, such as speed bumps, potholes, or sharp turns, can disrupt the system's ability to maintain accurate detection. These jolts can result in blurred images or misaligned frames, making it challenging to track facial features like eye closures or head posture consistently. Additionally, frequent vibrations or shifts in the camera's position can lead to inaccurate focus or calibration issues, further impacting detection reliability. To address this, stabilization mechanisms, such as gimbals or software-based image correction techniques, are essential to mitigate the effects of camera movement and ensure consistent performance in real-world driving conditions.

Individual Variability in Blink Patterns: Drivers display unique blinking frequencies, durations, and eye closure patterns, which significantly influence their levels of fatigue. These variations are shaped by several factors, including individual physiology, age, health conditions, and environmental factors such as lighting and driving conditions. Accounting for these differences is crucial for developing personalized fatigue detection systems that can provide more accurate and reliable results.

7. Concluding Remarks

The paper begins by discussing the significant damages caused by vehicular accidents and presents various statistics highlighting the severity of these hazards. A comprehensive review of 24 different driver approaches for detecting drowsiness has been provided. For building an efficient drowsiness detection system, behavioural measures, particularly those utilizing camera-based systems to detect subtle changes in facial expressions, are recommended. The core principle involves identifying abnormalities in the driver's behaviour and driving pattern. The existing drowsiness detection methods can be further extended by exploring improvements in real-time facial feature detection, particularly under varying lighting conditions and in low-capacity edge-based IoT environments. It is also advised to apply dimensionality reduction techniques to extract meaningful features, followed by classification using a hybrid approach to achieve high accuracy in detecting drowsiness. The survey of literature emphasizes the challenges associated with physiological measures, which require expensive sensors and vehicle-based methods, which may not be reliable due to practical constraints. To address the critical issue of driver drowsiness, the paper explores four major approaches: vehicle-centric, behaviour- centric, biology-centric and hybrid-centric measures.

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