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CE-34 Vision-Based Driver Drowsiness Detection: A PRISMA-Guided Systematic Review of Algorithms, Indicators, and Real-Time Monitoring Architectures

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Abstract *-Driver fatigue and drowsiness are significant contributors to road traffic accidents worldwide, posing serious threats to public safety and increasing the need for reliable driver monitoring technologies. Vision-based driver drowsiness detection systems have emerged as an effective and non-intrusive solution for monitoring driver behavior using computer vision and artificial intelligence techniques. These systems analyze visual indicators such as eye closure, blink rate, yawning behavior, head pose, and gaze direction to assess the driver's level of alertness. This paper presents a PRISMA-guided systematic review of vision-based driver drowsiness detection approaches, focusing on detection algorithms, fatigue indicators, machine learning techniques and real-time monitoring architectures. The review examines widely used techniques such as facial landmark detection, Eye Aspect Ratio (EAR), PERCLOS-based fatigue estimation, yawning detection, gaze tracking, and deep learning models. Comparative analysis of existing methods indicates that deep learning and hybrid vision-based approaches significantly enhance detection accuracy, although challenges related to illumination variation, occlusion, head pose changes, and real-time deployment remain. The study highlights current research trends and outlines future directions for developing robust and efficient driver monitoring systems for intelligent transportation environments.*

Keywords: Driver Drowsiness Detection, Computer Vision, Eye Aspect Ratio (EAR), PERCLOS, Deep Learning, Driver Monitoring Systems, Intelligent Transportation Systems, PRISMA Systematic Review.

1. INTRODUCTION

Road traffic accidents represent a major global public safety concern and remain one of the leading causes of death worldwide. According to global road safety reports, approximately 1.19 million people die each year due to road traffic crashes, with millions more suffering serious injuries and long-term disabilities. These incidents impose a substantial socioeconomic burden on societies and highlight the importance of improving driver safety and monitoring systems. Among the numerous factors contributing to road accidents, driver fatigue and drowsiness have been identified as significant causes, particularly during long-distance travel, night driving, and monotonous highway conditions [1], [2].

Driver drowsiness can severely impair cognitive and motor functions, leading to slower reaction times, reduced situational awareness, and poor decision-making ability while driving. Studies have shown that insufficient sleep and fatigue significantly increase crash risk and degrade driving performance. For instance, systematic analyses have demonstrated that sleep deprivation and fatigue can substantially increase the probability of road traffic accidents, emphasizing the importance of early fatigue detection and prevention mechanisms [2]. Consequently, the development of intelligent driver monitoring systems capable of detecting early signs of fatigue has become an important research area in intelligent transportation systems and advanced driver assistance systems (ADAS).

Existing driver drowsiness detection techniques can generally be categorized into three major groups: vehicle-based methods, physiological signal-based methods, and vision-based methods. Vehicle-based approaches monitor driving behavior indicators such as steering wheel movements, lane departure patterns, braking activity, and vehicle speed variations. Although these methods are non-intrusive and can be implemented without direct driver monitoring, their reliability is often affected by external factors such as road conditions, weather, and driving style.

Physiological signal-based methods attempt to detect driver fatigue by measuring biological signals such as electroencephalography (EEG), electrocardiography (ECG), and heart rate variability. These signals provide direct information about the driver's physical and cognitive state and may offer high detection accuracy.

In contrast, vision-based driver monitoring systems have gained considerable attention because they provide a non-intrusive and cost-effective approach to fatigue detection. These systems analyze visual cues from the driver's face using cameras and computer vision algorithms. Common visual indicators include eye closure, blink frequency, gaze direction, head pose, and yawning behavior. Among these indicators, the Percentage of Eye Closure over Time (PERCLOS) has been widely recognized as one of the most reliable measures of driver fatigue and reduced alertness [3].

Another widely used technique in vision-based fatigue detection is the **Eye Aspect Ratio (EAR)** method, which estimates eye closure by analyzing geometric relationships between facial landmarks around the eye region. Soukupová and Čech introduced a real-time blink detection method based on facial landmarks that computes the ratio between vertical and horizontal eye distances to determine whether the eyes are open or closed [4]. Due to its simplicity and computational efficiency, the EAR approach has been widely adopted in real-time driver monitoring applications. Subsequent studies have further improved the robustness of this method by adapting EAR thresholds and improving landmark detection accuracy for different eye shapes and environmental conditions [5].

Recent advances in artificial intelligence and deep learning have further accelerated research in driver drowsiness detection. Machine learning and deep learning models such as convolutional neural networks (CNNs) have been employed to analyze facial features and detect fatigue-related patterns from images and video streams.

To address these challenges and provide a comprehensive overview of the field, this paper presents a PRISMA-guided systematic review of vision-based driver drowsiness detection systems. The review analyzes recent research studies with respect to detection algorithms, fatigue indicators, machine learning techniques, and real-time monitoring architectures. By systematically evaluating existing approaches, this study aims to identify research trends, highlight key limitations, and provide insights into future research directions for intelligent driver monitoring systems.

2. LITERATURE REVIEW

This study adopts a systematic approach to review the existing literature related to vision-based driver drowsiness detection systems. To ensure transparency, reproducibility and methodological rigor in the literature framework, which provides standardized guidelines for conducting and reporting systematic reviews. The PRISMA methodology is widely used in scientific research to minimize bias during study selection and ensure that the review process is well documented. By following this framework, the present study systematically identifies, filters and analyzes relevant research articles related to driver drowsiness detection using computer vision and artificial intelligence techniques.

2.1 Literature Search Strategy

A comprehensive literature search was conducted to identify relevant publications addressing driver drowsiness detection using computer vision and machine learning techniques. Multiple academic databases were consulted to ensure broad coverage of peer-reviewed research in this field. The databases considered in this review include IEEE Xplore, ScienceDirect, SpringerLink, ACM Digital Library and Google Scholar. These databases provide extensive collections of research publications in the fields of computer vision, intelligent transportation systems, machine learning, and embedded monitoring technologies.

The literature search was carried out using combinations of keywords and Boolean operators to retrieve relevant studies. The primary search terms included phrases such as driver drowsiness detection, driver fatigue monitoring, vision-based driver monitoring, eye aspect ratio (EAR), PERCLOS fatigue detection, facial landmark driver fatigue detection and deep learning driver monitoring. The search mainly focused on publications published between **2015 and 2024**, which allowed the review to capture recent developments in artificial intelligence and computer vision techniques applied to driver monitoring systems.

2.2 Study Selection Criteria

To ensure the quality and relevance of the reviewed studies, predefined inclusion and exclusion criteria were applied during the study selection process. Studies were included if they focused on driver drowsiness or fatigue detection using vision-based techniques such as facial landmark detection, image processing or machine learning algorithms. Peer-reviewed journal articles and conference papers written in English were considered in this review. Studies reporting experimental validation, dataset evaluation or system implementation were also prioritized.

2.3 Study Screening and Selection Process

The study screening and selection process followed the four stages recommended by the PRISMA framework: identification, screening, eligibility assessment and final inclusion. For clarity, the article selection process is summarized in Table 1.

Table 1 Summary of the study selection process

Stage of Selection	**Number of Articles**
Records identified through database searching	150
Records after duplicate removal	118
Articles excluded after title/abstract screening	60
Full-text articles assessed for eligibility	58
Full-text articles excluded	22
Final studies included in the review	36

3.4 Data Extraction and Analysis

For each selected study, key information was extracted and organized in a structured format to facilitate systematic comparison and analysis. The extracted information included the authors and publication year, the detection method used, the algorithms applied, the fatigue indicators considered, the dataset used for evaluation, and the reported performance metrics. In addition, information regarding hardware platforms and system architectures was also recorded whenever available.

The collected data were subsequently analyzed to identify common research trends, widely used fatigue indicators, and emerging technologies in driver drowsiness detection systems. This analysis enabled the identification of dominant approaches as well as limitations in existing studies. The findings of this systematic review provide insights into potential research directions for improving the reliability and real-time performance of vision-based driver monitoring systems.

3. METHODOLOGY

3.1 Classification of Driver Drowsiness Detection Methods

Driver drowsiness detection has become an important research topic in intelligent transportation systems due to the increasing number of road accidents caused by fatigue and reduced driver alertness. Over the past decades, numerous techniques have been proposed to monitor driver behavior and detect early signs of fatigue. These approaches differ significantly in terms of sensing mechanisms, data processing techniques, and system implementation. Based on the type of indicators used for detecting driver fatigue, most studies categorize driver drowsiness detection systems into three major groups: vehicle-based methods, physiological signal-based methods, and vision-based methods [8],[11]. Each of these approaches utilizes different data sources and detection strategies, and they present unique advantages as well as limitations in practical applications.

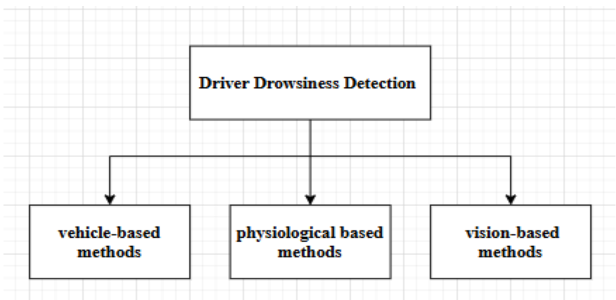

Figure 1. Classification of driver drowsiness detection methods based on sensing approaches

- **Vehicle-Based Methods**

Vehicle-based methods detect driver drowsiness by analyzing variations in vehicle dynamics and driving patterns. These approaches rely on the assumption that fatigue affects the driver's ability to control the vehicle consistently. Consequently, abnormal driving behavior can be used as an indirect indicator of reduced alertness. Typical parameters monitored in vehicle-based systems include steering wheel movement, lane deviation, acceleration patterns, braking behavior, and vehicle speed fluctuations [8], [10].

Despite their advantages, vehicle-based methods have several limitations. These systems rely heavily on external driving conditions such as road geometry, traffic density, weather conditions, and vehicle type. For example, lane deviation may occur due to road curvature rather than driver fatigue. Furthermore, experienced drivers may compensate for fatigue through corrective steering actions, which can reduce the accuracy of such methods. As a result, vehicle-based detection techniques are often used in combination with other monitoring approaches to improve reliability [9].

- **Physiological Signal-Based Methods**

Physiological signal-based methods detect driver fatigue by measuring biological signals that reflect the driver's physical and cognitive state. These approaches are often considered highly reliable because they monitor direct indicators of human fatigue rather than indirect behavioral cues. Common physiological signals used in fatigue detection include electroencephalography (EEG), electrocardiography (ECG), electrooculography (EOG), and heart rate variability (HRV) [8], [11].

Although physiological approaches provide accurate measurements, they have several practical limitations. Most physiological monitoring systems require sensors to be attached to the driver's body, such as electrodes placed on the scalp or chest. These sensors can cause discomfort and may interfere with normal driving behavior, making them less suitable for everyday vehicle environments. In addition, physiological monitoring systems can be expensive and complex to implement, which limits their adoption in commercial driver monitoring systems [9].

- **Vision-Based Methods**

Vision-based methods detect driver drowsiness by analyzing visual cues captured through cameras installed inside the vehicle. These approaches focus on monitoring the driver's facial features, eye movements, head pose, and other behavioral indicators that reflect fatigue. Compared to physiological methods, vision-based systems are non-intrusive, meaning they do not require physical sensors attached to the driver. This makes them more suitable for real-world applications and integration with modern driver monitoring systems [10].

A wide range of visual indicators have been used to detect driver fatigue. One of the most widely used indicators is eye closure, which can be quantified using metrics such as the Percentage of Eye Closure over Time (PERCLOS). PERCLOS measures the proportion of time that a driver's eyes remain closed within a specific time interval and has been shown to be a reliable indicator of fatigue.

Despite their advantages, vision-based systems still face several challenges. Variations in illumination, occlusion caused by glasses or face masks, and head movements can affect detection accuracy. Additionally, environmental conditions such as nighttime driving may require infrared cameras or advanced image enhancement techniques to maintain reliable performance. Nevertheless, vision-based approaches remain one of the most promising and widely adopted methods for driver drowsiness detection in modern intelligent transportation systems [11].

3.2 Vision-Based Driver Drowsiness Detection Techniques

Vision-based driver monitoring systems have emerged as one of the most widely adopted approaches for detecting driver fatigue due to their non-intrusive nature and compatibility with modern intelligent transportation technologies. Unlike physiological methods that require sensors attached to the driver's body, vision-based techniques rely on cameras and computer vision algorithms to analyze visual cues associated with fatigue. These systems typically monitor facial features such as eye movements, blinking patterns, gaze direction, head pose, and yawning behavior to infer the driver's alertness state. Advances in image processing, machine learning, and deep learning have significantly improved the performance and reliability of these systems in real-world driving environments. The following subsections discuss the major categories of vision-based detection techniques used in the literature.

- **Facial Landmark-Based Detection**

Facial landmark detection plays a fundamental role in many vision-based driver monitoring systems. Facial landmarks refer to specific key points on the human face, such as the corners of the eyes, eyebrows, nose, and mouth. By tracking the movement and geometry of these points, researchers can extract useful information about facial expressions and eye behavior associated with fatigue.

One widely used approach for detecting eye blinking and eye closure is the facial landmark-based method proposed by Soukupová and Čech [14]. Their work introduced an efficient algorithm that uses facial landmark positions to compute geometric features of the eye region for real-time blink detection. The method has been widely adopted in driver drowsiness detection systems because it provides accurate eye state estimation with low computational complexity. In practice, facial landmarks are typically detected using machine learning models trained on annotated facial datasets. Once these landmarks are identified, geometric relationships between them can be used to analyze eye movements and blinking behavior.

- **Eye Aspect Ratio (EAR) Methods**

The Eye Aspect Ratio (EAR) is one of the most commonly used metrics for detecting eye closure in vision-based fatigue detection systems. The EAR method calculates a geometric ratio between vertical and horizontal distances of the eye landmarks to determine whether the eye is open or closed. Because the ratio remains relatively constant when the eye is open and decreases significantly during eye closure, it provides a reliable indicator of blinking events and prolonged eye closure.

The EAR concept was introduced in the blink detection framework developed by Soukupová and Čech [14], and it has since been widely used in driver drowsiness monitoring applications. Subsequent research has improved the robustness of EAR-based detection by adapting the threshold values to accommodate variations in eye shapes among different individuals. For example, Dewi et al. [15] proposed an adjusted EAR technique that improves blink detection accuracy by dynamically adapting EAR thresholds based on facial landmark characteristics.

- **Eye-State and Yawning Detection Methods**

Another important category of vision-based fatigue detection approaches focuses on analyzing eye states and yawning behavior. Eye-state analysis methods aim to classify the driver's eyes as open, partially closed, or closed using image processing or machine learning techniques. Prolonged eye closure or slow blinking patterns often indicate increasing levels of driver fatigue.

Mandal et al. [16] proposed a vision-based fatigue detection framework that performs robust eye state analysis to detect driver drowsiness. Their method analyzes visual patterns in the eye region to determine whether the driver's eyes remain closed for extended periods. This approach has demonstrated promising results for fatigue detection under varying driving conditions.

Yawning detection is another important behavioral indicator used to identify driver fatigue. Abtahi et al. [17] introduced a yawning detection system that monitors mouth opening patterns using facial image analysis. Since yawning frequency tends to increase as drivers become fatigued, monitoring mouth movements can provide valuable information about the driver's alertness state. These behavioral indicators are often combined with eye-based features to improve detection accuracy.

- **Gaze Tracking and Deep Learning-Based Methods**

Recent advances in artificial intelligence have significantly expanded the capabilities of vision-based driver monitoring systems. Modern approaches increasingly rely on deep learning techniques to automatically learn complex visual features associated with driver fatigue. Deep neural networks can analyze large volumes of video data and identify subtle behavioral patterns that may not be captured by traditional handcrafted features.

Gaze tracking methods are commonly used to monitor the driver's attention and detect situations where the driver's eyes deviate from the road for extended periods. Vicente et al. [18] developed a driver gaze tracking system capable of detecting "eyes-off-the-road" events using visual tracking algorithms. Such systems can identify distraction and fatigue by analyzing gaze direction and visual attention patterns.

Sikander and Anwar [19] emphasized that integrating different behavioral cues, such as eye closure, gaze direction, and facial expressions, can significantly improve fatigue detection performance. Consequently, hybrid vision-based frameworks that combine multiple features and deep learning models have become a major research direction in recent driver monitoring systems.

Abouelnaga et al. [20] proposed a deep neural network-based driver monitoring system designed for real-time applications on mobile devices. By leveraging deep learning models, modern fatigue detection systems can achieve higher accuracy and better robustness under challenging conditions such as varying illumination or head pose variations.

3.3 Comparative Analysis of Vision-Based Drowsiness Detection Methods

Vision-based driver drowsiness detection systems have been extensively investigated in recent years due to their non-intrusive nature and compatibility with modern intelligent transportation systems. These systems analyze facial cues such as eye closure, blink rate, yawning behavior, and gaze direction to determine the driver's alertness state.

Early studies focused primarily on handcrafted feature extraction techniques derived from facial landmarks. For example, the eye aspect ratio (EAR) method proposed by Soukupová and Čech [14] detects eye closure events using geometric relationships between facial landmarks. This approach provides reliable blink detection with low computational cost, making it suitable for real-time driver monitoring systems. Later research introduced improvements to the EAR technique. Dewi et al. [15] proposed an adaptive EAR method that adjusts detection thresholds dynamically to accommodate variations in facial structures and environmental conditions.

Several studies have also explored visual eye-state analysis as an indicator of fatigue. Mandal et al. [16] proposed a fatigue detection method based on visual analysis of eye openness, demonstrating that prolonged eye closure can reliably indicate driver fatigue. Similarly, behavioral indicators such as yawning have been used to detect fatigue. Abtahi et al. [17] introduced a yawning detection framework that monitors mouth opening patterns using facial image analysis.

More recent approaches incorporate gaze tracking and deep learning models to improve detection accuracy. Vicente et al. [18] proposed a gaze monitoring system capable of detecting “eyes-off-the-road” events by analyzing gaze direction. Such systems help identify driver distraction and fatigue simultaneously. Deep learning approaches have further enhanced detection performance by automatically learning relevant visual features from facial images. Abouelnaga et al. [20] developed a real-time driver drowsiness detection system based on deep neural networks for mobile devices. These models demonstrate improved robustness under challenging conditions such as illumination changes and head pose variations.

3.4 Research Challenges and Future Directions

Despite significant advancements in vision-based driver drowsiness detection systems, several challenges still limit their widespread deployment in real-world driving environments. This section discusses the major challenges associated with current driver monitoring systems and outlines potential future research directions for improving fatigue detection technologies.

- **Illumination Variability**

One of the major challenges in vision-based driver monitoring systems is the variation in illumination conditions inside the vehicle. Many vision-based algorithms rely on facial feature detection, which can be significantly affected by poor lighting or shadows.

Although infrared cameras and advanced image preprocessing techniques have been proposed to address this issue, achieving robust performance under all lighting conditions remains a challenge. Future research should focus on developing illumination-invariant detection algorithms that can reliably detect facial features under varying environmental conditions.

- **Occlusion and Facial Accessories**

Another challenge arises from occlusions caused by facial accessories such as sunglasses, face masks, hats, or hands covering parts of the face. Many fatigue detection methods rely heavily on eye region analysis, and occlusion of the eye area can significantly reduce detection accuracy.

To overcome this limitation, future driver monitoring systems should integrate multiple fatigue indicators, such as head pose estimation, facial expressions, and behavioral patterns, rather than relying solely on eye-based features.

- **Head Pose Variations**

Driver head movements can also affect the performance of vision-based detection systems. In real driving scenarios, drivers frequently change their head orientation while checking mirrors, interacting with vehicle controls, or observing traffic conditions. Advanced head pose estimation techniques and multi-camera systems may help improve the robustness of driver monitoring systems under such conditions.

- **Real-Time Deployment Constraints**

Many modern fatigue detection approaches rely on deep learning models that require significant computational resources. Although these models can achieve high detection accuracy, they may not always be suitable for real-time deployment in embedded vehicle systems with limited processing power.

Future research should focus on developing lightweight and energy-efficient models that can operate efficiently on edge devices while maintaining high detection accuracy.

- **Integration with Advanced Driver Assistance Systems (ADAS)**

Driver drowsiness detection systems are increasingly being integrated with advanced driver assistance systems (ADAS). These systems can provide real-time warnings, adaptive cruise control adjustments, or autonomous safety interventions when driver fatigue is detected.

Future intelligent transportation systems may combine driver monitoring technologies with autonomous driving systems to improve overall road safety. Integration of fatigue detection systems with vehicle control mechanisms represents an important direction for future research.

CONCLUSION

Driver drowsiness detection has emerged as an important research area in intelligent transportation systems due to the growing number of road accidents associated with fatigue and reduced driver alertness. This study presented a PRISMA-guided systematic review of vision-based driver drowsiness detection methods, focusing on detection algorithms, fatigue indicators, and real-time monitoring architectures. Through a structured literature search and screening process, 36 relevant studies were selected and analyzed to identify current research trends and technological developments in this field. The review showed that driver drowsiness detection techniques can be broadly categorized into vehicle-based, physiological signal-based, and vision-based approaches, among which vision-based systems have gained significant attention because they offer a non-intrusive and cost-effective solution for monitoring driver behavior. Various visual indicators such as eye closure, blink rate, yawning behavior, gaze direction, and head pose have been widely used for detecting fatigue, while techniques based on facial landmark detection and Eye Aspect Ratio (EAR) provide efficient real-time performance. In recent years, deep learning approaches have further improved detection accuracy by automatically learning complex visual features from large datasets. However, several challenges remain, including illumination variations, facial occlusion caused by glasses or masks, head pose changes, and the limited availability of large annotated datasets. Future research should therefore focus on developing robust and lightweight algorithms, integrating multiple fatigue indicators, and improving real-time deployment capabilities in embedded automotive systems to enhance the effectiveness of driver monitoring technologies and contribute to safer transportation systems.

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