Driver Drowsiness Detection: A Journey from the Wheel to AI-Enabled Road Safety

Aayush Attal[1], Aniket Singh[2], Akshat Gupta[3], Varad Nangare[4], Soham Pal[5], Sheetal Mapare[6]

[1-5] *Department of Electronics and Telecommunication Engineering, Vidyalankar Institute of Technology, Wadala, Mumbai*

[6] *Associate Professor, Department of Electronics and Telecommunication Engineering, Vidyalankar Institute of Technology, Wadala, Mumbai*

[1]aayush.attal@vit.edu.in [2]aniket.singh@vit.edu.in [3]akshat.gupta@vit.edu.in

[4]varad.nangare@vit.edu.in [5]soham.pal@vit.edu.in [6]sheetal.mapare@vit.edu.in

Abstract— **Driver drowsiness is considered as one of the leading causes of road accidents around the globe, particularly among commercial vehicle drivers. Fatigue reduces reaction time, attention, and decision-making capabilities, often without the driver realizing it. This review covers the evolution of driver drowsiness detection systems from early behavioral-monitoring approaches to state-of-the-art AI-based techniques adopting a multimodal framework. Different methods have been categorized into behavioral, physiological, vision-based, and hybrid systems. Particular emphasis has been given to recent research works involving deep learning and event-response mechanisms such as alarms, vehicle control, and SOS. The paper also discusses current challenges and future directions of research on this topic, positioning drowsiness detection as an indispensable aspect of intelligent transportation and advanced driver-assistance systems.**

Keywords— **driver drowsiness detection, fatigue monitoring, computer vision, deep learning, intelligent transportation systems, road safety.**

I. INTRODUCTION

The story of transportation is the story of human progress. Thousands of years ago, humans struggled to carry heavy loads across uneven terrain until an ingenious mind carved out a circular stone and rolled it. The wheel, first documented in Mesopotamia around 3500 BCE, was not invented for transport but for pottery. Yet soon, carts with wooden wheels emerged, drawn by animals, making it possible to move farther and faster. These wooden wheels were fragile, and as centuries passed, they evolved into spoked wheels in Egypt and later into iron-rimmed wheels in Greece and Rome, making them sturdier and better suited for long journeys [1].

As civilizations advanced, the wheel became central to trade caravans, horse-drawn carriages, and ultimately, the invention of the steam engine in the 18th century. The industrial revolution turned wheels into gears and locomotives, while the late 19th century gave us the internal combustion engine. Karl Benz's 1886 "Motorwagen" is widely considered the first true automobile, and with it, the age of motorized transport began [2]. By the early 20th century, Henry Ford's assembly lines made cars accessible to ordinary people. Rubber tires, invented by John Boyd Dunlop in 1888, added comfort and grip, and the world's highways expanded to match the growing fleet [3].

But as roads lengthened and vehicles became faster, a silent enemy crept in: fatigue. Unlike a flat tire or an empty fuel tank, drowsiness leaves no warning light on the dashboard. Drivers, especially truckers travelling overnight with heavy loads, often struggle to stay alert. Studies by the World Health Organization suggest that 20–25% of serious road accidents worldwide involve fatigue [4]. It is against this backdrop that scientists, engineers, and policymakers began to ask: how can we detect sleep before it steals lives?

This review paper explores that question, tracing the journey of drowsiness detection systems from crude behavioral tools to sophisticated AI-driven safety networks.

II. CLASSIFICATION OF TECHNIQUES TO ASSESS DRIVER DROWSINESS

A. Early Attempts: Behavioral Monitoring

Behavioral assessment methods focus on monitoring the behavior of an automobile (e.g., lane changes, steering movements, etc.) to detect when a driver is likely suffering from drowsiness. Early detection systems relied upon lane-departure alerts and measurement of the "entropy" of steering behavior, i.e., how often the steering wheel fluctuates [4]. While these techniques are typically cheaper than other drowsiness-assessment technologies, they are prone to generate false alarms due to changing environmental variables such as road conditions.

B. Physiological Monitoring: Looking Inside the Body

Physiological assessment is another method of measuring an individual's alertness; rather than observing behavior, this approach measures signals that correlate with alertness, such as EEG, EKG, and eye-closure metrics. The PERCLOS measurement device is widely recognized as a leading means of detecting driver fatigue [2]. While physiological measurement technology can be extremely accurate in controlled environments, its use is often limited by practicality and intrusiveness when continuously monitoring an individual during everyday driving.

C. Artificial Intelligence: A New Era

Vision-based drowsiness detection technologies utilize cameras to monitor specific facial features of drivers, such as eye blinking, gaze direction, head position, and yawning. Advances in computer vision have enabled real-time, non-intrusive facial monitoring in passenger vehicles [5]. However, vision-based systems may not provide reliable results in poorly lit or occluded environments.

D. Integrated SOS and Correction Systems

Combination systems utilize multiple assessment techniques, i.e., visual, behavioral, and physiological, to increase overall reliability. Studies indicate that multimodal fusion establishes a significant reduction in false detections while increasing the overall reliability of the system [7].

III. LITERATURE REVIEW

Driver drowsiness detection has been widely studied due to its strong correlation with road accidents, particularly in long-duration and night-time driving. Early research focused on understanding the impact of fatigue on driver performance and identifying measurable indicators that could reliably signal reduced alertness.

One of the most influential contributions to this field was made by Johns [2], who investigated sleepiness during driving and established standardized measures linking eyelid behavior to fatigue. This work laid the foundation for ocular-based detection techniques by demonstrating that prolonged eye closure is a direct indicator of reduced vigilance, and it remains a cornerstone for many modern detection systems.

Building on this understanding, Park [4] proposed one of the earliest vehicle-behavior-based fatigue detection systems using lane-departure analysis. The study showed that fatigued drivers exhibit increased lane deviation and irregular steering patterns. While effective in controlled scenarios, the work highlighted limitations such as sensitivity to road curvature and environmental conditions, which reduced reliability in real-world applications.

To overcome the intrusiveness of physiological sensors and the limitations of vehicle-based methods, Grace et al. [5] introduced a camera-based drowsiness detection system designed specifically for heavy vehicles. Their system monitored eye closure and head position in real time, demonstrating that non-intrusive vision-based monitoring could be practically deployed inside vehicles, and shifting research focus toward vision-based approaches suitable for commercial drivers.

With advancements in computing power and machine learning, research progressed toward data-driven models. Guo et al. [6] applied convolutional neural networks (CNNs) to driver facial images, enabling automatic extraction of complex features related to eye blinking, gaze, and facial expressions. Their results showed superior accuracy compared to traditional rule-based methods, particularly under varying lighting conditions, marking a major transition toward deep-learning-based drowsiness detection.

Recognizing that single-sensor systems are often unreliable, Lee et al. [7] proposed a multimodal sensor-fusion framework that combined visual features with steering behavior and vehicle dynamics. Their findings demonstrated that multimodal systems significantly reduce false alarms and improve robustness across different drivers and driving conditions, reinforcing the consensus that hybrid approaches are more suitable for real-world deployment.

Further extending deep learning techniques, Vicente et al. [8] explored driver vigilance monitoring using temporal modeling. By incorporating time-dependent features, their system enabled early prediction of drowsiness rather than reactive detection, a capability particularly valuable for preventing accidents before critical fatigue levels are reached.

A practical and application-oriented contribution is presented by Sharma et al. [9], whose system closely aligns with the approach proposed in this paper. Their work integrates eye-blink detection and head-position monitoring with an embedded controller to trigger alarms, reduce vehicle speed, and transmit SOS alerts using GSM and GPS modules, representing a shift from passive warning systems to active safety and emergency-response mechanisms especially relevant for truck and long-haul drivers operating in remote areas.

Finally, Ahmad et al. [10] provided a comprehensive review of driver drowsiness detection techniques, systematically comparing behavioral, physiological, vision-based, and AI-driven approaches. Their analysis concluded that AI-based multimodal systems offer the best balance between accuracy, practicality, and scalability, while also identifying challenges such as privacy concerns, computational cost, and lack of standardized datasets.

In parallel with these application-specific studies, several works have systematically reviewed the broader landscape of driver drowsiness detection. Sikander and Anwar [12] and Zhang et al. [13] each surveyed a wide range of behavioral, physiological, and vision-based techniques, highlighting persistent challenges such as inter-driver variability and the lack of standardized evaluation protocols. Fu et al. [16] extended this discussion to modern deep-learning-based methods, noting a clear shift toward multimodal and real-time architectures. On the physiological front, Arefnezhad et al. [15] and Zhu et al. [18] demonstrated that EEG-based approaches, when combined with encoder-decoder models and attention mechanisms, can capture subtle neurological markers of fatigue that are not visible through behavioral or vision-based cues alone. Complementing these physiological studies, Baccour et al. [14] compared vehicle-based and driver-based feature sets using support vector machines, finding that driver-based features generally yield more consistent performance across diverse driving conditions. On the vision-based side, Yu et al. [11]

introduced a condition-adaptive representation learning framework that adjusts to varying illumination and occlusion, while Safarov et al. [17] achieved high real-time accuracy using lightweight eye-blink analysis suitable for embedded deployment. Most recently, Liu et al. [19] and Hassan et al. [20] have explored RGB-D sensing and transformer-based architectures, respectively, pointing toward a new generation of drowsiness detection systems capable of even greater robustness than earlier CNN-based models.

Overall, the literature clearly indicates an evolution from simple behavioral monitoring to intelligent, AI-enabled, and integrated drowsiness detection systems. Current research emphasizes robustness, real-time performance, and safety intervention, positioning multimodal deep-learning systems with SOS integration as the most promising direction for future driver-safety technologies.

IV. METHODOLOGY

A. System Overview

The proposed system monitors the driver's physiological behavior using sensors for eye movement and head position. The methodology is outlined in Fig. 1. The system operates in three main stages:

1. Drowsiness Detection: Sensors continuously monitor the driver's eyes and head position and check for fatigue-related movements, such as eyes closed for more than 2 seconds, the head moving up and down continuously, or the head relaxed downward for more than 4 seconds.
2. Intervention: Upon detecting drowsiness, the system triggers warnings through alarms and gradually reduces vehicle speed using motors integrated with the vehicle's tires, eventually stopping the vehicle at a safe spot.
3. Accident Detection and SOS Activation: If an accident occurs, it is detected with the help of an accelerometer, and the system sends location details and alerts to nearby emergency services and family members.

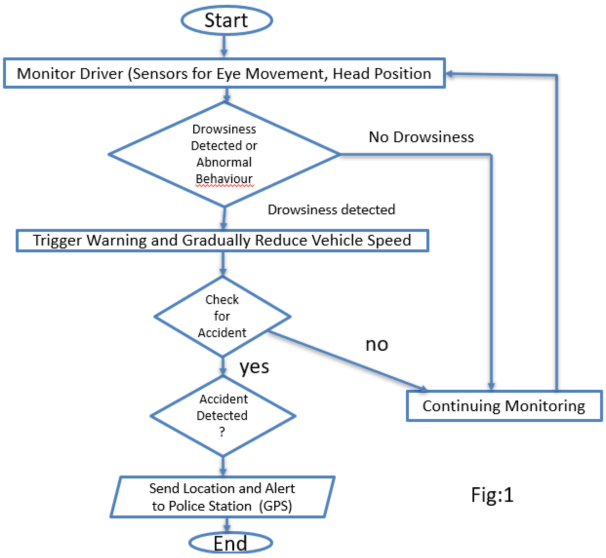

Fig. 1 System methodology flowchart for driver drowsiness detection and SOS activation.

B. Technologies Used

1) Hardware Components:

- Arduino: Acts as the central processing unit for sensor data.
- Eye Blink Sensor: Detects changes in blink patterns indicative of drowsiness.
- GSM Module and GPS Module: Facilitates communication with emergency contacts.
- Alarm System: Provides alerts to wake the driver.
- Accelerometer: Measures the vibration or acceleration of motion of the vehicle structure.

2) Software:

- Developed using C language for efficient real-time processing.
- Simulated using online tools to validate functionality before deployment.

C. Flowchart Description

Fig. 1 illustrates the step-by-step operation of the system:

1. Start monitoring the driver using sensors for eye movement and head position.

2. If no drowsiness is detected, continue monitoring.
3. If drowsiness is detected, trigger warnings through alarms and gradually reduce vehicle speed.
4. Check for accident occurrence: if an accident is detected, send an alert with GPS location to emergency services and family members; if not, resume monitoring.

V. RESULTS

The system was tested using an Arduino board and associated sensors, with the overall design validated in simulated environments through Arduino-based prototypes. Initial results demonstrate high accuracy in detecting drowsiness through eye-blink patterns and head-position changes. The accelerometer successfully detected the occurrence of an accident using generated vibrations, and the SOS mechanism successfully transmitted alerts with location details within seconds of detecting an accident.

VI. CHALLENGES AND FUTURE DIRECTIONS

Key challenges include robustness under varying lighting conditions, driver variability, privacy concerns, and computational constraints for real-time processing. Future work should focus on lightweight AI models, explainable decision-making, and seamless integration with advanced driver-assistance systems.

VII. CONCLUSION

The invention of the wheel reshaped humanity, and centuries later, its descendants — cars and trucks — carry our goods and ambitions across continents. But with progress came risk: fatigue. The story of driver drowsiness detection mirrors the journey of the wheel itself. From crude behavioral systems to advanced AI and integrated SOS mechanisms, the field has grown into a beacon of modern road safety. Just as airbags and seatbelts became non-negotiable, fatigue-detection systems may soon be standard in every vehicle. This review shows that, in the long arc of transportation history, drowsiness detection is not just a technology — it is the next wheel, a lifesaving invention that will keep humanity rolling safely into the future.

REFERENCES

[1] World Health Organization, Global Status Report on Road Safety, Geneva, Switzerland, 2019.

[2] M. W. Johns, “Sleepiness at the wheel,” Journal of Sleep Research, vol. 9, no. 3, pp. 202–210, 2000.

[3] J. F. May and C. L. Baldwin, “Driver fatigue and performance,” Accident Analysis & Prevention, vol. 41, no. 4, pp. 676–684, 2009.

[4] D. W. Park, “Lane-departure-based driver fatigue detection,” in Proc. IEEE Vehicular Technology Conf., 1995.

[5] A. Grace et al., “A drowsy driver detection system for heavy vehicles,” in Proc. IEEE Intelligent Transportation Systems Conf., 2003.

[6] Y. Guo et al., “Driver drowsiness detection using CNNs,” IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 9, 2020.

[7] S. Lee et al., “Multimodal sensor fusion for driver fatigue detection,” Sensors, vol. 21, no. 2, 2021.

[8] R. Vicente et al., “Driver vigilance monitoring using deep learning,” IEEE Access, vol. 8, 2020.

[9] A. Sharma et al., “Driver drowsiness detection and correction system with SOS integration,” in Proc. Int. Conf. on Emerging Technologies, 2024.

[10] N. A. Ahmad et al., “Review of driver drowsiness detection techniques,” Int. Journal of Automotive Technology, vol. 22, no. 5, 2021.

[11] J. Yu, S. Park, S. Lee, and M. Jeon, “Driver drowsiness detection using condition-adaptive representation learning framework,” IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 11, pp. 4206–4218, 2019.

[12] G. Sikander and S. Anwar, “Driver fatigue detection systems: A review,” IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 6, pp. 2339–2352, 2018.

[13] Z. Zhang, H. Ning, and F. Zhou, “A systematic survey of driving fatigue monitoring,” IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 11, pp. 19999–20020, 2022.

[14] M. H. Baccour, F. Driewer, T. Schäck, and E. Kasneci, “Comparative analysis of vehicle-based and driver-based features for driver drowsiness monitoring by support vector machines,” IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 12, pp. 23164–23178, 2022.

[15] S. Arefnezhad, J. Hamet, A. Eichberger, M. Frühwirth, A. Ischebeck, I. V. Koglbauer, M. Moser, and A. Yousefi, “Driver drowsiness estimation using EEG signals with a dynamical encoder–decoder modeling framework,” Scientific Reports, vol. 12, 2022.

[16] B. Fu, F. Boutros, C.-T. Lin, and N. Damer, “A survey on drowsiness detection—modern applications and methods,” IEEE Transactions on Intelligent Vehicles, 2024.

[17] F. Safarov, F. Akhmedov, A. B. Abdusalomov, R. Nasimov, and Y. I. Cho, “Real-time deep learning-based drowsiness detection: Leveraging computer-vision and eye-blink analyses for enhanced road safety,” Sensors, vol. 23, no. 14, p. 6459, 2023.

[18] M. Zhu, H. Li, J. Chen, M. Kamezaki, Z. Zhang, Z. Hua, and S. Sugano, “EEG-based system using deep learning and attention mechanism for driver drowsiness detection,” in Proc. IEEE Intelligent Vehicles Symposium Workshops (IV Workshops), 2021, pp. 280–286.

[19] F. Liu, D. Chen, J. Zhou, and F. Xu, “A review of driver fatigue detection and its advances on the use of RGB-D camera and deep learning,” Engineering Applications of Artificial Intelligence, vol. 116, p. 105399, 2022.

[20] O. F. Hassan, A. F. Ibrahim, A. Gomaa, M. A. Makhlouf, and B. Hafiz, “Real-time driver drowsiness detection using transformer architectures: A novel deep learning approach,” Scientific Reports, 2025.