



iJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** IX **Month of publication:** September 2026

DOI: <https://doi.org/10.22214/ijraset.2026.84937>

www.ijraset.com

Call: ☎ 08813907089

E-mail ID: ijraset@gmail.com

AI Powered Drowsiness and Lane Departure Warning System Using Deep Learning

Prof. Swapnil Warade¹, Fazilat Sheikh², Snehal Sahare³, Himanshu Lute⁴, Palak Kalamkar⁵, Dr. Amit Welekar⁶

¹Professor, Department of IT, J D College of Engineering & Technology, Nagpur Maharashtra, India

^{2,3,4,5}U.G Student, Department of IT, J D College of Engineering & Technology, Nagpur Maharashtra, India

⁶Professor, Department of IT, J D College of Engineering & Technology, Nagpur Maharashtra, India

Abstract: Driver drowsiness and unintended lane departure are two of the many factors that can increase the possibility of traffic accidents. The traditional driver assistance systems typically take one of the two approaches to detect the status of drivers and the road conditions; either monitor the driver or analyze the car positioning in the road. With the recent developments in the field of artificial intelligence and deep learning, it has become possible to analyze the face characteristics, eyes movement, yawning, road scene, and lane marks using camera-based system. In this regard, this review paper discusses an AI-driven driver safety system that involves the use of two cameras for the simultaneous detection of driver drowsiness and lane departure. The first camera is set toward the driver and analyses the face characteristics, eye closure, yawning, and other signs of fatigue through deep learning algorithms. The second camera is set toward the road and continuously analyzes the lane marks and position of the car to detect lane departure. The outputs of both the camera-based detection systems are processed at the decision layer and provide corresponding real-time warnings.

Keywords: Driver Drowsiness, Lane Departure Warning, Deep Learning, Computer Vision, Driver Monitoring, Lane Detection, Dual-Camera System, Artificial Intelligence, Real-Time Warning, ADAS

I. INTRODUCTION

Modern day transportation is an essential component of modern society, yet fatigue of the driver, lack of concentration, and unintentional car movements remain an important problem for safety. Driver sleepiness is known to be responsible for a decrease in concentration capabilities, quick decision making, and appropriate reactions to changes in traffic conditions. Therefore, monitoring of driver's condition became an important part of intelligent transport systems and Advanced Driver Assistance Systems (ADAS). Modern researches have studied various methods for identification of driver sleepiness based on physiological signs, information related to the vehicle, and image analysis of driver's behavior [1], [2]. Traditional methods for drowsiness detection can be classified into physiological, vehicle-related, and vision-based. The physiological methods rely on estimation of fatigue level from EEG, EOG, and other biometric data. Despite the fact that these methods give a good source of information about the state of the driver, they still need to attach some sensors to the driver's body [3].

Vision-based approaches offer a non-invasive solution through the analysis of visible characteristics such as eye closure, blink frequency, yawning, facial expression, and head movements. The advancement of artificial intelligence and deep learning technology has enabled an enhanced vision-based driver monitoring through the automation of visual feature extraction from images and video frames [1], [2]. From the list of the visual signs of drowsiness, long eye closures and yawns are two of the most studied due to the possibility that they offer evidence of drowsiness. Deep learning algorithms have been increasingly employed in the automatic extraction of facial and eye-related features. Recent systematic research has shown the increasing use of deep learning algorithms in driver drowsiness classification and the need for suitable datasets, evaluation, and real-time performance [4]. Nonetheless, the task of detecting drowsiness reliably is difficult due to differences in driver appearance, lighting conditions, camera placement, face occlusions, and driver behavior between driving situations.

As far as driving sleepiness is concerned, accidental lane deviation is also an important contributing factor to the loss of control over the vehicle. Lane detection technology gives the details regarding the lane structure of roads; hence, it is an integral part of intelligent driving and driver assistance systems [5]. The traditional lane detection technologies usually apply image processing techniques such as edge detection, thresholding, perspective transformation, and geometric modeling. The conventional technologies can be applied successfully in easy road environments but fail under difficult situations like blurred lane markings, incomplete or curved lane markings [5], [6].

II. RELATED WORK

There have been several scientific studies done to enhance road safety through driver monitoring, driver drowsiness detection, lane detection, and intelligent driver assistance system. All of the above-mentioned techniques could basically be classified as physiological based approach, vehicle based approach, vision based driver monitoring, deep learning based driver drowsiness detection, and lane departure detection [1], [2]. In recent times, due to advancements in the field of artificial intelligence, there has been a rise in the use of camera-based systems, since they do not require any physical contact with the driver to monitor his status and the surrounding road environment [1], [2].

A. Driver Drowsiness Detection

The problem of detecting drowsiness of drivers has been studied using physiological signals, behavioral cues, and vehicle based measurements. Physiological based approaches utilize information like EEG, EOG, heart rate, and biometric signal information to estimate driver fatigue level [3].

Driver monitoring with vision offers a non-intrusive solution. The technology involves using cameras for continual tracking of the driver's face and recognition of features that signal signs of tiredness. Eye closure, eye blink rate, yawning, head position, and face direction are some examples of common features. Various studies reviewing driver fatigue detection have found growing interest in computer vision and artificial intelligence since they enable continual observation without any need for hardware sensors on the driver [1], [2].

The conventional methods that employ computer vision involve facial landmark identification along with geometric parameters like Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR). EAR can determine if the eyes are closed for a certain time period, whereas MAR can give data regarding mouth opening and yawning. Despite efficiency, the methods suffer from several limitations related to camera position, illumination, facial pose, glasses, and individual variance.

Thus, deep learning provided a solution by allowing learning discriminative visual features automatically from face images and video sequences. CNNs have been used to categorize eye states, facial expressions, and drowsiness states. Recent systematic reviews have shown that deep learning models became one of the promising directions in driver drowsiness detection research, where the architecture of the model, data set, input modality, and methodology were varied [4]. Recently, another aspect of drowsiness detection has gained attention; it is a temporal phenomenon, thus it cannot always be detected from one picture. The sequence of the observed actions, such as long closure of eyes or repeated yawns, gives more evidence about the driver's state. Thus, LSTM, GRU and other sequence learning models can be combined with CNNs for feature extraction [4].

B. Deep Learning for Driver Monitoring

The standard scheme of implementing a deep learning-based driver monitoring system includes the following: camera, face detection, feature extraction using deep neural networks, classification into particular states and alarm generation. With a constant frame acquisition by the camera, the next step is face or facial area recognition. Then appropriate features are extracted via deep neural networks and classified into such states as alert, drowsy, sleepy, yawning, etc.

The usage of deep learning technology can make a system independent from manually engineered features. However, the system should be trained by a sufficiently large number of datasets, which will allow dealing with the diversity of the skin colors, facial structures, lightening conditions, positions of the camera, etc. Moreover, surveys recently revealed such issues as real-time processing, dataset bias, generalization and computational constraints as significant challenges in practical drowsiness detection systems [4].

The other problem that should be solved is discrimination between normal driving behavior and fatigue. A person driving may blink, look aside, speak and turn his/her head. Thus, an approach based on one particular visual feature can cause a false alarm.

C. Lane Detection

Lane detection is a significant part of intelligent transportation and Advanced Driver Assistance Systems since it gives information about road structure and vehicle positions. Traditional methods of lane detection are based on image processing procedures like grayscale conversion, edge detection, thresholding, ROI selection, perspective transformation, and Hough-transform line detection. While classical methods are usually fast, they can become inefficient when working with complex road conditions. The difficulty of recognizing lane markings lies in such factors as faded lines, shadows, illumination, road curvature, occlusion, and adverse weather. This has led to a new direction of research in the lane-marking detection field, i.e., the usage of deep-learning methods [5], [6]. Deep learning allows training lane detection systems to recognize visual features from annotated road images directly. There are

different approaches of treating the problem as either segmentation, object detection, parameter estimation, or instance-level prediction. Some recent surveys have systemically analyzed deep-learning methods for lane detection and have evaluated their efficiency by standard benchmarks [6], [7].

D. Lane Departure Warning Systems

Lane Departure Warning Systems (LDWS) use information obtained from lane detection to determine whether a vehicle is moving outside its intended lane. A typical system identifies the left and right lane boundaries, estimates the center of the lane, and compares the estimated vehicle position with the lane geometry.

The basic operating principle can be represented as:

Road Camera → Lane Detection → Lane Position Estimation → Vehicle Position Estimation → Departure Decision → Warning

While traditional lane departure warning systems are effective on roadways under controlled circumstances, their efficacy is heavily dependent on proper lane detection. In cases where lane detection is erroneous, it may result in false alarms or even missed lane departures.

The recent deep learning literature has attempted to tackle such shortcomings by advancing in feature extraction and lane modeling. The surveys conducted recently indicate that current lane detection research aims at increased accuracy and speed [6], [7]. Lightweight CNN models have also been considered for low computational demands of driver assistance applications [9].

E. Integrated Driver Assistance

Advanced Driver Assistance System is progressively employing the use of multi-perception in order to enhance the safety of driving. Driver monitoring helps to gather information about the state of the driver, while road perception helps in gathering information about the environment surrounding the driving process.

In most of the existing studies on ADAS, most attention is paid to the study of drowsiness detection and lane detection as two distinct problems. A drowsiness detection algorithm may detect that the driver is fatigued but not if the car is deviating from its lane. In the same way, a lane departure detection algorithm detects deviation of the vehicle but cannot detect whether the deviation is caused due to the fatigue of the driver. This becomes the motivation for dual-camera design for both driver and road and lane perception.

F. Proposed Research Direction

Based on the reviewed literature, the proposed system utilizes two camera inputs for simultaneous monitoring. The first camera observes the driver and analyzes facial characteristics associated with drowsiness. The second camera observes the road and detects lane markings and vehicle deviation.

The proposed processing architecture can be represented as:

Camera 1 → Driver Detection → Eye/Mouth Analysis → Drowsiness Classification

Camera 2 → Road Detection → Lane Detection → Lane Departure Classification

The outputs of both modules are subsequently passed to a decision-making unit. This enables the system to distinguish between normal driving, drowsiness, lane departure, and the simultaneous occurrence of drowsiness and lane departure.

The proposed approach therefore extends conventional single-purpose monitoring systems toward a combined driver-and-road safety framework. The use of separate camera inputs also allows the two visual tasks to be optimized independently while maintaining a common warning mechanism.

III. CHALLENGES AND LIMITATIONS

There are various challenges associated with the development of an AI-powered drowsiness and lane departure warning system. Since the proposed system uses two independent camera inputs, both driver-monitoring and road-monitoring conditions must be considered for reliable real-time operation. One of the major challenges in driver drowsiness detection is variation in facial appearance and behavior. Different drivers may exhibit different patterns of eye closure, blinking, yawning, and head movement. A fixed threshold-based approach may therefore not provide consistent results for all drivers. In addition, glasses, sunglasses, facial hair, masks, and partial facial occlusion can affect the quality of facial information obtained by the camera. These factors can reduce the reliability of vision-based drowsiness detection [1], [2], [4]. Illumination is another important limitation. A driver-monitoring camera may operate under bright daylight, low-light conditions, or nighttime conditions. Changes in illumination can affect face detection and eye-state classification.

Night-time driving is particularly challenging for conventional RGB cameras because insufficient light can reduce the visibility of facial features. Infrared or near-infrared cameras can potentially improve performance under such conditions, but they may increase system cost and hardware complexity [2], [4].

An additional difficulty faced is that of separating ordinary driver behavior from drowsiness. Blinking eyes, turning away from the road, head movement and opening mouth while talking are natural actions of any driver. Hence, detection of drowsiness from just one picture or from just one facial feature may result in false alarms. Time factor plays an essential role since drowsiness usually emerges gradually from a series of observations and not in one sudden act [1], [4]. There are many difficulties involved in the use of the road facing camera as well. Lane markings can be faded, missing or obstructed by other vehicles; moreover, shadows and reflections can affect the marking visibility. The problem with curved roads is that lane models based on geometry become unreliable [5], [6].

Weather conditions like rain, fog, snow, and even bright sun light can make lane detection even worse. In case of precipitation, water on the road surface can cause visual illusions, similar to lane markings. Fog decreases image contrast. Sun light and shadow areas can create problematic zones for lane segmentation. The recent research in the area of lane detection using deep learning algorithms highlights environmental conditions, lane occlusion, variability in road structure, and generalization as the critical issues [6], [7]. The recognition of a lane departure event is a complex process, much more complicated than just the detection of crossing over a lane boundary by the vehicle. A driver may deliberately change lanes, maneuvering around obstacles or driving on roads with unique lane structure. Hence, the system should be able to differentiate between a deliberate movement of the vehicle and an unintentional lane departure event. Temporal consistency and additional information, such as vehicle speed, steering, and lane geometry may potentially increase the reliability of the decision [6], [7]. Computational constraints is another limitation of the proposed system. The algorithm operates simultaneously on two video feeds, which makes the processing load greater than in case of a one-camera setup. Facial analysis

False-positive and false-negative detections are additional concerns. A false-positive warning may unnecessarily distract the driver, while a false-negative result may fail to warn the driver during an actual dangerous situation. Therefore, model evaluation should consider not only classification accuracy but also precision, recall, F1-score, false alarm rate, inference time, and warning latency [1], [4], [7]. Finally, the proposed system is dependent on camera placement and image quality. The driver-facing camera must maintain a sufficiently clear view of the driver's face, while the road-facing camera must provide an appropriate field of view for lane detection. Camera vibration, improper mounting, lens obstruction, and changes in camera orientation can negatively affect system performance. Despite these challenges, the integration of deep learning, temporal analysis, and dual-camera monitoring provides an opportunity to develop a more comprehensive driver safety system. Future improvements may include infrared driver monitoring, lightweight deep-learning architectures, adaptive thresholds, temporal models, vehicle-state information, and additional sensors to improve reliability under real-world driving conditions.

Table I Challenges and possible Solutions

Sr. No.	Challenge	Affected Module	Possible Solution
1	Variable facial appearance	Driver Camera	Diverse training datasets
2	Glasses/sunglasses	Drowsiness Detection	Robust facial models
3	Low illumination	Driver Camera	IR/NIR camera
4	Normal blinking vs. drowsiness	Drowsiness Detection	Temporal analysis
5	Yawning variation	Drowsiness Detection	CNN-based classification
6	Faded lane markings	Road Camera	Deep-learning lane segmentation
7	Curved roads	Lane Detection	Curve-aware lane modeling
8	Shadows/reflections	Lane Detection	Robust training augmentation
9	Rain/fog/night	Road Camera	Multi-condition datasets

10	Intentional lane changes	Departure Warning	Temporal/context analysis
11	Two video streams	Complete System	Optimized parallel processing
12	False warnings	Decision Module	Decision fusion and temporal filtering
13	Processing latency	Complete System	Lightweight/edge models
14	Camera vibration	Both Cameras	Stable mounting/calibration

IV. INTERPRETATION

The proposed AI-based system for drowsiness and lane departure warning is an illustration of the use of computer vision and deep learning technologies to monitor the driver's status and the surrounding road conditions. As opposed to technologies that focus only on driver monitoring or lane detection, the proposed technology employs two cameras to get complementary data about the drive conditions.

The first camera is installed on the driver's side and continuously collects facial images. The collected images are then analyzed to detect the driver's face and visual features related to drowsiness. Critical features include long-term eyelid closure, frequent blinking, yawning, and change in facial expressions. This feature can be classified using deep learning classifiers to determine the driver's state of alertness or drowsiness [1], [2], [4].

The interpretation of driver condition should not depend on a single frame. A driver may naturally close the eyes briefly while blinking or may open the mouth while speaking. Therefore, a sequence of observations is more useful for identifying persistent fatigue-related behavior. Temporal information can be incorporated into the detection process to distinguish normal facial activity from sustained drowsiness [1], [4].

The second camera is directed toward the road ahead of the vehicle. The camera continuously captures the road scene and provides input for lane detection. The lane detection module identifies the visible lane boundaries and estimates the position of the vehicle relative to the detected lane. Deep-learning-based lane detection can improve the ability to recognize lane structures under different road configurations compared with approaches that depend exclusively on manually defined image-processing rules [5], [6], [7].

The lane departure decision is generated by comparing the estimated vehicle position with the detected lane boundaries. When the vehicle moves toward or beyond a lane boundary for a sufficient period, the system can classify the condition as a possible lane departure. Temporal filtering is important because short-term variations in vehicle position should not necessarily result in an immediate warning.

The outputs generated by the two camera modules are then transferred to a decision-making unit. The decision unit determines the overall driving condition by considering both driver state and lane state. The resulting interpretation can be represented as follows:

Driver Camera → Drowsiness Detection → Driver State

Road Camera → Lane Detection → Lane State

Driver State + Lane State → Decision Fusion → Warning

The decision-making mechanism can classify the driving condition into four major categories. When the driver is alert and the vehicle remains within the detected lane, the system considers the situation normal. When drowsiness is detected but the vehicle remains within the lane, a drowsiness warning is generated. When the driver is alert but the vehicle departs from the lane, a lane departure warning is generated. When drowsiness and lane departure occur simultaneously, the system can classify the situation as a critical driving condition and generate a higher-priority warning.

Table II: Decision Interpretation of the Proposed System

Driver Condition	Lane Condition	Interpretation	Warning
Alert	Within Lane	Normal driving	No warning
Drowsy	Within Lane	Driver fatigue detected	Drowsiness alert
Alert	Lane Departure	Vehicle deviation detected	Lane departure alert
Drowsy	Lane Departure	Combined high-risk condition	Critical warning

The interpretation of both inputs can therefore provide more contextual information than either module independently. For example, lane departure occurring together with detected drowsiness may indicate that fatigue is contributing to the loss of lane control. In such a case, the warning mechanism can prioritize the combined condition. The proposed system can generate an audio or visual warning when a safety condition is detected.

A drowsiness warning may inform the driver that reduced alertness has been detected, while a lane warning may indicate that the vehicle is moving away from its lane. When both conditions are detected, a stronger warning can be generated to attract the driver's immediate attention.

The effectiveness of the complete system depends on the accuracy and response time of both camera modules. Therefore, the interpretation of system performance should include not only detection accuracy but also precision, recall, F1-score, false-warning rate, frame processing speed, and alert latency. These parameters are particularly important for real-time driver assistance applications [1], [4], [7].

The proposed dual-camera framework consequently provides a basis for integrating human-state monitoring and road-state monitoring within a single driver safety system. The architecture can also be extended in the future by incorporating additional vehicle information such as speed, steering angle, GPS position, or other ADAS sensors to improve the contextual interpretation of driving conditions.

V. FINDINGS

From the reviewed research, it can be observed that artificial intelligence and deep learning provide promising approaches for developing real-time driver safety systems.

Existing studies demonstrate that driver drowsiness can be estimated using visual characteristics such as eye closure, blinking, yawning, facial behavior, and head movement, while lane detection techniques can be used to estimate the position of a vehicle with respect to road lane boundaries [1], [2], [4], [5].

The reviewed drowsiness detection approaches indicate that camera-based monitoring provides a non-contact method for continuously observing the driver. Deep-learning models can automatically learn relevant facial characteristics and classify different driver states. However, the performance of such systems depends on factors including illumination, facial occlusion, camera position, individual driver behavior, and the quality and diversity of the training dataset [1], [2], [4].

The analysis of lane-detection research shows that deep-learning-based methods can identify lane markings and road structures under a range of driving conditions. Recent research has explored different representations and network architectures for improving lane detection accuracy and robustness. Nevertheless, faded lane markings, shadows, curved roads, occlusions, adverse weather, and complex road structures continue to present challenges for reliable lane detection [5], [6], [7].

The findings further indicate that real-time operation is an important requirement for both drowsiness detection and lane departure warning. A system that detects a hazardous condition but produces a delayed warning may not provide sufficient assistance to the driver. Therefore, inference speed, processing latency, and warning response time should be considered along with conventional classification metrics such as accuracy, precision, recall, and F1-score [1], [4], [7].

The proposed dual-camera concept provides a method for monitoring two complementary aspects of driving. The driver-facing camera provides information about the driver's state, while the road-facing camera provides information about the vehicle's position relative to lane boundaries. This separation allows each detection task to use a processing method appropriate to its respective visual information.

The decision-fusion mechanism provides an additional advantage by allowing the system to interpret the two conditions together. If the driver is alert and the vehicle remains within the lane, the system can continue normal operation. If drowsiness is detected, a drowsiness warning can be generated. Similarly, if lane departure is detected, a lane departure warning can be provided. When both conditions occur simultaneously, the system can generate a higher-priority warning because the combined condition may represent a greater safety risk.

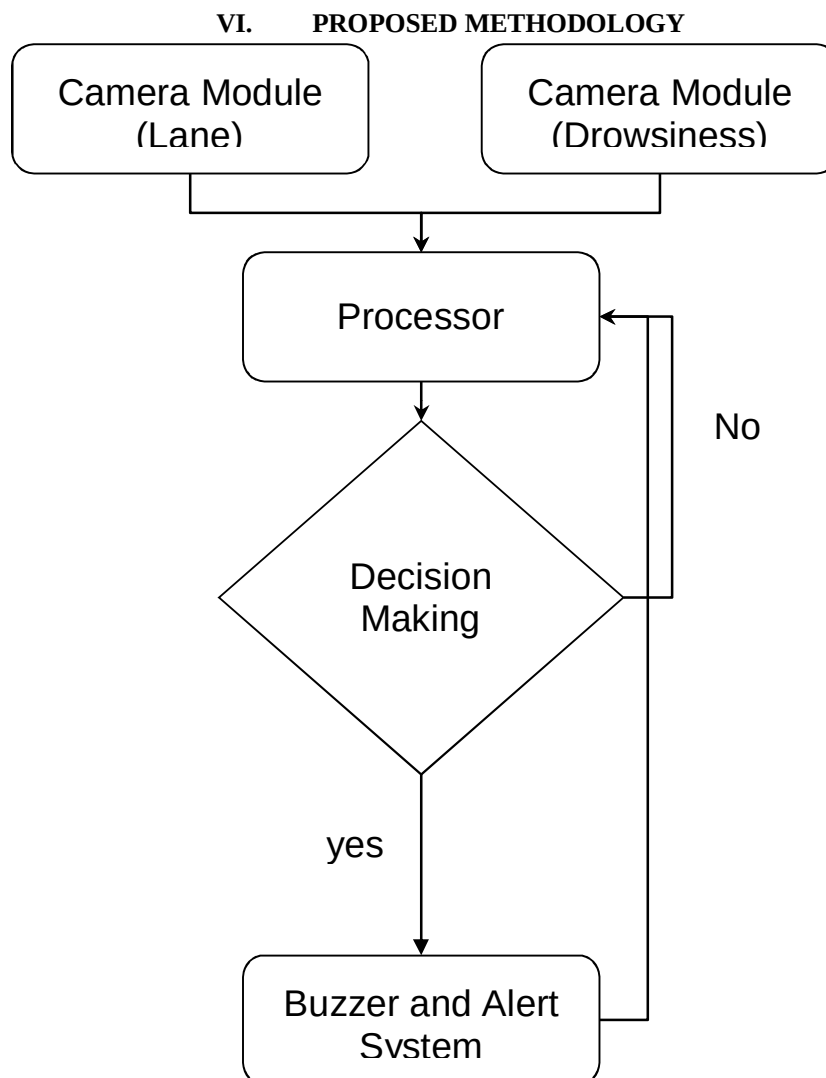


Fig 1. Proposed Block Diagram

VII. FUTURE ENHANCEMENT

Further improvements can make the proposed AI-powered drowsiness and lane departure warning system more reliable, intelligent, and suitable for real-world driving conditions. The current concept focuses on two camera inputs for monitoring the driver and road environment; however, additional sensing and artificial intelligence capabilities can be integrated to improve the overall safety performance. Integration of an infrared or near-infrared camera can improve driver monitoring during nighttime and low-light conditions. Such a camera can provide improved visibility of facial characteristics when conventional RGB cameras experience reduced performance. The driver-monitoring module can also be enhanced using more advanced deep-learning architectures capable of analyzing temporal patterns in eye closure, blinking, yawning, and head movement. The lane-monitoring module can be extended to recognize complex road structures such as curved lanes, merging lanes, intersections, faded markings, and multiple lane boundaries. Advanced lane-segmentation and lane-instance detection models can be investigated to improve robustness under challenging road and weather conditions. Vehicle information can also be integrated into the proposed framework. Data such as vehicle speed, steering angle, acceleration, GPS position, and other available vehicle parameters can provide additional contextual information for determining whether a lane movement is intentional or represents an unsafe departure. Another possible enhancement is the integration of object detection. The forward-facing camera can be used not only for lane detection but also for identifying vehicles, pedestrians, traffic signs, road obstacles, and other potentially hazardous objects. This would allow the proposed system to evolve from a drowsiness and lane departure warning system into a more comprehensive vision-based Advanced Driver Assistance System.

The warning mechanism can also be improved through adaptive alert levels. Instead of generating the same warning for every condition, the system can determine the severity of the situation using driver state, lane deviation, vehicle speed, and temporal persistence. For example, simultaneous drowsiness and lane departure can generate a higher-priority warning than either condition individually.

Future development can further include edge-AI optimization, model quantization, hardware acceleration, and parallel processing of the two camera streams. These improvements can reduce inference latency and enable deployment on embedded computing platforms with limited computational resources.

The system may also be extended to include driver-specific adaptation. Since different drivers can exhibit different blinking, yawning, and facial behavior patterns, an adaptive model could learn normal behavior for an individual driver and identify deviations from that baseline.

VIII. OBJECTIVES

The main objectives of the proposed project are:

- 1) Development of an AI-powered driver safety system for real-time monitoring of driver and road conditions.
- 2) Detection of driver drowsiness using a driver-facing camera and deep-learning-based visual analysis.
- 3) Identification of visual indicators of drowsiness such as prolonged eye closure, blinking, yawning, and facial behavior.
- 4) Detection of road lane boundaries using a forward-facing road camera.
- 5) Identification of unintended lane departure using lane position and vehicle trajectory information.
- 6) Integration of two independent camera inputs for simultaneous driver and road monitoring.
- 7) Development of a decision-making mechanism for combining drowsiness and lane-departure information.
- 8) Generation of real-time audio and/or visual warnings when unsafe driving conditions are detected.
- 9) Development of different warning levels according to the severity of the detected condition.

A. Project Overview

The intended research project, entitled “AI-Powered Drowsiness and Lane Departure Warning System Using Deep Learning,” seeks to develop an intelligent driver assistance system that can monitor the driver’s state and the road environment on an ongoing basis. There are two cameras involved in this design, and each camera performs a particular safety monitoring task.

Firstly, there is a camera located in the interior of the car and aimed at the driver. It continually takes images of the driver’s face region and supplies visual data necessary to detect signs of drowsiness. The images are analyzed by computer vision and deep learning algorithms that detect signs of drowsiness, such as closing eyes for a long time, frequent blinking, yawning, etc. Secondly, there is a camera facing the road in front of the car. It takes continuous images of the road scene and feeds the input into the lane detection system. The system detects lane boundaries and determines the vehicle’s location relative to those lanes. The system determines lane departure when the vehicle leaves the lane boundary or approaches it for some defined time period.

The outputs from both of the camera modules are fed to a single decision-making module. The decision-making module analyzes the status of the driver and the status of the lane and gives the system response as per the situation. In case the driver is not drowsy and the car stays within the lane, then the system runs normally. In case of drowsiness, then the drowsiness warning is triggered. In case of lane departure, then the lane departure warning is triggered. If both of them are present, then a priority warning is triggered.

IX. CONCLUSION

The review of existing research demonstrates that artificial intelligence and deep learning have become important technologies for developing intelligent driver safety systems. Driver drowsiness detection approaches have progressed from physiological and manually designed visual features toward deep-learning-based analysis of facial behavior, eye closure, yawning, and temporal driver characteristics [1]–[4]. Similarly, lane detection research has increasingly adopted deep neural networks to improve the identification of lane markings and road structures under different driving conditions [5]–[8].

Despite these developments, driver drowsiness detection and lane departure detection are commonly addressed as separate problems. A system that monitors only the driver’s condition may not identify the resulting vehicle deviation, while a lane departure system may not determine whether fatigue or reduced driver alertness is contributing to the deviation. This limitation motivates the development of an integrated driver-and-road monitoring framework.

The proposed AI-Powered Drowsiness and Lane Departure Warning System Using Deep Learning aims at filling the above-mentioned research gap by using a double-camera design. In particular, the first camera is responsible for monitoring the driver's face and detecting signs of drowsiness, while the second one monitors the road and detects lane boundaries and lane departure.

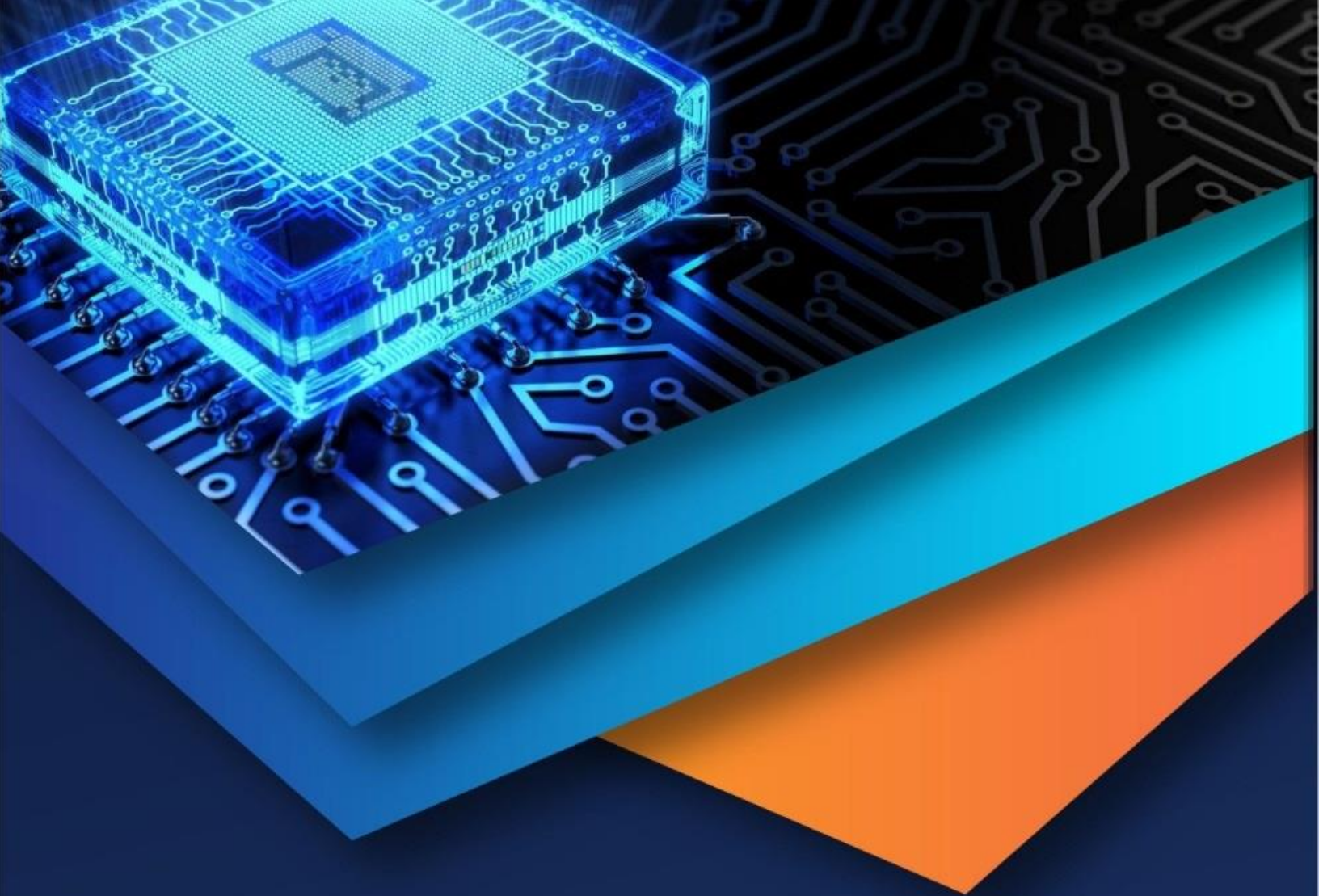
The information provided by both modules is combined using decision-making logic to produce a suitable alert.

The use of two cameras allows obtaining additional information about the driving process. Namely, the information obtained by the driver-facing camera relates to the human condition, while the information obtained by the road-facing camera concerns the car-road interaction. Therefore, such a combination may allow distinguishing among normal driving, drowsiness, lane departure, and their coexistence.

The literature review reveals that there are multiple challenges that should be overcome in order to implement the above-mentioned system into the real-life application. They include different lighting conditions, face occlusion, individual driver variations, adverse weather conditions, faded lane markings, road curvature, computing power limitations, false alarms, and real-time processing delays [1], [4], [6], [7].

REFERENCES

- [1] T. Arakawa, "Trends and Future Prospects of the Drowsiness Detection and Estimation Technology," **Sensors**, vol. 21, no. 23, 2021.
- [2] Y. Albadawi, M. Takruri, and M. Awad, "A Review of Recent Developments in Driver Drowsiness Detection Systems," **Sensors**, vol. 22, no. 5, 2022.
- [3] G. Li and W.-Y. Chung, "Electroencephalogram-Based Approaches for Driver Drowsiness Detection and Management: A Review," **Sensors**, 2022.
- [4] "Drowsiness Detection in Drivers: A Systematic Review of Deep Learning-Based Models," **Applied Sciences**, vol. 15, 2025.
- [5] Y. Zhang et al., "Deep Learning in Lane Marking Detection: A Survey," **IEEE Transactions on Intelligent Transportation Systems**, 2021.
- [6] X. He et al., "Monocular Lane Detection Based on Deep Learning: A Survey," 2024.
- [7] X. Luo et al., "Deep Learning-Based Lane Detection for Intelligent Driving: A Comprehensive Survey of Methods, Datasets, Challenges and Outlooks," **Neurocomputing**, 2025.
- [8] "Lane Detection for Autonomous Driving: A Comprehensive Review," **Neurocomputing**, 2026.
- [9] M. Kamboj et al., "Advanced Detection Techniques for Driver Drowsiness: A Comprehensive Review of Machine Learning, Deep Learning, and Physiological Approaches," **Multimedia Tools and Applications**, 2024.
- [10] I. Latreche et al., "A Review on Deep Learning Techniques for EEG-Based Driver Drowsiness Detection Systems," **Informatica**, 2024.
- [11] P. Mukherjee, "A novel deep learning-based technique for driver drowsiness detection," *Human Factors and Ergonomics in Manufacturing & Service Industries*, vol. 34, no. 6, pp. 667–684, 2024, doi: 10.1002/hfm.21056.
- [12] C. Zhou, Y. Zhao, S. Liu, Y. Zhao, X. Li, and C. Cheng, "Research on Driver Facial Fatigue Detection Based on YOLOv8 Model," 2024.
- [13] S. S. Sengar, A. Kumar, and O. Singh, "VigilEye—Artificial Intelligence-based Real-time Driver Drowsiness Detection," 2024.
- [14] D. Ghimire, S. Jeong, S. Yoon, S. Park, and J. Choi, "Real-Time Sleepiness Detection for Driver State Monitoring System," 2025.
- [15] R. N. Hidayat and P. D. Ibnugraha, "The Dashboard of Remote Monitoring System for Driver Fatigue," *Journal of Engineering and Applied Sciences*, vol. 58, no. 6, pp. 1089–1100, 2025, doi: 10.18280/jesa.580601.
- [16] Q. Zhang, Z. Sun, and H. Shu, "Research on Vehicle Lane Change Warning Method Based on Deep Learning Image Processing," *Sensors*, vol. 22, no. 9, 3326, 2022, doi: 10.3390/s22093326.
- [17] Y. Zhang, Z. Tu, and F. Lyu, "A Review of Lane Detection Based on Deep Learning Methods," *Mechanical Engineering Science*, vol. 5, no. 2, 2023.
- [18] S. Swain and A. K. Tripathy, "Real-time lane detection for autonomous vehicles using YOLOV5 Segmentation Model," 2024, pp. 718–728, doi: 10.1080/19397038.2024.2400965.
- [19] M. Mirdanies, R. P. Saputra, E. Yazid, and R. A. Rashid, "Implementation of Real-Time Lane Detection on Autonomous Mobile Robot," 2024.
- [20] Y. Zhang, K. Hongrui, C. Wang, Z. Guo, Z. Wang, and Z. Lv, "Lane detection for autonomous driving: A comprehensive review," *Neurocomputing*, 2026.



10.22214/IJRASET



45.98



IMPACT FACTOR:
7.129



IMPACT FACTOR:
7.429



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089  (24*7 Support on Whatsapp)