

Driver Drowsiness Detection for Accident Prevention

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Abstract: *Among the main causes of traffic accidents and fatalities worldwide is sleepiness among drivers. Driving safety is seriously compromised by prolonged driving without enough rest because it causes microsleeps, reduces reaction times, and diminished awareness. Steering pattern analysis and physiological sensors are two examples of conventional monitoring methods that are frequently costly, invasive, or unreliable in practical settings. To get around restrictions, these studies propose deep learning and non-intrusive computer vision methods for real-time driver drowsiness detection. The device takes frontal pictures of the driver using a camera and facial landmark identification to locate and extract eye regions. A convolutional neural network model is then used to classify the eyes as either open or closed. When eye closure lasts longer than a certain threshold a indication of drowsiness and alarm is set off to alert the driver.*

TensorFlow, OpenCV, and Python frameworks have been used to implement the proposed system. Experimental results show that the model is robust against factors like as the presence of spectacles and achieves an overall accuracy of more than 83% under a range of scenarios, including driving during the day and at night. Furthermore, the CNNs lightweight architecture which has a maximum model size of 75 KB ensures efficient deployment on mobile devices and embedded platforms. Compared to existing systems, the suggested approach significantly reduces false alarms while maintaining real-time performance.

This study demonstrates the possibilities of CNN-based methods to offer a practical, cost-effective, and scalable solution for integration enter ADAS (Advanced Driver Assistance) to improve road safety and prevent fatigue- related accidents.

Keywords: Computer vision, deep learning, convolutional neural network, Eye Tracking, OpenCV, Fatigue Monitoring, Advanced Driver Assistance is referred as ADAS Systems

I. INTRODUCTION

Road safety is now among the most pressing global concerns, with driver drowsiness recognized as a primary contributor to mishaps and fatalities. According to The World Health Organisation (WHO), road traffic crashes result in approximately 1.35 million deaths every year, and a significant proportion of these are linked to exhaustion and reduced alertness behind the wheel Drowsiness, defined as a state of sleepiness accompanied by symptoms such as delayed reaction time, reduced awareness, and microsleeps, severely compromises a driver's ability to operate a vehicle safely. Long-term weariness has been shown to reduce performance to an extent comparable to that of alcohol intoxication, underscoring the urgent requirement for efficient counter measurements in transportation safety.

Due to microsleeps and attentional lapses, a drowsy driver is frequently more hazardous than someone who is speeding since they may miss traffic signs, drift across lanes, or fail to respond quickly enough to avoid collisions. Physiological sensors like electroencephalography (EEG), electrocardiography (ECG), or photoplethysmography (PPG) as well as behavioural indicators such steering patterns and vehicle dynamics are examples of conventional techniques for tracking tiredness. Even while certain techniques have shown successful in controlled environments, they usually have disadvantages such being obtrusive, expensive, or unreliable in real-world situation.



Recent advances in artificial intelligence, namely in the areas of computer vision and deep learning, have opened up new avenues for non-intrusive driver monitoring systems. When paired with strong classification models, camera-based methods can efficiently analyse facial characteristics and eye movements to gauge weariness. One of these, as demonstrated by Convolutional Neural Network, exception performance in picture classification tasks due to its ability to autonomously extract hierarchical features without the need for human interaction.

This study suggests a method for real-time driver sleepiness detection that uses CNNs to categorise the driver eye condition from webcam images. The device tracks eye closure over a sequence of frames and sound a warning when fatigue is detected. With a maximum size of 75 KB, the suggested CNN architecture is lightweight in comparison to more complex classification models, making it appropriate for implementation on android devices and embedded systems. The novelty of this research lies in its ability to achieve reliable drowsiness detection while minimizing false alarms, thereby ensuring driver safety without causing distraction.

This paper remaining sections are arranged as follows: Part II reviews related work and existing approaches to driver drowsiness detection. The suggested system design and technique are presented in Section III. The experimental setup and implementation are outlined in Section IV. The evaluation and outcomes are covered in Section V. The task is concluded and the directions for future research are described in Section VI.

Systems like the one suggested in this stud not only increase road safety but also fit with the larger advance driver assistance system (ADAS) vision and intelligent transportation. Though many commercial sleepiness detection systems are either too costly or have poor accuracy, automakers are progressively implementing AI-driven safety features. This research contributes to practical applied in automobiles in addition to academic advancements in deep computer vision and learning by creating a lightweight, real-time, and affordable solution. The system potential for widespread adoption is further enhanced by its capacity to function well on low- resource platforms like mobile devices and embedded headwear.

II. LITERATURE SURVEY

[1] NCRB (2019): Accidental Deaths & Suicides in India Report

The National Crime Records Bureau (NCRB) provides annual statistics on road accidents across India, serving as an important dataset for traffic safety research. The 2019 report highlighted a significant proportion many collisions brought on by fatigued drivers and drowsiness. By systematically aggregating police- reported cases and analysing year-over-year changes, the report presented a comprehensive picture of accident trends. These results highlight the fact that weariness is not only a human factor issue but also a matter of public health that needs technological intervention. This baseline data is crucial for motivating the evolution of driver-monitoring technologies such as drowsiness detection systems, which can be essential to reducing fatigue-related fatalities on Indian roads.

[2] WHO (2018): Global Status Report on Road Safety

The World Health Organization's Global Status Report on Road Safety (2018) reinforced the urgent must deal with driver fatigue as a significant factor in road crashes worldwide. The report stressed that human error—including drowsiness, distraction, and impairment—remains a leading cause of road trauma, especially in low- and middle-income countries. It advocated for a multi-layered approach combining infrastructure improvements, strong law enforcement, and in- vehicle technologies such as driver monitoring systems. By framing drowsiness detection as part of the global "Safe System" approach, the report positioned fatigue-monitoring solutions as essential to achieving the Sustainable Development Goals (SDGs). This offers compelling evidence in favour of research into intelligent, real-time fatigue detection systems.

[3] Deng & Wu (2019): Real-Time Facial Recognition for Drowsiness Features

Deng and Wu developed DriCare, a non-contact, camera-based system for detecting tiredness that integrates multiple facial features, including blink duration, PERCLOS (percentage of eye closure), and yawning frequency. The Convolutional neural network was used in the system for eye state classification and robust face tracking using Kernelized Correlation Filters (KCF) enhanced with deep models. By fusing visual cues at the decision level, the model



reduced false alarms that typically affect single-cue systems. Their experiments demonstrated approximately 92% accuracy in naturalistic environments, showing the practicality of real-time fatigue detection without intrusive sensors. This study set a benchmark for vision-based approaches in driver-monitoring systems.

[4] Sun, Wang & Tang (2013): Deep CNN Cascade for Facial Landmark Detection

Sun, Wang, and Tang proposed a deep learning-based coarse- to-fine cascaded CNN framework for detection of facial landmark, a critical step for fatigue monitoring. Their method predicts key facial points such as eyes, eyebrows, and mouth in successive stages, refining results with local CNNs after an initial global detection. The approach effectively handled common challenges such as head pose variation, lighting changes, and occlusion. Accurate localization of facial landmarks improved the reliability of downstream tasks such as blink detection, gaze estimation, and yawning analysis, which are fundamental to detecting drowsiness. This contribution provided the foundation for many modern fatigue detection systems that rely heavily on precise facial feature tracking.

[5] Bolme et al. (2010): Object Tracking Using the MOSSE Filter

In 2010, Bolme et al. introduced the MOSSE (Minimum Output Sum of Squared Error) adaptive correlation filter, marking a milestone in real-time visual tracking. The method achieved frame rates exceeding 600 FPS on standard hardware and demonstrated strong robustness to changes in illumination, scale, and partial occlusions. They also proposed the Peak-to-Sidelobe Ratio (PSR) to detect tracking failures and reduce the risk of model drift. MOSSE filters proved effective for tracking facial features such as eyes and mouth, ensuring consistent monitoring during quick head movements or short-term occlusions. This combination of speed and reliability established MOSSE as a key advancement toward lightweight, real-time driver monitoring systems.

[6] Danelljan et al. (2017): Discriminative Scale-Space Tracking (DSST)

Danelljan and colleagues addressed the persistent problem of tracking objects under scale variations by introducing the Discriminative Scale-Space Tracker (DSST). Their approach used separate correlation filters for translation and scale, updating them dynamically to maintain robust tracking. Unlike traditional exhaustive search methods, DSST achieved both higher accuracy and faster execution. In driver monitoring, this ensures that eye and mouth regions remain consistently tracked even when the driver shifts position or moves closer to/farther from the camera. By providing stable region-of-interest (ROI) tracking under variable conditions, DSST significantly improves the accuracy of subsequent drowsiness detection models.

[7] Jung, Shin & Chung (2014): Steering-Wheel ECG Monitoring

Jung, Shin, and Chung developed an embedded ECG-based driver monitoring system that used conductive fabric electrodes on the steering wheel to capture palm-based signals. The system analysed heart-rate variability (HRV) both in the frequency and temporal domains to identify fatigue and drowsiness. Compared to traditional chest electrodes, the steering wheel solution offered greater comfort and reduced intrusiveness, making it practical for long-term driving. Their experiments showed clear correlations between HRV markers and fatigue levels, confirming the feasibility of integrating physiological monitoring into vehicle controls. This approach demonstrated that physiological sensing could complement vision-based methods, especially in conditions where cameras may fail.

[8] Li, Lee & Chung (2015): Smartwatch-Based EEG Monitoring

Li, Lee, and Chung explored a novel approach to wearable EEG monitoring by embedding sensors into a smartwatch. The system extracted spectral and temporal EEG features and classified drowsiness using a Support Vector Machine with a posterior probabilistic model. Unlike binary classifiers, this model generated continuous drowsiness scores, enabling adaptive and graded alerts for the driver. The study demonstrated that EEG-based systems could be made portable, comfortable, and practical for everyday use. This research is significant as it moved EEG-based drowsiness monitoring from bulky, laboratory-based setups toward ergonomic solutions for real-world driving.



[9] Warwick et al. (2015): Wireless Wearable Bio-Sensors

Warwick and colleagues evaluated the possibility of commodity wireless wearable technology to combat driver fatigue detection. Using the Zephyr Bio Harness 3, a chest- worn sensor, they captured physiological variables like cardiac rate, respiration rate, and posture. Data were transmitted wirelessly to a smartphone application, which analysed signals to identify drowsiness transitions. Their findings indicated that physiological changes—such as reduced breathing rate and elevated heart rate—occur just before falling asleep, offering reliable markers for fatigue detection. This study emphasized the feasibility of using low-cost, commercially available wearable sensors incorporated into mobile platforms for real- time fatigue monitoring.

[10] Omid Yeganeh, Javad talab & Shi Mohammadi (2011): Fusion of Yawning and Eye Closure

Omid Yeganeh and colleagues proposed an early vision-based multi-cue system that combined yawning detection with eye closure monitoring. Their pipeline involved face detection, feature extraction for eyes and mouth, and independent detectors whose results were fused to make final drowsiness decisions. By correlating two complementary facial indicators, the system reduced false alarms compared to single-cue approaches such as PERCLOS alone. This work demonstrated the benefits of multi-modal feature fusion and laid the foundation for subsequent hybrid drowsiness detection systems that integrate multiple visual and physiological cues for enhanced accuracy.

III. METHODOLOGY

A. System Overview

The proposed system is a non-intrusive, vision-based framework that continuously monitors the driver's eye state in real time to identify preliminary indications of fatigue. A webcam mounted on the dashboard serves as the primary input device, capturing live video of the driver's face. The acquired frames are pre-processed using OpenCV, where face and eye regions are detected, converted to grayscale, normalized, and resized to guarantee uniformity for further analysis. After processing, these photos are sent into a model of a convolutional neural network, which is trained to ascertain whether the eyes are open or closed. The system keeps a frame- based score to differentiate between extended eye closure and regular blinking. The motorist is identified as drowsy if their eyelids remain shut down for more than a certain amount of time. The technology sounds an alarm to alert the driver and stop possible collisions as soon as drowsiness is detected. This methodology strength is its lightweight CNN design, which has a maximum model size of 75 KB and requires very little processing power, making it ideal for real-time deployment on mobile devices and embedded systems. The suggested method offers a workable, affordable, and effective solution for real- world applications with fewer false alarms and enhanced driver safety, in contrast to conventional sensor-based techniques that are expensive or invasive.

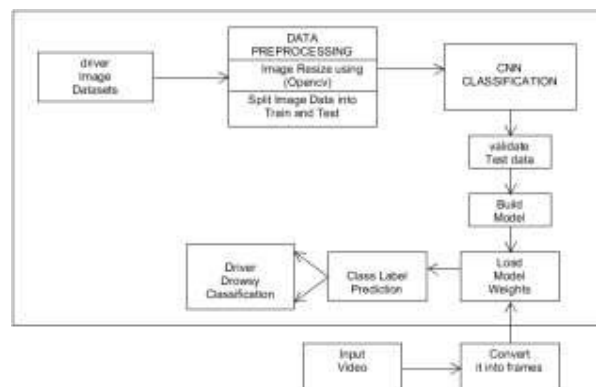


Fig. System Overview



B. Data Preparation Phase

To create and evaluate the proposed driver drowsiness detection framework, a dataset of eye images showing two main states (open and closed) was generated. Videos were recorded using a standard camera to reflect real-world driving conditions, including variations in lighting and head angles. After detecting the face in each frame, OpenCV Haar cascade classifiers were employed to extract the eye regions as the area of interest.

To maintain uniformity and satisfy CNN input requirements, the extracted eye images were resized to 24×24 pixels, normalized, and converted to grayscale. The dataset was split into two classes to prevent training bias. To enhance generalization, augmentation techniques including rotation, scaling, flipping, and shifting were applied. These transformations improved the model's robustness, enabling reliable performance under situations such as drivers wearing glasses or having limited head motion. Part of the dataset was assigned for CNN training, while the rest was used for testing and validation purposes. The proposed model was able to learn discriminative characteristics between open and closed eyes because of the dataset methodical preparation, which is essential for precise real-time drowsiness detection.

C. Model Architectures

The Convolutional Neural Network is used in the suggested system as the primary architecture for classifying the driver's eye state. CNNs are ideally suited for image-based chores due to their ability to automatically extract hierarchical spatial features from enter information. The model utilised in this work is intended to be lightweight and computationally efficient, ensuring real-time performance even on resource-constrained devices such as embedded platforms or smartphones. Along with bending, flipping, and scaling, rotation was performed on the dataset as part of augmentation. These modifications enhanced the model's robustness, allowing it to manage varied situations such as drivers wearing spectacles or showing restricted head motion. A portion of the dataset was reserved for CNN training, while the remaining images were used for testing and validation. To reduce overfitting and improve generalization, dropout regularization was incorporated during model training. The system achieved high classification accuracy while maintaining a compact size of only 75 KB, making it much lighter than traditional deep learning architectures. This streamlined design is beneficial, supporting real-time frame processing and smooth deployment in real driving environments without requiring powerful computing resources.

D. Training Procedure

The training process was completed to optimize for accuracy, a convolutional neural network classification of eye states. The prepared dataset has labelled images of eyes open and closed divided into test, validation, and training sets so that testing was carried out independently. The images were read from a file in batch as training process and the network weights are adjusted through backpropagation. Adam optimiser was used with its adaptive learning rate capabilities, which helped speed convergence, and improve stability. The loss function was categorical cross-entropy because the problem is a binary classification problem. To improve the model's robust, data augmentation techniques like flipping, scaling and rotation are used to help the network generalise well against variations in lighting conditions, head pose and presence of eyeglass. Dropout layers were included to the model to prevent over-fitting during training, where neural cells are randomly turned off and force the network to learn more generalised features. Various epochs were used for training the model until there is no further increase in validation accuracy and early stopping criterion was applied not to continue training after reaching performance plateau. Due to this automatic training process, it has obtained stable accuracy and remained lightweight enough for real-time application in driver drowsiness detection.

E. Metrics for Evolution

Several common evaluation metrics were used to evaluate the performance of the proposed system for drowsiness detection in drivers. Accuracy was utilized as the leading measure of the percent with which eye state has been correctly predicted over test dataset. In addition, precision-recall was estimated in order to evaluate the ability of the model to detect closed eyes that are necessary when drowsiness is considered and false alarms must be minimized. Precision is the proportion of correctly predicted drowsy states out of all predicted drowsy states, and recall is the



number of correctly detected drowsy states out of all true drowsy states. The F1- Score, defined as the precision and recall harmonic mean, was also used to provide a balanced evaluation of the system's performance, especially under class-imbalance conditions. Furthermore, the confusion matrix was analysed to provide detailed insights into the classification outcomes by quantifying true negatives, false positives, and true positives, and false negatives. These metrics together ensured a comprehensive evaluation, allowing the system to be validated not just with regard to overall accuracy yet also in its effectiveness at correctly identifying drowsiness without producing excessive false alerts.

F. Deployment Framework

The proposed driver detection system sleepiness was designed with a lightweight architecture to enable seamless real-time deployment on both desktop and mobile platforms. It has been trained off-line using TensorFlow and the Python OpenCV library, after which we were able to export it in a lightweight format with no more than 75 KB. The lightness of this framework enables the integration into embedded systems and Android applications with no need of high-performance hardware. When in deployment, the webcam or built-in cell video frames are continuously captured by the unified camera and analysed locally to recognize the driver's eyes. The pre-trained CNN model assigns a class to each state of the eye in real time, and the alert system comes into action as soon as keeping eyes closed for too long is recognized. The deployment structure can provide low-latency, memory-friendly operation which results in general system endurance during yet-long drives. It also has a platform-independent nature that makes adaptation easy in different environments like personal to commercial fleet vehicles without much high extra cost. This practicality highlights the potential of the suggested framework for real-world adoption as part of Advanced Driver Assistance Systems (ADAS).

IV. RESULTS AND DISCUSSIONS

A. Quantitative Results

The proposed driver detection system sleepiness was evaluated on the prepared dataset and achieved promising results. The lightweight Convolutional Neural Network (CNN) attained an overall accuracy of approximately 83%, demonstrating its effectiveness in differentiating between closed and open eyes states under varying conditions. The Precision and Recall ratings confirmed the durability of the system; a competitive precision meant reliable detection of sleepy states. The F1-n Score provided additional evidence of the model balanced performance across the two classes. The analysis of the confusion matrix revealed that the majority of incorrect classifications occurred during quick or blinks or partial eye closures, which might sometimes mimic sleep patterns. Notwithstanding these difficulties, the model continuously maintained stable categorisation in a variety of test circumstances, such as when driving in different lighting conditions and when wearing spectacles. With a footprint of about 75 KB, the small design allowed for real-time processing without compromising accuracy, which made it ideal for deployment on Android-based devices and embedded systems. These numerical results show that the suggested approach is a dependable and affordable means of enhancing driver safety via early sleepiness identification.

B. Qualitative Analysis

The Suggested system performance in real-world driving scenarios was evaluated both quantitatively and qualitatively. The framework was evaluated in a variety of conditions, such as slight head motions, drivers wearing spectacles, and lighting conditions both during the day and at night. The system robustness against common variations observed when driving was demonstrated by its consistent detection of prolonged eye closure and successful differentiation of them from regular blinking. The system practical effectiveness in averting accidents was demonstrated by the audio alarm timely alerts that successfully brought the driver attention back to the road. On occasion, though, misclassifications were noted when the driver face was partially obscured by hand gestures or unfavourable camera angles, or when they were blinking quickly. Notwithstanding these drawbacks, the system functioned with low latency and did not impede regular driving behaviour, therefore overall, the user experience was favourable. These qualitative findings imply that the lightweight CNN-based method can be successfully incorporated into practical applications, providing a cost-effective and useful substitute for more intricate or invasive sleepiness detection techniques.



C. Contrastive Analysis

While both YOLOv5 and YOLOv8 are widely recognized for real-time object detection, they differ in structure and performance. YOLOv5 relies on an anchor-based approach, utilizing CSPDarknet53 as its backbone and DCN- PANet for feature aggregation. Its design emphasizes speed and minimal computational demand, making it suitable for deployment on resource-limited devices like embedded systems or mobile platforms. It remains popular due to ease of training, a wide range of pretrained models, and strong community support. However, despite its efficiency, YOLOv5 may struggle in complex situations, such as detecting small objects or targets that are partially occluded.

On the other hand, YOLOv8 represents a newer iteration in the YOLO series. It adopts an anchor-free strategy, updates both backbone and head modules, and integrates advanced data augmentation techniques. These enhancements allow YOLOv8 to attain higher accuracy, especially in detailed detection tasks, like recognizing eye closure, yawning, or subtle head movements associated with fatigue. It also offers improved generalization across various datasets and greater flexibility during training. Although YOLOv8 achieves superior precision and robustness for practical applications, it demands significantly more computational resources. Therefore, YOLOv5 is ideal for lightweight, real-time automotive deployments, whereas YOLOv8 is preferable in scenarios where accuracy and reliability outweigh resource constraints.

V. CONCLUSION

Fatigued driving is recognized as a leading cause of road accidents globally, emphasizing the importance of reliable detection and prevention methods. In this work, we employed deep learning and computer vision with facial CNN analysis to monitor driver drowsiness. The system captures live video, identifies facial landmarks, and analyses eye behaviour to differentiate between alert and fatigued states. By tracking blink duration, it separates long eye closures associated with fatigue from normal blinking. When signs of tiredness are detected, an alert system triggers timely warnings to prevent potential accidents.

Results from experiments demonstrate that CNN- based models can reliably detect subtle visual signs of fatigue even under complex conditions. Unlike conventional methods that depend on hand-crafted features, CNNs automatically extract discriminative features from raw images, achieving high classification accuracy. The model's compact design and real- time capability further illustrate its applicability in practical driving scenarios. The comparison of YOLOv5 and YOLOv8 highlights the trade-off between speed and accuracy. Although YOLOv8 provides superior precision for fine-grained indicators like partial eyelid closure or yawning, YOLOv5 is better suited for embedded platforms and situations with limited computational resources. This study demonstrates the feasibility of building intelligent, non-intrusive monitoring systems capable of addressing road safety challenges. The outcomes confirm when deep learning models combined with computer vision, can play a vital role in reducing drowsiness- related accidents. However, the success of such systems in real- world applications will also depend on their robustness under a variety of environmental circumstances, including low-light scenarios, head movements, and occlusions. Future research may integrate additional bio signals (ECG, EEG, or PPG), multimodal data fusion, and hardware acceleration to further enhance detection accuracy and reliability. Ultimately, the work presented here contributes to advancing intelligent transportation systems and paves the way for safer driving environments by leveraging artificial intelligence technologies.

Overall, this study adds to the growing domains of intelligent transportation systems by illustrating how AI can be leveraged to increase traffic safety. The combination of CNN- based classification and advanced detection architectures ensures a balance between accuracy, efficiency, and usability. However, to make such systems truly reliable for commercial deployment, further refinements are required. These include improving robustness against environmental challenges such as poor lighting, camera angle variation, and driver occlusion, as well as ensuring low-latency processing on embedded devices. With continuous advancements in computer vision as well as deep learning, method for identifying driver fatigue have the potential to become an integral part of future smart vehicles, ultimately helping to save lives and reduce accidents on the road.



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