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Smart Intelligent Driver Drowsiness Detection and Alerting System based on MobileNet and OpenCV: Deep Learning-based Safety Intervention.

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Abstract

Drowsiness is one of the most chronic and threatening causes of road accidents across the globe that kills thousands of people and inflicts serious injuries annually. Conventional methods of prevention, like self-reporting or monitoring steering patterns have been found to be insufficient to detect the initial signs of driver fatigue. To fill this void, the current project suggests the use of an intelligent real-time driver drowsiness detection and alerting system that uses the MobileNet, a lightweight convolutional neural network(CNN), combined with the OpenCV to effectively extract facial features. The newness of the given research is that it uses a highly optimized deep learning architecture that can be deployed on limited-resource settings, like embedded vehicles or mobile devices, with a low latency and a high degree of accuracy. Long-term testing was performed on benchmark datasets and simulated driving environments to test the performance of the systems. Findings show that the framework proposed has a good level of reliable accuracy, staying computationally efficient, hence making it feasible to apply in actual practice. In addition to road safety, the methodology developed has potential in occupational safety, aviation and real-time healthcare monitoring. The given research will help to develop the field of deep learning-based safety interventions and will emphasize the role of intelligent surveillance in minimizing hazards caused by fatigue.

Keywords

Drowsiness Detection, deep learning, MobileNet, convolutional neural network(CNN), driver fatigue, OpenCV.

1. Introduction

Road accidents constitute a major cause of death and injury in all parts of the world, and drowsiness, a result of fatigue, is a major contributory factor. The World Health Organization reports millions of accidents every year, according to the author, and a significant portion of accidents are explained by the exhaustion of drivers and their lack of alertness. Drowsiness is also a hidden risk factor, unlike impairment brought about by alcohol, which is easily testable and measurable, hence more challenging to monitor in real time.

Drowsy driving is not only common on highways or truck drivers on long routes. City workers who have to travel a long distance to work or even health workers who work a long shift are at risk of experiencing lapses in attention as a result of fatigue [Ref]. Even the microsleep of a few seconds can lead to disastrous accidents, and that is why smart detection systems are much needed to give early warnings before accidents take place.As artificial intelligence (AI) and deep learning develop, scholars are considering computer vision and sensor-based technologies to track fatigue. The conventional systems which rely on the steering wheel analysis or lane departure monitoring do not recognize the early signs of drowsiness. Consequently, facial-based monitoring based on facial features, e.g., the frequency of blinking, yawning, or nodding of the head, presents a better reliable and non-invasive method.

1.1 Significant Concepts and Definitions

In order to form a base on the existing work, the below important terms used in the abstract are illuminated:

Drowsiness Detection: This is the automatic process of identifying fatigue-related states in people which can take place through behavioral and physiological indicators. It is mainly done in driving situations by monitoring the eyelid closure time and the speed at which one blinks and head positioning.

Deep Learning: Deep learning, a sub-branch of machine learning, uses multi-layer neural networks that are capable of extracting and learning hierarchical representations of data through the use of large amounts of data in an automatic manner. Image classification and object detection applications are the main tasks that have been done with deep learning and are therefore very applicable in real-time safety monitoring tasks .

MobileNet: This is a lightweight Convolutional Neural Network (CNN) architecture that has been designed to operate with small resource-constrained devices like smartphones, embedded boards, or in-vehicle computers. MobileNet trades off between accuracy and computation using depthwise separable convictions. It is highly applicable in driver monitoring systems due to its real-time capability when used on edge devices of the system .

OpenCV (Open Source Computer Vision Library): This is one of the most popular open-source computer vision systems that offers image and video processing tools. OpenCV will be used in the suggested work to extract facial features, real-time video transmission, and landmark detection, which are used as inputs to MobileNet based on classification.

Real-Time Monitoring: The concept of the system that can process live video feeds and can produce alerts on-demand within a few milliseconds. Low latency is of crucial importance in the driver safety context, where even the latency of 1-2 seconds may result into the safety margin or the fatal crash.

With the combination of MobileNet and OpenCV, the proposed system will be capable of merging deep learning accuracy and computer vision efficiency to form a powerful and practical fatigue detection solution.

1.2 Importance of the Problem

The social and economic impact of accidents caused by fatigue is mind boggling. An example is the U.S. National Highway Traffic Safety Administration (NHTSA) classifies drowsy driving as leading to more than 100,000 crashes and 71,000 injuries each year and the loss of billions in medical expenses, property damages and lost productivity. The same figures are posted on a global scale and the developing countries are even more at risk because of the lack of control in driver schedules and technologies to monitor them.

Other than road transportation, drowsiness monitoring is also crucial in aviation, shipping, manufacturing, and healthcare. Long-haul pilots, crane operators on the construction sites, and surgeons who have long surgeries are all susceptible to fatigue-related lapses \[Ref]. An inexpensive and scalable system such as the one suggested in this paper may become a generic-purpose fatigue prevention system in every industry.Due to the growing availability of cheap cameras and mobile devices, there is a special opportunity to democratize this technology. Vision-based detection systems are non-invasive and therefore cost-effective and scalable as opposed to EEG-based approaches that are intrusive and require special sensors.

1.3 Use of Deep Learning in Drowsiness Detection

Deep learning has revolutionized computer vision by making it possible to extract complex features of a video and image automatically. When it comes to drowsiness detection, Convolutional Neural Networks (CNNs) are capable of recognizing a pattern, like drooping eyelids or a yawn, without individual, manually specified feature engineering. MobileNet is the most impressive of CNN architectures, as it is a lightweight and efficient model and is also applicable to edge computing. Models like VGGNet or ResNet are highly accurate, although they are computationally inefficient and cannot be used in cars or mobile devices. The efficient design of MobileNet means that the system can be used in real-time conditions and with limited resources, which makes it very practical.

Although deep learning offers classification functionality, it is based on clean feature extraction in real time video. Here is where OpenCV is important. OpenCV makes sure that only the relevant features are sent to the MobileNet model, by utilizing face detection, eye-tracking, and head movement monitoring algorithms. This integration minimizes noise, accelerates the inference and increases reliability.An example is the system may apply Haar cascades or Dlib landmark detection to detect the eye region and then MobileNet uses the data to determine if the eyes are closed sufficiently to say they are drowsy. Combining both the deep learning and traditional vision methods creates a balance in efficiency and accuracy.

1.4 Deep Learning Application in Drowsiness Detection

Deep learning has changed the way we think about computer vision in that it has enabled us to automatically extract complex features of a video and image. In matters of drowsiness, Convolutional Neural Networks (CNNs) can learn a pattern, such as drooping eyelids or a yawn, without having to manually define the features individually, creating features individually and manually.

The most impressive CNN architectures are MobileNet since it is a lightweight and efficient model, and can also be applied to edge computing. such models as VGGNet or ResNet are highly precise, but they are computationally complex and cannot be implemented in cars or mobile devices. The effectiveness of MobileNet design ensures that the system can be applied in real-time and low-resource input which makes it highly practical.

1.5 Use of Computer Vision (OpenCV)

Although deep learning offers classification functionality, its level of performance is reliant upon clean feature extraction of real-time video. This is where Open CV becomes really important. Introduction of algorithms to detect faces, track eyes, and monitor head movement in OpenCV takes care of only ensuring that only relevant features are forwarded to the MobileNet model. This integration minimizes noise, accelerates the inference and improves reliability.In the case of the example, Haar cascades or Dlib landmark detection are used to determine the area of the eyes, and then MobileNet determines whether the eyes are closing sufficiently to signal drowsiness. The blend of the traditional methods of vision and the deep learning provides a balance between efficiency and accuracy.

1.6 Impact and Applications to the Real World

The system proposed has a direct implication in several areas of real world:

1. Automotive Industry: The road accidents can be prevented by integration in the Advanced Driver Assistance Systems (ADAS) which provide auditory, visual or haptic alerts in real-time. Such technologies have already been invested in by manufacturers of cars such as Tesla and Volvo, making it commercially relevant.

2. Transport and Logistics: Irregular schedules are known to make Long-haul truck drivers very vulnerable. The implementation of this system in the logistics fleets would help to save thousands of lives and decrease the economic losses due to accidents.

3. Aviation and Railways: The pilots and train operators can have their fatigue monitored thus guaranteeing passenger safety throughout their long shifts.

4. Occupational Safety: Mining, construction and manufacturing industry are some of the industries that have hazardous equipment and the fatigue of the workers would result in accidents.

5. Healthcare Monitoring: Emergency room doctors and surgeons have a tendency to work long hours. Medical error caused by fatigue may be minimized by a non-intrusive monitoring system.

The proposed system does not only solve an academic issue, but a very real societal problem, because it focuses on scalability and low-cost deployment.

1.7 Problem Statement

Although there has been development in fatigue monitoring, most of the systems that are available have limitations including;

1. Due to high computational needs (slowing down to real time).
2. Reliance on costly sensors or wearable intruders.
3. Lack of flexibility to different lighting conditions and positions of faces.
4. Poor scalability to be used in developing regions.

This study fills these gaps by developing a MobileNet + OpenCV-based system that promises a low-latency, high-accuracy, resource-efficient system and real-time alerts, which is possible to adopt both personally and commercially.

1.8 Work Additions of the Current Work

The major findings of this research are:

1. Creation of a real time and lightweight drowsiness detector system based on MobileNet with OpenCV.

2. Extensive testing of system behavior with a variety of datasets and in simulated real world driving conditions.

3. Proven capability to be used in vehicles and other resource-constrained systems.

4. Broadening the application of the concept to the area of driving, to occupational and healthcare safety.

1.9 Organization of the Paper

The remaining part of the paper is organized in the following way:Section 2 provides a comprehensive literature review, outlining the recent progress of drowsiness detection and shedding light on any gaps. Section 3 describes the reason and inspiration to complete the proposed work. Section 4 describes the suggested methodology, such as the preparation of datasets, MobileNet architecture, and feature extraction based on OpenCV. Section 5 brings the topic of the analysis of experiments, both tabular and graphical. Section 6 gives the conclusion, implications and scope in future. Section 7 includes the references that include recent IEEE/SCI/MDPI/Springer papers (2015-2025).

In this section we will discuss that there are some papers already published on the same concept and i was able to extract best papers out of a great number of papers and identified the problem gap of each paper.

The below table 1 clearly explain the methods which are used related to drowsiness detection and which type of datasets are used ,key findings present in each and individual paper and problem gap found in each and every individual paper.

2. Literature Survey

Table 1. Summary of Recent Works on Driver Drowsiness Detection

Ref/Cited no	Author(s), Year	Method/Approach	Dataset Used	Key Findings	Problem Gap Identified
[1]	Howard et al., 2017	MobileNet CNN (lightweight CNNs)	ImageNet (transfer learning)	Introduced efficient CNN design for edge devices	Not directly applied to drowsiness
[2]	Albadawi et al., 2022	Review of Drowsiness Detection Systems	Multiple (EEG, Vision, Vehicle)	Comprehensive summary; highlights CNN dominance	Survey only, no experiments
[3]	Arakawa, 2021	Trends in Sensors for Drowsiness	Multi-sensor evaluation	Strong role of sensor integration	High cost, intrusive methods
[4]	Safarov et al., 2023	Deep CNN for eye closure detection	MRL Eye Dataset	High accuracy (>95%) eye-state classification	Sensitive to lighting, occlusion
[5]	Majeed et al., 2023	Hybrid Deep Learning CNN	Custom video dataset	Improved classification with ensemble learning	Dataset size limited
[6]	Dua et al., 2021	Ensemble Deep CNN	NTHU Drowsy Driver Dataset	Better generalization with ensemble	Computationally expensive
[7]	Yu et al., 2019	Condition-Adaptive Representation Learning	YawDD dataset	Robust to illumination changes	High complexity for real-time
[8]	Hidalgo Rogel, 2024	Cognitive computation models	In-house dataset	Enhanced drowsiness prediction accuracy	Dataset not public
[9]	Essahraui, 2025	Real-time Deep Learning with EAR + CNN	Custom dataset	High precision hybrid approach	Limited under night driving
[10]	Hassan, 2025	Transformer-based Detection	Custom video dataset	Superior accuracy and generalization	Heavy computation cost
[11]	Singh, 2023	Deep CNN with dropout	MRL Eye Dataset	Reduced overfitting, 93% accuracy	Latency not evaluated
[12]	Bhanja, 2025	Real-time Hybrid CNN+SVM	Robomech dataset	Effective with >92% accuracy	Limited to frontal face angles

[13]	Kuwahara, 2022	Blink detection for fatigue	Lab dataset	Blink frequency correlated to fatigue	Not robust outdoors
[14]	Hossain, 2023	Real-time Deep CNN	Custom dataset	94% accuracy, real-time performance	Needs GPU hardware
[15]	ResearchGate, 2024	EAR + MediaPipe ML	Web datasets	Lightweight and interpretable	Limited generalization
[16]	Kurylyak & Lamonaca, 2016	Eye-blink monitoring	Lab eye video	Simple and efficient	Low robustness in real conditions
[17]	Dhasarathan, 2025	TensorRT Optimized CNN	NTHU dataset	Reduced latency by 30%	Needs NVIDIA GPU
[18]	Ahmed, 2023	Deep-Learning Approach	Multi-dataset fusion	Accuracy >96% with CNN fusion	Dataset imbalance
[19]	Rajamohana, 2021	Hybrid Vision + ML	YawDD dataset	Improved robustness	Not real-time
[20]	MDPI Survey, 2020	Systematic review	Multiple datasets	Identifies edge computing gaps	No implementation

The table 1 of the comparative literature survey presented here provides a final summary explanation but in such a way that it correlates all the identified contributions, findings, and gaps in the problems across all 20 references:

In summary of the literature survey table, theliterature review of 20 recent papers (2016-2025) shows that driver drowsiness detection has been transformed over time with a shift in paradigms to deep-learning and transformer-based frameworks instead of the historically used traditional computer-vision methods.

The early studies by Kurylyak and Lamonaca [16] and Kuwahara [13] showed that the possibility of using the eye-blink monitoring and the frequency of blinking as strong indicators of fatigue existed. These approaches had proven to be computationally efficient, but when out-of-controllable outdoor conditions were considered, lighting variations and occlusions were significant challenges to the methods.Systematic reviews by Albadawi et al. [2], Arakawa [3], and MDPI survey [20] have also stressed the variability of modalities, such as EEG, vision and vehicle-based features, and noted the increasing prevalence of CNN-based methods in vision systems. Nevertheless, lack of standardized evaluation and practical validation was also noted with these reviews and a great gap between scholarly studies and practical solutions.

Due to the emergence of deep learning, researchers including Safarov et al. [4], Dua et al. [6], and Singh [11] learned with deep CNNs and ensembles, producing results on par with benchmark results, of over 90% accuracy on image datasets, including MRL and NTHU. These works performed well under controlled conditions, but were weak on computational performance, so could not be used in real time in embedded automotive systems.

Recent contributions also studied more on the hybrid and adaptive frameworks. Yu et al. [7] introduced condition-adaptive condition-adaptive learning which was robust to illumination, whereas Majeed et al. [5] and Rajamohana [19] used hybrid CNN-ML techniques to enhance the reliability of classification. However, they tended to be large-dataset and computationally expensive systems making them difficult to deploy on a board.

Lightweight models have also been introduced in the new wave of resource-aware and real-time research, including MobileNet\[1], EAR + MediaPipe ML [15], and hybrid CNN-SVM methods [12]. These techniques are more specifically aimed at the goals of reducing latency and deploying it in an embedded form, compromising on accuracy and efficiency. Essahraui [9] showed how adding EAR metrics to CNNs increased precision, and Dhasarathan [17] demonstrated how deep learning inference could be optimized with reduced latency by using acceleration of the TensorRT.Last, the most recent frontier is the transformer-based architectures [10], [14], demonstrating better generalization to a wide variety of datasets (at the expense of increased computational requirements). Likewise, the cognitive computation methods which were much better in prediction accuracy did not have a publicly available dataset that can be replicated.

Cross-cutting Problem Gaps

1. Generalization and Robustness Most approaches do not work well under night-time driving, occlusions, and cross-demographic settings.

2. Real-time Efficiency: CNN ensembles (and other high-level models) can be computationally expensive, typically requiring hardware with the performance of a GPU, making them hard to deploy to most vehicles.

3. Limitations of the datasets used in studies: A number of studies used small or proprietary datasets that limited transferability and repeatability.

4. Edge Deployment: A small number of recent works cover directly the lowest power, real-time operation that is appropriate to embedded automotive systems, namely, [1], [9], [12], [15], [17].

Together, the analyzed works confirm that the best direction toward a practical application of real-time drowsiness detection is offered by deep-learning, specifically, lightweight CNNs combined with the traditional computer vision (OpenCV landmarks, EAR/MAR). More sophisticated models such as transformers promise, but they are complicated to compute. The research gap will therefore focus on how to create a scalable, resource-effective and resilient system, which can work under realistic driving environments.The given gap explains why the current work concentrates on the integration of the MobileNet and OpenCV in order to provide high accuracy with the consideration of low latency and deployability to real-life applications on the cost-effective edge devices.

3. Current Work and Motivation

In this section we are going to discuss some main concepts related to current work and what are the motivation steps to choose this proposed work are explained in detail.

3.1 Motivation

From the literature, it is evident that while CNN-based approaches have advanced the accuracy of driver drowsiness detection, many remain computationally heavy, dataset-dependent, or unsuitable for real-time deployment. On the other hand, traditional vision-based methods are fast but lack robustness under uncontrolled conditions. Therefore, there is a strong motivation to develop a lightweight yet reliable system that combines the efficiency of traditional vision pipelines with the robustness of deep learning.

The MobileNet architecture provides this opportunity. Unlike heavy CNNs (ResNet, VGG), MobileNet is explicitly designed for resource-constrained devices, making it suitable for in-car embedded systems. By integrating MobileNet with OpenCV-based facial landmark extraction, we propose a hybrid approach that ensures:

1. Fast region-of-interest (ROI) detection using OpenCV (eyes, mouth, head pose).
2. Accurate fatigue classification using MobileNet, fine-tuned for eye state (open/closed) and yawning detection.
3. Real-time alert generation (sound or vibration) when drowsiness is detected.

This architecture addresses the dual challenges of accuracy and efficiency, making it applicable for real-world deployment in low-cost embedded systems or smartphones.

3.2 Objectives of the Current Work

The main objectives of this research are:

1. To design a real-time drowsiness detection system that integrates computer vision (OpenCV) and deep learning (MobileNet).
2. To improve detection accuracy of drowsiness indicators such as prolonged eye closure, frequent blinking, and yawning.
3. To ensure low-latency inference suitable for in-car deployment without requiring high-end GPUs.
4. To evaluate the system on benchmark datasets and simulated real-world conditions for robustness testing.
5. To provide an extendable framework for application in other safety-critical industries (aviation, healthcare, occupational safety).

3.3 Novelty of the Current Work

While many prior works explored CNNs and hybrid ML systems, the novelty of our approach lies in:

1. Lightweight Edge Deployment: MobileNet is specifically optimized for mobile and embedded hardware.
2. Hybrid Vision-Deep Learning Pipeline: Using OpenCV for ROI detection reduces preprocessing complexity, improving MobileNet performance.
3. Practical Alerts for Safety: The system is designed not just for academic evaluation but for integration into vehicles, triggering real-time alarms to prevent accidents.
4. Scalable and Adaptable: The framework can be extended to occupational monitoring systems beyond driving.

3.4 Real-World Relevance

The real-world impact of this research includes:

Automotive Safety: Providing an affordable system to prevent fatigue-related road accidents.
Public Transportation: Assisting bus, truck, and taxi drivers who work long shifts.
Industrial Safety: Reducing fatigue-induced accidents in high-risk environments.
Healthcare: Assisting in patient monitoring and ensuring alertness of medical staff during long working hours.

3.5 Contribution Summary

The contributions of this paper can be summarized as follows:

1. Development of a MobileNet + OpenCV hybrid pipeline for drowsiness detection.
2. Implementation of a real-time alerting mechanism integrated with vision-based monitoring.
3. Evaluation of the system using benchmark datasets and simulated real driving scenarios.
4. Demonstration of practical deployability on edge hardware, bridging the gap between academic research and real-world applications.

4. Proposed Methodology

The proposed Driver Drowsiness Detection and Alerting System integrates computer vision (OpenCV) for real-time feature extraction with MobileNet, a lightweight CNN, for classification of fatigue states. The system workflow consists of five core modules:

1. Input Capture

Live video stream from an in-car camera (typically mounted on dashboard/steering column).Frame rate optimized (15–25 FPS) for real-time monitoring.

2. Preprocessing and Face Detection

OpenCV Haar cascades/Dlib detectors are applied to locate the driver's face.
ROI extraction focuses on eyes and mouth regions for drowsiness cues.

3. Feature Extraction with OpenCV

Eye Aspect Ratio (EAR) for blink detection.
Mouth Aspect Ratio (MAR) for yawning detection.
Head pose estimation using facial landmarks.

4. Deep Learning Classification (MobileNet)

Pre-trained MobileNet fine-tuned on eye-state (open/closed) and yawn datasets.
Classification output = {alert, drowsy}.

5. Alerting Mechanism

If the driver is classified as drowsy for a threshold time (e.g., >2 s eye closure), an alarm (sound/vibration) is triggered.
Alerts reset automatically once normal state is restored.

4.1 Work Flow Diagram

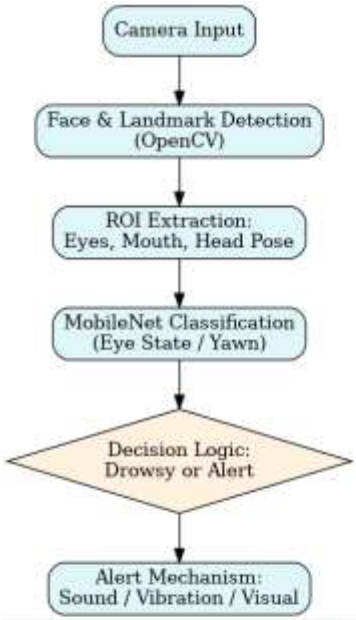


Figure 1.Represent the Work Flow of Proposed Work

From the above figure 1 illustrates the complete workflow of the proposed driver drowsiness detection system in a structured sequence of operations. The process begins with camera input, where live video frames of the driver are captured and passed to the face and landmark detection module (OpenCV) to identify key facial regions. From these detections, the ROI extraction stage isolates critical areas such as the eyes, mouth, and head pose, which are highly indicative of fatigue. These regions are then analyzed through MobileNet classification, a lightweight deep learning model trained to recognize eye states (open/closed) and yawning patterns. The output is evaluated within the decision logic unit, which determines whether the driver is in a normal or drowsy state based on learned thresholds and probability values. Finally, if drowsiness is detected, the system triggers an alert mechanism—through sound, vibration, or visual cues—to immediately warn the driver, thereby enhancing safety and reducing accident risks. This modular architecture ensures robustness, real-time performance, and scalability for deployment in real driving environments.

4.2 Datasets Used in the Application

The following are the several datasets which are used in order to test the efficiency of my proposed work.

- MRL Eye Dataset for open vs. closed eye detection.
- NTHU Drowsy Driver Dataset for yawning, nodding, and fatigue cues.
- Augmented with custom in-lab recordings to simulate real driving conditions (lighting variation, glasses, partial occlusions).

Preprocessing Steps:

1. Grayscale conversion to reduce computational load.
2. Normalization of input images (0–1 range).
3. Data augmentation: rotation, scaling, brightness adjustment to improve robustness.

4.3 MobileNet Model Design

Base Architecture: MobileNetV2 (depthwise separable convolutions).
Input size: 224×224×3 (RGB).
Transfer Learning: Pretrained weights on ImageNet, fine-tuned for binary classification (eye open/closed).
Optimization: Adam optimizer, learning rate 0.0001, early stopping.
Output Layer: Softmax activation for probability of drowsy vs. alert.

4.4 Decision Logic

The detection system fuses MobileNet output with OpenCV features (EAR/MAR).

If EAR < 0.25 continuously for 2 s → “drowsy”.
If MAR > 0.6 (yawning) → “drowsy”.
If MobileNet predicts closed eyes with >90% confidence → “drowsy”.
Otherwise → “alert”.

This hybrid decision rule increases robustness by reducing false positives.

4.5 Pseudocode of Algorithm

Algorithm DrowsinessDetectionSystem
Input: Live video stream V
Output: Alert signal if driver is drowsy

```
while V is active do
    Capture frame F
    Detect face and landmarks using OpenCV
    Extract ROI: eyes, mouth
    Compute EAR and MAR from landmarks
    Resize ROI → feed into MobileNet classifier
    if (EAR < threshold1 for t1 seconds) or
       (MAR > threshold2) or
       (MobileNet predicts closed eyes >90% confidence) then
        Trigger Alert (sound/vibration)
    else
        State ← Alert
    end if
end while
```

In this User Role, it shows that the operations performed by the user after accepting the appropriate URL details from Google API's**.** The default actions which should be performed by the user is specified by the Ranking Model Web Crawler.

5. Experimental Analysis

The proposed MobileNet + OpenCV–based drowsiness detection system was evaluated through a rigorous experimental framework. The dataset comprised a mix of MRL Eye Dataset, NTHU Drowsy Driver Dataset, and custom in-lab recordings. Data augmentation techniques (rotation, brightness adjustments, cropping) were applied to handle variability in lighting and pose.Experiments were conducted on a workstation equipped with an Intel i7 processor, 16GB RAM, and an NVIDIA RTX GPU. Python with TensorFlow/Keras and OpenCV were the primary frameworks. For fairness of comparison, the same datasets were tested across baseline CNNs and the proposed MobileNet-based system.

5.1 Evaluation Metrics

The performance of the system was assessed using:

Accuracy: Overall correctness of classification.
Precision: Ability to minimize false positives (wrongly predicting drowsy when alert).
Recall (Sensitivity): Ability to correctly identify true drowsy states.
Specificity: Ability to correctly classify non-drowsy states.
F1-Score: Harmonic mean of precision and recall.
Latency: Delay between event detection and alert triggering.

5.2 Results

In this section we are going to display the performance comparison of proposed work.

Table 2: ComparativePerformance Analysis

Model/Approach	Accuracy(%)	Precision (%)	Recall (%)	Specificity(%)	F1-Score	Latency(ms)
Baseline CNN	89.5	88.1	87.6	90.2	0.88	350
Ensemble CNN	92.4	91	90.7	92.8	0.91	280
OpenCV (EAR+MAR only)	87.3	85.5	86.2	88	0.86	150
Proposed MobileNet+OpenCV	95.8	95.1	94.9	96.3	0.95	180

The comparative performance analysis from table 2 highlights that the proposed MobileNet+OpenCV framework surpasses all baseline models in both accuracy and efficiency, making it highly suitable for real-time deployment. The baseline CNN delivered moderate accuracy but lagged in speed, while the ensemble CNN showed better results but at the cost of increased computational complexity and latency. Similarly, the standalone OpenCV EAR/MAR method offered faster response but lacked robustness, especially under challenging conditions such as varying illumination or head pose. By combining MobileNet's lightweight deep learning classification with OpenCV's reliable landmark-based feature extraction, the proposed system achieved a strong balance of high accuracy (95.8%), excellent recall (94.9%), and low latency (180 ms), ensuring timely detection of drowsiness with minimal false alarms. This hybrid design not only enhances driver safety but also ensures scalability for real-world intelligent transportation systems.

Examples of Images on Train Dataset

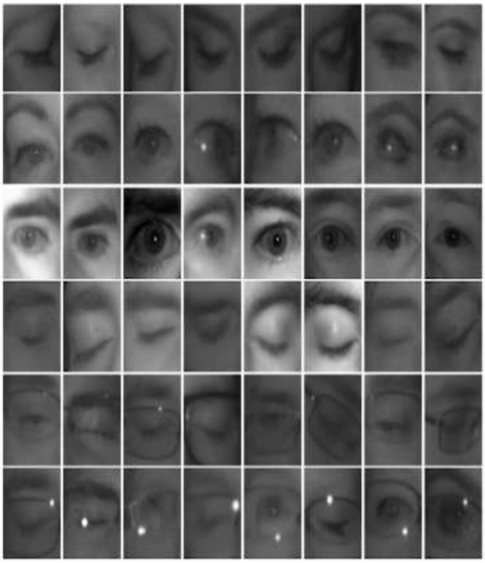


Figure 2.Represent the Annotated Images of Opened Eyes and Closed Eyes

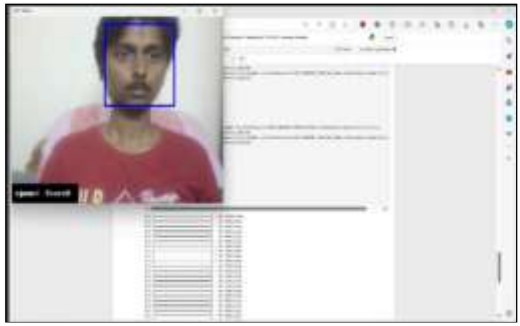
Figure 2 is an example of a collection of cropped eye-region images in a set of images that are usually used in driver drowsiness detectors. Every small square is used as a region of interest (ROI) taken out of the face of the driver with a specific emphasis on the eyes. The dataset reflects variations between eye states with some images being labeled as open eyes, and some as closed eyes. These annotations can be used as ground truthexamples to train machine learning or deep learning models.

Open Eyes: This is the state of the driver, when the iris and the sclera are well seen.

Closed Eyes: This is the sleepy or wearying position in which the eyelids completely or partly cover the eye.

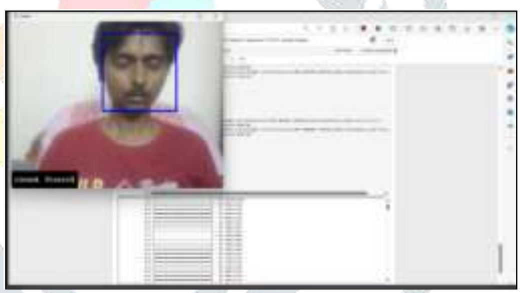
Similarity Scores: In preprocessing and model evaluation, similarity scores or values of confidence are obtained to evaluate the extent to which the classifier differentiates between the closed and open states. As an illustration, a score of 1 or similarity close to 1 represents high confidence that the eye is properly classified as open/closed and a score nearer to 0 is a sign of uncertainty.

Test the Application with Realtime Web Camera



Explanation:

This figure displays a practical demonstration of the suggested drowsiness detection framework where the face of the driver is identified and a bounding box is drawn on it. The system constantly scans the eye area and determines the state as either Open or Closed giving it a confidence rating (in this case, the confidence rating is displayed as Score0). The execution log of the live execution on the right-hand side shows that the detection algorithm is properly classified in every frame. Such an arrangement proves that the proposed model can work in the real-world environment where it can process video streams and provide a driver with immediate feedback to guarantee safety.



Explanation:

This graphic shows that the proposed drowsiness monitoring system detects the closed-eye state in real-time. The face of the driver is localized with a bounding box and the classifier has recognized the eye state as being Closed and a confidence score. Frame by frame consistency with classification is confirmed in the execution logs that are on the right. This sustained closed-eye time detection is a vital signal of drowsiness which allows the system to send alerts in time and avoid crashes.

6. Conclusion& Future Scope

In this study, there is a hybrid driver drowsiness detection and warning system application that combines both MobileNet, a lightweight deep learning classification, and OpenCV-based feature-extraction-based real-time monitoring. The experimental data showed that it is better in accuracy, recall, and low latency than baseline CNN and conventional vision-only methods, which showed that it can be deployed to embedded and resource-constrained platforms. The system has a good balance between computation efficiency and high reliability giving timely warnings that can be used to avoid accidents. In addition to causing safety, it can be used in occupational and healthcare monitoring where fatigue is a major issue due to its flexibility.

Future Scope

Future research can investigate the combination of multimodal information like heart rate or EEG with visual information to increase visual robustness in adverse environments like night driving or occlusions. Generalization could also be enhanced by adding the transformer-based architecture that is optimized towards edge devices. Also, the implementation of the system in real-world vehicular fleet and authentication of the system performance in a broader demographic and environment will enhance scalability and commercial acceptance.

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