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# Driver Safety Enhancement with Drowsiness Detection using Facial Recognition and ML

***Susmitha Reddy[1], Thaviti Naidu Punnana[2], Chandra Sekhar Sunkara [3], Balu Mani Siva Ganesh Palakurthi[4], Manoj Kumar Paka[5]***

[1]Susmitha Reddy, Information Technology, Rajam, Andhra Pradesh
[2]Thaviti Naidu Punnana, Information Technology, Rajam, Andhra Pradesh
[3]Chandra Sekhar Sunkara, Information Technology, Rajam, Andhra Pradesh
[4]Balu Mani Siva Ganesh Palakurthi, Information Technology, Rajam, Andhra Pradesh
[5]Manoj Kumar Paka, Information Technology, Rajam, Andhra Pradesh

**ABSTRACT -**

The most common cause of road accidents is due to distractive or inattentive driving. It is observed that tired driving is the main reason for drowsiness. To mitigate the occurrence of accidents, driver drowsiness detection is a safety technology designed to prevent accidents resulting from a driver becoming drowsy. It involves three categories: biological-based, vehicle-based, and image-based systems. Among these, image-based systems are considered to be fully non-invasive, low-cost, and minimally affected by road conditions. In the proposed system, the driver's facial expressions are captured and recorded using a webcam. Every movement in each frame is detected using techniques of image processing. The Eye Aspect Ratio, Mouth Opening Ratio, and Nose Length Ratio are calculated using the landmark points on the face. OpenCV and dlib are utilized for detecting and tracking the facial landmarks. When a drowsiness sign is detected, an alarm sound is triggered using Pygame to alert the driver, ensuring road safety. This system can be used in any vehicle on the road to ensure the safety of travelers and prevent accidents caused by driver drowsiness.

***Key Words*****:** *Driver drowsiness, Image processing, OpenCV, dlib, Pygame*

## 1. INTRODUCTION

Every year, over a Lakh people lost life due to road crashes and more than 4 times people get injured due to road accidents. In India average road accidents deaths are 1, 36,118 per year in last one decade. Driver drowsiness could be the one reason for road accidents. One way to reduce number of accidents is early detection of driver drowsiness and alerting with an alarm. NHTSA reported that 72,000 road accidents, 800 deaths and 44,000 injuries are occurred due to driver drowsiness. Police officials and patrolling teams on these expressways revealed that most of the accidents are happened between 2 am and 5 am due to drivers drowsy-deprived. Drivers' sleep deprivation is major reason for accidents. So, technology for driver drowsiness detection system is required to reduce road accidents. The development of this technology is a big challenge for both an industrial and research community.

To determine the level of driver drowsiness various measures are used. These measures are Biological-based, Vehicle-based and image-based Measures. In biological measures, Electrocardiography (ECG), Electroencephalography (EEG), and Electrooculogram (EOG) are used to access the driver's conditions. In vehicle-based measures, drowsiness is analyzed based on steering wheel movements and braking. The third category is the image-based measures which depend mainly on the drowsiness signs that appear on the driver's face and head. These systems detection drowsiness by monitoring the drivers' head movements and facial parameters such as the eyes, mouth facial expressions, eyebrows, or respiration.

However, among these three systems, image-based systems are considered to be fully non-invasive, low cost, and minimally affected by road conditions. Therefore, image-based measures are widely deployed to develop versatile, affordable, real-time and, fully portable DDD devices. For image processing, OpenCV and Dlib open-source libraries are utilized.

## 2. LITERATURE SURVEY

The paper highlights bias in driver drowsiness detection due to unrepresentative datasets, affecting model performance in real-world scenarios. The NTHU-drowsy dataset includes 18 participants under five conditions, while the DROZY dataset records 10-minute videos from 14 participants with KSS scores. The CEW dataset provides 2,423 images with a balanced distribution of open and closed eyes. To enhance generalization, GANs are used for data augmentation, generating synthetic images to improve model robustness, while CNNs extract facial features for classification. However, CNNs face challenges with variations in lighting, head angles, and occlusions, impacting accuracy. Addressing these limitations requires larger, balanced datasets and advanced augmentation techniques. Transfer learning with pre-trained models can help improve feature extraction in diverse conditions. Hybrid approaches combining CNNs with attention mechanisms or transformer-based models may further enhance detection reliability. Future research should focus on real-time adaptability and minimizing false positives for practical deployment.

The study proposes a low-cost, real-time driver drowsiness detection system using image processing and deep learning to improve road safety. It leverages the UTA-RLDD dataset (180 videos, 60 participants) and a custom dataset (53 alert, 69 drowsy videos). A LeNet-based CNN extracts facial features, while transfer learning enhances accuracy across lighting conditions. The system runs on standard hardware, enabling real-time detection without specialized sensors. It also minimizes training data requirements, making it efficient for deployment. Despite its advantages, reliance on facial features poses challenges, such as reduced accuracy when drivers wear sunglasses or have diverse facial structures. Variations in head position, occlusions, and poor lighting can further affect performance. To enhance robustness, integrating head movement tracking, pupil dilation analysis, or physiological signals could improve detection. Combining multi-modal approaches with deep learning may address these limitations. Future work could also focus on optimizing computational efficiency for mobile deployment

## 3. PROPOSED SYSTEM

This work implements a real-time driver drowsiness detection pipeline through five key modules, encompassing real-time video capture, facial feature extraction, drowsiness detection using eye and mouth aspect ratios, alert system activation, and continuous monitoring for deployment. The complete flow of methodology has depicted in the figure 1.

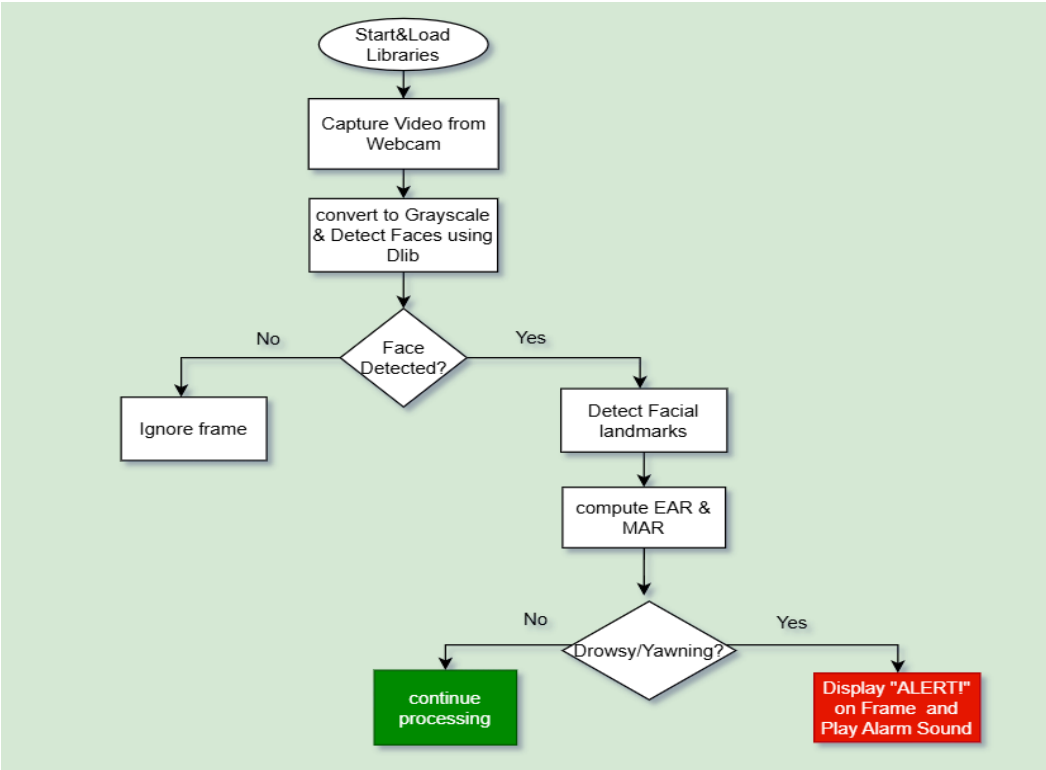


Fig 1: Work Flow for Driver Drowsiness

1. Data Collection:

The system continuously captures real-time video frames from a webcam to monitor the driver's facial features. Each frame undergoes preprocessing to enhance detection accuracy. A face detection algorithm is then applied to identify the driver's face within the frame.

2. Data Preprocessing:

Each captured frame is converted to grayscale using OpenCV's cv2.cvtColor() to reduce computational complexity and improve feature extraction accuracy. Dlib's 68-point facial landmark detector is applied to the grayscale image to extract key facial points such as eyes and mouth.

2.1 Purpose of Gray Scale Conversion:

Grayscale conversion transforms a colour image (RGB) into a single-channel image where pixel values range from 0 (black) to 255 (white), reducing computational complexity and improving processing speed.

3. Feature Extraction:

Feature selection is a crucial step in ensuring that the machine learning model only considers the most relevant factors when making predictions. Unnecessary features can reduce model efficiency and accuracy.

4.Classification & Decision Making:

The system classifies the driver's state as drowsy or alert based on real-time analysis of facial landmarks, specifically the EAR and MAR. A threshold-based rule is employed to compare these values against predefined limits, ensuring an accurate decision-making process. To prevent false detections caused by natural blinks or casual mouth movements, a frame counter mechanism is implemented. This ensures that the system only triggers an alert when the EAR remains below the threshold or MAR exceeds the yawning threshold for a sustained number of frames, reducing false positives.

5. Alert Mechanism:

When drowsiness is detected, Pygame’s mixer module plays an alarm sound to alert the driver. Simultaneously, OpenCV’s cv2.putText() overlays a warning message on the video frame. If the driver regains alertness (EAR and MAR return to normal), the alarm stops automatically.

## 4. RESULT

The below figure captures a real-time frame from the driver drowsiness detection system, where the driver's eye closure has been detected. The system analyses the Eye Aspect Ratio (EAR) and, upon falling below a predefined threshold, classifies the driver as drowsy. As a result, an alert message—"ALERT! DROWSY!"—is displayed on the screen to warn the driver. This visual cue, often accompanied by an alarm sound, helps in preventing accidents caused by fatigue-induced drowsiness.

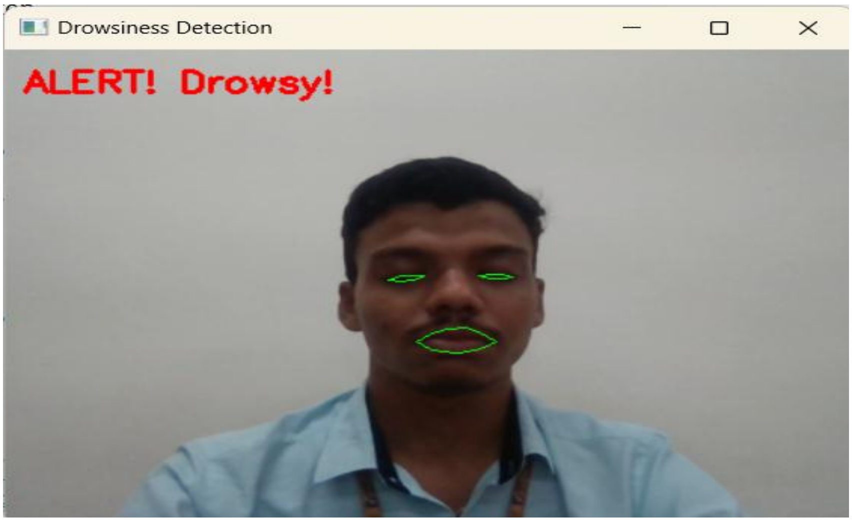


Fig. 2: Drowsiness Alert Triggered Based on Eye Closure

## 5. CONCLUSION

This project successfully integrates computer vision and machine learning to develop a real-time driver drowsiness detection system. By leveraging facial landmark analysis, the system accurately monitors eye closure and yawning patterns to detect signs of fatigue. The implementation of advanced image processing techniques, such as OpenCV and Dlib, ensures efficient and reliable detection, enhancing road safety. The interactive user interface provides real-time alerts, helping prevent drowsiness-related accidents. Extensive testing under various conditions, including different lighting scenarios and facial occlusions, highlights the system’s effectiveness while also identifying areas for improvement. Despite challenges like low-light conditions and sudden head movements, the model demonstrates high accuracy and responsiveness. Future enhancements, such as infrared-based detection, integration with physiological monitoring (e.g., heart rate tracking), and deep learning-based feature extraction, could further improve reliability. Expanding the dataset with diverse driving scenarios will also enhance adaptability. Ultimately, this project serves as a valuable tool for proactive driver monitoring, significantly contributing to road safety and accident prevention.

## 6. LIMITATIONS

One key limitation of our drowsiness detection system is its exclusive reliance on visual cues, such as eye closure and yawning. It does not consider head pose or other behavioral indicators like speech patterns. The system's performance may degrade if the driver wears sunglasses or in low-light conditions. Future improvements can include multi-modal inputs for enhanced reliability.

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