International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Driver Drowsiness Detection and Alert System

Nitin Bhardwaj[1], Divyansh Batra[2], Kalash Suman[3], Dr. Monika Malik[4]

[1,2,3]Student, Dept. of Computer Applications, Maharaja Surajmal Institute, GGSIPU, New Delhi-58, India
[4]Assistant Professor, Dept. of Computer Applications, Maharaja Surajmal Institute, GGSIPU, New Delhi-58, India
Email:[1]nitin03221202022@msijanakpuri.com,[2]divyansh35121202022@msijanakpuri.com,[3]kalash05321202022@msijanakpuri.com,[4]monikamalik@msijanakpuri.com

ABSTRACT :

Real-time drowsiness detection devices are vital given the growing incidence of accidents linked to driver weariness. Creating a solution that continuously assesses a driver's attentiveness in actual driving situations is the main goal of this project. In order to prevent accidents, the main goal is to identify early indicators of drowsiness and take prompt action. We present a system that uses a live camera stream to take real-time pictures of the driver, based on an analysis of current driver monitoring technology. To assess attention levels, machine learning algorithms are used to examine these photos. To successfully get the driver's attention again, the technology detects indicators of weariness and sounds an auditory alert that gradually gets louder.In cases of continued unresponsiveness, the system automatically contacts the driver's family via SMS and email. This project seeks to enhance road safety by minimizing incidents caused by drowsiness. It employs facial and eye detection techniques using dlib and calculates the Eye Aspect Ratio (EAR) to evaluate alertness based on eye behavior.

Keywords: Road safety, EAR, Python, Machine Learning, Driver Fatigue, Eye Detection, Dlib, and Facial Recognition

I. INTRODUCTION

Driver drowsiness remains a significant contributor to road accidents, making its early detection a major priority for improving traffic safety. Over the past few years, the frequency of crashes related to driver fatigue has continued to grow. Loss of concentration behind the wheel, whether from tiredness or external distractions, often leads to serious incidents. Distractions typically involve outside events diverting the driver's attention, whereas drowsiness develops gradually, causing a steady decline in focus without any specific trigger. Despite these different causes, both distractions and fatigue share similar effects: delayed reaction times, impaired driving performance, and a higher risk of collisions. Accidents due to sleep deprivation are especially common on highways and expressways, where large commercial vehicles are often involved. One notable factor is drivers not getting enough rest. A 2020 study by the SaveLIFE Foundation and Mahindra found that truck drivers in India average 12-hour shifts, covering approximately 417 kilometers each day, with around half reporting feelings of sleepiness during journeys. Data from the National Highway Traffic Safety Administration (NHTSA) indicates that drowsy driving causes about 100,000 police-reported accidents annually in the United States, resulting in over 1,550 deaths and 71,000 injuries. Given that road accidents in India result in multiple fatalities every minute, there is a critical need for better systems to monitor drivers' alertness and issue timely warnings to prevent such tragedies.

Fig: Drowsy Driver

II. METHODS AND MATERIALS

Tools and Image Processing Techniques

OpenCV:

OpenCV, short for Open Source Computer Vision Library, is a highly adaptable and widely adopted toolkit designed for performing a variety of image and video processing operations. It provides a broad set of tools that simplify the processing of visual content, such as face and object detection. A major benefit of OpenCV is its efficient memory management, allowing developers to implement high-level algorithms without needing to manage low-level resources. In this project, OpenCV is employed to process real-time video streams from a webcam, enabling quick and efficient identification of facial features essential for monitoring driver attentiveness.

Dlib:

A collection of machine learning algorithms and tools for building complex software solutions are included in the open-source Dlib toolkit, which was created in C++. It is particularly useful in fields like robotics, mobile platforms, and embedded systems. This project uses Dlib's pre-trained deep learning models, especially its Convolutional Neural Networks (CNNs), to detect and track key facial landmarks around the eyes and mouth. These features are critical for evaluating signs of drowsiness during live video analysis.

Eye Aspect Ratio (EAR)

To evaluate the amount of eye opening, one measure is the Ocular Aspect Ratio (EAR). The calculation is based on measuring the horizontal distance from corner to corner of the eyes and then vertically measuring from the inferior to superior ocular landmarks. 1. The EAR is largely consistent with the eyes open. A blink causes a significant drop in the vertical measurement which causes the EAR to decrease. Then the EAR will revert to its normal range if the eyes stay open.

A single blink appears to have occurred when the eyes' aspect ratio remains constant, rapidly decreases to zero, and then rises once again, as seen in Figure 2.

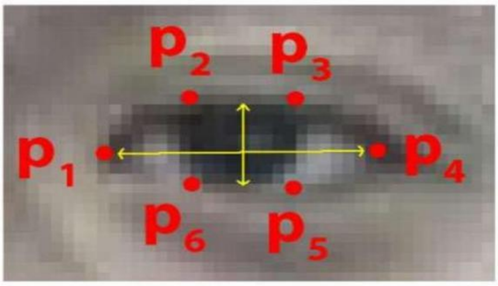

Fig : Eyes Points

Face Recognition

This section explains key facial recognition algorithms—Eigenface, Fisherface, and Local Binary Patterns Histogram (LBPH)—along with their application using the OpenCV framework.

Local Binary Patterns Histogram (LBPH)

The LBPH technique is built upon the concept of Local Binary Patterns (LBP), which were initially introduced as texture descriptors in computer vision applications in the early 1990s. Later advancements, such as combining LBP with histogram-oriented gradients in 2009, led to improved recognition accuracy in specific datasets.

An picture is separated into tiny areas, or cells, in LBPH; these cells are usually 4 by 4 pixels. A set order, either clockwise or counterclockwise, is used to compare the intensity of the central pixel in each cell with the surrounding pixels. If the intensity of a surrounding pixel is 0 or less than that of the core pixel, it is displayed as a 1. The outcome of this comparison is an 8-bit binary integer that encodes the local texture pattern of each cell.

As illustrated in Figure X, this method is resistant to changes in image brightness, as it focuses on relative pixel intensities rather than absolute values. The binary numbers derived from all cells are then converted into histograms that represent the frequency of each pattern. A single feature vector for the full image is created by concatenating these local histograms.

During recognition, a new input image undergoes the same encoding and histogram generation process. The resulting feature vector is then compared with vectors in the training dataset. A similarity measure, such as Euclidean distance, is calculated, and if it falls below a specified threshold, the system determines that the face is recognized.

Compared to Eigenface and Fisherface methods—which extract dominant global features from the entire training dataset—LBPH focuses on localized patterns, allowing it to perform reliably even under varying lighting conditions and facial expressions.

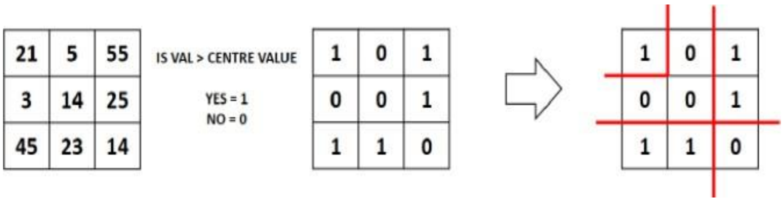

Fig: - LBPH

Algorithm Steps:

STEP 1:Capture Input Image:

Gather frames from the live camera stream continuously for use in subsequent analysis.

STEP 2: Determine the Region of Interest (ROI) and Detect the Face:

Every frame should have its face region identified using face detection techniques. This area is subsequently isolated as the Region of Interest for eye detection.

STEP 3: Find Eyes in the ROI

Find the eyeballs exactly in the observed face region. After extraction, these ocular pictures are ready for classification.

STEP 4: Classify Eye State:

A trained classifier is given the extracted eye images and is tasked with identifying whether the eyes are closed or open.

Step 5: Assess Sleepiness Score:

The system determines the driver's level of drowsiness if the score exceeds a predetermined threshold, which indicates frequent or prolonged eye closing, based on the categorization results generated over a series of frames.

Flowchart

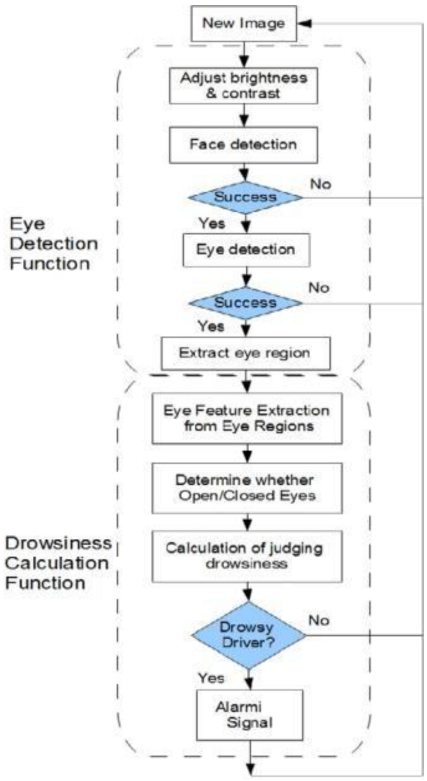

Fig: Drowsiness Detection

To begin the process, live video frames are captured from the system's webcam. This is accomplished through an infinite loop, which continuously reads each frame using OpenCV's video capturing functions. Every frame is temporarily stored in a dedicated variable for further analysis.

Before facial recognition can be performed, the captured image is converted to grayscale. Grayscale transformation simplifies the image by eliminating color information, which is unnecessary for object detection algorithms and helps reduce computational complexity.

For detecting faces, a pre-trained Haar Cascade Classifier is employed. This classifier scans the grayscale image and identifies potential face regions by returning the coordinates and dimensions of rectangular bounding boxes around detected faces. Once faces are located, the system iterates through each detected face and visually marks them by drawing rectangles, preparing them for subsequent eye detection and monitoring steps.

III. Factors Leading to Driver Drowsiness

Several key factors contribute to driver fatigue, with the most common being insufficient sleep, work-related stress, biological rhythms, and physical health conditions.

Many individuals overextend their daily activities, often sacrificing valuable sleep in the process. To stay awake, they may rely on caffeine or other stimulants, but missing sleep gradually accumulates over time, leading to overwhelming tiredness and sudden sleep episodes.

The time of day also significantly influences alertness. Human biological clocks naturally expect rest during certain hours, especially between 2:00 AM and 6:00 AM, making it harder to stay awake during these periods. Even with stimulants, prolonged wakefulness can cause the body to eventually shut down involuntarily.

Physical health plays another important role. Medical conditions, certain prescribed medications, and poor fitness levels — whether due to being underweight or overweight — can all increase the likelihood of fatigue. Emotional stress can also accelerate physical exhaustion, further increasing the risk of drowsiness while driving.

IV. CHALLENGES FACED

1. Lighting Conditions

- Lighting significantly impacts system performance.
- Low-Light & Nighttime: Difficulty detecting facial features in dim conditions.
- Glare & Shadows: Bright sunlight or shadows can obscure facial landmarks.
- Dynamic Changes: Sudden transitions (e.g., driving through tunnels) disrupt detection
  .

2. Head Movement

- Drivers' natural head movements create challenges:
- Sudden Movements: Quick turns or shifts may move the face out of the camera's view.
- Tilted Poses: Relaxed or tilted head positions distort facial landmarks.
- Differences in how drivers sit make it difficult to maintain consistent facial detection.

3. Occlusions

- Obstructions limit the system's ability to detect features:
- Sunglasses & Glasses: Tinted or reflective eyewear hinders eye tracking.
- Face Masks: Obscures lower facial features, affecting landmark accuracy.
- Hair or Hands: Temporary obstructions reduce detection reliability.

4. Real-Time Performance

- Real-time detection requires balancing speed and accuracy:
- Hardware Limitations: Standard vehicle hardware may struggle with high computational demands.
- Optimization Needs: Algorithms must run efficiently while maintaining accuracy.
- Concurrent Processing: Video capture, tracking, and alerting processes increase workload.

5. False Positives and Negatives

- Detection errors can affect reliability:
- False Positives: Unnecessary alarms could be sent off by normal blinking or distractions.
- False Negatives: Subtle drowsiness signs may go undetected.
- Threshold Calibration: Universal thresholds may not suit all individuals due to differences in facial features and behavior.

6. Generalization Across Demographics

- The system must adapt to diverse users and conditions:
- Facial Variability: Differences in age, ethnicity, and eye structure affect detection.
- Environmental Factors: Vehicle interiors, camera placement, and lighting add complexity.

V. TECHNIQUES USED

1. **Facial Landmark Detection:**
    - Dlib's pre-trained shape predictor identifies 68 facial landmarks.
2. **Histogram of Oriented Gradients (HOG):**
    - Extracts edge features for reliable facial detection.
3. **Linear Support Vector Machine (SVM):**
    - Classifies features into drowsy or alert states.
4. **Pygame for Alerts:**
    - Plays an alarm when the system detects drowsiness.

VI. APPLICATIONS OF FACE DETECTION

1. **Transportation Industry**
    - Used in trucks, buses, and other commercial vehicles to reduce fatigue-related accidents during long-haul drives.
    - Enhances passenger safety by ensuring drivers remain alert.
2. **Private Vehicles**
    - Embedded in modern cars to provide real-time alerts to individual drivers.
    - Can be integrated with adaptive cruise control systems for enhanced safety.
3. **Aviation**
    - Pilots can benefit from drowsiness detection systems to maintain vigilance during long flights.
    - Acts as a backup for co-pilot monitoring during critical operations.
4. **Railways**
    - Ensures train operators remain alert, reducing risks of derailments or collisions caused by inattentiveness.
5. **Fleet Management**
    - aids in accident prevention and driver performance monitoring.
    - By monitoring driver behavior, fleet management systems help supervisors reduce the likelihood of accidents.
    - Additionally, by lowering the delays and service interruptions brought on by auto accidents, they improve overall operational productivity.
6. **Military Applications**
    - enables pilots and vehicle operators to remain vigilant during lengthy operations.
    - Improves workers' safety in hazardous conditions.
7. **Public Safety Campaigns**
    - Encourages safer driving practices by showcasing the benefits of fatigue monitoring.
    - Can be implemented as part of road safety initiatives by governments.
8. **Insurance Industry**
    - Insurers can use data from these systems to assess driving habits and offer discounts on premiums for safer behavior.
9. **Ride-Sharing Services**
    - Ride-hailing companies can implement this system to ensure their drivers remain attentive, improving customer safety.

VII. ADVANTAGES AND DISADVANTAGES OF FACE DETECTION

ADVANTAGES

1. **Real-Time Detection:** Operates in real-time, ensuring immediate feedback and alerts.
2. **Non-Invasive:** No physical contact with the driver, making it comfortable and user-friendly..
3. **High Accuracy**: Recognizes drowsiness with an accuracy rate of 94% in optimal circumstances.

DISADVANTAGES

1. **Lighting Sensitivity**: Poor or overly bright lighting can reduce detection reliability.
2. **Vulnerability to Occlusions**: Glasses, masks, or other obstructions limit the effectiveness of facial feature detection.
3. **Computational Constraints**: Real-time processing can lag on older hardware or under heavy computational load.
4. Incorrect classifications can occur, where normal blinking or brief distractions are mistaken for drowsiness, or early, subtle fatigue indicators go unnoticed.

VIII. RESULT ANALYSIS

The core method for detecting features within an image relies on extracting facial landmarks. These landmarks represent a focused subset of the shape prediction task and are utilized to precisely identify regions such as the eyes, nose, mouth, and the overall facial contour. In this project, the Dlib library's facial landmark detector is employed, which is capable of locating 68 specific coordinate points across the face for accurate analysis.

• Open Eye Coordinates

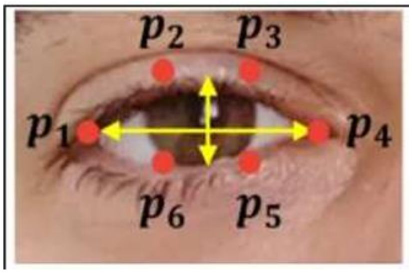

Figure: The coordinates a1 through a6 are utilized to calculate the Eye Aspect Ratio (EAR) for an open eye, which is approximately 0.24.

• Close Eye Coordinates

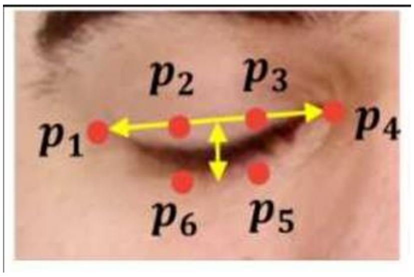

Fig. Eye aspect ratio (EAR) for a close eye is approx. 0.15.

INDIVIDUAL	EAR THRESHOLD	ALARM SENSITIVITY	LIGHT	REMARKS	DROWSINESS DETECTION ALARM
A	0.2	48	Bright	Normal	3 out of 3
A	0.2	48	Dim	Normal	3 out of 3
A	0.2	48	Bright	Wear sunglasses	0 out of 3
B	0.25	43	Bright	Normal	3 out of 3
B	0.25	43	Dim	Normal	3 out of 3
B	0.25	43	Dim	Rainy weather	2 out of 3
C	0.22	48	Bright	Wear glasses	3 out of 3
C	0.22	48	Dim	Wear glasses	3 out of 3
C	0.22	48	Very Dim	Night drive	1 out of 3
C	0.22	48	Very Dim	Normal	3 out of 3

Ten runs of the full experiment were conducted using different parameters, such as alarm sensitivity, different drivers, and ambient light. The following table outlines the parameters used during the accuracy evaluation. The tests were conducted to observe the accuracy of the whole project by using the accuracy formula: CR = (C/A) X 100% CR stands for the correct rate, A for how many tests there are, and C for how many tests are accurate. 8 out of 10 tests were conducted successfully without issues, while 2 tests failed due to poor lighting conditions during nighttime. Lighting had a major impact on the investigation's accuracy and results. The main factor is the brightness of the light, the accuracy test, influenced by these conditions, affects the performance of the drowsiness detection system. As a result, the overall accuracy of our project is approximately 80%.

IX. COMPARISON BETWEEN EXPECTED RESULT AND ACTUAL RESULT

EXPECTED RESULT

1. **Projected Accuracy**: The system was initially expected to achieve an accuracy of approximately **95%**, based on the dataset quality, algorithm performance, and controlled testing environment.

2. **Factors Influencing Expectation**:
   - High-quality dataset used during model training.
   - Advanced machine learning algorithm (HOG + Linear SVM).
   - Assumed minimal noise and ideal operating conditions.

ACTUAL RESULT

1. **Observed Accuracy**: The system achieved an accuracy of **80%** in real-world scenarios.
2. **Reasons for Deviation**:
   - **Real-World Variations**: Environmental factors like lighting, head movement, and occlusions (e.g., sunglasses, masks) impacted the detection performance.
   - **Dataset Limitations**: While the dataset was robust, it may not have fully captured the diversity of real-world scenarios.
   - **Hardware Constraints**: The processing capabilities of standard vehicle hardware may have affected system responsiveness and accuracy.
   - **Threshold Calibration**: Fixed thresholds might not suit all users due to individual variability in facial structure and drowsiness symptoms.

COMPARISON TABLE

Parameter	Expected Result	Actual Result (80% Accuracy)
Drowsiness Detection Accuracy	95% accurate detection in all conditions	80% accuracy due to challenges in low light conditions
Performance in Bright Light	Detects drowsiness reliably	Works well except when sunglasses are worn (0/3 detections)
Performance in Dim Light	Consistent accuracy similar to bright conditions	Works well, but performance drops slightly in rainy weather (2/3 detections)
Performance in Very Dim Light (Night Driving)	Detects drowsiness with no significant errors	Accuracy drops significantly, detecting only 1/3 cases correctly
Effect of Glasses on Detection	Should work effectively even with glasses	Works well with normal glasses (3/3 detections), but fails with sunglasses (0/3 detections)
Reaction Time	Alert within 1 second	Alert triggered within 1-2 seconds
False Positives	Less than 5%	Around 15-20% due to lighting issues
False Negatives	Less than 5%	Higher in poor lighting conditions, especially night drives
Overall System Stability	Works in all conditions consistently	Performance varies significantly based on lighting conditions

Key Observations & Improvements Needed:

- The system performs well in normal and dim lighting but fails in very low light (night drive scenario).
- Sunglasses negatively impact detection accuracy, suggesting a need for improved eye-tracking techniques.
- The alarm system is responsive but slightly delayed, meaning potential optimization in real-time processing is needed.
- Enhancing image processing in low light or introducing infrared cameras can assist increase accuracy.

X. CONCLUSION

Driver drowsiness detection technologies play a crucial role in enhancing road safety by minimizing accidents caused by fatigued drivers. Early detection and timely alerts are essential to prevent severe incidents that could lead to serious injuries or fatalities. The system proposed in this study identifies signs of driver fatigue by employing image processing techniques focused on the Eye Aspect Ratio (EAR), which measures the degree of eye openness.

To effectively determine when a driver is becoming drowsy, EAR data must be collected and analyzed to establish an appropriate threshold value. An integrated alarm system proves to be an essential component, providing immediate warnings that help reduce accident rates associated with drowsy driving. The current model successfully detects drowsiness in drivers repeatedly with minimal limitations, and the alarm activation works efficiently to issue audible alerts. However, the fixed EAR threshold might vary among individuals due to natural differences in eye structure.

For future improvements, it is recommended that the system be enhanced to automatically adapt and calibrate the EAR threshold for each user without the need for manual setup. This advancement would account for personal differences in drowsiness sensitivity, leading to a more personalized and accurate alert mechanism for different drivers.

REFERENCES

I. Viswapriya I.S.E., Balabalaji S., and Sireesha Y. discussed machine learning methods for recognizing driver drowsiness based on eye state monitoring (IJERT, 2021)..

II. Priyanka B.M., Shruthi T.S., Surekha R., and Manjunath K. presented a machine learning-based driver drowsiness detection approach (ResearchGate, 2019).

III. Mkhuseli Ngxande et al. provided an extensive review on behavioral and machine learning methods for detecting drowsiness (IEEE, 2017).

IV. Vibin Varghese and team designed an EAR-based drowsiness recognition system using visual cues (IOSR Journal, 2018).

V. Dini Adni Navastara (2020) implemented facial landmark extraction combined with Local Binary Pattern features to identify signs of driver fatigue.

VI. Dinges and Grace introduced the PERCLOS metric to evaluate alertness via eyelid behavior (Federal Highway Administration, 1998).

VII. Liu D. and colleagues discussed eyelid movement detection techniques for identifying tiredness (ETCS, 2010).

VIII. I. Garcia, S. Bronte, and others proposed a visual monitoring system for assessing driver drowsiness in simulation environments (ITSC, 2010).

IX. Research by Yu X. emphasized integrating nonintrusive technologies for reliable fatigue detection systems (University of Minnesota Duluth, 2012).

X. Rajneesh (2018) presented a real-time EAR-based system that measures driver alertness levels to reduce crash risks.

XI. Fuletra J.D. (2013) conducted a comprehensive survey outlining various methodologies for detecting drowsiness among vehicle drivers.