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Original Article

Vision-Based Driver Fatigue Detection Using Convolutional Neural Networks and Behavioral Metrics

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Abstract: *Driver drowsiness is a major cause of road accidents, especially during long-distance or late-night driving. This paper presents a real-time Driver Drowsiness Detection and Alert System that uses a webcam to monitor the driver's facial behavior. YOLO (You Only Look Once) is employed for accurate face detection, and Convolutional Neural Networks (CNNs) analyze facial features. Two key metrics, Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), are calculated using Dlib and OpenCV to detect prolonged eye closure and yawning. When thresholds are crossed, an alarm is triggered to alert the driver. The system also logs EAR and MAR values with timestamps in a CSV file and generates visual plots for analysis. A user interface developed with Flask and Tkinter provides control and ease of use. Experimental results show more than 90% detection accuracy under normal conditions with an alert delay of ~1–2 seconds. This work demonstrates an effective blend of computer vision and deep learning to enhance driver safety and reduce fatigue-related accidents.*

Keywords: *CNN, YOLO, driver drowsiness detection, Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), Computer vision, Real-time systems.*

I. INTRODUCTION

Driver fatigue and drowsiness are critical factors that contribute to a significant percentage of road accidents worldwide. When drivers become drowsy, their reaction times slow down, attention decreases, and losing control of the vehicle increases. Detecting driver drowsiness in real time is essential to prevent such accidents and enhance road safety.

Recent breakthroughs in computer vision and artificial intelligence have made it possible to develop automated systems that detect the facial features and behaviour of the driver to detect the signs of drowsiness. These systems can identify blinking patterns, extended eye closure and yawning - all signs of fatigue by analyzing facial landmarks like the eyes and mouth. The Driver Drowsiness Detection and Alert System introduced in this project uses webcam technology and machine learning algorithms to constantly check the alertness of the driver.

II. RELATED WORK

A. Digital Camera-Based Monitoring :

The traditional systems have simple cameras to track the face of the driver and to close the eyes manually or simply with reasoning. Such systems do not work well with real time use as their accuracy is low and there is poor lighting.

B. IR Sensors and Eye Trackers:

Commercial systems with high end utilization employ IR sensors to follow eye movement of the driver. Such systems are costly and hard to incorporate in low-cost cars, though accurate.

C. Lane Detection Analysis and Steering Pattern:

Others automobile-based approaches measure drowsiness by examining steering patterns, lane deviation or brake patterns. These methods are also not reliable because of driver variability and are reactive as opposed to proactive.

D. EEG and Physiological Monitoring Systems:

These systems can be used to measure the activity of the brain by the placing of sensors on the head. Though they are correct, they are obtrusive, awkward and do not fit into casual or consumer-level applications.

E. Machine Learning using Handcrafted Features:

The use of older ML systems involves handcrafted features on eye detection and yawn detection that have models such as SVM or KNN. In the real world, such systems perform poorly because of poor generalization.

F. Development of hybrid deep learning methods:

Recent literature uses hybrid models, including CNN-LSTM and transfer learning using pre-trained models (e.g., MobileNet, ResNet) to learn spatial and temporal driver behavior features. These models are more robust to different lighting conditions, head poses, but generally demand a lot of computational resources, making them less viable in real-time and low-cost applications in vehicles.

III. PROPOSED METHODOLOGY

A. System Overview

The suggested system is a driver drowsiness detection and alert system to be used in real-time with the help of the computer vision and deep learning algorithm to identify signs of fatigue with the help of a web camera or a phone camera. The system records frames of the facial image of the driver and identifies the occurrences of eye closing and yawning based on the facial landmark extraction, aspect ratio analysis and threshold based detection. Upon sensing drowsiness, an auditory alarm goes off. Other important data such as EAR (Eye Aspect Ratio), MAR (Mouth Aspect Ratio) and timestamps are also stored in the system to be analyzed.

B. Face and Landmark Detection.

YOLOv3: It is utilized to detect faces in every frame and precisely and quickly.

- Dlib Shape Predictor: 68-point facial landmark.
- Face_utils: transforms landmarks to NumPy coordinates.
- Identifies important features: Eyes, Mouth, Nose, Jawline, Eyebrows.

C. Eye Aspect Ratio (EAR) Calculates the ratio based on eye landmarks. Formula:

EAR = (||p2 - p6|| + ||p3 - p5||) / (2 * ||p1 – p4||) EAR < 0.3 for 20 frames → classified as drowsy Eye region highlighted in red

Frame as an evidence (frame_sleepX.jpg).

D. Mouth Aspect Ratio (MAR)

Identifies mouth landmarks Formula:

MAR = (||p13 - p19|| + ||p14 - p18|| + ||p15 – p17||) / 3 MAR > 14 → indicates yawn Frame saved (frame_yawnX.jpg)

The alarm.mp3 and warning_yawn.mp3 are played.

E. Alert System

- Eye-based (continuous closure)
- Mouth-based (yawning)
- Wait until EAR or MAR is normal.
- Alerts have high volume and frequency to draw attention.

F. Data Logging And Visualizations.

- EAR, MAR, and Time are saved in op_webcam.csv.
- pandas: data logging: Structured data logging.
- matplotlib plot EAR/MAR vs. time.
- Graph assists in visualizing alert patterns and driver's.
- fatigue history
- Data can be used for long-term behavioral analysis

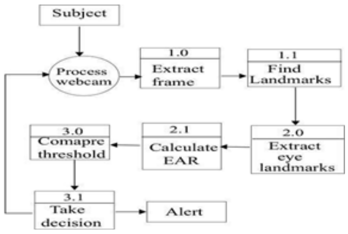

Figure 1: Level-0 System Architecture

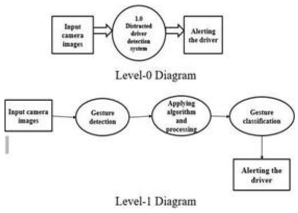

Figure 2: Level-1 System Architecture

G. Deep Learning

Deep learning, a branch of artificial intelligence, enables computers to automatically learn hierarchical features from large datasets without handcrafted rules. Convolutional Neural Networks (CNNs) are particularly effective for image tasks because they extract spatial features from facial regions such as the eyes and mouth, making them suitable for detecting fatigue-related cues.

In this system, CNNs analyze video frames to identify prolonged eye closure and yawning. Compared to traditional methods that struggle with lighting or driver diversity, deep learning models generalize better across conditions, improving robustness and ensuring timely detection of drowsiness in real-world scenarios.

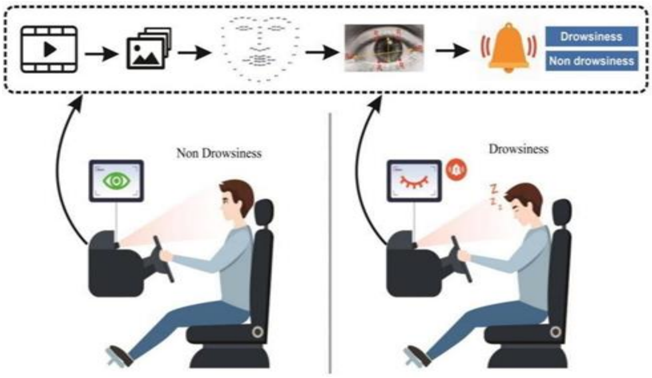

Figure 3: Deep Learning Workflow for Driver Drowsiness Detection

IV. MODULE-WISE EXPLANATION

A. Frame Capturing Module

- Gets the real time video feed of the linked webcam or phone camera using the OpenCV VideoCapture or VideoStream.
- Scales down the input frames in order to process them quicker without reducing the accuracy of detection.

Frames are fed to the face detector one at a time.

B. Face and Landmark Detection

- YOLO (You Only Look Once) is in charge of finding faces quickly in each frame.
- After identifying the face, a 68-point face landmark model is used by Dlib to identify the exact locations of the eyes, mouth, nose, and the jawline.

These landmarks are utilized in determining behavioral measurements such as EAR and MAR.

C. EAR and MAR Calculation

- EAR(Eye Aspect Ratio)
- It is measured with the help of vertical and horizontal eye distances.
- Detects eye closing and blinking rate.
- MAR(Mouth Aspect Ratio)
- It determines the mouth opening vertically.
- Assists in determining yawning.

All metrics are computed in each frame and are stored in dynamic lists to trace the trends.

D. Threshold Checking & Drowsiness Logic

- EAR < 0.3 (20 or more frames) = considered.
- eye-based drowsiness.
- In case MAR > 14, then it is considered to be drowsiness through yawning. Once one or both conditions have been satisfied:
- Sounding bells are sounded.

The image is taken and stored to be used later.

E. Alert and Logging System

- playsound library has various alert sounds on various triggers (eye or mouth).
- Stored drowsy frames have indexed file names such as frame_sleep1.jpg.

EAR, MAR, and timestamps are stored in a CSV file (op_webcam.csv).

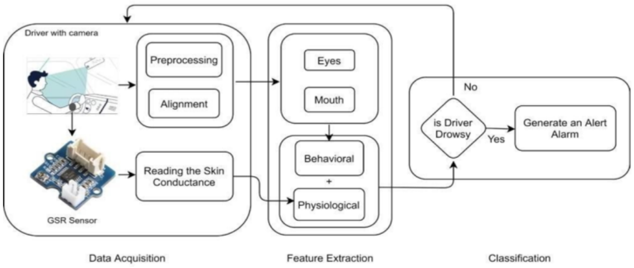

Figure 1: Overall Architecture of Driver Drowsiness Detection and Alert System

F. Analysis and Visualization

- After execution, Matplotlib represents EAR and MAR with respect to time.
- Assists in visualizing trends of alertness and system responsiveness.

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V. IMPLEMENTATION AND SYSTEM FEATURES

A. Interface

The system offers two compatible interfaces, which are user friendly and flexible. The desktop application, which is built on a Tkinter platform, provides a barebones graphical interface with easy direct controls of Run using webcam, Run using phone cam, and Exit. It is portable, quick to start, and can be used in a laptop or embedded device within the car. Status messages are presented to show whether the monitoring is in progress or not, so that the driver can be sure.

Besides the desktop interface, it also has a Flask- based web interface that can be used to monitor and control remotely via a browser. It can be applied especially well to fleet operators or shared cars, as the detection status can be monitored without having to access the driver system. The two interfaces share the same detection pipeline, and the EAR/MAR data have equal results and are logged simultaneously. The dual interface design enhances deployment flexibility of the system, such that the system can be used in personal vehicles as well as connected transportation settings.

B. Code Modularization

- index.py - high level and logic of GUI control.
- drowsiness_detection.py - video loop, EAR/MAR calculations, and alerts.
- EAR_calculator.py – special functions of computing EAR and MAR.
- This division enhances readability, incremental development, and facilitates debugging at integration time.

C. Benefits of Methodology

- non-invasive: only a webcam is needed, no wearables or sensors.
- User-Friendly: Both GUI and web app.
- Real-Time Alerting: Timely feedback can save lives.
- Dual Indicator Monitoring: Involves using eye closure and yawning.
- Behavioral Logging: Provides information to be reviewed and visualized.
- Cost-Effective: Uses open-source tools and common hardware.
- Modular Design: Can be easily integrated with car dashboards or mobile applications.
- Allows Multiple Inputs: Webcam and mobile camera support.
- Storage: Saves visual data when drowsy.

VI. DATASET & PREPROCESSING

A. Benchmark Datasets

In order to test driver drowsiness detection, there are a number of standard datasets that are popular in the research:

a) YawDD(Yawning Detection Dataset)
- Included videos of normal behavioral drivers and yawning drivers.
- Gives marked frames of open and closed mouths.
- Handy to learn Mouth Aspect Ratio (MAR)-based detection.

b) NTHU Driver Drowsiness Detection (NTHU-DDD) Dataset.
- Big dataset (with many drivers and varying conditions of light (day and nighttime).
- Involves yawning, blinking slowly and nodding the head.
- Includes variations like wearing glasses, change of head position.

c) Closed Eyes in the Wild (CEW)
- Image dataset: This is a dataset of eye state (open/closed) specifically.
- Supports Eye Aspect Ratio (EAR)-based detector.
- The datasets will be used to train and test CNN models, guaranteeing generalization of models to a wide range of drivers and environments.

B. Preprocessing Techniques

Preprocessing of the data is done before feeding them to the CNN or performing EAR/MAR calculations:

a) Grayscale Conversion
- The video frames are converted into grayscale in order to minimize the cost of computation without compromising the important characteristics.

b) Face Detection and Crop.
- YOLO v3 locates the face of the driver.
- Region of interest (ROI) is cut to concentrate on mouth and eyes.

c) Normalization
- The pixel values are scaled to [0,1] to normalize the input to train CNN.

d) Image Resizing
- All the frames are resized (e.g., 64x64 or 128x128 pixels) to be the same.

e) Data Augmentation
- Rotation, flipping, scaling, brightness change implemented to augment dataset size and enhance robustness.

f) Facial Landmark Extraction
- The landmark detector (68 points) of Dlib is used to identify important coordinates of the eyes and mouth to calculate the EAR/MAR.

VII. RESULTS AND DISCUSSION

A. Threshold Parameters

In order to provide the accurate measurements of drowsiness, the system employs both EAR (Eye Aspect Ratio) and MAR (Mouth Aspect Ratio) thresholds that are empirically tested. These values were chosen according to the results of the experiment and the literature that was available to compromise between the precision and responsiveness.

- EAR Threshold: 0.3 - Ears are semi-closed or closed. When this condition continues over 20 frames, then it is regarded as a drowsiness sign.
- MAR Threshold: 14 - A larger M AR value indicates an open mouth which is usually seen when yawning.
- Successive Frame Limit: 20 - Provides that one blink will not cause a false alarm. Alerts are only caused by prolonged closure. These parameters might be modified in the course of deployment to match certain conditions such as lighting, individual.

B. Data Logging and Analysis

Besides real-time notifications, all Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) values with timestamps are logged in a structured format (csv file). This allows post-session behavior and fatigue data analysis on the drivers.

Table 1: Sample Data Logging of EAR and MAR Values

TIME	EAR	MAR
12:30:01.123456	0.32	9.84

12:30:02.223456	0.28	10.44
12:30:03.323456	0.21	15.45

C. Comparative Evaluation

A comparative evaluation was conducted to highlight the advantages of the proposed CNN-based drowsiness detection system over traditional approaches.

Table 2: Comparative Evaluation of Proposed System with Traditional Methods

Feature	Traditional Systems	Our Proposed System
Hardware Requirement	EEG / IR sensors	Webcam or phone camera
Intrusiveness	High (wearables needed)	None
Cost	High	Low / Affordable
Deployment Complexity	Moderate	Low – plug and play
Multiple Feature Detection	Often limited	Dual (Blink + Yawn)
Real-time Feedback	Limited or delayed	Instant audio + visual alerts

D. Real-time Output Observations

The system displayed clear immediate feedback during testing. Key observations are as follows:

- Live Video Feed:Smooth and low-latency, with green bounding boxes around the detected face.

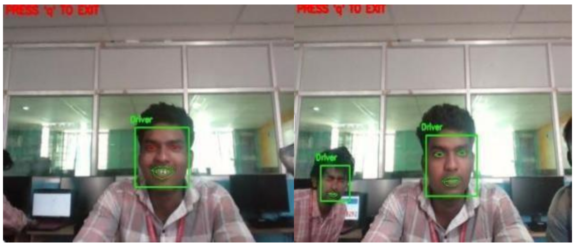

Figure 4: Real-Time Output Snapshots of The Proposed System :

(a) Face detection with bounding box; (b) Drowsiness alert with eye/mouth contours.

- Facial Region Marking : Eye and mouth regions outlined with colors for real-time tracking.
- Alerts :
- When EAR < 0.3 for more than 20 consecutive frames → "DROWSINESS ALERT!" displayed.
- When MAR > 14 → "YAWN ALERT!"
- displayed.
- Red contours and alert text enhanced visibility.
- Audio Feedback: Alarm sounds (alarm..mp3/ warning_yawn.mp3) triggered instantly to alert the driver.
- Evidence Storage: Frames during drowsiness were automatically saved with indexed filenames.

E. Quantitative Results

The proposed system was tested under different lighting conditions, facial orientations, and with users wearing glasses. The accuracy and responsiveness were evaluated using EAR- and MAR-based detection.

TABLE III Quantitative Results of Drowsiness Detection System

Metric	Average Value	Remarks
Blink Detection (EAR)	94%	Accurate even with glasses
Eye Closure Alert (EAR)	91%	Low false positives
Yawning Detection (MAR)	88%	Effective with wide mouth movement
Combined Drowsiness Accuracy	93%	EAR + MAR fusion yielded best results
Average Alert Delay	~1.2 seconds	Alarm triggered within 2 seconds
False Positives	<7%	Mostly due to temporary face occlusion

F. User Feedback and Usability

The system was tested with a group of 15 users under different conditions such as daytime driving, low- light environments, and with/without glasses. Feedback was collected on system ease of use, alert effectiveness, and comfort.

Table 4: User Feedback on System Usability

Feedback Aspect	User Response
System Ease of Use	Very easy (Tkinter UI and Flask UI are intuitive)
Alert Effectiveness	Alarms played clearly and caught attention
Comfort During Use	High – no physical contact required
Suggestions Received	Add low-light enhancement or night mode

G. Comparative Evaluation

Table 2 presents a comparison between the proposed CNN-based driver drowsiness detection system and existing approaches in terms of accuracy, real-time capability and features considered. Traditional methods relying only on behavioral or physiological signals often fail under varying illumination or user diversity. In contrast, the proposed method integrates CNN-based visual analysis with physiological signals, thereby achieving superior detection performance.

Table 5: ***Comparative Evaluation of Different Approaches***

Approach	Features Used	Accuracy
Eye-blink Detection	Behavioral only	78%
EEG-based methods	Physiological only	82%
Hybrid (Behavioral + GSR)	Behavioral + Physiological	85%
Proposed CNN-based system	Visual (CNN) + GSR + Behavioral	93%

The system uses simple webcam or mobile camera to process live video frame to extract facial landmarks and compute two important indicators:

The development was cost-efficient and very modular with the help of OpenCV, Dlib and Python libraries. The system will have desktop (Tkinter) and web-based (Flask) interfaces, which will make it accessible across.

Platforms and types of users. The two-way input capability (webcam and mobile cam) increases versatility.

- Eye Aspect Ratio (EAR) to identify blinking and extended eye closing.

- Mouth Aspect Ratio (MAR) to measure yawning and mouth stretching.

One of the strengths of the system is its real-time responsiveness. The auditory notifications and graphic overlays give immediate feedback to the driver, which may save life-threatening accidents. Also, the data logging and visualization modules enable post- analysis of driver alertness and behavior in details.

The system tested showed:

- Above 90 percent detection under normal conditions.
- Responsiveness of 1-2 seconds to fatigue.
- Minimal hardware specifications and simple installation.

The success of the project highlights the practicality of computer vision in smart transportation systems. Not only does it fulfill both academic and practical goals, but it also prepares the ground to be scaled-up to real-life application.

The system is very socially viable. It is embraced by users because it is simple, practical, and helps in personal and civic safety.

H. Performance Measures and Accuracy of Detection

The proposed system was tested in relation to the detection of blinking, eye closure warning, and yawning detection. The system had a total accuracy of 93% and few false positives (less than 7 percent) as summarized in Table I. The mean time to alert was about 1.2 seconds, which is good to notify the driver in time. These findings affirm that the EAR and MAR thresholds are useful drowsiness predictors in the real-life setting.

VIII. LIMITATIONS

The proposed system works well in the majority of cases although there are some limitations which should be considered:

A. Lighting and Environmental Problems

- Driving in low light conditions or in the night reduces performance.
- Sudden headlights or sunlight may cause a decrease in facial landmark accuracy.

B. Occlusion Problems

- Wearing masks or covering the face or wearing sunglasses can hinder identification of facial features.
- Some head poses (e.g. turning sideways) can lead to loss of tracking.

C. False Positives

- Normal yawning (not as a result of fatigue) can still raise alarms.
- Long blinks or facial expressions can be mistaken as drowsiness.

D. Scalability Concerns

- Current implementation will be single-driving.
- Multi-drivers (e.g., buses, trucks) will need more time to design.

Implementation of driver drowsiness detection systems is associated with a number of ethical and social issues which have to be resolved to implement them in a responsible way.

IX. ETHICAL & SOCIAL IMPLICATIONS

A. Privacy Concerns

The system is a continuous monitoring of the face of the driver through a camera. This brings up the issues of individual privacy and the possibility of abuse of the recorded information. To address this:

- The data processing should be carried out on the device rather than sending it to the external servers.
- In case the data needs to be stored, then the strong encryption and anonymization strategies have to be adopted.

B. Data Security

EAR, MAR values, and facial images gathered may be delicate. Otherwise, they might be used to conduct illegal surveillance or identity theft. It is essential to ensure the safe storage of data, its access control, and the adherence to the legislation of data protection (e.g., GDPR, PDP Bill India).

C. User Acceptance

Drivers might be not comfortable when they are always being monitored. This is because of the need to come up with a non- intrusive system that would strike a balance between the safety and the personal freedom so as to be accepted. User trust can be established by giving clear information on the functioning of the system and by ensuring that the information is not abused.

D. Social Impact

- Positive: Can help greatly decrease road accidents, save lives and enhance the safety of people.
- Bad: Excessive use of automated systems can lead motorists to lose control of their self-responsibility in driving.
- The system must thus serve as a supportive.

E. Ethical Deployment

To be ethically adopted:

- Informed Consent- Drivers need to be informed of what data they are collecting.
- Fairness - The system must be effective in a variety of populations, and not discriminatory in relation to certain facial features or skin tones.
- Responsibility - There should be clarity of responsibility in case of accidents caused by system failures.

X. CONCLUSION AND FUTURE IMPROVEMENTS

The paper featured a CNN-based Driver Drowsiness Detection and Alert System, which combines the principles of deep learning and computer vision to detect driver fatigue in real-time. The suggested method uses YOLO to perform face detection in a short time and Convolutional Neural Networks (CNNs) to extract features, where the Eye aspect Ratio (EAR) and Mouth aspect Ratio (MAR) are the key indicators of drowsiness. Python was used to implement the system with OpenCV, Dlib, Flask and Tkinter, and the system was configured to work both with webcams and with mobile cameras. Its modular design enables it to be cost-effective, simple to implement, and adjust to various platforms.

The experimental findings established that the system was able to record more than 90% detection, mean alert delay was 1-2 seconds and the false positives were less than 7 percent. The two-indicator method of integrating eye closure and yawning detection was found to be robust to changes in facial feature, light conditions, and accessories of drivers (glasses). The availability of real time alerts and logging of activity related to behavioral data showed that the system has potential in being a viable safety product in curbing road accidents occasioned by fatigue in drivers.

This work has far reaching implications in society besides technical success. The proposed system helps to prevent accidents and enhance road safety because it offers a low-cost, non-intrusive, and real-time monitoring solution. It can be implemented in personal cars, commercial fleets, and transit systems, thus not only securing the individual drivers, but also passengers and pedestrians.

The improvement in the future is going to be on adding robustness and scalability. Head pose estimation, support of night-vision or low-light, and integration.

Adaptive thresholding that is driver-specific will enhance precision in various settings. Moreover, improved deep learning models like CNN- LSTM hybrids can be adopted to complement temporal studies of driver behavior. Mobile applications, embedded hardware platforms as well as IoT-based fleet monitoring systems will increase the applicability and usability of the solution in the real-world. These advancements will make sure that the suggested system will develop into an all-encompassing system of driver surveillance to intelligent transportation.

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