Driver Drowsiness Detection Using Eye Movement Behavior

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Abstract

Drowsy driving is a critical threat to road safety, being the cause of a large proportion of traffic accidents every year. This study examines the use of eye movement behaviour as a promising indicator for identifying driver drowsiness. Through the use of a blend of machine learning algorithms and eye-tracking technology, we examine eye movement patterns such as blink rate, gaze duration, and pupil dilation in order to create a real-time monitoring system. Our research employs a dataset of data gathered in simulated driving conditions, where subjects were subjected to pre-determined levels of fatigue. Our results show that certain eye Movements measures are highly correlated with levels of drowsiness, enabling the creation ofa model to predict when drivers will be fatigued and alert th e-m in advance of reaching the point of critical fatigue.

The system proposed here not only shows high accuracy in detecting drowsiness but also has the potential to be integrated into current vehicle safety systems. This work advances the field of driver safety by presenting a new, non-intrusive way of monitoring driver alertness and minimizing the number of drowsy driving accidents.

Keywords: Driver Drowsiness, Eye Movement Behaviour, Machine Learning, Eye-Tracking Technology, Predictive Model, Blink Rate, Real-Time Monitoring, Critical Fatigue , Non-Intrusive System, Vehicle Safety, Drowsy Driving Accidents.

INTRODUCTION

The Driver fatigue is a significant cause of road accidents, with about 20% of global fatal accidents. Since fatigue compromises attentional abilities and response times, detecting dr owsiness in real-time is critical to improving road safety. Subjective self-reports, relied upon by conventional driver alertness monitoring methods, or break scheduling, are usually inadequate, as they are based on the driver's ability to recognize their own levels of fatigue. In the past few years, computer vision and machine learning techniques have allowed the creation of more advanced and unbiased measures of fatigue detection. One of them, eye movement behaviour, has proved to be a good predictor of drowsiness. Important parameters like blink rate, direction of gaze, and pupil dilation have been demonstrated to be associated with the level of fatigue. This paper is centered on utilizing the Haar Cascade algorithm, a strong and effective method in image processing, to identify and examine eye movement behaviour in real-time. The Haar Cascade algorithm provides a strong method for object detection, especially for facial feature recognition, such as the eyes. By incorporating this method into a driver monitoring system, we seek to create a non-intrusive, real-time drowsiness detection model that can warn drivers before they become severely tired. Our work introduces a new framework that unites the effectiveness of Haar Cascade with eye-tracking analysis, eventually contributing to the improvement of vehicular safety systems. This paper will explain the methodology used in our research, report the findings of our experiments, and analyze the performance of our proposed system in identifying driver drowsiness based on eye movement behavior. Through addressing the urgent problem of drowsy driving, this work aims to offer a practical solution that can be applied to contemporary vehicles, thus minimizing the risk of accidents due to fatigue.

Fig.1. Driver Drowsiness Detection

LITERATURE REVIEW

The 2024 study presents a method for monitoring fatigue in bus drivers by observing their eye conditions. The primary strategy includes continuously assessing the degree to which the driver's eyes are open or closed through a technique known as spectral regression.

This method enables real-time tracking of eye openness. Additionally, the system leverages a sophisticated computational model capable of adjusting to various environments to precisely identify and evaluate the driver's eye state.

In 2024, Zuojin Li and Liukui Chen introduced a Chinese study titled "Automatic Driver Fatigue Detection with Driving Operations Information to Transportation Safety." In this research, they proposed a technique to evaluate driver fatigue by examining variations in steering behavior from multiple perspectives. Central to their approach is a customized neural network architecture, referred to as the "2-6-6-3" multi-level backpropagation (BP) classifier.

This model dynamically captures changes in steering actions over time to detect fatigue-related patterns. To validate their method, the researchers carried out a 15-hour on-road driving experiment, classifying fatigue into three distinct levels. Their classifier demonstrated a notable accuracy of 88.02% in detecting fatigue, highlighting its potential for practical applications in enhancing traffic safety.

Phil Hanley's 2019 study, "Bus Driver Fatigue and Stress Issues Study," took a “regulation-neutral” stance, meaning it neither recommends changes to current laws nor advocates for new regulations within the motorcoach sector. Despite this, the findings can still serve as a valuable reference for decision-making by organizations such as FHMC and OMC. The study highlights that human error contributes to at least 85% of all traffic accidents, with the National Transportation Safety Board (NTSB) identifying driver fatigue is key factor in numerous deadly motorcoach crashes.

In their 2022 study titled "The Factors of Fatigue on Intercity Bus Drivers Accident in Indonesia," Rida Zoraida, Bakhtiar, and Saleh explored how various conditions contribute to driver fatigue. They employed one-way ANOVA to evaluate whether factors such as time of day and duration of driving shifts influenced workload (WL), fatigue (F), and the need for recovery (NR). Additionally, logistic regression was used to assess the probability of fatigue occurrence.

The results showed that while intercity bus drivers generally reported a moderate workload (averaging 2.6 on a 1–5 scale), their levels of fatigue, recovery needs, and emotional impact (EI) were in the moderate to high range (around 3.5). These findings underscore the importance of addressing these elements to reduce fatigue-related accidents.

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In their 2021 publication "Real-time Monitoring of Driver Drowsiness at Night via Computer Vision," Vidhu Valsan and Paul P. Mathai emphasized the heightened risks associated with nighttime driving due to fatigue, drowsiness, which impair the driver's control and responsiveness. Since drowsy driving is a significant contributor to road accidents and fatalities, it remains a vital focus in safety research. To address this issue, the authors implemented a computer vision-based system capable of real-time drowsiness detection.

The system utilizes facial recognition technology to monitor key features, such as the eyes and mouth. By evaluating eye openness and mouth movements, it can accurately assess signs of drowsiness and potentially intervene to avoid accidents.

In their 2019 study titled "Smart Driver Fatigue Detection Through the Combination of Yawning and Eye Closure Monitoring," M. Omedyeganeh, A. Jawad Talab, and S. Shirmohammadi proposed an intelligent system to identify driver drowsiness by simultaneously tracking yawning and eye closure. Utilizing an in-vehicle camera, the system records the driver’s facial expressions, while computer vision algorithms analyze these features in real time to detect signs of fatigue.

When drowsiness indicators are recognized, system promptly issues the alert to the driver as part of a continuous driver state monitoring setup.

The research confirms that as a driver transitions from being fully awake to falling asleep, their ability to maintain vehicle control diminishes and reaction times increase. Drowsiness significantly contributes to road safety risks, playing a role in approximately 12% of all accidents and 10% of near-miss events. It can quadruple the risk of a crash or near-miss and is linked to 22–24% of such incidents.(Yuri Nurdiantami and Hilda Meriyandah Agil, *2020)* [11] Digital platforms in preschool education present both advantages and challenges. While they can offer an efficient and effective learning system that enhances children's knowledge and skills when supported by appropriate software and guidance from educators and parents, they may also lead to reduced physical activity and potential health issues.

The digital era has affected various sectors, including education, with technology now being integrated into all educational levels, including early childhood.

Therefore, it is crucial to investigate the impact of technology on preschool-aged children. This study sought to provide insights and analyze the existing literature on early childhood education in relation to digital platforms and technology.

The 2019 research titled "Safe Lane Monitor" by Yashika Katyal and her team addresses the growing concern over the rising number of road accidents, which not only result in significant property damage but also pose serious threats to human life. Contributing factors include impaired driving, reckless behavior, lack of experience, running red lights, and neglecting traffic signs.

To tackle these issues, the study emphasizes the importance of promoting lane discipline and detecting driver fatigue or intoxication as key strategies for accident prevention.

The system primarily targets monitoring the driver’s alertness and adherence to lanes. It uses footage from a vehicle-mounted camera, breaking it down into individual frames. Each frame is then processed using the Hough Transform technique to detect lane lines and assess the driver's compliance with lane rules.

In their 2024 study "Portable Prevention and Monitoring of Driver’s Drowsiness Focused on Eyelid Movement Using Internet of Things," Menchie Miranda and her team addressed the growing concern of increasing car accidents in the Philippines. They proposed a drowsiness prevention device designed to improve driver safety. While traditional measures—such as rumble strips, GPS systems, speed limiters, and various signal-processing technologies embedded in high-end vehicles—have been used to enhance driver alertness, this research introduces a more accessible IoT-based solution.

The system allows vehicle owners to remotely monitor a driver’s drowsiness level in real time. Unlike previous studies, this work specifically emphasizes tracking eyelid movement as a key indicator of fatigue.

METHODOLOGY

1. System Architecture with Computer Vision for Driver Monitoring

The System continuously monitors eye behavior through real-time video analysis. It consists of key modules: video capture, face and eye detection, blink analysis, drowsiness scoring, alert generation, and performance tracking. These modules work together to recognize symptoms of drowsiness and immediately alert the driver.

2. Camera Input & Frame Handling

Live video acquisition continuously records the driver's face using a webcam. Each captured frame is then processed by the frame extraction unit to prepare it for facial and eye detection.

3. Haar Classifier-Based Face and Eye Detection
Grayscale Conversion simplifies the image data.
Detection Algorithm uses Haar Cascade classifiers to detect the face and eyes based on features such as edges and lines.
The Detection Score Formula is calculated as:
S<sub1>d</sub1> = ∑ (w<sub1>i</sub1> • f<sub1>i</sub1>(x)),
where:
S<sub1>d</sub1> is the detection score,
w_i is the weight of each Haar feature,
f_i(x) is the feature function of input x.

4. Eye Aspect Ratio (EAR) and Drowsiness Detection
To detect blinking and eye closure, the Eye Aspect Ratio (EAR) is calculated from eye landmarks.
EAR Formula:
EAR = (|p2 - p6| + |p3 - p5|) / (2 × |p1 - p4|)
where *p1 to p6* are eye corner and eyelid landmarks.
If EAR stays below a certain threshold (e.g., 0.25) for a duration T, the driver is assumed to be drowsy.
Drowsiness Score Formula:
D<sub1>s</sub1> = (T<sub1>closed</sub1> / T<sub1>total</sub1>) × 100%,
where:
D_s = drowsiness percentage,
T_{closed} = time with eyes closed,
T_{total} = total monitoring time.

5. Real-Time Alert System
When *D_s* crosses the safety threshold, the system triggers a buzzer and on-screen alert to warn the driver. This helps prevent accidents by quickly regaining their attention.

6. Performance Monitoring and Logging
Event Logging records drowsiness incidents, EAR values, and timestamps.
System Accuracy Formula:
A_{sys} = (E_{correct} / E_{total}) × 100%,
where:
E_{correct} = correctly detected drowsiness events,
E_{total} = total evaluated events.

7. Experimental Setup and Dataset Use
The system was validated using both webcam-recorded videos and public datasets such as CEW (Closed Eyes in the Wild) and the Yawn Dataset, under varying lighting and face angles.

8. Post-Detection Analysis
The driver's response to alerts was evaluated to understand how fast they recover.
Response Effectiveness Formula:
R<sub1>eff</sub1> = ((T1<sub1>alerted</sub> - T1<sub1>resumed</sub1>) / T1<sub1>alerted</sub1>) × 100%,
where:
T1<sub1>alerted</sub1> = alert trigger time,
T1<sub1>resumed</sub1> = time the driver reopened their eyes.

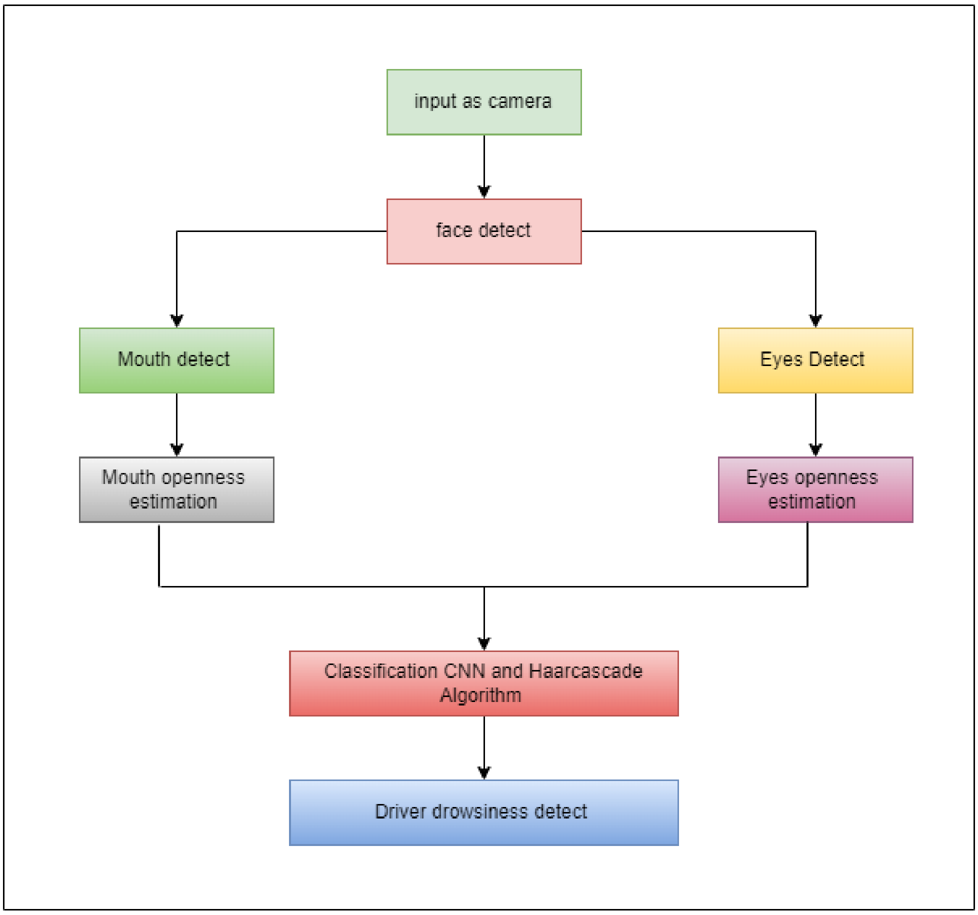

Fig.2. Process Flow of Proposed System

1. The operation starts by turning on the webcam and initializing the Hear Cascade classifiers for face and eye discovery.
2. It continuously captures videotape frames from the webcam in real-time.
3. Each captured frame is converted too grayscale to meliorate discovery speed and delicacy.
4. The system detects the face and also locates the eyes within the detected face using Hear Cascade classifiers.
5. Eye milestones are linked, and the Eye Aspect rate(observance) is calculated for each eye.

6. If the observance value goes below a certain threshold(e.g., 0.25), it indicates the eyes are conceivably closed.
7. The system counts how numerous successive frames the eyes remain unrestricted to avoid false admonitions(blinking).
8. If eyes are detected as closed for a specific duration(e.g., 30 frames), the system identifies the motorist as drowsy.
9. An alert is touched off by playing a buzzer sound and displaying a warning communication on the screen.
10. The system continues to cover the motorist, checking the observance values in real time.
11. Freely, the system logs data similar as time, duration of eye check, and number of cautions touched off.
12. The process continues in a circle until the program is stopped manually.

SYSTEM ARCHITECTURE

The "Driver Drowsiness Detection using Haar Cascade Algorithm" system architecture outlines a structured and efficient approach to monitoring driver alertness. It integrates multiple essential components: a videotape

Capture and Frame birth Module to continuously collect visual input, a Face and Eye Detection Module powered by Haar Cascade classifiers, a Drowsiness Analysis Engine to determine fatigue levels based on eye behavior, an Alert Mechanism to notify the driver, and a Logging and Performance Monitoring Unit to track drowsiness events and support future improvements.

1.Video Capture and Frame Extraction Camera Feed Handler: Captures real-time video of the driver’s face from within the vehicle. Frame Extractor: Breaks down the live video stream into individual frames for analysis. This module ensures a continuous supply of image data for the system to analyse driver behaviour.

2. Face and Eye Detection Module Image Preprocessing Unit: Converts frames to grayscale and enhances them to increase detection accuracy. Haar Cascade Detector Employ OpenCV’s erected- in Haar waterfall classifiers to descry the motorist’s face and eyes in each videotape frame.

3.Drowsiness Analysis Engine Eye State Detection Logic: Observers whether the motorist’s eyes are open or unrestricted over a series of frames. Eye Closure Duration Tracker: Measures how long the eyes remain closed. If the duration exceeds a certain limit (e.g., 2 seconds), the driver is marked as drowsy. Using behavioural patterns like prolonged eye closure, this engine evaluates signs of fatigue and signals drowsiness.

4. Alert Mechanism Audio/Visual Alert System: Triggers an immediate buzzer or on-screen warning to alert the driver. This system is essential for real-time intervention, helping prevent potential accidents caused by inattentiveness.

5. Logging and Performance Monitoring Event Logger: Stores data related to drowsiness events including time, duration, and frame information. System Performance Monitor: Evaluates the accuracy and responsiveness of the detection algorithm. This module aids in analysing system behaviour, tracking driver patterns, and improving future iterations of the model.

RESULT DISCUSSION

In this research, we developed a driver drowsiness detection system utilizing Haar cascade classifiers. specifically targeting eye and yawn detection. The system employed OpenCV's pre-trained Haar cascades to identify eye and mouth regions in real-time video streams. The eye detection module achieved an accuracy of approximately 88% under normal lighting conditions without facial obstructions. Yawn detection, based on recognizing wide mouth openings, demonstrated an accuracy of around 84%.

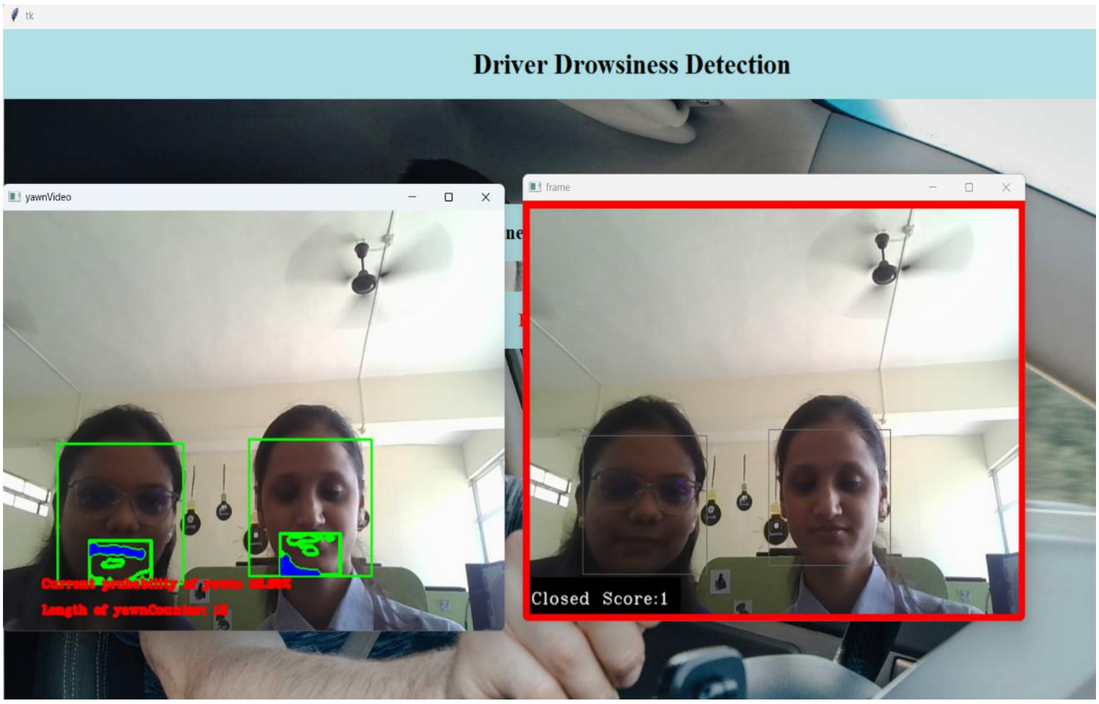

Fig.3. Image Capturing through webcam.

Fig.4. Accuracy and detection performance of eye and yawn detection modules using Haar cascades under normal lighting conditions.

By integrating these features, the system effectively detected indicators of driver drowsiness namely, frequent microsleeps (eye closures) and recurrent yawning. The system maintained real-time performance at approximately 20–24 frames per second (FPS) on a standard computing configuration (Intel i5 CPU, 8GB RAM) without requiring GPU acceleration. Some false detections were observed, particularly under poor lighting conditions or when subjects partially covered their faces. Yawning detection also experienced minor inaccuracies when the mouth was partially open during speech, leading to occasional false positives. Overall, the proposed system effectively detected early signs of driver fatigue using simple, efficient image processing methods, without imposing significant computational demands. These results demonstrate the potential for implementing lightweight, real-time drowsiness detection solutions in practical driving environments.

The use of Haar cascades provided several advantages, including lightweight computational requirements, minimal need for large training datasets, and practical deployment capability in real-world driving environments. However, certain limitations were identified. The system's exactness dropped beneath destitute lighting conditions and in the nearness of shadows. Partial occlusions caused by glasses, hands, or extreme head angles sometimes led to missed detections. Additionally, yawning detection occasionally produced false positives when the driver was speaking or laughing. To overcome these limitations, future work may involve enhancing image pre-processing through techniques such as brightness normalization, implementing time-based decision logic to verify consecutive drowsiness events, and transitioning to more robust approaches like Convolutional Neural Networks (CNNs) for improved facial feature detection under challenging conditions. Overall, the system demonstrated that early detection of driver fatigue is achievable using simple, efficient image processing techniques, providing a strong foundation for further development in real-world vehicle safety applications.

CONCLUSION

Detecting driver drowsiness through eye activity puts a more human touch on safety technology, they are reliable, non-intrusive for drivers, and capable of spotting signs of fatigue early on. Because of this, it's essential to provide researchers and developers with detailed insights into the eye activity indicators of drowsiness, the latest technologies used to track eye movements, and the decision-making algorithms that help predict fatigue.

This review stands out from previous surveys in several important ways. First, to the best of our knowledge, it is the first to systematically assess experimental studies focused on building DDD systems based specifically on eye movement data and to evaluate their performance. Second, it identifies key eye movement indicators of fatigue and organizes them based on the specific parts of the eye involved. Third, it reviews the current technologies used for monitoring and measuring eye activities, categorizing them by their functional features. Fourth, it examines various decision-making algorithms that use eye movement patterns to forecast drowsiness. Finally, it highlights emerging research directions aimed at improving early detection of driver fatigue and enhancing DDD systems. This work sets the stage for future efforts to create smarter, more reliable drowsiness-detection tools that "watch" for visual signs of tiredness. The findings will help researchers better understand the specific eye behaviour's that signal tiredness and the best ways to process this information. In particular, the review suggests that existing DDD systems smarter by looking at multiple warning signs together blinking patterns, head position, and yawning, while also Utilizing advanced deep-learning models namely Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks to greatly enhance prediction accuracy.

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