Vision-Based Fatigue Detection Using a Smartphone

Hudson Assumpção, Rigel P. Fernandes, Anna Beatriz Nunes Barbosa, and Pedro Henrique Portugal Gusman

***Abstract*— Driver fatigue is a critical factor in traffic accidents, especially in long-duration or nighttime driving. This project aims to develop a near real-time driver fatigue detection system capable of identifying early signs of drowsiness and alerting the driver to prevent potential accidents. The system uses computer vision techniques to analyze facial features such as eye closure, yawning, and head movements, captured through a smartphone camera. Data processing occurs locally to ensure low latency and immediate response. The goal of the suggested solution is to provide a low-cost, non-invasive, and efficient tool for enhancing road safety, especially in the passenger and freight transportation industries.**

***Keywords*— Driver Fatigue Detection, Computer Vision, Smartphone-based Monitoring, Real-Time Alert System, Drowsiness Detection.**

I. Introduction

Road transportation is a pillar of the Brazilian economy, accounting for approximately 65% of the country's freight transport [1]. In 2023, there were over 2.18 million trucks in operation (according to the Sindipeças circulating fleet report). Despite its essential role, the sector faces a major challenge: driver fatigue. This issue is a significant factor in road accidents, responsible for 15–20% of them, with over 3,000 fatalities recorded in 2024, based on data from the Federal Highway Police. Truck drivers in Brazil often work long hours with insufficient rest, increasing the risk of accidents [2].

Globally, countries such as the United States, United Kingdom, and Australia have implemented strong regulations and adopted advanced fatigue monitoring systems to enhance road safety [3]. In contrast, Brazil still lacks accessible and effective real-time solutions capable of addressing this issue at scale.

Generally, fatigue is characterized as a state of reduced mental and physical performance capacity, often caused by prolonged wakefulness, insufficient sleep, or extended periods of monotonous activity [4]. In drivers, fatigue can lead to slower reaction times, impaired judgment, diminished vehicle control, and cognitive disengagement-often occurring without conscious awareness. In response, various fatigue detection technologies have emerged, broadly categorized into camera-based, steering behavior analysis, vehicle dynamics monitoring, and biometric monitoring systems. However, these often present limitations in terms of cost, invasiveness, or adaptability to diverse real-world conditions, especially for large-scale deployment.

To address the lack of accessible solutions in Brazil, this study proposes a low-cost, non-invasive, and accessible smartphone-based fatigue detection system. The system employs MediaPipe to track facial landmarks and analyzes key indicators such as eye closure and yawning using Euclidean distance calculations. When signs of fatigue are detected, the system immediately issues alerts, prompting the driver to take necessary action. The proposed solution stands out for its accessibility, as it utilizes widely available smartphone hardware, making it feasible for large-scale deployment in Brazil's trucking sector.

The remainder of this paper is organized as follows: Section II provides a comprehensive review of existing driver fatigue detection technologies. Section III describes the methodology used in our proposed system. Section IV presents the experimental results and a detailed discussion, and Section V concludes with final thoughts and future directions.

II. Related Work

Driver fatigue detection systems are commonly categorized by their sensor modalities. One approach involves direct physiological measures from biometric sensors, which monitor signals like heart rate variability (HRV) and electrodermal activity (EDA) [5], [6], [7]. While these methods offer high precision, they are often considered intrusive and can be costly to implement [8].

A second category includes indirect methods that infer drowsiness from vehicle behavior, such as lane deviation, speed variability [9], [10], and steering patterns [11], [12]. However, the reliability of these vehicle-based indicators can be affected by driving conditions. Consequently, camera-based systems have become a more prominent approach. These non-invasive systems analyze visual cues from the driver—including eye closure [13], yawning frequency [14], [15], head pose [16], and the Eye Aspect Ratio (EAR)—offering a balance of high accuracy and practicality for real-time applications [17].

The computer vision techniques for these systems have evolved from traditional libraries like OpenCV and Dlib to deep learning (DL). Convolutional Neural Networks (CNNs), in particular, offer superior accuracy and robustness by enabling end-to-end learning from video [18], [19]. While smartphones provide a ubiquitous platform for deployment [20], they face challenges related to high computational demands,

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variable lighting, and ergonomics. Nonetheless, the demand for low-cost, accessible monitoring solutions continues to drive innovation in the field [21].

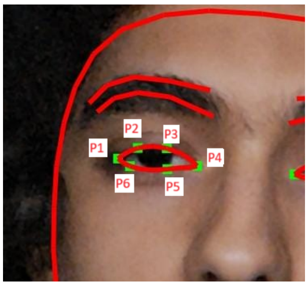
III. Computer Vision-Based Fatigue detection

A. Problem statement and assumptions

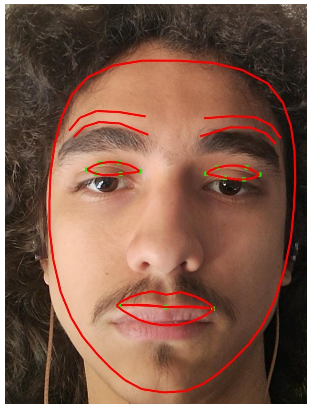
Fatigue, in the context of driving, is a state of physical and mental exhaustion that significantly reduces the ability of a driver to operate a vehicle safely [22]. Tools like the Karolinska Sleepiness Scale (KSS) [TABLE I] attempt to quantify subjective sleepiness by rating drowsiness on a nine-point scale, but such self-assessment methods are not practical for continuous, real-time monitoring in operational environments. To overcome the challenges of traditional driver monitoring systems, this project proposes a computer vision-based approach with only a front-facing smartphone camera and on-device processing.

TABLE I. Karolinska Sleepiness Scale (KSS)

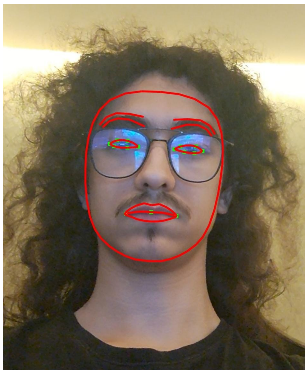
Score	Description
1	Extremely alert
2	Very alert
3	Alert
4	Rather alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy, but no effort to keep awake
8	Sleepy, some effort to keep awake
9	Very sleepy, great effort to keep awake, fighting sleep



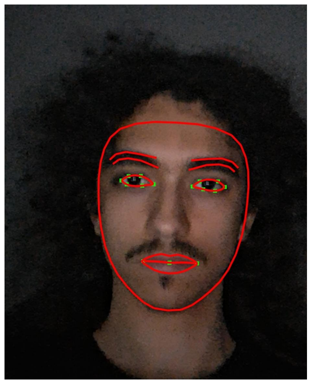
(a) Landmarks Collected



(b) 115-121 Lux



(c) 5-8 Lux



(d) 0.001-1 Lux

Fig. 1. Test images under varying illumination levels.

B. The proposed method

The proposed system performs real-time facial landmark detection using **MediaPipe**, an open-source framework developed by Google. MediaPipe provides detailed facial mapping with up to 468 3D facial landmarks. Key landmarks associated with fatigue include regions around the eyes and mouth, which are used to infer the driver's state.[23]

The fatigue is assessed by analyzing facial landmarks and identifying behaviors such as eye closure and yawning.

- **Eye State Detection:** The system calculates the Eye Aspect Ratio (EAR) using six landmarks around each eye:

$$\text{EAR} = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2 \times \|p_1 - p_4\|} \tag{1}$$

  A low EAR indicates eye closure. If EAR falls below a threshold (for example, 0.25), it is considered a sign of drowsiness.
- **Yawning Detection:** The Euclidean distance between upper and lower lip landmarks is calculated. A value above a predefined threshold is interpreted as a yawn, and therefore potential fatigue.
- **Temporal Filtering:** To reduce false positives, temporal consistency checks are applied to ensure that short-term actions such as blinking or talking are not misclassified as fatigue.

3. System Latency and responsiveness: Latency plays a crucial role in real-time fatigue detection. The system logs three timestamps:

- t_0: Initial detection of eye closure or yawning.
- t_x: Time when the detection threshold is satisfied.
- t_y: Time when the alert is triggered.

The system latency is calculated as:

$$\text{Latency} = t_y - t_0 \tag{2}$$

Minimizing this value is essential for timely alerts. In addition to algorithmic latency, camera latency is also important, specifically the time MediaPipe takes to process video frames. MediaPipe includes tools to measure this latency directly.

4. Performance in Low-Light and Variable Lighting Conditions: Figure 1 displays examples of images captured under various illumination levels during testing, to better evaluate robustness in real world environments. Performance is assessed based on:

- **False Positives:** Incorrectly triggered fatigue alerts.
- **False Negatives:** Missed fatigue events.

These evaluations help validate the reliability of the system in varying ambient light conditions.

IV. Results

The experimental results indicate that system performance is highly dependent on camera stability, a crucial factor for applications in moving vehicles. In a test with a moving camera over 27.56 seconds, the system achieved 19.88 FPS but registered a high median latency of 1337 ms across 548 inferences, rendering it unsuitable for real-time use. In contrast, a test with a stable camera and a seated subject over 205.47 seconds yielded a significantly lower median latency of 110 ms. Although the frame rate dropped to 7.50 FPS, this stable setup allowed for 1542 inferences, demonstrating more reliable and timely detection.

Regarding the processing speed of the core algorithms, the latency ranges of 22–46 ms for eye closure detection and 41–56 ms for yawning detection confirm that the processing itself is sufficiently fast for real-time alerts once video frames are stably acquired. Lighting conditions also significantly affected accuracy, as illustrated by the visual quality of inputs in Figure 1. As demonstrated in Tables II and III, the system performed excellently in bright light (115–121 Lux). However, in dimmer (5–8 Lux) and very low light (0.01–1 Lux) settings, both mouth opening and eye closure detection experienced a rise in false negatives and false positives. This confirms that sufficient and stable illumination is crucial for reliable operation.

TABLE II. Mouth Opening Detection Under Varying Light Conditions

Light Level (Lux)	**TP**	**FN**	**FP**
115–121 (Ceiling lamp)	24	1	1
5–8 (Dim room light)	21	4	1
0.01–1 (TV light)	22	3	2

TABLE III. Eye Closure Detection Under Varying Light Conditions

Light Level (Lux)	**TP**	**FN**	**FP**
115–121 (Ceiling lamp)	25	0	3
5–8 (Dim room light)	24	1	2
0.01–1 (TV light)	23	2	4

V. Conclusions

The application demonstrated promising performance, with fast response times and high accuracy under ideal lighting and camera conditions. However, to ensure consistent reliability during nighttime driving-common among truck drivers-it is important to improve the algorithm's robustness in low-light environments. Future work should explore the use of discreet, directed auxiliary lighting that does not interfere with driving, as well as training models specifically tailored for low-light scenarios.

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