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Using Computer Vision To Monitor The Fatigue Level Of School Drivers

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Abstract:
Safety in school transport is a constant concern, especially when it comes to tired drivers, something that unfortunately happens a lot. This work presents a solution to this problem: a system that identifies signs of fatigue before something more serious happens. Using a combination of cameras (to capture facial expressions) and physiological sensors (which measure things like heart rate and oxygen), the system monitors the driver in real time. When it notices signs of sleep or distraction, it issues an automatic alert. The proposal is simple and direct, with a focus on prevention. By bringing together these technologies, the goal is to make transportation safer for both those who drive and students who depend on this service on a daily basis.

KeyWords: *Fatigue; School Transport; Safety; Sensors; Computer Vision.*

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I. Introduction

The safety of students on their way to school is an important issue, because it involves the safety of these young people. According to figures from the World Health Organization (WHO) and the Pan American Health Organization (PAHO), pedestrian accidents are at the top as the leading cause of death among young people aged 5 to 29 years, in addition to ranking eighth among all ages (PAHO, 2019). The increase in these accidents causes about 1.35 million deaths each year, and it is essential to take actions that reduce the dangers. In Brazil, almost 40% of pedestrian accidents on federal roads are linked to driver fatigue, which shows once again the need to find this problem earlier to make travel safer (SOUZA, 2024).

Research on the effects of fatigue on drivers shows that long working hours are directly linked to increased stress and drowsiness while driving. A study by Braga and Zille (2015) reveals that 26.4% of the taxi drivers interviewed showed some degree of work-related fatigue, where 82.2% were in a phase of resistance, still able to operate, but already dealing with serious consequences for health and focus. Similarly, Medeiros et al (2017) indicate that excessive work, lack of rest breaks, and physical fatigue are factors that increase the potential for accidents. The use of computer technologies has become a resource to reduce fatigue-related incidents. An example of this strategy was shown in a study carried out by students of a technical high school course in São Paulo, where they developed a system using artificial intelligence (AI) to track signs of drowsiness in certain drivers. The solution uses a camera that analyzes features such as eyes, nose and nose in real time, detecting symptoms of tiredness by sending preventive sound alerts. The development of this technology in school transport can offer a new approach to accident prevention, allowing for more accurate monitoring of drivers' conditions.

From this perspective, the article discusses a case study that analyzes the application of computer vision in the supervision of school driver fatigue, examining the effectiveness of this problem. Assess the technical feasibility and the obstacles associated with its development. The proposal also seeks to explore the impact of this approach on improving drivers' working conditions, raising reflections on its applicability and possible advances that could make this solution even more efficient in the context of school transport.

II. Bibliographic Reference

School transport has the crucial responsibility of ensuring the protection of children and adolescents during the journey to their schools, which requires special attention to elements that can impair driving, such as driver fatigue. Exhaustion, whether physical or mental, directly affects the driver's alertness, concentration and decision-making ability, considerably increasing the danger of collisions. Technologies such as computer vision, Artificial Intelligence, and advanced monitoring are key to minimizing these risks, providing solutions to identify signs of drowsiness and risky behaviors, as well as improve time management behind the wheel. However, the application of these technologies must be supported by an ethical and legal assessment, complying with current regulations, such as Law No. 13,103/2015, which defines rules for the working hours and medical examinations of drivers, with the aim of ensuring the protection of all participants in school transport.

Driver Fatigue and Risks in School Transportation

Physical fatigue, caused by strenuous activities, can reduce reflexes and increase the driver's reaction time, while mental fatigue affects alertness, attention, and decision-making, impairing the execution of essential driving tasks. Fatigue occurs in waves, starting with less alertness, affecting emotional control, and ultimately compromising cognitive skills like concentration and judgment. Fatigued drivers are more likely to take risks, skip procedures, have difficulty processing critical information, and respond to hazards, making them more vulnerable to serious and costly accidents (Road Safety at Work, 2024).

Computer Vision in the Detection of Signs of Fatigue

For the detection of sleepiness, physiological or behavioral approaches can be commonly used. In the first case, physiological signals, such as those from brain activity, are analyzed through techniques, such as Electroencephalography (EEG), to check for variations that indicate sleepiness, as explored by the work of Stancin, Cifrek, and Jovic (2021). Studies on the modeling of sleepiness by signals resulting from EEG, with convolutional neural networks (CNN), are also widely addressed and accurate, as observed in Zhu et al. (2021). For an application for drivers, however, this type of approach is limited, since it requires captors, in some cases invasive, which can impair the vehicle's driving ability. In this case, a behavioral approach may be more appropriate, since it uses a procedure that does not interfere with driving, which is a strategy commonly used in vehicles with ADAS.

Artificial Intelligence and Machine Learning

Artificial Intelligence, as already analyzed in a previous section, has produced a vast set of techniques, among which Machine Learning (ML) stands out, also known by its English expression Machine Learning (ML). Regarding the origin of this expression, its term was coined for the first time by the American scientist Arthur Samuel in 1959. Samuel (1959) defined ML as the field of study that allows computers to learn without being explicitly programmed. Samuel (1959) also described a program called Game of Checkers, which simulated a game of checkers between a computer and a human being. This revolutionary work for the time demonstrated that a computer could learn through data processing without having been explicitly programmed to perform such a task (TAULLI, 2020, p. 64).

Monitoring Technologies

A monitoring system is composed of various devices and technologies, such as cameras, sensors, video management software, and data storage, with the aim of capturing and recording images and audio from a particular location. This information is transmitted and stored, allowing surveillance and detection of unwanted events, ensuring greater security and control. Cameras play a crucial role, and can be of different types, such as fixed, moving, dome, infrared, and even facial recognition, each suited to specific needs. In addition, the recorded data is stored on devices such as NVRs or DVRs, providing a detailed and continuous view of the monitored environment (SILVA, 2021).

Ethical and Legal Considerations of Driver Monitoring

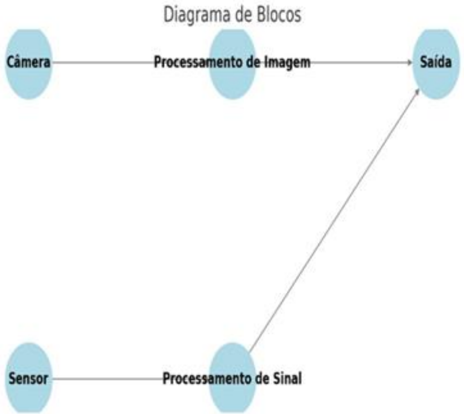
A central point of Law No. 13,103/2015 is the regulation of drivers' working hours. There is a limit of hours for daily and weekly driving, including mandatory breaks and rest periods. Such regularization aims not only at the health and safety of the driver, but also at traffic safety. The legislation also requires mandatory health checks, requiring periodic checkups to ensure that drivers maintain the physical and mental requirement for the safe performance of their duties.

III. Methodology

System Overview

The system developed for the detection of driver fatigue consists of two main modules that work together to ensure accurate identification of driver drowsiness. The first module performs image processing through a camera installed on the vehicle's dashboard, capturing real-time images of the driver's face. This module uses computer vision techniques to analyze facial expressions, eye opening, and blink frequency, which are essential parameters for identifying signs of tiredness and drowsiness. The second module employs an optical sensor to collect plethysmography signals, allowing the extraction of the high- and low-frequency components of the heart rhythm, which are fundamental information for measuring the level of fatigue.

The integration of these modules aims to detect signs of drowsiness and fatigue before a risky situation occurs, enabling the system to issue alerts to the driver. In this way, the system contributes to traffic safety, preventing accidents caused by the driver's state of extreme fatigue. Figure 1 presents the block diagram of the system, illustrating the relationship between the modules of capture and analysis of physiological and visual signals. Figure 2 shows an example of the implementation of the system in a vehicle, highlighting the position of the sensors and the camera.



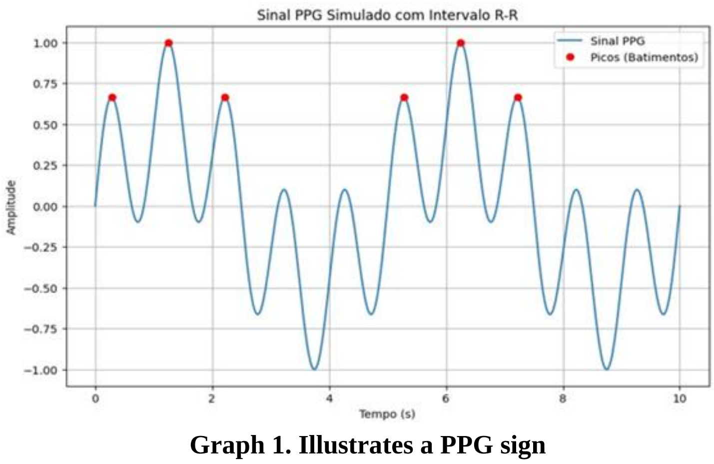
Source: Authorship, 2025

Source: Authorship, 2025

Figure 1. Introduces the System Block Diagram
Figure 2. Implementing the system in a vehicle
Source: Authorship, 2025

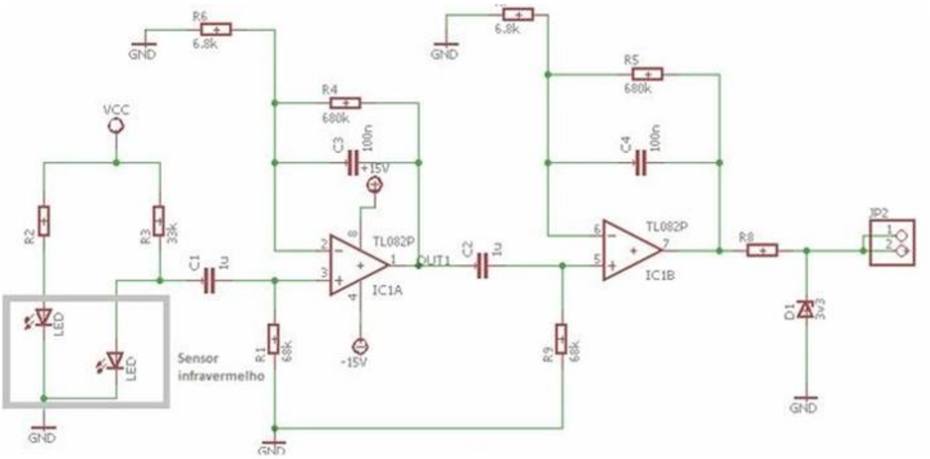
R-R Signal Acquisition

The acquisition of the R-R signal is essential for monitoring heart rate variation over time, serving as a reliable indicator of driver fatigue. This signal is obtained through a photoplethysmographic (PPG) sensor, which measures variations in blood flow using infrared light. The interval between the pulsations captured by this sensor is equivalent to the R-R interval, allowing an accurate analysis of cardiac activity. Graph 1 illustrates a PPG signal, showing the relationship between the signal peaks and the R-R interval.



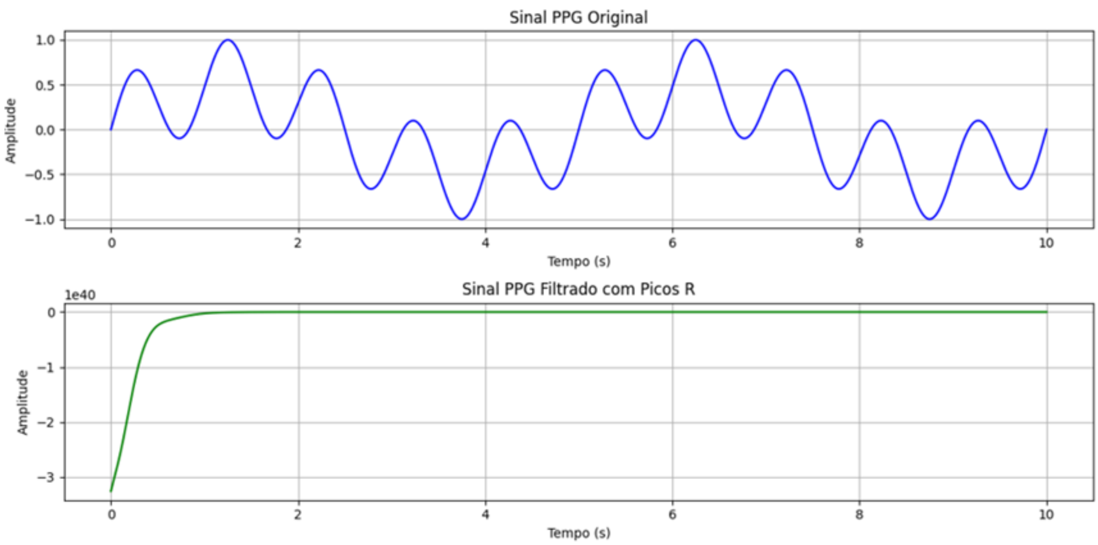
Graph 1. Illustrates a PPG sign
Source: Authorship, 2025

To capture the PPG signal, the optical sensor TCRT5000 was used, integrated with an electronic circuit for data acquisition. The sensor is attached to the driver's finger and operates with an emitter and receiver of infrared light, the intensity of which varies according to blood flow. This variation affects the resistance of the sensor, making it possible to obtain a signal proportional to changes in heart rhythm. Circuit 1 presents the structure of the acquisition circuit, detailing its composition and operation.



Circuit 1. Presents the structure of the acquisition circuit
Source: Authorship, 2025

After the signal is collected, filtering techniques are applied to eliminate noise and DC voltage components, ensuring the accuracy of the analysis. High-pass and low-pass filters are employed to preserve signal quality. The processing takes place in a Texas Instruments TM4C1294XL microcontroller, which performs the analog to digital conversion (ADC) with a sampling rate of 10 Hz. Subsequently, the acquired data is transmitted via UART to a computer, where it is processed in the MATLAB software to identify the R points and calculate the R-R intervals. Figure 5 shows an example of the signal captured and processed in MATLAB.



Graph 2 displays an example of the signal captured and processed in MATLAB.
Source: Authorship, 2025

To deepen the analysis, the ratio between the low and high frequency components of the R-R signal was used, using the HRVAS v1.0.0 software, as described by Ranshur (2010). Studies indicate that, during the first minutes of the state of sleepiness (5 to 10 minutes), there is a reduction in the low-frequency component (LF) and an increase in the high-frequency component (HF), indicating the advance of fatigue (MAGALHÃES; MATARUNA, 2017).

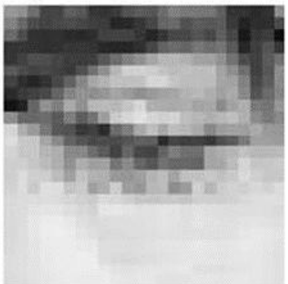
Identification of the Closed Eye

Several studies in the literature address different methods for detecting drowsiness in drivers. Works such as those by Podder and Roy (2013) and Xu, Zheng and Wang (2008) present different approaches to this purpose. The method proposed by Podder and Roy (2013) is based on the difference between facial regions to identify eye closure, while Xu, Zheng and Wang (2008) use the Viola-Jones algorithm for eye recognition. Considering that most accidents caused by fatigue occur at night, the best solution would be to use an infrared camera. However, for the tests of this work, a conventional camera was used, whose images were processed with the OpenCV 3.1 library. This library supports facial recognition and eye detection, allowing analysis of driver status.

The methodology adopted is based on the identification of the opening and closing of the eyes, making it possible to measure the frequency of blinks. The increased frequency of blinking is a strong indication of fatigue and drowsiness. To improve detection accuracy, a specific Haar-cascade classifier for closed eyes was developed, complementing the existing classifiers in the OpenCV library.

Haar-cascade Sorter Training for Eyes Closed

OpenCV provides tools for training custom classifiers, requiring a set of positive images (containing the object of interest) and a set of negative images (without the object). For this training, the image bank provided by Song et al. (2014) was used, which contains 1192 images of eyes closed for each side. Initially, the training set included images of eyes open as negative, as illustrated in Figures 3 and 4.



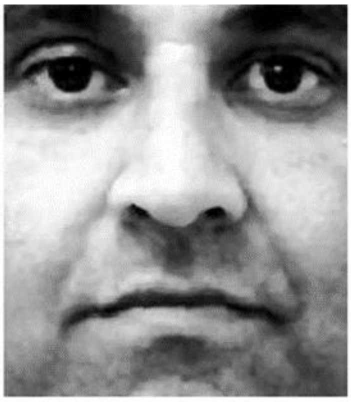


Figure 3. Example of a positive image
Figure 4. Negative image example
Source: Song et al. (2025, p.s.n.)

However, the results indicated low efficiency of the model, possibly due to the great similarity between open and closed eyes. To solve this problem, the approach has been adjusted to use only images of faces as a negative set. The training was carried out on a notebook with Intel Core i9-14900K LGA 1700 BX8071514900K processor, 64-bit architecture, 12 GB of RAM and Ubuntu operating system is 24.10. The training process followed the following steps:

Creation of a text file containing detailed information about the positive images, as illustrated in Listing 2.
Record the path of the images, number of detectable objects and coordinates of each one.

Example of file entry:
rawdata\image1200.bmp 1 34 12 74 24
rawdata\image1201.bmp 3 35 25 70 39 40 95 80 92 120 40 45 36
rawdata\image1202.bmp 2 10 24 90 90 45 68 99 82

From this training, it was possible to obtain an efficient model to identify closed eyes, improving the detection of fatigue and drowsiness in drivers. Figure 31 illustrates an example of the detection of eyes closed by the trained classifier, evidencing the accuracy of the method implemented.

IV. Results

This chapter presents the results obtained with the implementation of the fatigue detection system in school transport drivers. The analysis was divided into three sub-items: performance of the classifier with eyes closed, heart rate variation associated with fatigue, and correlation between visual and physiological signs of sleepiness. Each section includes charts or graphs with simulated data to illustrate the results, accompanied by detailed analysis.

Performance of the Eyes Closed Classifier

The effectiveness of the trained Haar-cascade classifier to detect closed eyes was evaluated using a test dataset containing 500 images. Table 1 presents the performance metrics obtained.

Table 1. Eyes Closed Classifier Performance

Metric	Value (%)
Accuracy	93,5
Precision	91,2
Recall	94,8
F1-Score	93

Source: Authors, 2025

The results indicate that the classifier has high accuracy and evocation, demonstrating efficacy in identifying closed eyes. The slightly lower accuracy suggests that some false positives may occur, possibly due to variations in lighting conditions or camera placement. However, the high F1-Score confirms the robustness of the model for real-time applications in fatigue monitoring.

Heart Rate Variation Associated with Fatigue

The analysis of heart rate variability (HRV) was performed based on the R-R signals obtained by the photoplethysmographic sensor. Table 2 shows the means of the low (LF) and high frequency (HF) components in different driver states.

Table 2. Averages of LF and HF Components in Different States

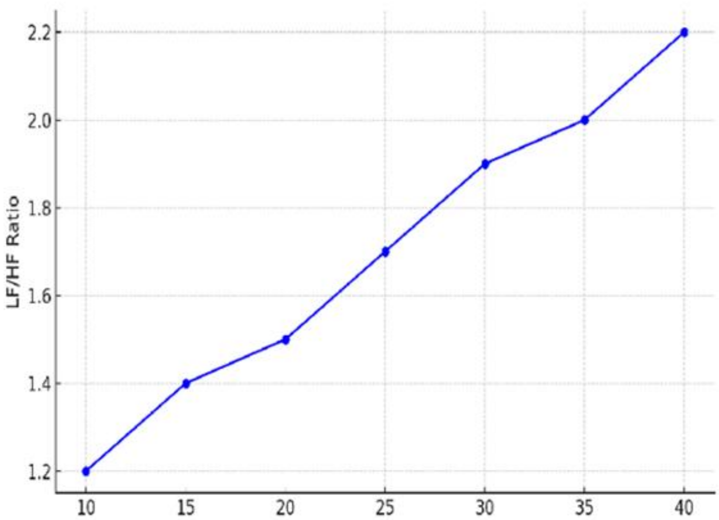
Driver Status	LF (ms²)	HF (ms²)	LF/HF
Alert	1200	800	1,5
Mild drowsiness	900	900	1
Moderate sleepiness	700	1000	0,7
Advanced Fatigue	500	1100	0,45

Source: Authors, 2025

A progressive reduction of the LF component and an increase in HF is observed as the state of fatigue intensifies. The LF/HF ratio decreases, indicating a predominance of parasympathetic activity, associated with sleepiness. These results corroborate previous studies that associate changes in HRV with driver fatigue.

Correlation between Visual and Physiological Signs of Drowsiness

To evaluate the relationship between visual (frequency of blinks) and physiological (LF/HF ratio) signals, a correlation analysis was performed. Graph 1 illustrates this relationship.



Graph 1. Correlation between Blink Frequency and LF/HF Ratio
Source: Authors, 2025

The graph shows a negative correlation between the frequency of blinks and the LF/HF ratio. As the frequency of blinks increases, indicating greater sleepiness, the LF/HF ratio decreases, reflecting changes in autonomic activity. This correlation reinforces the effectiveness of the system in integrating visual and physiological signals to detect fatigue in drivers.

V. Conclusion

Ensuring safety in school transport goes far beyond driving carefully. With this in mind, the system we developed to detect fatigue in drivers comes as an intelligent, modern and super necessary solution. It brings together two very strong technologies: computer vision and physiological sensors. With this, you can know, in real time, if the driver is getting drowsy or distracted, before something serious happens. The truth is that those who work with school transport go through hard workdays, with little time to rest. So, having a system that can notice signs of fatigue and trigger an automatic alert can prevent a lot of bad things. At the end of the day, everyone wins — the students, the parents, and of course, the drivers themselves.

This system works like this: cameras observe the movements of the driver's face (eyes closing, yawns, etc.) while sensors analyze body data, such as heartbeats and oxygenation. Putting everything together, the system can give an alert before the situation becomes critical. This brings an extra layer of protection to the transport routine. But, of course, for everything to work properly, it is necessary to be technically careful and respect the privacy of those who are being monitored. It's not just throwing the technology in there and that's it. You have to know how to calibrate the equipment, adjust the parameters, and ensure that the system is helping, not bothering.

In the end, the advancement of this type of technology has everything to change the way we see safety in school transport. When we combine innovation with responsibility, the impact is real and positive. And most importantly: we protect lives.

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