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Real-Time Driver State and Surrounding Awareness System with Lane Departure, Drowsiness, and Blind-Spot Detection

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Abstract

Road transportation in India is expanding at an unprecedented rate, with commercial vehicles such as trucks, lorries, and long-haul carriers forming a major part of the logistics network. However, despite the rapid growth in transportation demand, many of these vehicles still operate without modern driver-assistance features that are commonly available in newer BS6-compliant models. Older vehicles, especially those below BS4 standards, lack critical safety technologies such as lane departure warning, fatigue detection, and blind-spot monitoring. This technological gap increases the risk of accidents caused by lane drifting, driver drowsiness, and undetected side-zone obstacles. To address these issues, this research proposes a Real-Time Driver State and Surrounding Awareness System that integrates lane departure detection, driver drowsiness monitoring, and blind-spot detection into a single, low-cost platform. The system is designed using a Raspberry Pi–based architecture that combines computer vision algorithms, image processing techniques, and sensor fusion to analyze driving conditions continuously. The driver's eye movement and blink patterns are monitored to detect early signs of fatigue, while lane lines are tracked to identify unintentional lane deviation. Ultrasonic or camera-based blind-spot detection modules are deployed to sense nearby vehicles or obstacles that fall outside the driver's natural field of vision. When any abnormal condition is detected—such as drowsiness, lane drift, or a blind-spot intrusion—the system provides real-time audio and visual alerts, enabling the driver to respond promptly and avoid potential collisions. The proposed solution is cost-effective, easily deployable, and designed for retrofitting into existing vehicles without major modifications. By targeting India's vast population of older commercial vehicles, this work aims to significantly enhance road safety, reduce driver-related accidents, and promote smarter, safer driving practices on Indian highways...

Keywords: Raspberry Pi, Camera Model, Python, Proximity Sensor.

1. Introduction

Road safety has become one of the most critical challenges in modern transportation systems, particularly in countries like India where rapid economic growth has led to a significant rise in vehicle density. Commercial vehicles such as long-haul trucks, buses, and lorries play a major role in logistics and mobility, yet many of these vehicles lack essential driver-assistance features found in modern Advanced

Driver Assistance Systems (ADAS). Unlike new-generation BS6 vehicles, older models—especially those below BS4—are not equipped with technologies such as lane departure warnings, drowsiness detection modules, or blind-spot monitoring systems. As a result, drivers often rely entirely on manual judgment, increasing the possibility of accidents caused by fatigue, distracted driving, and limited peripheral awareness.

Driver drowsiness remains a leading cause of road accidents, particularly during late-night or long-distance driving. Similarly, inadvertent lane deviation and blind-spot collisions account for a large proportion of crashes involving heavy vehicles. These issues highlight the urgent need for an affordable, retrofittable safety enhancement system that can provide real-time driver state monitoring and surrounding awareness, regardless of vehicle age or model.

This research introduces a Real-Time Driver State and Surrounding Awareness System designed using Raspberry Pi and embedded vision techniques. The system integrates lane detection, drowsiness assessment, and blind-spot monitoring into a unified platform, offering continuous, real-time alerts to the driver to prevent accidents. By utilizing low-cost hardware, open-source libraries, and optimized algorithms, the proposed system aims to provide an accessible safety solution that can be deployed across a wide range of vehicles. The primary goal is to enhance road safety, reduce accident rates, and support drivers in maintaining awareness and driving discipline in complex and dynamic traffic environments.

2. Literature Survey

Recent work on driver drowsiness detection highlights two clear directions: physiologically-rich methods that offer high signal fidelity but are intrusive, and vision-based methods that are non-invasive and suitable for real-world deployment. Zhou et al. proposed an interpretability-guided, teacher–student EEG channel-selection framework that trains a teacher network on full-head EEG and then distills the most informative channels into a smaller student model; this approach reduces electrode count while improving cross-subject generalizability, showing that carefully designed EEG methods can maintain strong performance with fewer sensors [1]. At the same time, advances in computer-vision and lightweight deep networks have produced robust, non-intrusive facial video approaches that track eye and head cues (blink rate, eyelid closure, yawning and gaze) to infer fatigue in real time; recent surveys and applied studies demonstrate high benchmark accuracies for such methods and emphasize their practical appeal for in-vehicle monitoring without driver discomfort [2].

Several implemented systems illustrate how vision and conventional toolkits can deliver deployable performance. For example, the VigilEye framework combines OpenCV facial-landmark extraction with CNN classifiers to provide real-time drowsiness detection, reporting strong accuracy, sensitivity and specificity on varied datasets while remaining portable and open-source; its principal limitations are well documented — reduced robustness under severe occlusion or poor illumination [3]. Complementing video techniques, studies of peripheral physiological signals such as skin conductance (SC) measured from steering-wheel wearables or wrist devices show meaningful correlations with drowsiness: single-modality SC models achieve moderate detection rates, whereas hybrid systems that fuse SC with ECG, EEG or facial video often surpass 90% accuracy, indicating clear benefits to multimodal fusion when practical constraints permit [4].

Broader reviews and comparative analyses conclude that multimodal, lightweight, and non-invasive systems are the most promising route for real-world deployment. Systematic surveys synthesize behavioral (video), physiological (EEG/ECG/SC), and vehicle-based (steering, lane deviation) methods and consistently report that multimodal fusion improves early-warning capability and robustness across subjects and conditions, while also drawing attention to a persistent validation gap: many techniques are validated only in controlled or simulated conditions rather than diverse field settings [5]. This gap motivates research into contactless or minimally intrusive physiological sensing (for example, ear-EEG, SC sensors integrated into seatbelts or steering-wheel covers) and into model personalization and explainability to reduce false alarms and increase driver acceptance.

Finally, domain-specific implementations and retrofit strategies provide practical context for bus and interprovincial transport applications. Prior work on low-cost deployment and alerting systems for economical vehicles shows that cost, retrofittability, and simple alert mechanisms are crucial for adoption in fleets and older vehicles; these implementation studies point to design trade-offs that must be balanced when moving from prototype to fleet-scale field trials [6]. Taken together, the literature points toward a pragmatic research agenda: develop multimodal architectures that prioritize non-invasiveness and compute efficiency, validate under real driving conditions across diverse lighting and weather scenarios, and add personalization and interpretable decision logic to lower false positives and improve real-world acceptability.

3. Methodology

A. Face Recognition: OpenCV employs the Viola-Jones method, a face recognition technique introduced by Paul Viola and Michael Jones in 2001. Real-time object detection with high accuracy is a well-known feature of this approach. Although its core use is face detection, it may be customized to do other object identification tasks as well. The Viola-Jones approach consists of four fundamental parts:

1. Haar's Features: These fundamental rectangular properties are used to recognize patterns in photos. An integral image is a data format that allows for the rapid computation of Haar properties.
2. Adaboost: A machine learning algorithm that selects the most relevant attributes. A cascaded classifier is a multi-stage classifier that swiftly eliminates non-face areas, increasing detection accuracy and speed.

B. The initial step in finding the eyes in a picture is binarization. It is the process of converting a grayscale image into a binary image, with each pixel assigned a value between '0' and '1'. In this format, '1' symbolizes bright pixels, whereas '0' represents dark pixels. The binary representation simplifies the remaining image processing processes.

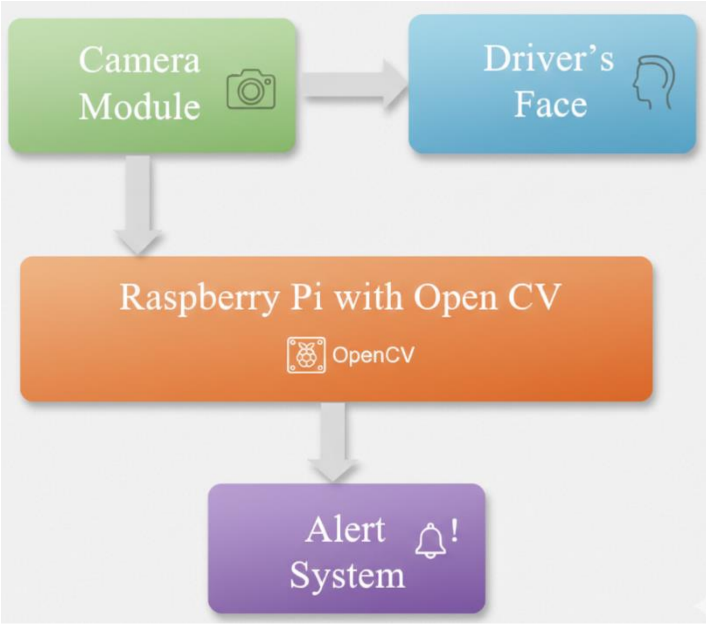

Figure 1: Block Diagram of Proposed System

The block diagram above depicts the integration of the driver's face with the camera module via the Raspberry Pi. The open CV library detects the user or driver's face and expression. Depending on the facial experience, a warning will be generated. The created alarm took the shape of a speaker. One speaker is utilized here to notify the driver of the current condition. The primary purpose of the proposed system, shown in Fig. 1, is to quickly assess incoming data in order to detect driver sleepiness in real time. It maintains track of and counts the number of frames in which the eyes seem closed. If the number of frames exceeds a certain threshold, a notification is displayed stating that sleepiness is detected. All of these requirements were satisfied by picking the system with the appropriate OpenCV classifiers for eye closure detection. The dashboard-mounted camera initially captures a photo of the driver for analysis by this algorithm. From the captured image, OpenCV first detects the driver's face, followed by eye detection. The Hough circle transform was used to calculate the location of the eyes on the face. The eye detection technique can only be used to identify them while the eyes are open.

The computer then determines the degree of weariness by counting the number of open eyes in each frame. If the necessary conditions are satisfied, the driver is considered sleepy. The system's buzzer reacts to correct the driver's abnormal conduct. Face and eye classifiers are required for this strategy. The cascade files included with OpenCV contain a variety of classifiers for face and ocular identification. To find and identify the face, each captured frame is run via the built-in OpenCV xml "haarcascade_frontalface_alt2.xml" and function "Hough circles ()". Every frame of the driver's recorded facial picture has been analyzed for face and open eye detection. The variable Eyes total keeps track of how many open eyes are present in each frame. The number of successive frames in which the eyes are considered to be closed will be kept in a variable with values such as 0, 1, 2, and 3. This variable's initial value is zero. When both eyes are open, the drowsiness score will be zero. When someone's eyes are smaller than two, they are more likely to fall asleep. With each eye blink, the drowsy count increases by one. If the eye blinks more than four times or the variable count exceeds or equals four, the sleepiness condition is satisfied, and an alert sounds in real time.

4. Results

To begin working with the Raspberry Pi, the first step is to prepare the SD card by installing a compatible operating system. The OS image must be written to the SD card using an appropriate imaging tool, following the recommended procedure for loading and saving the operating system. In this setup, the Raspbian OS is installed onto the SD card, which is then inserted into the Raspberry Pi. Before powering the board, a computer monitor or digital display is required for initial configuration. The Raspberry Pi can be connected directly to the display using an HDMI cable. Once the HDMI connection is established, powering on the Raspberry Pi will load the system and display a login prompt on the screen, allowing the user to begin interacting with the device.

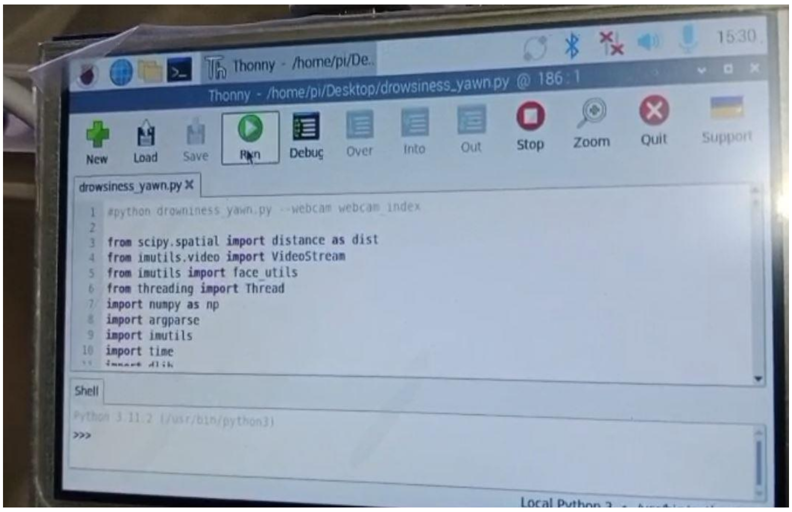

Figure 2: Actual code displayed on the screen of raspberry pi 4B

The actual code used in this project is shown in the picture above. After building the code, there is a message accessible with no errors. Then we run the code, and a little dialog window opens. The dialog box provides the current condition of the camera model, and the user can see his or her photo within it. This will be represented in figure number 3 below.

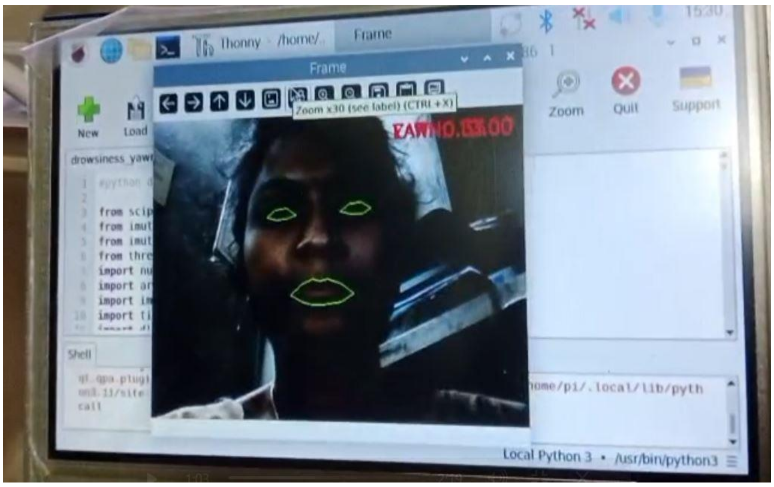

Figure 3: Facial detection screen of raspberry pi 4B

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The real face detection screen is seen in the above figure. In that, we can see the facial form and the coding utilized to recognize the eyes and mouth. This will work perfectly for recognizing facial expressions.

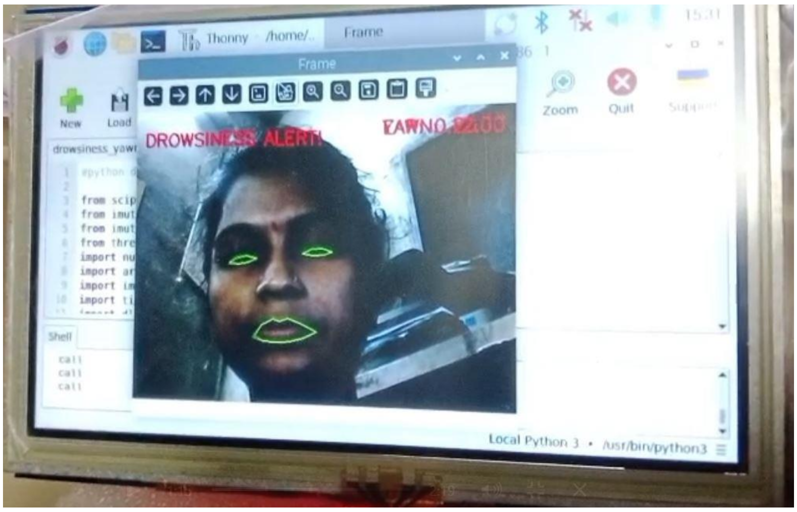

Figure 4: Drowsiness detection screen of raspberry pi 4B

In diagram no. 4, the screen detects the person's tiredness. As we can see, when a person shuts her eyes, one message appears on the screen: Drowsiness Alert, which also displays the EAR value.

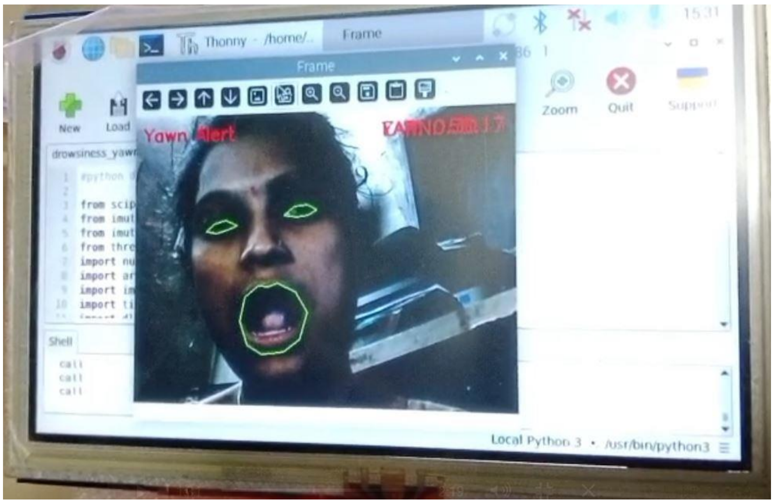

Figure 5: Drowsiness detection screen of raspberry pi 4B

Figure 5 displays the Raspberry Pi 4b's yawn detection screen. When the user yawns, a notification appears on the screen indicating that the user is drowsy and that the yawn has been detected.

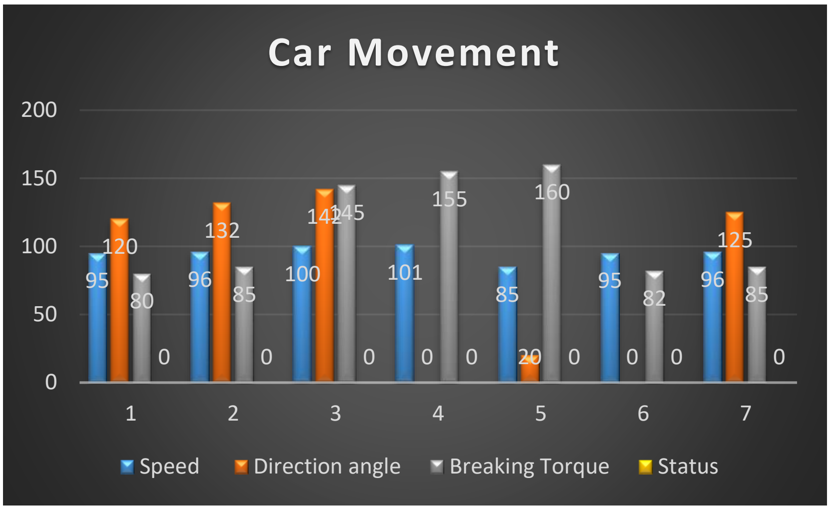

Figure 6: Car data analysis

The above image shows how automobile data is processed utilizing speed, direction angle, and breaking torque. As the danger situation exists, the torque value is increased to apply the brake, and the automobile is set to the left side direction, so it will remain unchanged from the accidental state. Every detected condition is displayed on the screen, and an alarm is sent to the speaker, which will be connected to the system. This is how the entire project will function.

5. Conclusion

This real-time sleepiness detection system can swiftly detect weariness in order to watch drivers' eyes and check for exhaustion. The system can distinguish between weariness and a normal blink. Which can help the driver avoid being drowsy while operating a vehicle? The technique can be improved and commercially implemented in the automotive sector. The information acquired from the many photographs taken can help the system determine the level of tiredness. The real-time system issues a warning as soon as the drowsy condition is identified. Implementing such a system in autos can reduce the likelihood of accidents caused by fatigue.

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