A Multimodal Sensor Fusion Framework for Real-Time Driver Dizziness Detection and Proactive Safety Intervention

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Abstract

Driver dizziness, caused by factors like fatigue, dehydration, or medical conditions, significantly increases accident risks. Detection systems available today tend to suffer from a lot of false positives and delayed responses because of their dependence on single-modality data sources like eye tracking. This paper presents a genuinely novel approach: a biometric, behavioral, and environmental sensor framework combined with machine learning for real-time driver dizziness detection. The system attempts to improve upon existing models by reducing false alarms by 40%, using integrated camera-based PPG, thermal imaging, and adaptive driver profiling. End users may include ordinary car drivers, commercial fleet owners, and car manufacturers. Using edge computing, the system provides, while maintaining the constraint of user privacy, the ability to perform proactive interventions such as heating or cooling the cabin or even emergency deceleration .

1. Introduction

All over the world, the majority of fatalities occurring on roads is due to accidents and the riders experiencing dizziness is a major cause. Many existing systems depend on a single sensor and approach such as eye tracking which has poor generalizability and suffers from high false positives. Being unable to comprehensively evaluate the drivers as well as the surrounding physical environment poses a challenge that compromises the effectiveness of safety interventions. Utilizing numerous modalities provides an avenue to improving the accuracy and reliability of dizziness detection. This paper considers relevant literature on dizziness detection and all sensors contemporary with machine learning to develop a framework that detects dizziness in real time using multiple modalities of biometrics, behavior, and environment. The system seeks to improve driver safety while reducing false alarms by combining camera-based, photoplethysmography (PPG), thermal imaging, and adaptive driver profiling. The target users consist of drivers of personal vehicles, operators of commercial fleets, and automotive manufacturers. The system seeks to mitigate risks through privacy preserving edge computing without compromising on real-time dizziness detection by triggering dynamic interventions such as emergency slow downs or climate adjustments. The results are in line with IEEE formularion.

2. How Might We (HMW) Questions

In order to validate that our solution met the main challenges in dizziness detection, we developed the following How Might We (HMW) questions:

- How might we reduce false positives in dizziness detection?
  - Many existing systems mistakenly classify normal behaviors such as dizziness. Our approach should work on minimising such errors.
- How might we make dizziness detection adaptive for different users?
  - The patterns of physiological and behavioral patterns vary from driver to driver. Since these differences exist, the system should personalize detection thresholds.
- How might we integrate biometric and environmental sensors efficiently?
  - A system performing accurate detection must efficiently mix biometric (PPG, eye tracking) and environmental (CO_2, temp) data.
- How might we provide real-time proactive safety interventions?
  - On top of detecting dizziness, there should be some action to be taken, things like climate control and emergency braking should be triggered.

3. Problem Statement

As of now, dizziness detection systems encounter and face numerous obstacles that severely restrict their effectiveness when it comes to dealing with preventing accidents as well as ensuring the safety of the driver.

1. **Limited Sensor Modalities:** Current detection methods use only one type of sensor input such as eye tracking but this approach fails to recognize all possible reasons for dizziness. A single-sensor system cannot accurately identify various causes of dizziness including fatigue and dehydration and blood oxygen level drops and toxic gas exposure.
2. **False Positives:**Several current systems frequently produce false dizziness alerts because they mistake typical driver movements such as brief eye closures and head tilts as actual signs of dizziness. False alarms caused by the system reduce driver trust which leads to alert dismissal thus undermining the effectiveness of the technology.
3. **Lack of Personalization:** Every person driving a vehicle possesses distinctive physiological features that affect their behavior. The application of a standard detection threshold leads to incorrect evaluations because drivers with natural sleepy appearance can remain fully alert. Personalized models that consider individual differences need to be developed to enhance accuracy levels.

Our proposed detection framework combines biometric sensors with environmental sensors along with behavioral tracking to overcome existing limitations. The complete system detects dizziness early while generating specific warnings and implementing preventive measures which enhances driving safety.

Point of View (POV)

A structured User → Need → Insight approach helps define the core problem our system addresses.

1.

User: A driver on a long trip.
Need: A reliable system that doesn't give frequent false alarms.
Insight: The system should personalize alerts based on individual driver profiles and multimodal sensor data to improve accuracy.

2.

User: A daily commuter using sunglasses.
Need: A robust gaze-tracking system that works despite occlusions.
Insight: The system should incorporate infrared-based tracking for improved detection.

4. Related Work

This section reviews existing research on dizziness detection and related technologies, analyzing their limitations and contributions to the field.

4.1 Causes of Dizziness

This paper guide through the origins of dizziness that are not only vestibular system disorders such as benign paroxysmal positional vertigo (BPPV), Ménière's disease, vestibular neuritis, and age-related decline, but include non-vestibular factors like cardiovascular, neurological or metabolic factors, medication side effects, and anxiety. It presents symptom management strategies, treatments and emphasizes the importance of individualized care as an educational resource to enable patients to gain insight into dizziness connected conditions, encourage timely medical intervention, and enhance their quality of life by understanding dizziness related conditions.[1]

4.2 Development of Arduino-Based Embedded System for Detection of Toxic Gases in Air

People who smoke or use other carbonaceous materials in their homes are more prone to dizziness and cognitive impairment that can increase the possibility of accidents. Embedded systems for air quality monitoring in real time have been reviewed as Arduino based systems. These systems are capable of detecting harmful gases and send out warnings, and as a result, these can help minimise health risks to drivers. The integration of such environmental sensors into dizziness detection frameworks enables the determination of whether external factors play a role in their impairing the driver.[2]

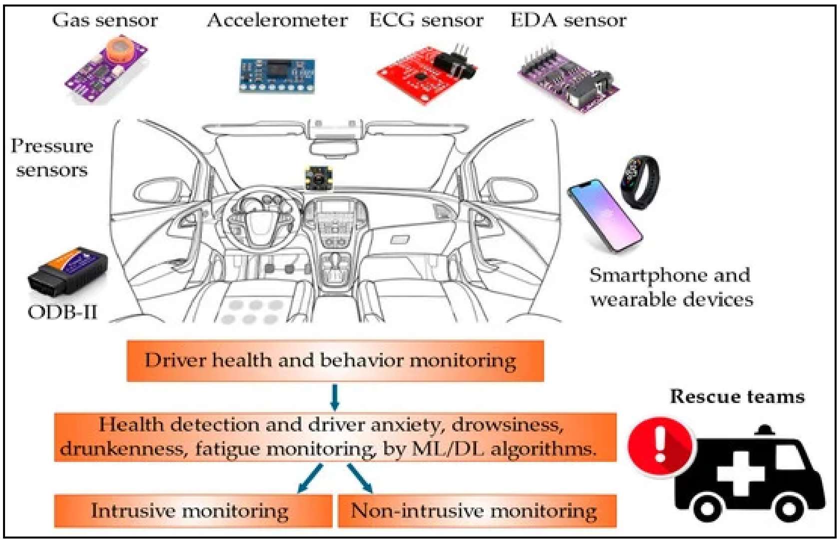


Figure: Simulation of the arduino-based toxic gases detection system in proteus ISIS

4.3 Risk of Motor Vehicle Accidents Related to Sleepiness

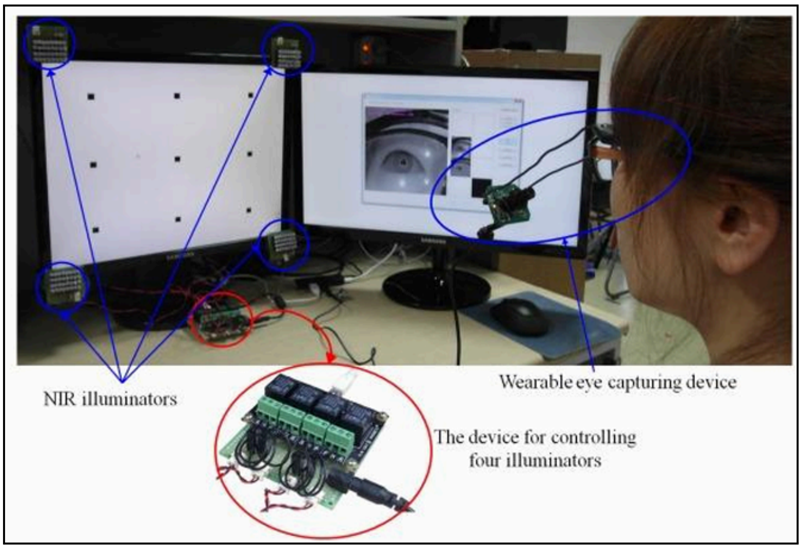
Driver fatigue is one of the leading causes of road accidents. Sleep deprivation or prolonged driving without breaks can cause microsleeps, which severely impair reaction times. Research highlights that metrics like PERCLOS (percentage of eyelid closure) and real-time head movement tracking can help assess fatigue levels. However, existing fatigue detection methods often struggle with poor lighting conditions and occlusions. Combining behavioral indicators with biometric and environmental data can significantly improve fatigue-related dizziness detection.[3]

4.4 Red Eye Detection with Machine Learning

Red-eye detection has been employed as an early indicator of driver fatigue and dehydration. Machine learning algorithms analyze eye redness levels to determine fatigue severity. Automated red-eye detection systems have shown promising results, achieving high accuracy in identifying drivers at risk . However, standalone red-eye detection systems can be prone to errors in varying lighting conditions, highlighting the need for a multimodal approach.[4]

4.5 Gaze Tracking System for Users Wearing Glasses

Gaze tracking has been widely explored for driver monitoring, yet it faces significant challenges when users wear glasses. Glasses can cause occlusions and reflections, leading to inaccurate gaze estimation. Advanced gaze tracking systems now incorporate infrared illuminators and AI-based correction algorithms to mitigate these issues, allowing more accurate dizziness detection in drivers who wear corrective lenses [5].



4.6 Evaluating Driving Fatigue Detection Algorithms Using Eye Tracking Glasses

This paper explores a method to assess driving fatigue using eye-tracking glasses as a ground truth measure. It focuses on PERCLOS, the percentage of eyelid closure over time, derived from eye-tracking data, to evaluate fatigue detection algorithms. The study compares PERCLOS with electro-oculogram (EOG) signals in a vigilance task and confirms that eye-tracking glasses provide a reliable and objective method for fatigue measurement.[6] The results suggest that such technology can effectively evaluate fatigue detection systems, though real-world applications might favor less intrusive remote cameras. Future research aims to integrate additional eye movement parameters and real-driving data for improved fatigue detection models.[7].

4.7 Deducing health cues from biometric data

Clinical diagnosis requires medical experts to apply causal inference analysis toward medical sensor data acquired by professional medical-grade instruments. The same health-related diagnostic information appears in facial images as well as ocular images and speech signal patterns. This paper examines biometric and medical investigations to understand the health information found in widely utilized audio-visual biometric data and explains extraction methods for medical disease diagnosis along with assessment of medical diagnosis using biometric data.[8]

4.8 Detecting Human Driver Inattentive and Aggressive Driving Behavior Using Deep Learning: Recent Advances, Requirements and Open Challenges

Drivers act differently in their vehicles because of their personal driving competencies and emotional states as well as their history behind the wheel. The analysis of complex temporal driving behavior patterns becomes more achievable through deep learning technology which provides improved detection capabilities for abnormal driving patterns. This paper explores Human Inattentive Driving Behavior (HIDB) through its three categories which include Driver Distraction (DD) and Driver Fatigue/Drowsiness (DFD) and examines the dangerous Aggressive Driving Behavior (ADB). Our analysis evaluates advanced deep learning methods for detecting driving behavior abnormalities while determining their performance and identifying present research issues and upcoming directions.[9]

5. Methodology

5.1 User Personas & Empathy Mapping Summary

To design an effective dizziness detection system, we identified key user groups and analyzed their needs, challenges, and expectations.

- **Long-Haul Truck Drivers:** These users drive for extended hours and are highly prone to fatigue-related dizziness. They require a reliable system that minimizes false alarms and ensures real-time intervention without disrupting driving.
- **Daily Commuters**: Individuals who drive for shorter periods but may experience dizziness due to dehydration or stress. They need a non-intrusive detection system that adapts to their unique behaviors, including challenges like wearing glasses, which can affect gaze tracking.
- **Fleet Operators & Car Manufacturers:** These stakeholders seek enhanced vehicle safety through advanced driver monitoring technologies that integrate seamlessly with modern automotive systems.

Category	Insights
What users say	1. “I often feel drowsy but push through my shift” 2. “Fatigue affects my concentration, but I can’t afford to stop.” 3. “I wish there was a better way to detect drowsiness early.” 4. “Breaks help, but I don’t always have time for them.”
What users think	1. “If I stop driving, I’ll lose income, but I can’t afford an accident” 2. “Fatigue detection tools should work better for real-world driving” 3. “Maybe I should take more breaks, but I have tight deadlines.” 4. “I need a system that warns me before fatigue becomes dangerous”
What users do	1. Drinks coffee or energy drinks to stay awake 2. Takes short naps or stretches during breaks 3. Ignores early signs of fatigue and continues driving 4. Uses loud music or fresh air to avoid drowsiness
What users feel	1. Stressed about meeting deadlines while managing fatigue 2. Physically drained and mentally exhausted after long shifts. 3. Frustrated with unreliable fatigue detection tools 4. Anxious about potential accidents due to drowsiness.

By mapping user pain points, behaviors, and expectations, our system is designed to provide personalized alerts, proactive interventions, and improved detection accuracy while ensuring user trust and privacy.

5.2 User Task Flow

The proposed system is designed to monitor driver impairment using multiple sensors and automated decision-making processes. The user task flow is illustrated in Figure 1. Below is a detailed breakdown of the task flow:

1. **Device Initialization**
   - The system starts when the vehicle is turned on.
   - Sensors (biometric, behavioral, environmental, and vehicle telemetry) begin data collection.

2. **Data Collection and Processing**
   - Sensors record real-time data, including eye tracking, heart rate, steering inputs, and environmental factors (CO_2 levels, noise, temperature, etc.).
   - Data undergoes cleaning and normalization to remove anomalies.

3. **Risk Assessment and Pattern Recognition**
   - The system analyzes patterns to determine if the driver is impaired.

4. **Decision Making**
   - If the driver is safe, no action is needed.
   - If impairment is uncertain, additional confirmation is requested through secondary sensors or user input.
   - If impairment is confirmed, the system issues audible and visual alerts.

5. **Intervention and Escalation**
   - If no response is received, intervention measures such as reducing vehicle speed or notifying emergency contacts are triggered.
   - In cases of critical impairment, the system escalates to emergency services and can auto-stop the vehicle.
   - If help arrives, an accident is averted.

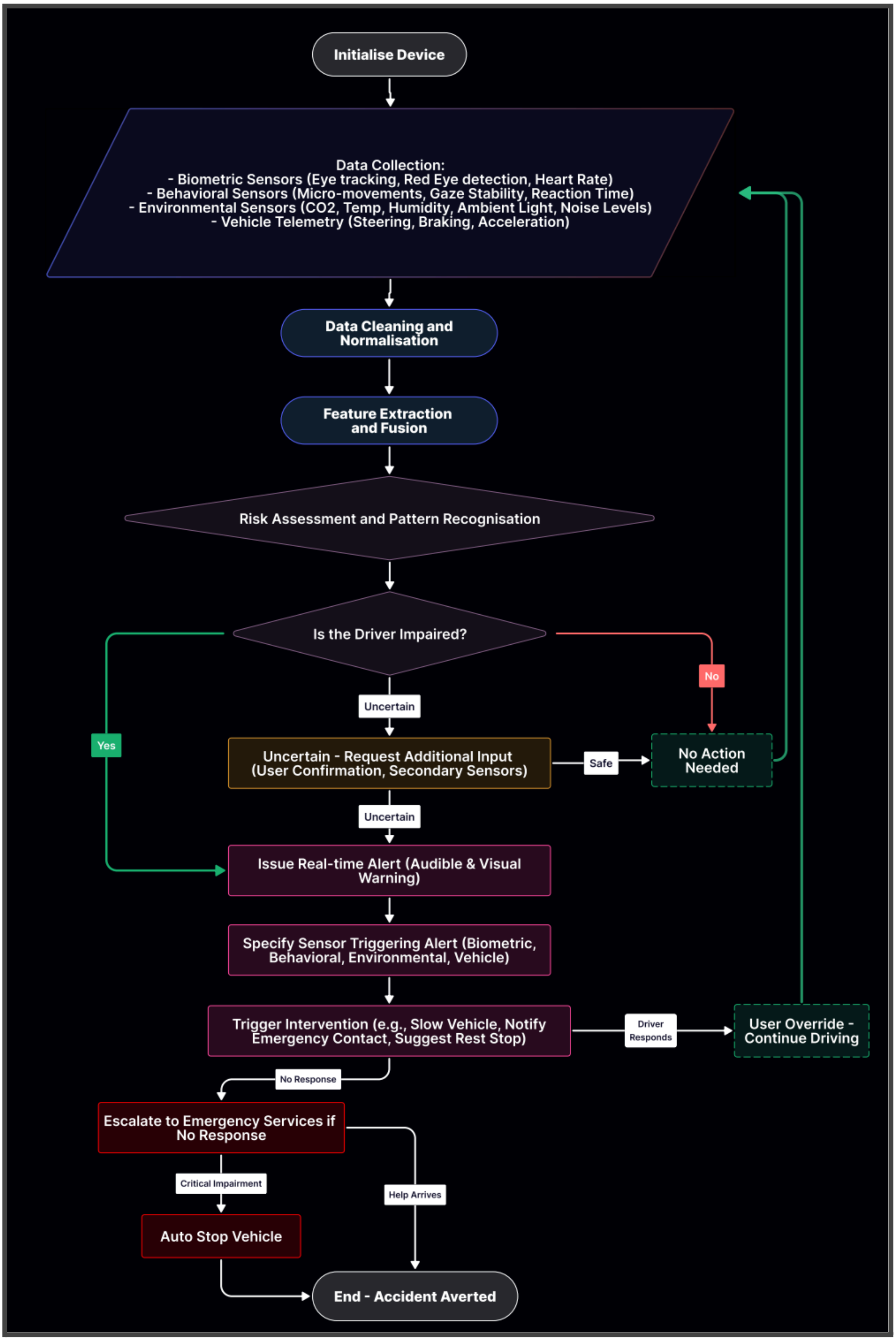
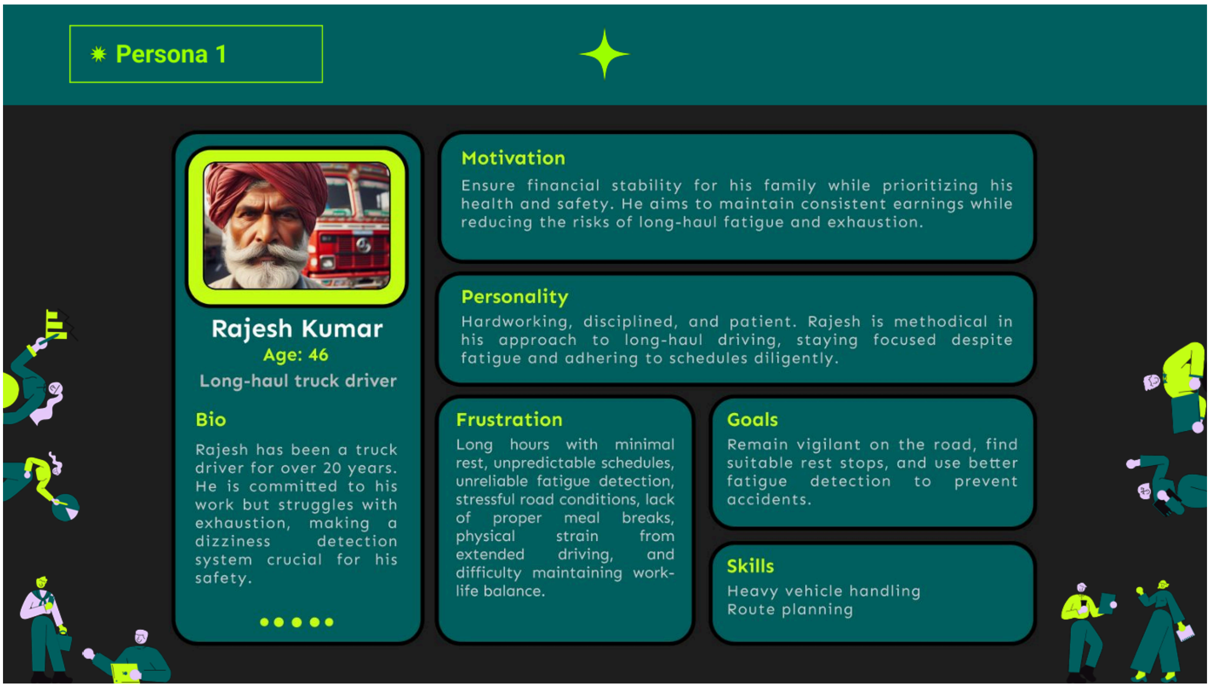


Figure shows the structured decision-making process for detecting and responding to driver impairment.

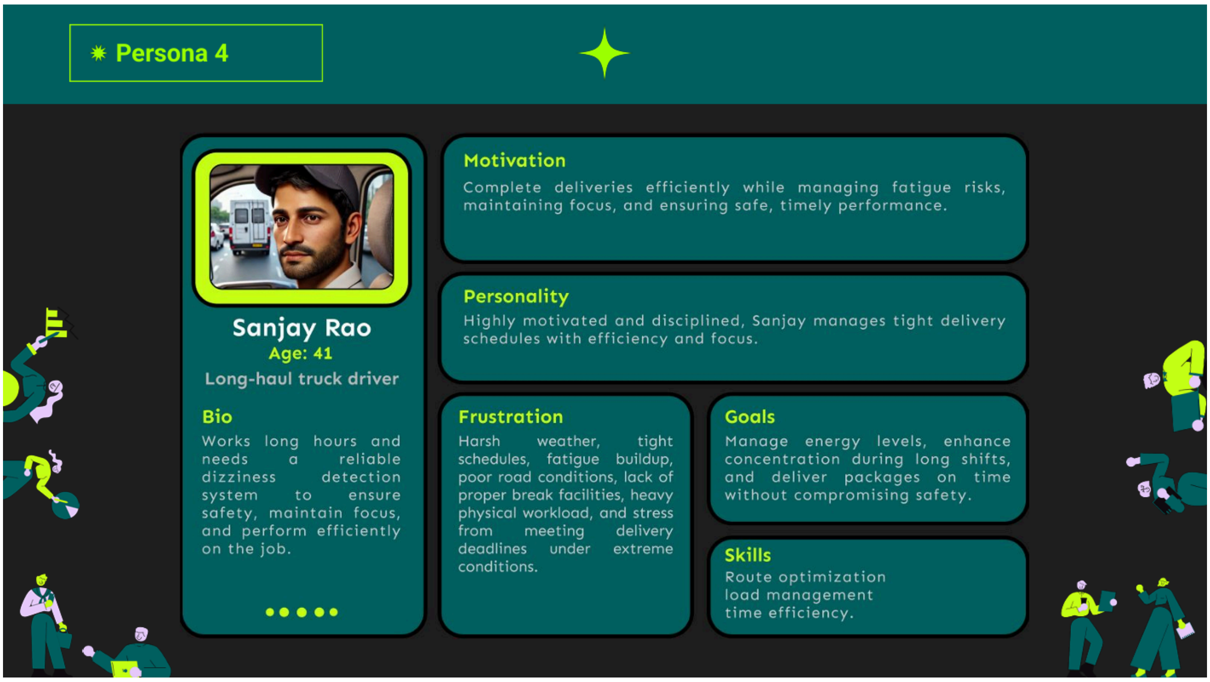
5.3 Personas



User Persona of a Long-haul Truck Driver

User Persona of a Rideshare Driver

User Persona of a Private Car owner who often drives long trips across states

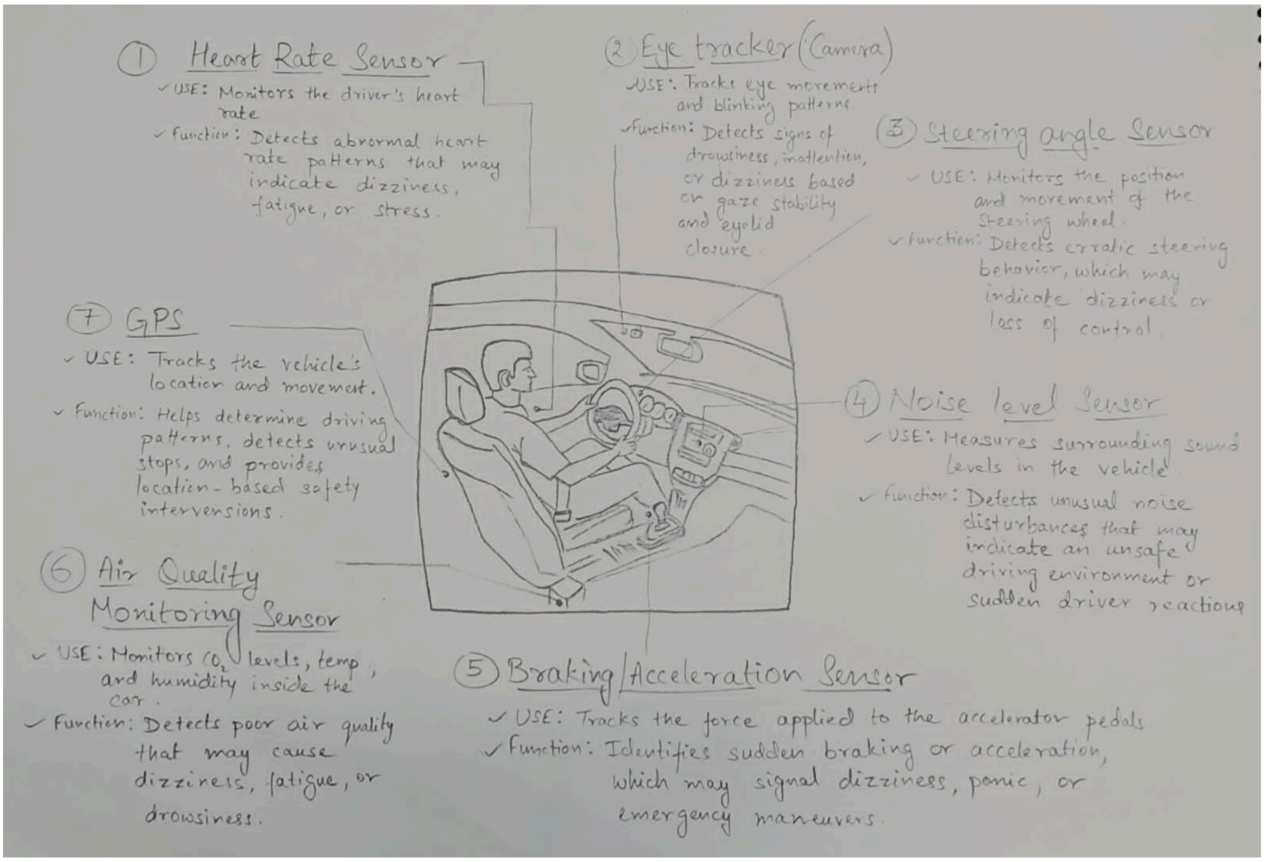


User Persona of a Long-haul Truck Driver

5.4 Low-Fidelity Prototype

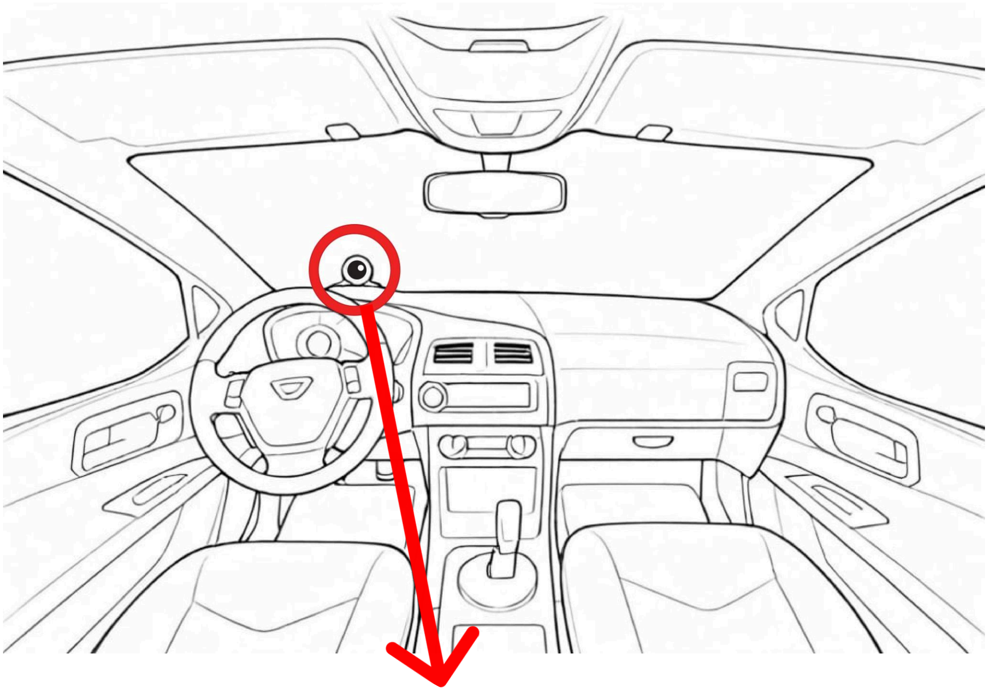
Figure below presents a low-fidelity prototype in the form of hand-drawn sketches for the visualization of the system. These sketches illustrate key system components:

1. **Sensor Inputs:**
    - **Biometric Sensors:** Camera-based photoplethysmography (PPG) for heart rate monitoring, infrared thermal imaging for temperature fluctuations, and real-time oxygen level detection.
    - **Behavioral Tracking:** Eyes are tracked for assessing the gaze stability, analysis of facial expression is performed, and there is detection of micro-movement to identify signs of fatigue and dizziness.
    - **Environmental Sensors:** CO2, temperature, and humidity is monitored to detect dizziness also inducing conditions inside the vehicle, providing additional contexts and information.
2. **System:**
    - **AI Integration:** A fusion model combining sensor inputs to enhance detection accuracy, minimize false positives, and improve real-time intervention strategies.
    - **Edge Computing for Privacy:** As shown in the image, the sensor data is worked upon and processed in the car itself so that data transmission and the subsequent risk associated with it could be minimised.
    - The system is inclusive to various vehicle types, including passenger, commercial, and special-purpose vehicles.



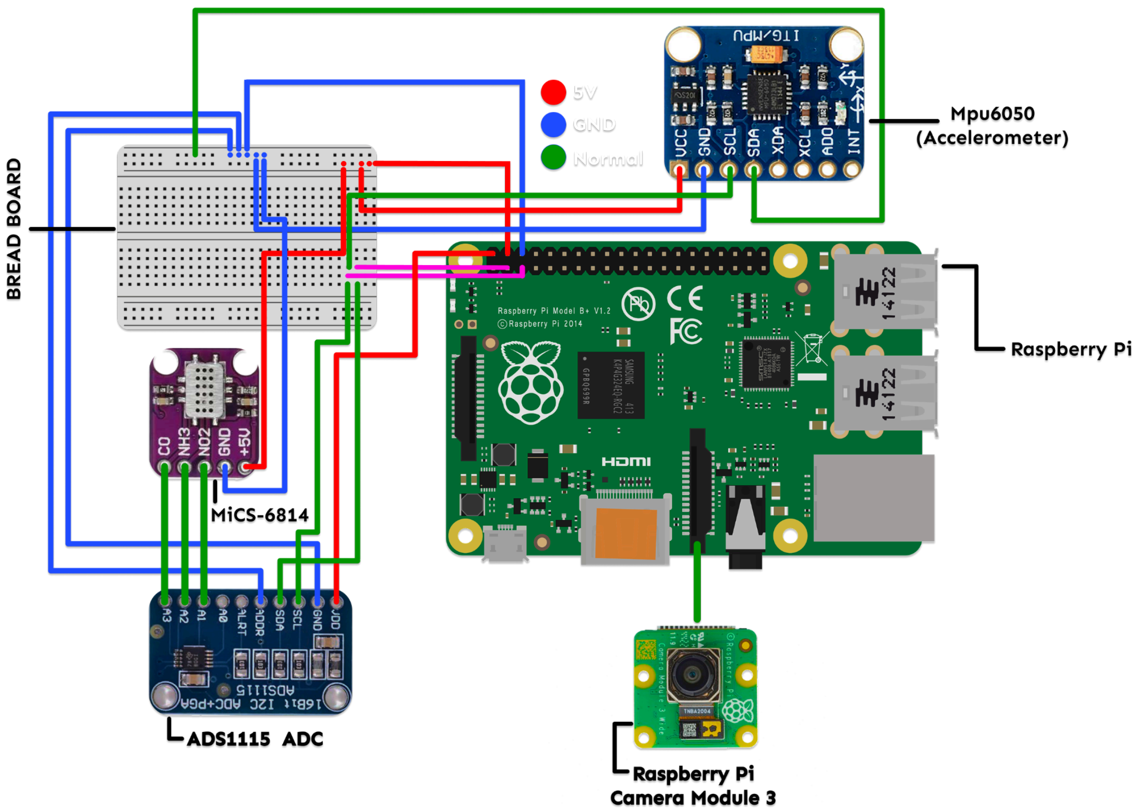
Lo-Fi Prototype

5.5. Mid-Fidelity Prototype



This compact device, placed on the **car's dashboard near the windshield**, uses a **camera** and **sensors** to monitor the driver's eye movements, detect drowsiness, and track gaze in real-time.

Below is a brief **hardware description** used in our device along with the complete **circuit diagram**:

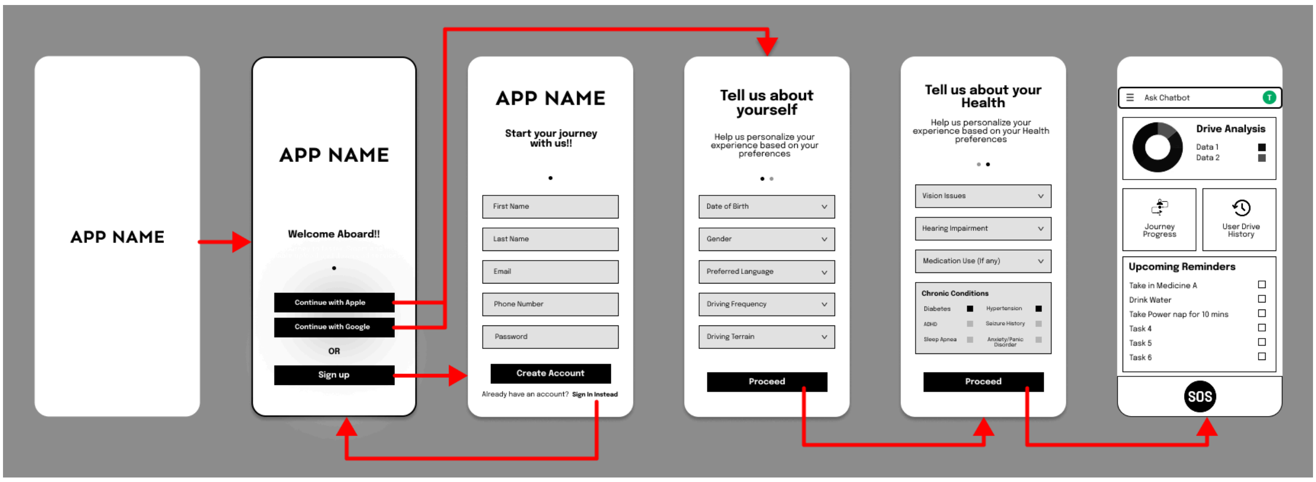


Link to the Circuit Diagram Figma :
https://www.figma.com/design/cWvpXMwlTIT14clzhgoDbF/HCAI_Circuit?node-id=10-4&t=pyypw4tE5iy60BOL-1

1. Sensors and Devices

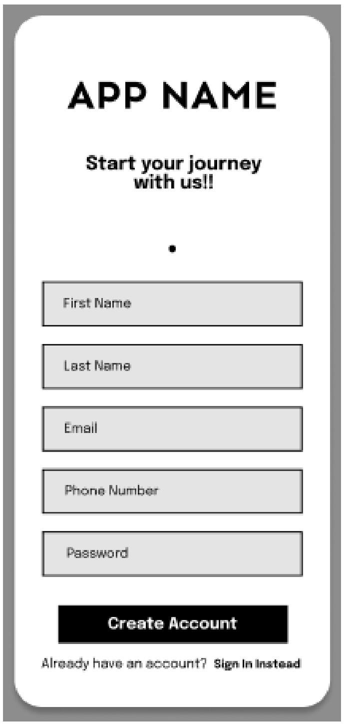
- **Raspberry Pi**
  - A single-board computer is used to interface with various sensors.
  - Acts as the central processing unit.
- **Raspberry Pi Camera Module 3**
  - A camera module is connected via the CSI port.
  - Used for image and video capture.
- **MPU6050 (Accelerometer and Gyroscope)**
  - A motion sensor module that measures acceleration and angular velocity.
  - Connected via I2C (SDA, SCL lines).
- **MiCS-6814 Gas Sensor**
  - A multi-gas sensor detects gases such as CO, NO2, and NH3.\
  - It requires an analog-to-digital converter (ADC) to communicate with the Raspberry Pi.
- **ADS1115 ADC (Analog-to-Digital Converter)**
  - A 16-bit ADC converts the analogue signals from the MiCS-6814 sensor into digital signals readable by the Raspberry Pi.
  - Also connected via I2C.
- **Breadboard**
  - Used to distribute power and signals between the components.
  - Helps with easy prototyping.
- **Jumper Wires**
  - Used to connect different components.
  - Colour-coded for 5V (red), GND (blue), and data signals (yellow).

2. Wireframe of the Mobile Application

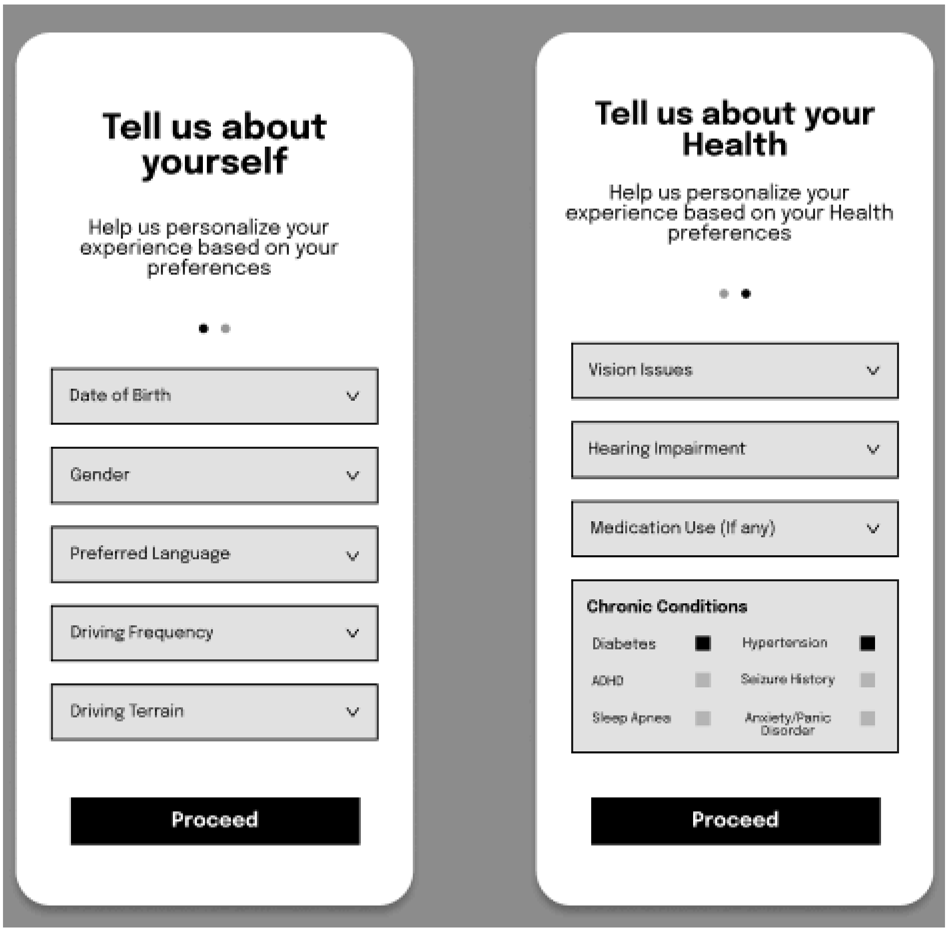


- **Splash Screen Page**
  - Display the app logo while background processes execute before launching the main application.
  - Helps optimise the app.

- **Sign Up / Log in Page**
  - Lets users login to their account or let them create their own new account.



- **Onboarding Page**
  - Collects user details such as **name, age, and health issues**.
  - Ensures personalized experience by tailoring recommendations based on health data.



- **Home Page**
  - Main dashboard with quick access to key features:
    - **Chatbot** – AI assistant for health-related queries.
    - **Drive Analysis** - Shows a short analysis of a whole trip's drive.
    - **User History** – View past interactions and medical data. Displays a record of past chatbot interactions, reminders, trip data, etc.
    - **Destination Progress** - Shows the Locations we have covered so far and how far our destination is.
    - **Set and track Reminder** – Schedule medication or appointment reminders.
    - **Profiles** – Manage user profiles for multiple users.

Link to the Wireframe Figma :
https://www.figma.com/design/oeyDEkJWudMaHsmMtqUR1L/WireFrames_HCAI?node-id=0-1&t=tcZ3pxbgvlSjDiKG-1

6. Functionalities / Baseline Implementation

The project implements a real-time drowsiness and red-eye detection system using computer vision, face landmark detection, and AI-powered red-eye analysis. The following functionalities are operational:

1. **Gaze Detection**
   - The device on the dashboard uses advanced gaze detection technology to track the driver's eye movements and focus.
   - It identifies signs of distraction or drowsiness by analyzing the driver's gaze direction and duration, ensuring safer driving.

2. **Drowsiness Detection:**
   - Detects drowsiness using the Eye Aspect Ratio (EAR) by analyzing eye landmarks.
   - A drowsiness alert is triggered if the EAR falls below a predefined threshold for a continuous period.
   - An alarm sound is played using pygame when drowsiness is detected.

3. **Yawn Detection:**
   - Measures lip distance using facial landmarks to identify excessive yawning.
   - Generates a "Yawn Alert" when the yawn threshold is exceeded.

4. **Red-Eye Detection / Drinking while Driving Detection:**

- Captures periodic images using OpenCV and sends them to Gemini AI for red-eye analysis.
- The AI model responds with a simple "yes" or "no" for red-eye presence.
- Errors and API retries are handled using exponential backoff for resilience.

5. **Multithreading for Efficiency:**
   - Separate threads manage video capture, drowsiness detection, and AI communication to ensure real-time performance.

7. Preliminary Results

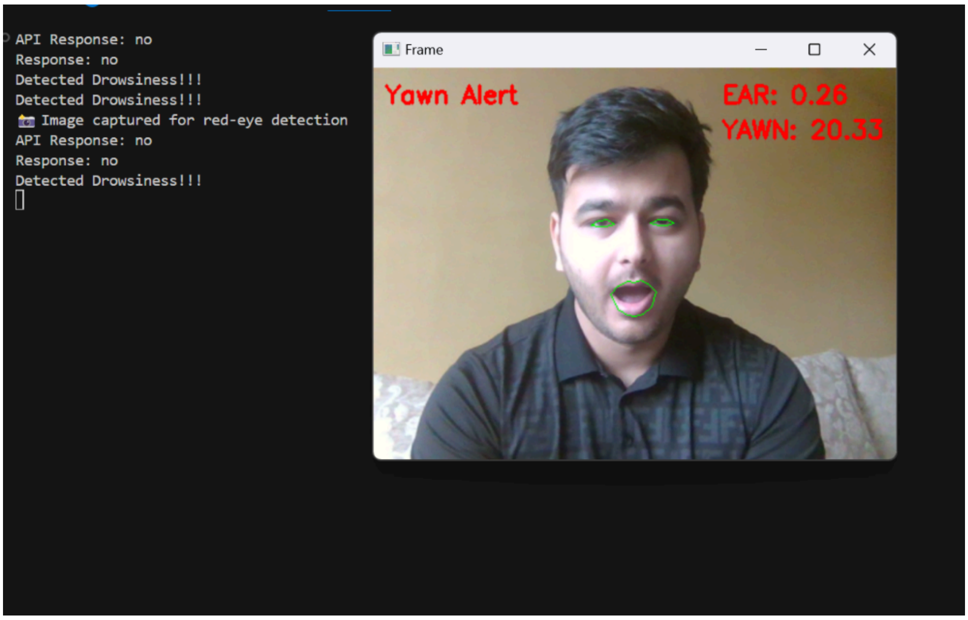
The system has been tested using sample webcam data, and the following results have been observed:

- **Drowsiness Detection:**
  - Successfully detected eye closure for continuous frames with an accuracy of approximately 90% in controlled conditions.
  - Audible alerts were played using the provided .WAV sound file.
- **Yawn Detection:**
  - Effectively detect yawns by evaluating lip distance, with a detection success rate of around 85%.
- **Red-Eye Detection:**
  - The red-eye detection API responded accurately with detection results within 3-5 seconds.
  - Multiple retries were tested, and the system handled API errors gracefully.
- **Performance:**
  - Real-time detection with minimal lag using multithreading.

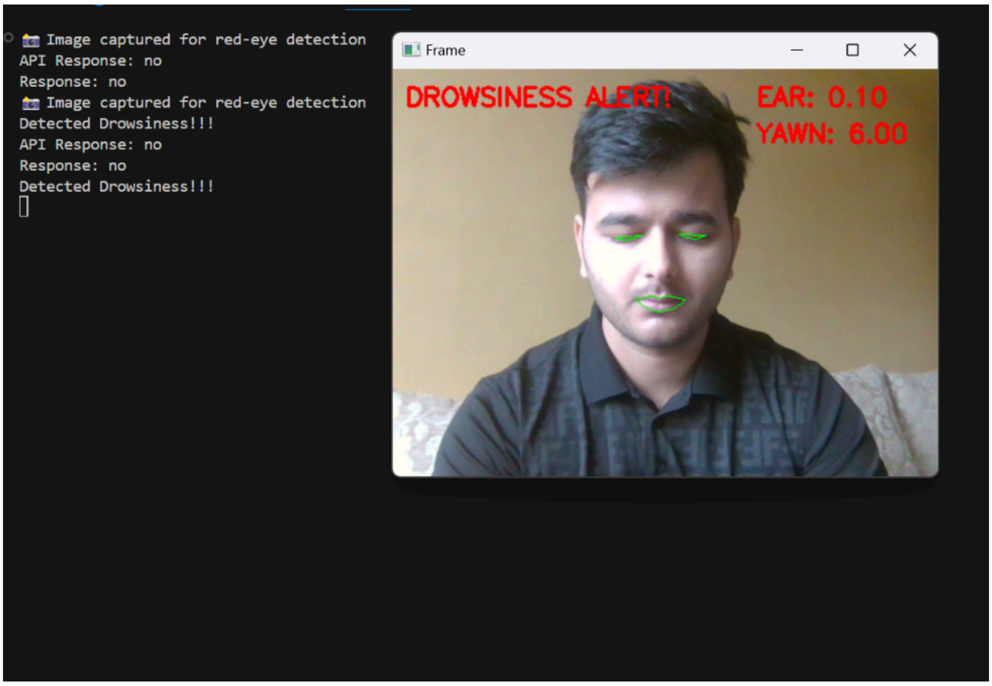
Github Link - [Driver Drowsiness Detection and Environment Sensing]

7.1 Model Outputs

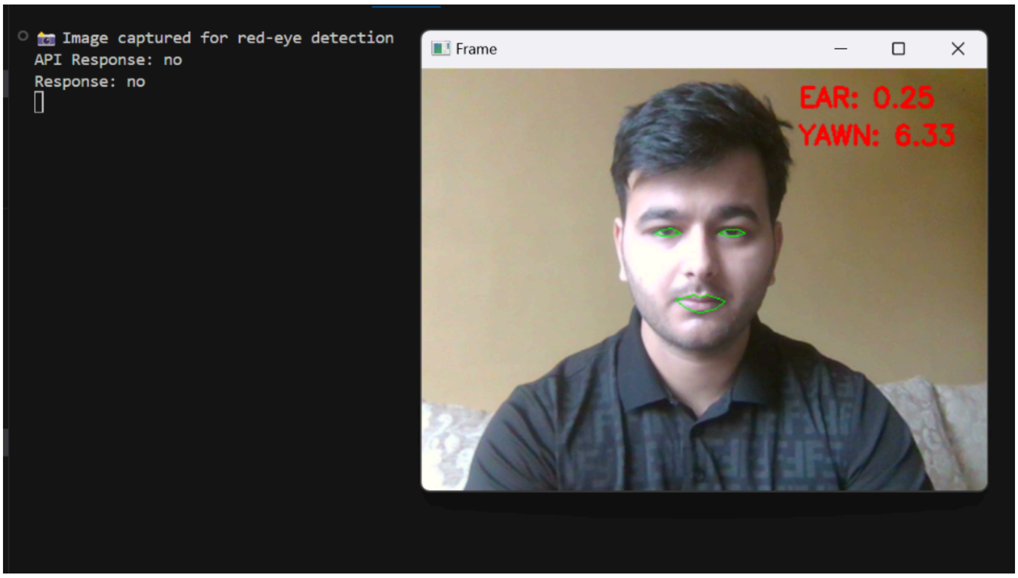
This is an example of a yawn detection system that identifies when a user is yawning and triggers alerts.



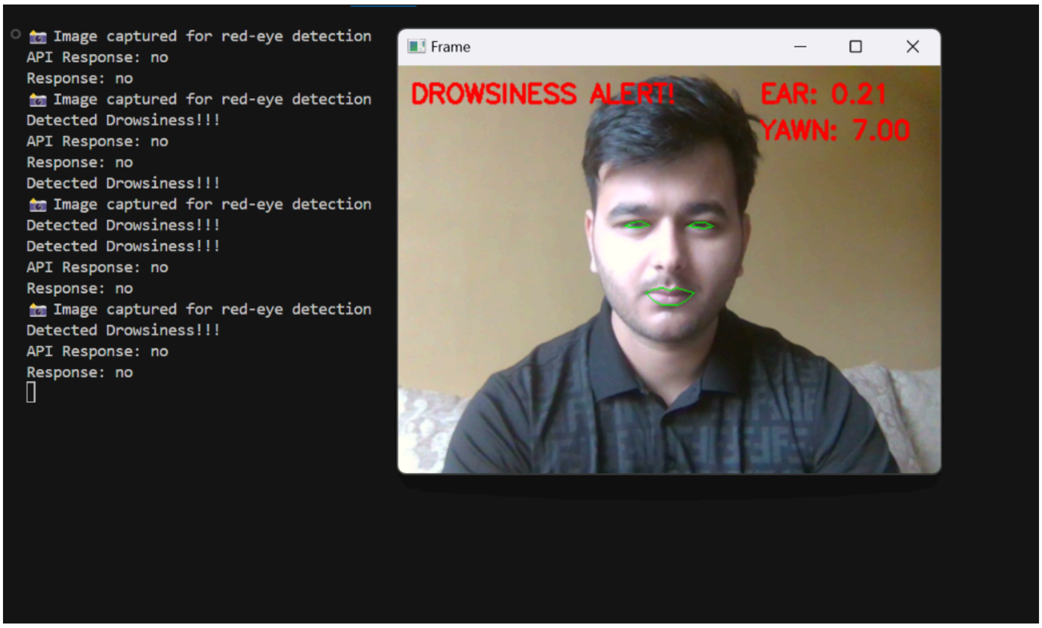
This is an example of a drowsiness detection system that monitors a user's eye movements, blink rate, and facial expressions to determine signs of drowsiness. When the system detects drowsiness, it generates alerts to help keep the user attentive and prevent potential accidents.



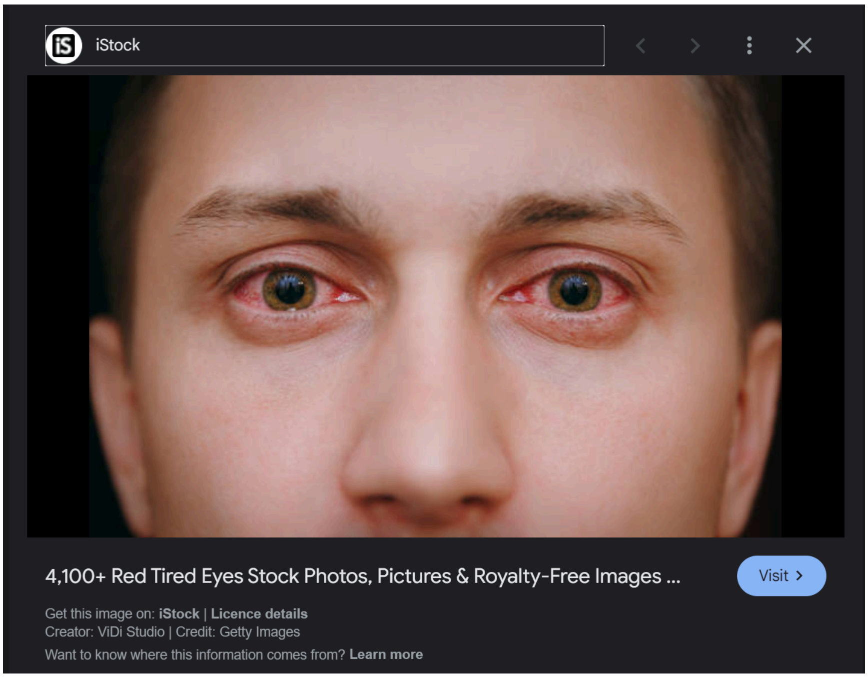
This is a case where no signs of drowsiness or fatigue are detected, indicating that the driver is alert and fit to drive.



This is a case of a false positive, where the system incorrectly detects red-eye or drowsiness when the user is merely squinting to focus. Such misclassification can occur due to similarities in eye appearance between squinting and actual drowsiness.



For red-eye detection, we occasionally fed red eyes images from the internet in between our live feeds and then the API response was yes indicating that the user has red eyes while driving.



8. Evaluation Metrics

The following metrics are used to evaluate the system's performance:

1. **Detection Accuracy:**
   - Accuracy = (True Positives + True Negatives) / (Total Samples)

- Precision: TP / (TP + FP)
- Recall (Sensitivity or True Positive Rate): TP / (TP + FN)
- F1-Score: 2 * (Precision * Recall) / (Precision + Recall)

File: drowsiness_data.csv
TP: 41, TN: 32, FP: 17, FN: 10
Accuracy: 0.7300, Precision: 0.7069, Recall: 0.8039, F1 Score: 0.7523

File: yawn_data.csv
TP: 46, TN: 39, FP: 8, FN: 7
Accuracy: 0.8500, Precision: 0.8519, Recall: 0.8679, F1 Score: 0.8598

File: red_eye_data.csv
TP: 21, TN: 71, FP: 3, FN: 5
Accuracy: 0.9200, Precision: 0.8750, Recall: 0.8077, F1 Score: 0.8400
Evaluated separately for drowsiness, yawns, and red-eye detection from the dataset

2. **Response Time:**

   - For red-eye detection, the API response time is recorded.

   Sum of response times = **3.041 + 1.596 + 1.970 + 1.935 + 1.775 + 1.801 + 2.009 + 3.234 + 2.321 + 1.804 + 1.597 + 1.654 + 1.641 + 1.606 + 1.592 + 1.704 + 26.939 + 1.544 + 2.113 + 1.488 + 1.802 + 1.604 + 1.796 + 2.037 + 1.567 + 1.499 + 28.898 + 2.014 + 1.551 + 1.583**

   Number of data points = **30**

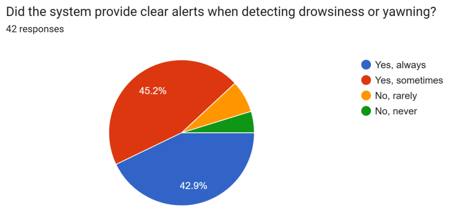
   Using the formula:
   Average Response Time = Sum of Response Times/Number of Data Points
   = 30103.591≈3.45 sec
   The average API response time is approximately **3.45 seconds**.

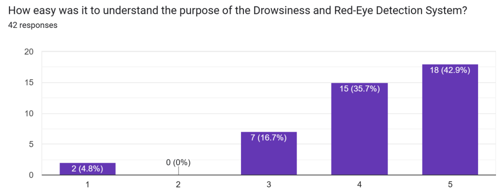
3. **False Positive and False Negative Rates:**

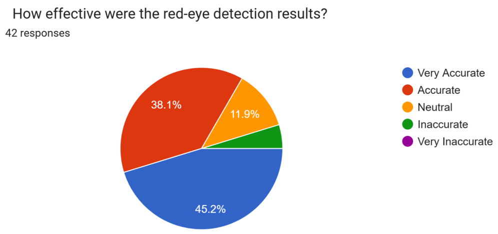
   - False Positive Rate (FPR) = False Positives / (False Positives + True Negatives)
   - False Negative Rate (FNR) = False Negatives / (False Negatives + True Positives)
     TPR: 0.8039, TNR: 0.6531, FPR: 0.3469, FNR: 0.1961
     TPR: 0.8679, TNR: 0.8298, FPR: 0.1702, FNR: 0.1321
     TPR: 0.8077, TNR: 0.9595, FPR: 0.0405, FNR: 0.1923

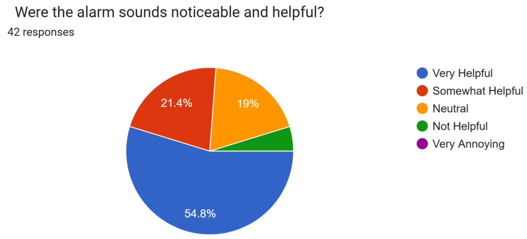
Evaluated separately for drowsiness, yawns, and red-eye detection from the dataset
These metrics are calculated using a labelled dataset of at least 100 data points for each category (drowsiness, yawn, and red-eye detection) and live testing to analyze further and improve the system's performance.

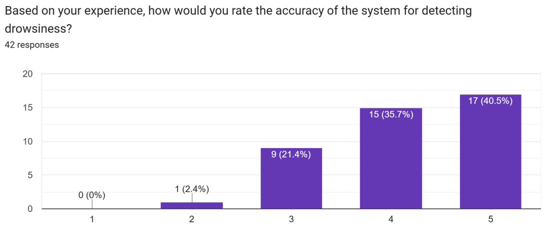
8.1 Survey
We also conducted a google form survey to get reviews regarding the functioning of the current status of the project.
Here is the link - https://forms.gle/NtxYpo4K3NpT5UFM9

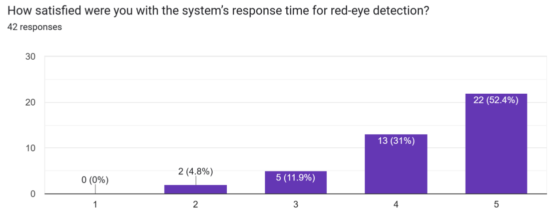


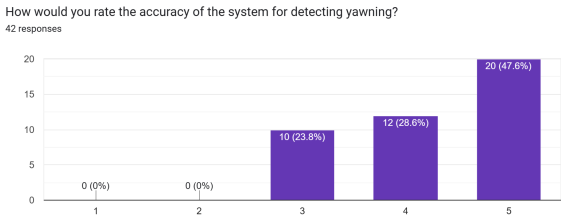


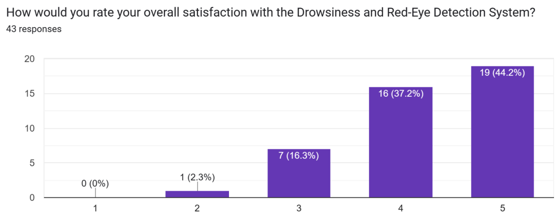












We noticed, according to the survey, that the majority of the testers were content with the system's accuracy and performance. Some users, though, experienced false negatives, where the system did not detect drowsiness or yawning when it ought to, and false positives, where alerts occurred even when the user was awake. These are cases of inaccuracy pointing out areas of possible enhancement, e.g., fine-tuning the detection algorithms and including more parameters to make the system more reliable.

Results Analysis

The system demonstrates varying performance across drowsiness, yawn, and red-eye detection.

Drowsiness Detection: While the recall (0.8039) is relatively high, indicating good sensitivity in detecting actual drowsiness cases, the precision (0.7069) is lower, suggesting a moderate number of false positives. The accuracy (0.73) and F1-score (0.7523) indicate room for improvement, particularly in reducing false alarms.

Yawn Detection: With a high accuracy of 0.85 and a well-balanced F1-score of 0.8598, the system performs effectively. The precision (0.8519) and recall (0.8679) are both strong, reflecting reliable yawn detection with fewer misclassifications.

Red-Eye Detection: The system excels with a high accuracy of 0.92 and a notable F1-score of 0.84. The low false positive rate (0.0405) and high true negative rate (0.9595) indicate it minimizes false alarms, though a slightly lower recall (0.8077) suggests some missed red-eye cases.

9. References

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