DRIVER DISTRACTION SYSTEM

By

JAWAD MAIMANI	**2136574**	**COE**
ZYAD ALZHRANI	**2138321**	**COE**
ABDULLAH ALGHAMDI	**2136513**	**COE**

TEAM NO.: ______14________ **FALL 2024 INTAKE**

Project Advisor

DR. MUHAMMAD SHEHZAD HANIF

Project Co-advisor

DR. MUHAMMAD BILAL

Project Customer

DR. MUHAMMAD BILAL

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ABSTRACT

DRIVER DISTRACTION SYSTEM

Driver distraction remains a significant contributor to road accidents worldwide, making the development of systems capable of detecting and mitigating such distractions essential for road safety. This project addresses this critical issue by designing a Driver Distraction Detection System that leverages advanced computer vision and deep learning technologies. The system aims to identify common driver distractions, including mobile phone use, talking to passengers, and the absence of hands on the steering wheel.

By utilizing the YOLOv8 model with Oriented Bounding Boxes (OBB), the system offers real-time, accurate detection of distractions with a high degree of localization precision. The solution incorporates both infrared (IR) and RGB cameras, ensuring reliable performance across varying lighting conditions, including day and night driving. The system provides immediate auditory alerts to warn drivers of detected distractions and generates detailed reports on the driver’s behaviour, which can be accessed for further analysis by fleet managers or safety auditors.

The development process also emphasized ease of installation, ensuring the system could be easily integrated into vehicles without major modifications. Additionally, the system is designed to operate under diverse temperature and environmental conditions, using a 12V vehicle power supply. The project meets the primary design requirements, achieving an accuracy rate of over 80%, and presents a robust solution for enhancing road safety by reducing the risks associated with distracted driving.

Index Terms — Driver Distraction, Computer Vision, YOLOv8, Real-Time Monitoring, Fleet Management, Road Safety, Deep Learning.

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CHAPTER – 1 INTRODUCTION

1.1 BACKGROUND

Driver distraction is a critical issue in modern transportation, leading to significant road risks. According to recent data from the World Health Organization (WHO) and the National Highway Traffic Safety Administration (NHTSA), driving accounts distracted for a large proportion of traffic accidents globally [1]. In Saudi Arabia, the General Department of Traffic revealed alarming statistics, stating that 78% of head-on collisions in the country are caused by drivers using mobile phones while driving [2]. This highlights the pressing need for innovative solutions to address any action that can lead to driver distractions,

Distraction can arise from various sources, including mobile phone usage, adjusting vehicle controls, or engaging in conversations, even eating while driving. These distractions affect critical driving tasks, delaying reaction times and reducing the ability to maintain safe driving practices. The physics of this issue lies in the delayed responses to road hazards, which, combined with vehicle speed and stopping distances, can lead to severe or fatal accidents.

Addressing driver distraction through engineering requires the development of advanced systems that monitor and detect when a driver is no longer focused on the road. By analyzing eye movements, head positions, and manual actions (like handling a phone), the system can assess whether a driver is distracted and issue timely warnings. This proactive approach can significantly reduce the likelihood of accidents and provide public safety.

1.2 PROBLEM STATEMENT

In today's world, driver distraction has become a significant contributor to road accidents globally. With the increasing use of smartphones, in-car entertainment systems, and other electronic devices, drivers are often diverted from focusing solely on the road. This diversion of attention can lead to delayed reaction times, impaired decision-making, and ultimately, accidents that could have been prevented. Driver distraction refers to any activity that diverts a driver's attention away from the primary task of operating the vehicle safely. Driver distractions can be broadly classified into four main categories: visual distraction (Occurs when the driver's eyes are taken off the road), auditory distraction (involves sounds that divert the driver's attention from driving), manual distraction (happens when the driver takes their hands off the steering wheel), and cognitive distraction (Occurs when the driver's mind is not focused on driving [3].

Implementing a driver distraction detection system can also significantly benefit fleet management in logistics organizations. By monitoring drivers' attentiveness in real-time, fleet managers can ensure that drivers remain focused, thereby reducing accident risks and enhancing overall safety. This proactive approach can also help in reducing operational costs related to accidents and vehicle damage while ensuring the timely and safe delivery of goods.

1.3 PROJECT OBJECTIVES

Higher level:-

• **Enhance Road Safety:** The overarching goal is to reduce the number of accidents caused by distracted driving, thereby saving lives and minimizing injuries on the road**.**
• **Contribute to the Advance driver assistant system (ADAS):** By providing real-time driver monitoring, the system can be integrated into vehicle technologies, helping the transition to safer, smarter driving environments.
• **Improve Public Awareness of Safe Driving Practices:** The project will support educational efforts to raise awareness about the dangers of distracted driving, fostering a culture of responsibility and safety among drivers.
• **improve fleet management**: the system would give the ability to the fleet managers to monitor the driver's distraction levels and make decisions based on these reports.

Low level:-

• **Real-Time Distraction Detection:** Implement a system that can detect various types of driver distractions, such as texting, talking on the phone, eating, or looking away from the road, in real-time.
• **Provide Immediate Feedback or Alerts**: Once a distraction is detected, the system should be able to alert the driver with auditory feedback to help refocus their attention on the road.
• **High Accuracy and Low Latency:** Ensure that the detection system operates with high accuracy (80%) and low latency to make timely interventions or notifications.
• **Generate Detailed Driver Performance Reports**: Automatically generate regular reports for summarizing each driver's performance for each driving session destined for driver's evaluation by the fleet manager.

1.4 PRODUCT DESIGN SPECIFICATIONS (PDS)

The correct identification and translation of the customer's needs into well-defined design specifications is crucial to the successful creation of the driver distraction detection system. This section provides an exhaustive set of technical measurable requirements that defines what shall the project be designed and implemented without defining any solution itself. By meeting such specifications, we guarantee the system will adequately satisfy the customer, follow industrial standards, and work under most real-life conditions.

Musts:-

1- The system must detect the four distractions including holding mobile phones in hands, holding mobile phones against his/her ear, talking while looking at the passengers and not holding the steering wheel.
2- The distractions must be detected with an accuracy of 80%.
3- The system must warn the driver if a distraction is detected using auditory feedback which must be generated with an interval of 60 seconds.
4- The system must save session data and generate a report summarizing the types and frequency of distractions observed. The report can be accessed and retrieved through the interface using external storage.
5- The system must be installed easily in vehicles.
6- The system must be powered by the 12 Volts vehicle battery.
7- The system should function effectively under various driving conditions (e.g., day/night, weather, traffic).

Wants:-

1- The system detects more than four distractions (driver's drowsiness, smoking, eating/drinking, listening to music, reaching for object, using the navigation system.)
2- The distractions must be detected with an accuracy of 90%.
3- The system must warn the driver using visual or haptic feedback.
4- Provide fleet managers with a dashboard to monitor driver behavior in real-time over the internet for immediate intervention.

Constrains:-

1- The device must be compact enough to be installed without obstructing the driver's view or interfering with vehicle controls.
2- The system must function reliably across a range of temperatures (-10°C to 70°)
3- It must withstand vibrations and shocks from vehicle movement without it affecting the performance.
4- The production cost must be kept within the range of 2000 SR.

Engineering standards:-

1- **ISO 15005:2017 - Road Vehicles – Ergonomic Aspects of Transport Information and Control Systems:**
ISO 15005 provides guidelines for the design of human-machine interfaces (HMIs) in vehicles, focusing on ergonomic aspects to ensure that information and control systems are usable and do not distract the driver.

   Our system generates visual and auditory alerts to warn the driver of detected distractions. Compliance with ISO 15005 ensures that these alerts are designed to capture the driver's attention effectively without causing additional distraction or annoyance.

2- **ISO 80601-2-59:2017 - Medical Electrical Equipment – Basic Safety and Essential Performance of Screening for Home-Care Environment:**
While originally intended for medical equipment, ISO 80601-2-59 provides standards for devices that monitor individuals to ensure safety and performance, which can be adapted for systems monitoring driver behavior.

   Our system monitors driver behavior to detect distractions. Applying principles from this standard helps ensure the system operates safely and effectively within the vehicle environment.

3- **Electromagnetic Compatibility (EMC) Standards - ISO 11452:**
ISO 11452 specifies test methods and limits for electromagnetic immunity and emissions in vehicles. They ensure that electronic devices do not interfere with each other or with the vehicle's operation.

   Our system comprises electronic components that could generate electromagnetic emissions or be susceptible to external electromagnetic interference. Adhering to EMC standards is essential to maintain the integrity of both our system and the vehicle's electronic systems.

4- **USB Interface Standards - USB Implementers Forum (USB-IF):**
USB-IF is the organization that defines the Universal Serial Bus specification, which defines the standards to be followed for connectors, cables, protocols, and power for USB. It ensures interoperability of USB devices and hosts of one manufacturer with other manufacturers.

   Our system will output this data through a USB interface to fleet managers. Conformity to the USB standard assures that the USB port on our device is always compatible with standard USB storage devices to ensure easy and reliable data transfer.

Assumptions:-

1- The system will have access to the vehicle's power supply during operation.
2- The system's sensors and cameras will have an unobstructed view of the driver to accurately detect distractions.
3- Drivers will not intentionally obstruct, tamper with, or disable the system.
4- The vehicles would have standard interior layouts regarding seating positions, dashboard design, and steering wheel placement.
5- The system will operate within the standard environmental conditions found inside vehicles, such as temperatures ranges from -10°C to 70°C and typical humidity levels.

Project deliverables:-

Following the successful execution of the driver distraction detection system project, the output of such a project would be the set of delivery features including state of the art answers to the needs of the customer. The deliverables in an embedded system include hardware artifacts, software, and documentation. The project deliverables are:

1-A system with pre-installed software for real-time driver distraction detection.
2-Instructions for installation, operation, and troubleshooting.
3-Firmware handling distraction detection, alerts.
4-Software for fleet managers to retrieve reports via USB.

CHAPTER – 2 LITERATURE REVIEW

Literature Review:

1-Automatic driver distraction detection using deep convolutional neural networks

The paper [4] discusses the development of a driver distraction detection system using deep learning models. The system identifies the following types of driver distractions:

- Texting on the right hand
- Texting on the left hand
- Talking on the phone (right hand)
- Talking on the phone (left hand)
- Operating the radio
- Drinking
- Reaching behind
- Doing hair and makeup
- Talking to passengers

The authors utilized several AI models, including CNN, VGG-16, ResNet50, and MobileNetV2, to detect driver distractions. Among these models, MobileNetV2 performed the best, achieving the highest accuracy of up to 99.98% in training and 98.12% in testing. ResNet50 also showed good performance with an accuracy of 97.93% in training and 94.28% in testing. These results indicate that deep learning models, particularly MobileNetV2, are highly effective in detecting various driver distractions.

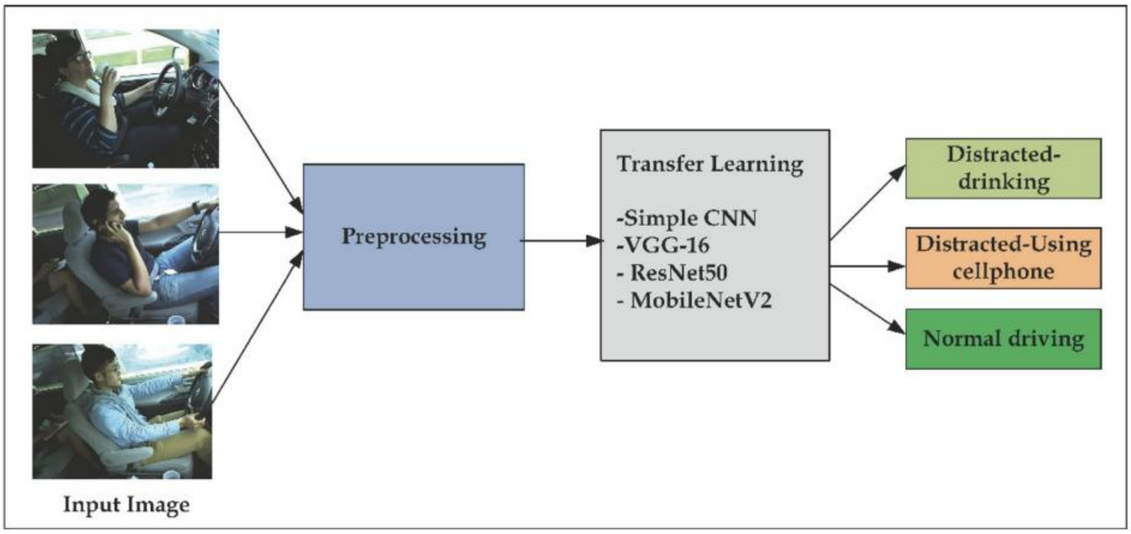


Figure (1) Driver Distraction Detection Model Using Transfer Learning

2- **Guardian system**

The Guardian system from Seeing Machines [5] is an advanced driver monitoring solution designed to detect and mitigate the risks of driver fatigue and distraction, particularly for commercial fleets. Technology uses advanced sensors and image processing technology, including artificial intelligence. A camera and sensor system installed in the cab tracks micro-movements of the driver’s eyes and head. Image processing technology, algorithms and artificial intelligence can identify fatigue or distraction. Seeing Machines detects several types of driver distractions using advanced AI and camera-based systems integrated into their **Guardian driver safety solution**. These distractions include:

1. **Mobile phone usage** (e.g., texting or making calls while driving).
2. **Drowsiness and fatigue**, identified through eyelid closures, microsleeps, and head nodding.
3. **Lack of attention** (measured by tracking the driver's eye gaze and head movements, such as frequent off-road glances).
4. **Cognitive distractions** occur when a driver's mind is not focused on driving, such as engaging in conversations.

The seeing machines system is typically installed near the rear - view or on the dashboard. This positioning allows the system to have a clear, unobstructed view of the driver's face, ensuring accurate tracking of eye movements, head position, and facial expressions.

3- Driver distraction detection and recognition using RGB-D sensor

The paper [6] presents a system designed to detect and identify different types of driver distractions. The system leverages an **RGB-D sensor (Kinect),** which captures both **color** and **depth data**, allowing for more detailed monitoring of the driver's body movements and facial expressions. The authors focus on detecting specific types of distractions, including:

1. Making phone calls
2. Drinking
3. Sending a text message (SMS)
4. Looking at objects inside the vehicle, such as adjusting the radio or reading a map
5. Normal driving (used as a baseline).

The detection system is built using four primary modules:

- Eye Behavior: Monitors the driver's gaze direction and blinking to check if the driver's attention is on the road.
- Arm Position: Identifies the position of the driver's right arm (whether it is raised, lowered, or moving sideways) to determine if they are interacting with objects.
- Head Orientation: Tracks the orientation of the driver's head to detect if they are looking away from the road.
- Facial Expressions: Analyzes the driver's facial features, such as mouth and eyebrow movements, to recognize possible distractions like talking or drinking.

These data points are processed using two machine learning techniques: AdaBoost classifier and Hidden Markov Models (HMM), which combine the outputs from the individual modules to detect and classify the type of distraction.

The Kinect sensor is used because it offers both RGB (color) and depth data, allowing the system to track not only the driver's facial features but also their body posture and movements in 3D. This dual capability provides more robust data for accurate distraction detection. The testing result came out with 85% accuracy in recognizing the specific types of distractions and 90% accuracy in general distraction.

4- Real-time Detection of Distracted Driving using Dual Cameras

The paper [7] presents a system designed to detect driver distractions in real-time using deep learning techniques. The system employs two cameras: one positioned in front of the driver to capture facial data and the other on the side to monitor the driver's body movements. These dual cameras help detect a variety of distractions more accurately. The data was collected from twelve subjects using a driving simulation from the two cameras and a six-minute video was recorded for each type of distraction with a total of 11 video and they use a data augmentation because of the variation of drivers.

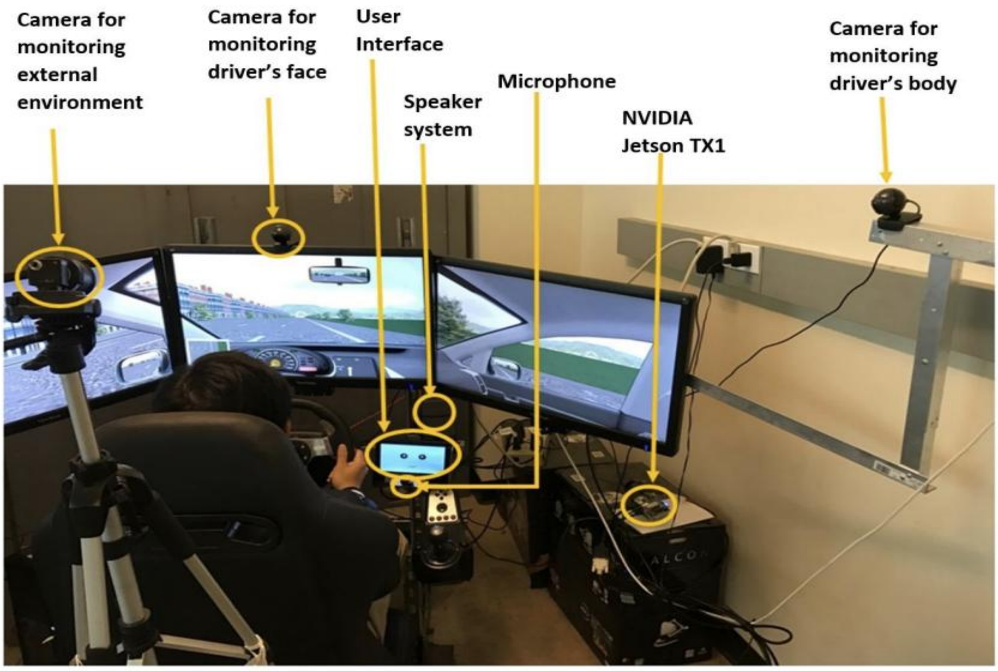


Figure (2) Driver Monitoring and Assistance System Setup for Simulation

The system focuses on identifying the following types of driver distraction:

1. Texting on the phone (left or right hand)
2. Talking on the phone (left or right hand)
3. Operating the radio
4. Drinking
5. Reaching behind
6. Doing hair and makeup
7. Talking to passengers
8. Drowsiness
9. Normal driving (as a baseline)

Components Used:

- Two Cameras: One facing the driver's face and the other capturing the driver's body movements.
- Embedded Computing System: The system is implemented on an NVIDIA Jetson TX1, which accelerates image processing using the onboard GPU. Additionally, a NanoPi M3 board is used for real-time alert generation via voice or visual notifications.

The system processes images from both cameras using deep learning models. These images are fed into VGG-16 Convolutional Neural Networks (CNNs) to extract features related to the driver’s facial expressions and body movements. The outputs from the two CNNs are combined and processed by fully connected layers, which classify the driver’s activity. If a distraction is detected, an alert is sent to the driver via voice or visual warning through the user interface.

Algorithms Used:

The primary deep learning model used is VGG-16, a well-known CNN architecture, chosen for its balance between accuracy and computational efficiency. The paper compares the performance of VGG-16 and MobileNet-v2, ultimately finding that while MobileNet-v2 is faster (25 fps), VGG-16 provides higher accuracy (96.5%) at 8 frames per second (fps).

5- Automatic system for detecting driver use of mobile phones

This paper [8] introduces an automatic system to detect when a vehicle driver uses a mobile phone, helping reduce driving risks from distraction. The method uses *Radio Frequency (RF) harvesting*, capturing RF signals from mobile phones with antennas placed near the driver’s headrest. These antennas measure signal strength, allowing the system to identify driver phone use based on voltage levels—driver use generates around 4 V, while passengers produce lower signals (under 2 V), ensuring accurate discrimination.

Results:-

Tests showed the system reliably detected driver’s phone use, filtering out peaks to avoid false alarms. In multi-passenger scenarios, passenger signals stayed below 2.5 V, preventing misidentification. This low-cost, real-time monitoring system could integrate into *Pay-As-You-Drive* insurance or vehicle safety features. It has appeared that this method has a good approach for detecting if the driver uses a mobile phone. You can see an example of where they install the antenna inside the car cabin.

Figure (3) Headrest-Mounted Sensor Setup for Driver Monitoring

6-Driver’s mobile phone usage detection using guided learning based on attention features and prior knowledge

This paper [9] presents a driver’s mobile phone usage detection model (DMPUDM) that leverages *guided learning* using *attention features* and *prior knowledge*. The model utilizes deep neural networks (DNNs) to extract attention-relevant features (such as the presence of a mobile phone) from driver images. A specialized attention mechanism, influenced by neuroscience and spatial suppression theories, calculates each neuron's importance for identifying driver phone use. They used a Vehicle simulation platform to collect datasets.

Method:-

The model integrates two main components:

1. **Attention Mechanism**: It uses 3D weights to prioritize attention-related features while suppressing background noise. This focuses the model on relevant image areas, like the phone or driver's hand.
2. **Prior Knowledge**: The model is pre-trained on the Kaggle cat vs. dog dataset to boost performance and generalization. This dataset provides abundant, high-quality data, helping the model learn essential image differentiation features. This foundation reduces overfitting risks when the model is later fine-tuned on the driver phone usage detection task, enhancing accuracy even with limited data.

Results:-

Testing demonstrated high detection accuracy, with a 99.4% success rate in distinguishing phone use (calling or texting) from other behaviors. Additionally, the attention feature visualization method improves user trust by highlighting image areas critical to the detection process.

Figure (4) Examples of attention map: (a) annotated fixation points in driver image; (b) attention m

CHAPTER – 3 PROJECT DESIGN

3.1 ALTERNATIVE DESIGNS

Table (1) Function and means

Function	Means			
Detect Holding Mobile (Hands/Ear)	CNN-based Image Recognition using a camera	Thermal Imaging-based Detection using an IR Camera	Radio Frequency harvesting	
Detect Hands-off Steering Wheel	camera-based Hand Detection	Capacitive Touch pads on Wheel	Pressure based detection on wheel	
Detect Talking to Passengers	Detecting Facial Expression and Lip Movement with a camera	Detect Driver's Position and Interaction with a camera and a microphone		
Alert Driver	Buzzer	Speaker System		
Computation and Integration	Jetson Nano	Raspberry pi 5	Jetson Xavier NX	Jetson TX2
Sensors	Monocular Cameras	Stereo Cameras	Infrared (IR) Cameras	Depth Camera
	Capacitive Touch Sensors	Pressure Sensor	antennas	Thermal Camera

Alternative 1:

This alternative solution uses CNN-based image recognition with Infrared (IR) and Depth cameras to detect if the driver is holding a mobile device near their hands or ear. For monitoring conversations with passengers, the system uses a camera and microphone to track the driver's head position and audio cues, identifying potential distraction from talking. A camera-based hand detection system monitors the driver's grip on the steering wheel to detect hands-off scenarios. All processing is handled by a Jetson Nano, which powers real-time alerts through a connected speaker system to enhance driver saftey

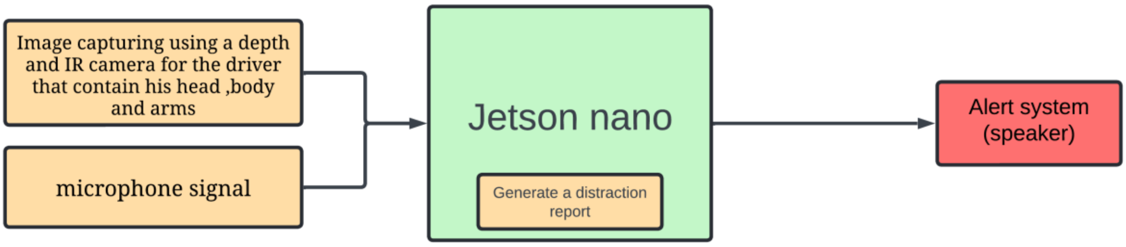


Figure (5) block diagram of Alternative (1)

Main Components of the System:

 Infrared (IR) Camera and Depth Camera with CNN-based Image Recognition: Detects if the driver is holding a mobile phone near their hands or ear. The combination of IR and depth sensing allows for accurate detection regardless of lighting conditions.

 Audio Input for Speech Detection and visual Head Position: A camera and microphone work together to monitor the driver's head orientation and detect speech patterns, signaling potential conversations with passengers.

 Camera-based Hand Detection on Steering Wheel: Identifies whether the driver's hands are on the wheel. When hands are removed for extended periods, the system flags it as a distraction.

 Jetson Nano Processing Unit: The Jetson Nano handles real-time data processing, running machine learning models to interpret camera and microphone inputs.

 Speaker Alert System: Provides immediate auditory alerts when the system detects a distraction, prompting the driver to refocus on the road.

How the system Satisfies Design Requirements:

 Detects Four Distractions: Uses IR and depth cameras for mobile detection and hand detection for hands-off scenarios , audio-visual input for passenger interaction.

 80% Accuracy: High-accuracy CNN models on the Jetson Nano ensure precise and reliable detection of distractions in real time.

 Auditory Alerts: The speaker system provides quick and clear audio feedback to alert the driver when any distraction is detected.

 Session Reporting: The Jetson Nano logs distraction data, enabling end-of-session report generation.

 Portability and Power: The system's compact components, powered by the vehicle's 12V battery, allow for straightforward installation and continuous operation.

 Environmental Robustness: The IR and depth cameras perform effectively in various lighting and weather conditions, ensuring reliable detection day and night.

Alternative 2:

This alternative solution utilizes thermal imaging with a Thermal Camera to detect mobile phone usage by recognizing the unique heat signature of a hand holding a device. Capacitive touch sensors on the steering wheel monitor the driver's grip to identify hands-off events. For detecting conversations with passengers, stereo cameras track facial expressions and lip movement, signaling potential distraction. All data is processed by a Jetson TX2, which, upon detecting a distraction, triggers a buzzer to alert the driver in real-time, enhancing overall safety and awareness.

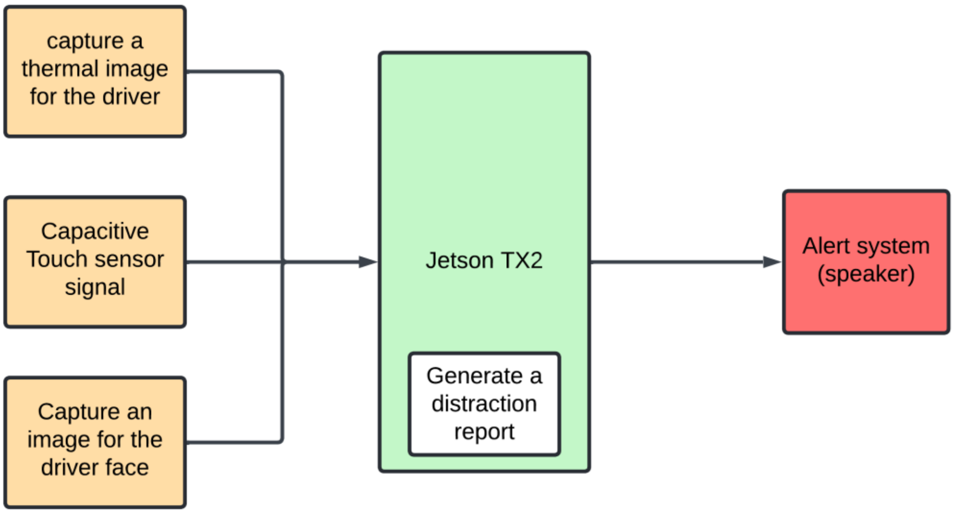


Figure (6) block diagram of Alternative (2)

Main Components of the System:

- **Thermal Imaging-based Detection using a Thermal Camera**: Detects if the driver is holding a mobile phone by identifying the heat signature of the device near the driver's hands or ear, enabling detection in low-light conditions.

- **Capacitive Touch Sensor on Steering Wheel**: Monitors the driver's grip on the steering wheel, signaling if hands are removed for an extended period, which could indicate distraction.

- **Stereo Cameras for Facial Expression and Lip Movement Detection**: Analyzes facial expressions and lip movements, identifying if the driver is engaged in a conversation with passengers.

- **Jetson Nano Processing Unit**: Processes inputs from the thermal camera, stereo cameras, and capacitive sensors, running machine learning models for real-time distraction analysis.

- **Buzzer Alert System**: Provides immediate auditory alerts to the driver when any distraction is detected, prompting the driver to refocus.

How the System Satisfies Design Requirements:

- **Detects Four Distractions**: The thermal camera identifies mobile use, stereo cameras monitor passenger interaction, and the capacitive sensor detects hands-off scenarios.

- **80% Accuracy**: High-precision thermal and stereo cameras paired with Jetson Nano's processing power ensure reliable and accurate distraction detection.

- **Auditory Alerts**: The buzzer provides clear audio alerts to keep the driver informed of detected distractions in real time.

- **Session Reporting**: The Jetson Nano logs all detected distractions, allowing for end-of-session reporting.

- **Portability and Power**: Compact and powered by the vehicle's 12V battery, the setup is easy to install and operate continuously.

- **Environmental Robustness**: The thermal camera provides reliable detection regardless of lighting, and stereo cameras enhance depth and accuracy in varied environments.

Alternative 3:

In this solution, RF Harvesting Antennas are used to detect the presence of a mobile phone, focusing on RF signals to identify when the driver is holding a device without needing a camera. Pressure Sensors on the steering wheel provide hands-off detection. To monitor conversations with passengers, and depth and IR Cameras paired with a CNN model tracks facial expressions and lip movements, identifying if the driver is talking. All data is processed by a Jetson Nano, which analyzes inputs in real-time and triggers a buzzer alert if a distraction is detected. This setup allows for reliable distraction detection across various lighting conditions, enhancing overall driving safety.

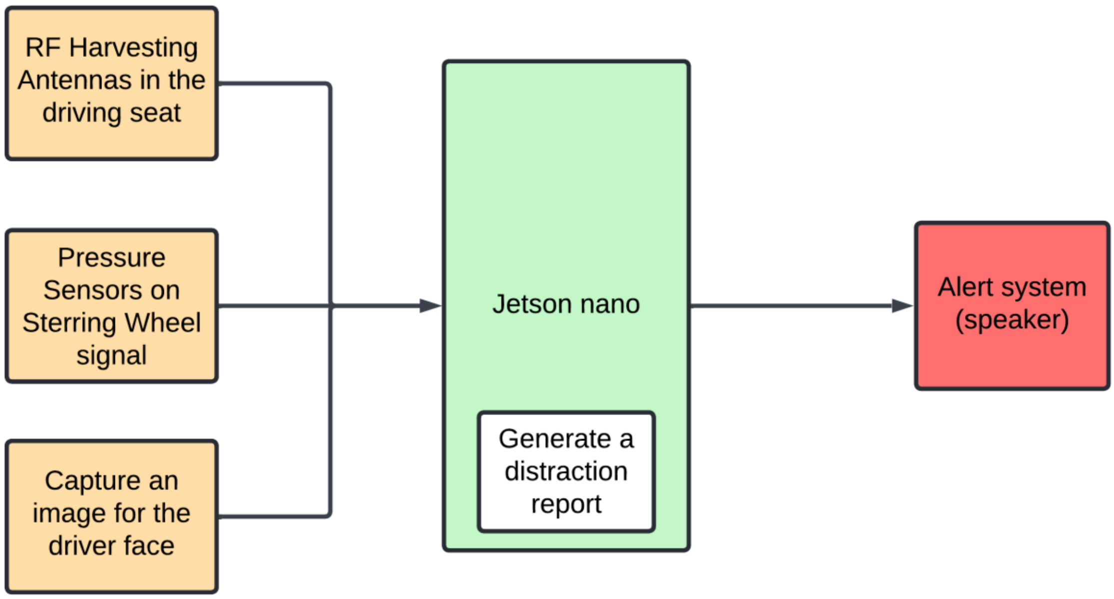


Figure (7) block diagram of Alternative (3)

Main Components of the System:

 RF Harvesting Antennas: Detects the presence of a mobile phone by capturing RF signals emitted by the device, enabling non-visual mobile detection and minimizing reliance on cameras.

 Pressure Sensors on Steering Wheel: Monitors whether the driver's hands are on the wheel, signaling a distraction if hands are removed.

 Depth and IR Cameras with CNN for Facial and Lip Movement Detection: Tracks facial expressions and lip movements to detect if the driver is engaged in conversation with passengers, even in low-light conditions.

 Jetson Nano Processing Unit: Processes data from RF antennas, pressure sensors, and cameras in real-time, running CNN models for accurate distraction detection.

 Buzzer Alert System: Provides immediate auditory alerts to the driver upon detecting a distraction, encouraging quick refocus.

How the System Satisfies Design Requirements:

 Detects Four Distractions: Uses RF antennas for phone detection, depth and IR cameras for passenger interaction, and pressure sensors for hands-off monitoring.

 80% Accuracy: High-precision CNN models, paired with depth and IR cameras, ensure effective detection across various conditions.

 Auditory Alerts: The buzzer provides immediate, clear audio feedback to notify the driver of distractions in real time.

 Session Reporting: The Jetson Nano logs distraction data, allowing for end-of-session reporting.

 Portability and Power: Compact components are powered by the vehicle's 12V battery, ensuring ease of installation and reliable operation.

 Environmental Robustness: Depth and IR cameras ensure reliable detection across diverse lighting environments, enhancing the system's adaptability.

Table (2) Advantage and disadvantage

	Advantages	disadvantages
Alternative 1	• High Accuracy • Speech-based passenger detection • Cost-effective • Simple installation	• Lighting sensitivity • Audio limitations • Power consumption
Alternative 2	• highly accurate object • Robust facial tracking • Versatile in varied lighting	• Higher cost • Installation complexity
Alternative 3	• Non-visual mobile detection • Energy-efficient processing • Reliable in low light • Easy installation	• Lower object-specific accuracy • Limited functionality • Audio limitations

PUGH'S METHOD :-

After selecting three feasible designs, Pugh's method is used to pick out the best one of them. The following **Table** is an application of Pugh's method.

Criteria in the Pugh Method and Their Relation to Musts and Wants:

1. Cost (Constraint 4): Ensures production cost stays under 2000 SR.
2. Detection Accuracy (Must 2, Wants 2): Measures the system's ability to detect distractions (80% minimum, 90% desired).
3. Ease of Integration and Installation (Must 5): Assesses simplicity of installation in vehicles.
4. Robustness in Different Lighting Conditions (Must 7): Evaluates performance under day/night, weather, and traffic conditions.
5. Processing Speed (Must 3): Ensures timely detection and alerts within 60 seconds.

Table (3) PUGH'S METHOD

No.	Objective	Musts And constrains	Weight		A1	A2	A3
1	Cost	Constrain 4	8	Datum	+	S	+
2	Detection accuracy	Must 2	10		+	S	-
3	Ease of integration and installation	Must 5	5		-	+	-
4	Robustness in different lighting conditions	Must 7	7		S	S	+
5	Processing speed	Must 3	6		+	+	-
		Total Positives (+)			24	11	15
		Total Negatives (-)			-5	-	-21
		Total Score			19	11	-6

Justification of Scores:

Alternative 1

- Cost: Affordable components (+).
- Detection Accuracy: Reliable with CNN models (+).
- Ease of Installation: Complex due to multiple components (-).
- Lighting Conditions: Infrared ensures decent performance (S).
- Processing Speed: Jetson Nano ensures real-time response (+).

Alternative 2

- Cost: Thermal cameras increase cost (S).
- Detection Accuracy: Good but varies with stereo cameras (S).
- Ease of Installation: Relatively simpler (+).
- Lighting Conditions: Strong performance with thermal imaging (S).
- Processing Speed: Jetson TX2 ensures fast processing (+).

Alternative 3

- Cost: Cost-effective components (+).
- Detection Accuracy: RF signals less reliable (-).
- Ease of Installation: Complex due to RF antennas (-).
- Lighting Conditions: Strong in varying conditions (+).
- Processing Speed: RF processing delays (-).

Using Pugh's method, we determined that the first alternative received the highest score, making it the most favorable choice among the three options. Additionally, the advantages and disadvantages analysis in the previous section supports this selection, as the first alternative offers the most benefits.

3.2 BASELINE DESIGN

The baseline design aims to refine the best solution through the elimination methods discussed in the previous section on alternative solutions. The first alternative was selected, as it meets all desired requirements, preferences, and constraints. This section will further develop the chosen solution to meet the project standards.

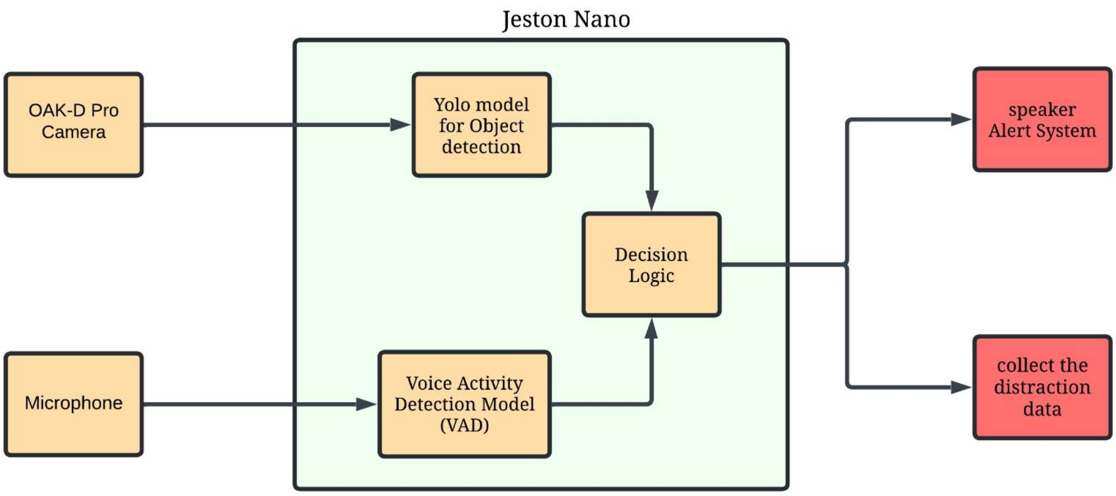


Figure (8) illustrates the selected alternative solution

The figure above illustrates the selected alternative solution. The first customization in developing the baseline design involves installing a Jetson nano and a camera positioned to the right of the driver, ensuring optimal image capture for the driver. An alert speaker system is also included to notify the driver whenever a distraction is detected.

IR & Depth Cameras:

The IR and Depth Cameras are responsible for detecting a range of distractions by continuously monitoring the driver's actions. The IR camera captures heat signatures, making it ideal for low-light and night-time detection, while the Depth camera provides spatial awareness to accurately detect hand, head, and object positions. As shown in figure (9), the cameras would be placed above the radio to the right of the driver, this angle would give us the ability to detect his hands and his head position at the same time which will allow us to detect the three main distractions.

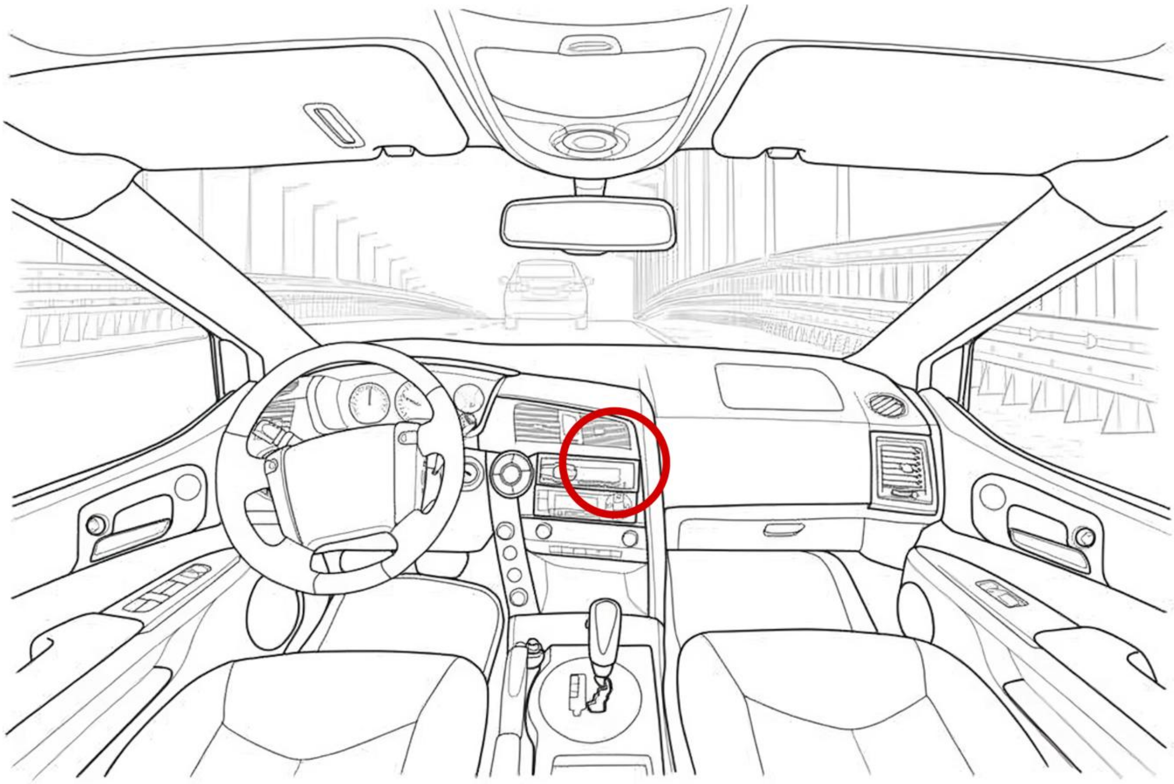


Figure (9) Location of the device

Detect Holding Mobile (Hands/Ear) :

For detecting the first/second distraction—whether the driver is holding a mobile phone in their hand or against their ear—the system captures an image of the driver and sends it to Jetson Nano for processing. Using a pre-trained Convolutional Neural Network (CNN) model, the AI algorithm analyzes the image to recognize both the presence and location of a mobile phone in relation to the driver's hand and ear.

The image goes through multiple layers within the CNN, where specific features, such as hand positioning and object shape, are extracted. These features are then matched with patterns in the model's training data, allowing the CNN to classify the driver's behavior as either distracted (holding a phone in hand or against the ear) or undistracted. By classifying each frame in this way, the system can continuously monitor and respond in real time.

Detect talking to the passenger:

For detecting the fourth distraction—whether the driver is talking to a passenger—the system captures an image of the driver along with an audio signal recorded through a microphone.

Both data inputs are sent to Jetson Nano for analysis. The image is processed by a pre-trained Convolutional Neural Network (CNN) model, which assesses the driver's head orientation. If the CNN determines that the driver is looking toward a passenger, it classifies this as a 'talking to passenger' distraction. If the driver is facing forward, the CNN categorizes the driver as distraction-free.

The recorded audio signal undergoes additional analysis to further confirm if a conversation is occurring in the cabin. By applying audio analysis techniques, such as speech detection and voice activity recognition (VAD), the system identifies spoken words and distinguishes between the driver's and passenger's voices, helping to confirm whether the driver is indeed talking. If the system detects conversational sounds without the driver looking directly at the passenger, it can still classify this behavior as a distraction.

Detect hands off steering wheel:

For detecting the third distraction—whether the driver is holding the steering wheel with both hands—a new image of the driver is captured and sent to the Jetson Nano for processing. Using a pre-trained Convolutional Neural Network (CNN) model, the AI algorithm analyzes the image to assess the driver's hand position relative to the steering wheel. CNN is specifically trained to classify images into two categories: holding the steering wheel with both hands and not holding it correctly with both hands. Within the CNN model, the image undergoes several layers of processing, where features such as hand location and orientation are extracted and analyzed. These features are compared to the model's training data to classify the driver's posture accurately.

This distinction enables the system to detect improper steering wheel grip, ensuring that the driver maintains safe control of the vehicle. If the model detects a distraction (e.g., only one hand on the wheel or no hands), it can trigger an alert using the speaker system to prompt corrective action. In the figure (10) you can see how the model will be used to predicate the type of distraction.

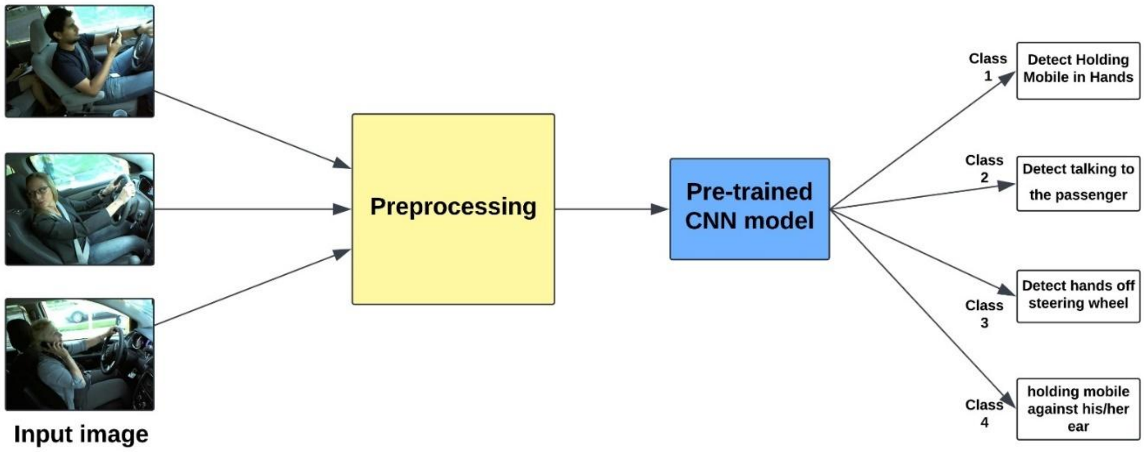


Figure (10) Driver Distraction Classification Pipeline Using Pre-trained CNN Model

Jetson Nano:

Once data from the camera and microphone are received by the Jetson Nano, several stages of processing and analysis occur to detect driver distractions accurately as shown in figure(10). Initially, the Data Aggregation stage collects inputs from multiple sources—images capturing hand positions, head orientation, and audio signals—combining them into a unified dataset for comprehensive analysis. In the Preprocessing stage, the data undergoes essential transformations to prepare for model analysis.

For images, this may include resizing, normalization, and noise reduction, while audio signals may undergo feature extraction or noise filtering to highlight conversational sounds. Next, the aggregated and preprocessed data is fed into Detection Models—pre-trained CNNs and audio analysis algorithms—designed to recognize specific distraction indicators.

These models analyze each input to classify potential distractions, such as 'holding mobile or talking by mobile,' 'talking to passengers,' or 'hands-off steering wheel.' The models leverage the distinctive patterns learned during training to produce accurate classifications. Finally, Decision Logic interprets the outputs from the detection models and makes an overall assessment of the driver's behavior. This module determines whether the detected behavior represents a distraction and, if so, may trigger an alert or record the incident for reporting. Decision Logic ensures that outputs are consistent, and only significant distractions are flagged, optimizing the system for real-time responsiveness and safety.

During each driving session, the Jetson Nano continuously logs detected distractions, capturing the type of distraction, timestamp, and an image of the driver at the moment of occurrence. This data is stored throughout the session. When the fleet manager requires a report, they can simply plug a USB drive into the user interface connected to the Jetson Nano. The system will automatically generate a report and save a copy to the USB drive.

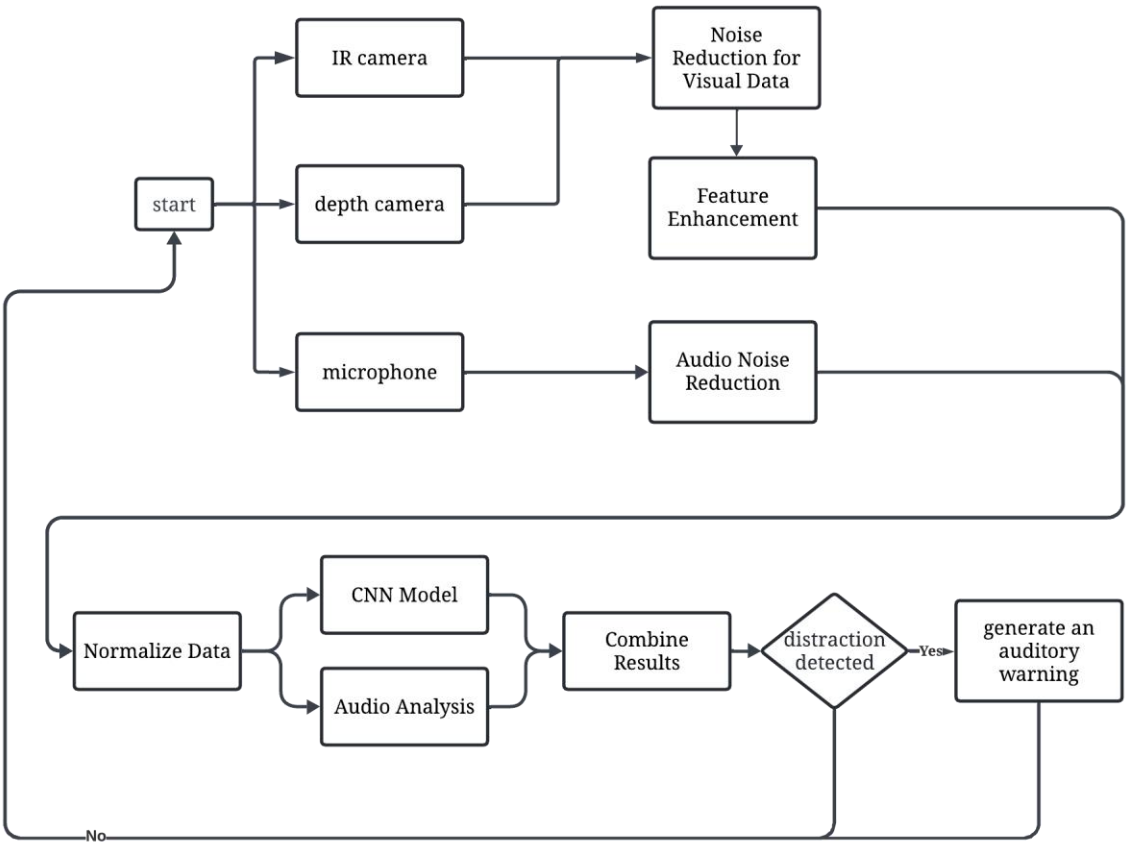


Figure (11) several stages of processing

Speaker Alert System and Data Collection:

The speaker will Provides an immediate audio alert if a distraction is detected, notifying the driver to refocus. After the distraction is detected, the system will Logs each detected distraction event for reporting and system analysis. This data then can be retrieved by fleet management which can be used for training, performance monitoring, or reporting.

Operation instructions:

1. Power on the system by connecting to the car's power source; the Jetson Nano and peripherals will initialize automatically.
2. Allow a few seconds for the cameras, microphone, and touch sensors to calibrate with the jetson.
3. Distraction detection would work as soon as the system is ready.
4. Each distraction detected is being recorded on the log
5. The system powers down automatically when the car is turned off.
6. When the fleet management plugs in the USB, the report is going to be generated and transferred to the USB.

System's input and output:

Table (4) System's input and output

Component	Type	**Function**
IR & Depth Cameras	Input	Captures visual and spatial data for detecting mobile phone usage and monitoring hand position.
Microphone	Input	Captures audio to monitor conversations, indicating potential distraction from talking to passengers.
Speaker System	Output	Issues audio alerts to warn the driver of detected distractions.
Data Logging	Output	Records detected distraction events for future analysis and reporting.

Component specification:

As seen in the figures (11), this is how the main components connections would be. This system setup features the Jetson Nano as the processing hub, connected to IR and Depth cameras for visual data, a microphone for audio capture, and a speaker for issuing alerts. The Jetson Nano processes input from the cameras and microphone, running algorithms to detect distractions, such as holding a mobile phone or talking to passengers. When a distraction is identified, the speaker issues an audio alert to prompt the driver to refocus. The entire system is powered by the car's power source, ensuring consistent operation throughout the drive.

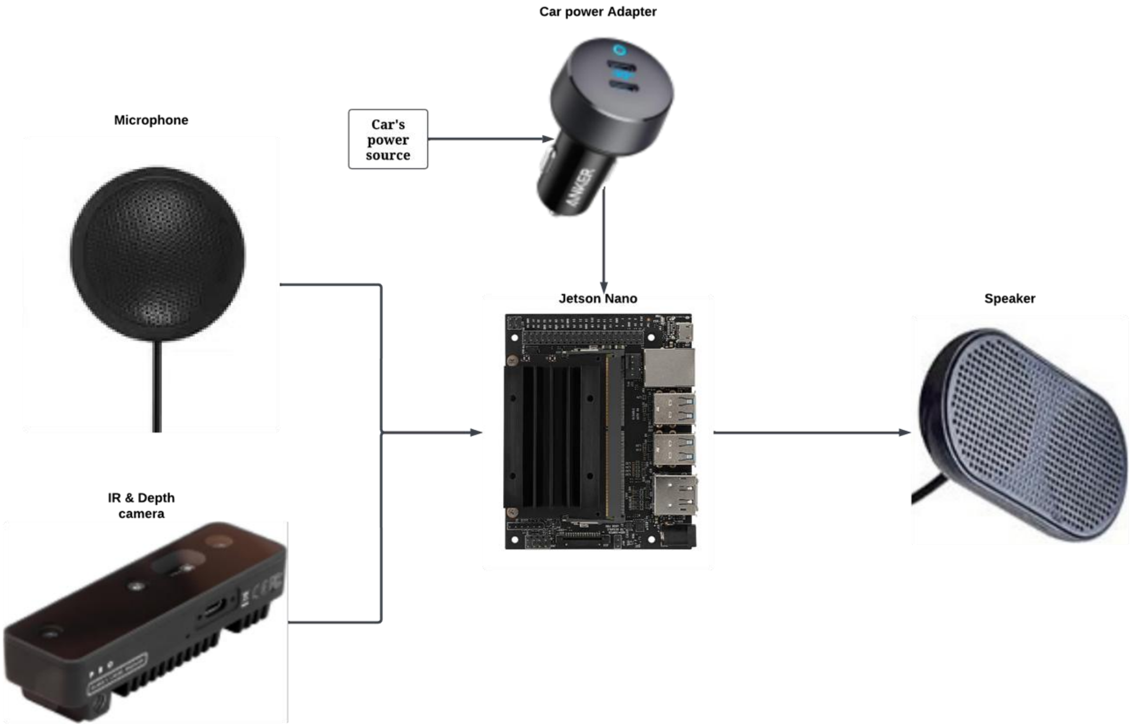


Figure (12) The Component specification

Table (5) The Component

Component	Specifications	Price in (SR)	Quantity	Picture
OAK-D Pro Camera	2 cameras equipped with **IR illumination** for **low-light** conditions and **active stereo** improving depth perception.	1000	1	
Jetson nano	CPU: Quad-core ARM Cortex-A57, 64-bit GPU: 128-core Maxwell GPU, providing up to 472 GFLOPS for AI processing Memory: 4GB LPDDR4 RAM Storage: microSD slot for storage expansion Power: Operates between 5W and 10W supports **CUDA 10** and **cuDNN 7.5**	600	1	
speaker	**Hardware interface:** **USB** **Surround sound:** 2.6W	50	1	

Andoer Mini Desktop Condenser Microphone	Frequency Response: 20Hz-16KHz Sensitivity: -30dB±3dB Power: 125mW Item Size: 5.8 * 5.8 * 1.3cm / 2.3 * 2.3 * 0.5in SNR: 84dB Impedance: ≤2.2KΩ	76	1	
Car Plug Adapter	input: 12/24V⎓ 5A output: 5V ⎓ 3A / 9V ⎓ 2.22A (20W Max Per Port) Total Output: 40W Max	64	1	
KKSB Case for NVIDIA Jetson Nano	he Jetson Nano case provides protection and cooling for the board, featuring a built-in heatsink and fan to ensure optimal performance. It is designed for easy access to all ports and includes mounting options for secure installation.	150	1	
Storage	The SanDisk Ultra 256GB microSDXC card offers high storage and fast performance with a Class 10 rating, ideal for HD video and app storage. It is durable, water-resistant, and shockproof.	50		

CHAPTER – 4 IMPLEMENTATION

4.1.1 Change the camera

Our baseline design specified the QAK-D camera as the primary vision sensor, but it was unavailable in the market. We then purchased the WayPonDEV FHL-D435i Depth Camera, but faced SDK integration issues, making it unreliable for our system. We tried a lot to use this camera. As a result, we returned it and selected the Arducam 1080p Day/Night Vision USB Camera, which offered better compatibility with OpenCV and consistent performance for our driver distraction detection system.

4.1.2 Dataset Collection and Annotation

For the development of our computer vision model, we began by setting up a normal RGB camera inside a car cabin to capture the driver's face, hands, and steering wheel during various driving scenarios.

At first, we decided to mount the camera in the middle of the car, positioned above the car radio on the dashboard, believing it would offer a good angle for monitoring the driver. However, after testing this setup, we found that the placement was not suitable—it didn’t provide a clear enough view of the driver's face, hands, and steering wheel due to obstructions and limited field of view.

As a result, we chose to relocate the camera to the grab handle above the passenger side window, which positioned the camera at the top-right corner of the windshield. This placement offers a wider and clearer view of the driver’s upper body, including the face orientation, hand positions, and steering wheel area, ensuring that the YOLOv8s-OBB model can effectively detect any distractions such as mobile phone use, talking to passengers, or hands not on the wheel. Picture x shows the camera’s place.

Figure (13) Driver Distraction Classification Pipeline Using Pre-trained CNN Model

Using this setup, we collected approximately 2,000 RGB images of a driver while performing typical actions such as driving normally, using a mobile phone, and talking to passengers. To improve the diversity and generalization of the dataset, we supplemented our collection with an additional 1500 images from a Kaggle dataset, which included different drivers, vehicles, and cabin environments. This ensured that our model could handle various lighting conditions, driver appearances, and cabin layouts.

After collecting the dataset, we used Roboflow, an online labeling platform, to annotate the images for object detection. In figure 13, you can see a screenshot for the annotating process The following seven classes were defined to identify key elements related to driver distraction:

- **Face** – Driver is looking at the passenger (distraction).
- **Normal Face** – Driver is facing forward (no distraction).
- **Hands** – To detect the driver's hands.

- **Steering Wheel** – To locate the car's steering wheel.
- **Using Mobile Phone** – Driver holding a mobile phone.
- **Talking on the Phone - Left** – Phone held to the left ear.
- **Talking on the Phone - Right** – Phone held to the right ear.

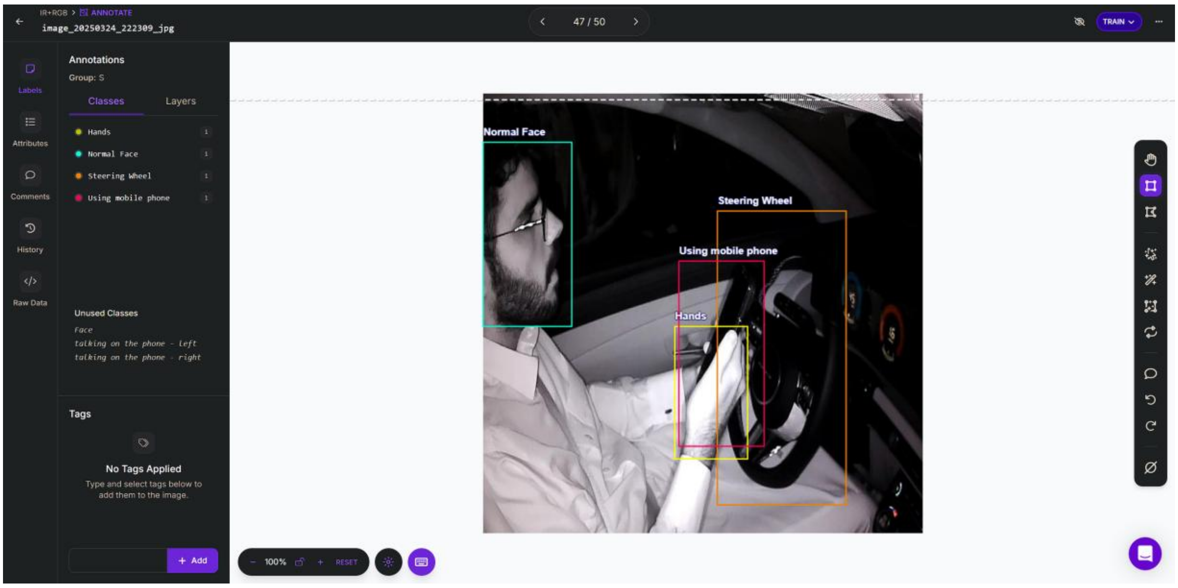


Figure (14) shows an image from the annotating process

Some classes, like Using Mobile Phone or Talking on the Phone, directly indicate distraction, while others such as Hands and Steering Wheel are used in algorithmic post-processing to determine distraction (e.g., detecting if the driver's hands are off the steering wheel).

After collecting and labeling the initial RGB dataset, we realized the importance of enhancing the system’s performance in low-light conditions such as night driving. To address this, we upgraded our setup by purchasing a camera equipped with both RGB and IR (infrared) capabilities. This allowed us to capture images that included infrared data, ensuring the model could detect distractions regardless of lighting conditions. Using this new camera, we collected an additional 1,000 IR images, which were then added to the dataset. These IR images provided valuable data for improving detection accuracy in challenging environments, complementing the existing RGB dataset and enhancing the overall robustness of the model. In this point, our dataset is containing a 4500 IR and RGB images

4.2.1 Model Selection and Training

After preparing the dataset, the next step was to choose a suitable object detection model for distraction detection. We evaluated various state-of-the-art detection models and ultimately. selected YOLOv8 due to its strong balance between accuracy, speed, and model size. YOLOv8 supports Oriented Bounding Boxes (OBB), which can provide more accurate localization of objects like hands and mobile phones in varied orientations.

However, YOLOv8 comes in different versions such as YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), YOLOv8l (large), and YOLOv8-OBB variants. Given Jetson Nano 4GB’s limited computational resources, we had to ensure that the model could run inference within our latency requirements. After comparison, we selected the YOLOv8s variant with approximately 11 million parameters, which provides a good trade-off between detection accuracy and inference speed. Jetson Nano can handle YOLOv8s comfortably, maintaining real-time performance.

For training, we utilized Google Colab, a cloud-based platform that offers free and paid access to powerful GPUs, eliminating the need for local GPU hardware. Colab is especially beneficial for fast prototyping, easy integration with Google Drive, and access to high-performance GPUs, which significantly reduces training time. We trained our model on an NVIDIA A100 GPU, one of the most powerful GPUs available, which accelerated the training process and allowed us to experiment quickly.

4.2.2 Experiment 1: Training without Custom Data Augmentation

In the first training experiment, we trained YOLOv8s on our dataset without applying any custom data augmentation techniques, relying only on YOLOv8's default augmentations (such as random flipping, scaling, and color adjustments). This baseline experiment was intended to evaluate the raw performance of the model on our dataset. In figure 15, you can see the training result of the model. To evaluate the model’s performance, we calculated the precision, recall, and F1-score the result is:

- **Precision**: 84.3%
- **Recall**: 79.7%
- **mAP@0.5**: 81.7%
- **mAP@0.5:0.95**: 45.9%

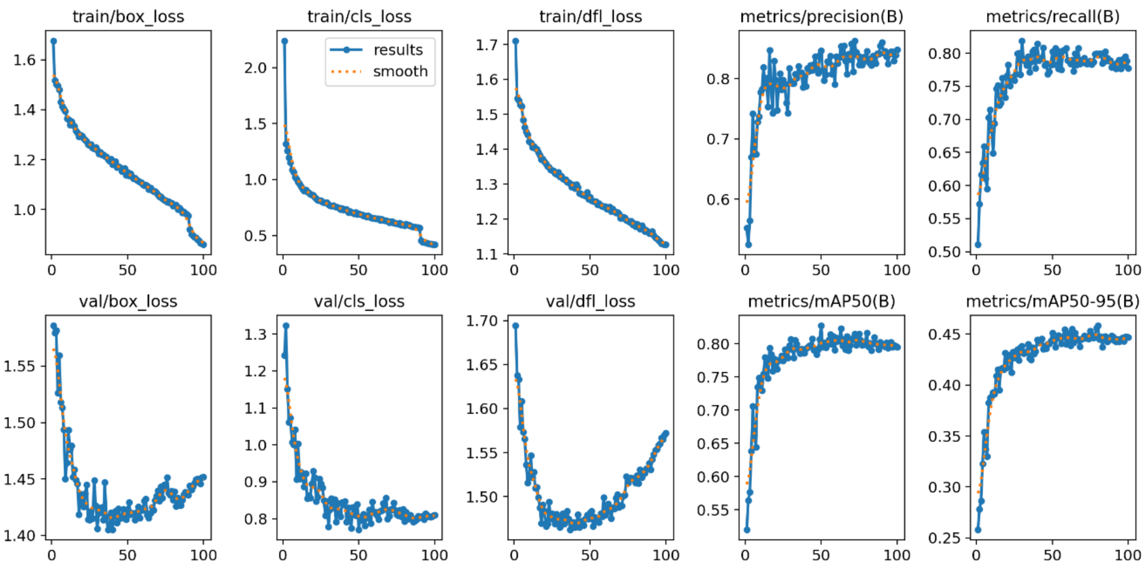


Figure (15) shows the training result for the experiment 1

The training results for Experiment 1 demonstrate steady improvements across all key metrics. Both training and validation losses (box, classification, and DFL loss) show a consistent downward trend, indicating effective model learning. The precision and recall metrics gradually improve, stabilizing after approximately 50 epochs. Additionally, the mAP@0.5 and mAP@0.5:0.95 metrics show significant gains, reflecting the model's increasing accuracy in detecting objects across various IoU thresholds. Overall, the results indicate that the model successfully converged during training.

This baseline experiment showed that the model could achieve moderate accuracy without custom augmentations. However, to improve performance, especially for the underperforming classes, we decided to conduct a second experiment with enhanced data augmentation techniques.

4.2.3 Experiment 2: Training with YOLOv8s-OBB, Data Augmentation, and Learning Rate Scheduling:-

For the second training experiment, we aimed to improve detection accuracy, especially for classes like talking on the phone and using a mobile phone, where the orientation of objects (like the driver’s head or phone) varies. To address this, we switched from the standard YOLOv8s to YOLOv8s-OBB (Oriented Bounding Box).

Unlike traditional YOLO, which uses axis-aligned bounding boxes (rectangles parallel to the x- and y-axes), OBB allows bounding boxes to be rotated, fitting objects more precisely at any angle. This is especially useful for detecting hands, phones, or faces when they are tilted or rotated, which frequently happens in real-world driving scenarios. Using YOLOv8-OBB helped improve the localization accuracy of these objects, making the model more robust to different orientations.

To further enhance the model's ability to generalize, we introduced custom data augmentation techniques beyond YOLO’s defaults:

- Rotation – Simulates variations in camera angles or object tilts.
- Flipping – Introduces horizontal/vertical inversions to diversify data.
- Cropping – Encourages the model to learn from partial views of objects.
- Noise Addition – Helps the model become resilient to camera noise or poor-quality images.

We also applied a cosine learning rate schedule, which gradually decreases the learning rate from a maximum value to a minimum, following a cosine curve. This method allows the model to explore more aggressively during the early stages of training and fine-tune carefully toward the end. The learning rate schedule helps prevent the model from getting stuck in local minima and encourages better convergence.

After training with YOLOv8s-OBB, enhanced data augmentation, and a cosine learning rate schedule, the model’s performance significantly improved compared to Experiment 1.

Table (6) YOLOv8s-OBB Performance Metrics

Metric	Value
Overall Precision	0.886
Overall Recall	0.892
mAP@0.5	0.917
mAP@0.5:0.95	0.684

The OBB model demonstrated significant improvements across most classes, particularly in precision, recall, and mAP@0.5. Notably, the steering wheel, hands, and normal face classes achieved excellent detection accuracy (mAP@0.5 > 0.90), which is critical for assessing the driver's hand-over-wheel position.

Performance in challenging classes like talking on the phone (left/right) and using a mobile phone also improved compared to Experiment 1, thanks to OBB's rotation handling and data augmentation. The mAP@0.5:0.95 metric, which evaluates detection quality across different IoU thresholds, improved to 0.684, indicating better localization precision.

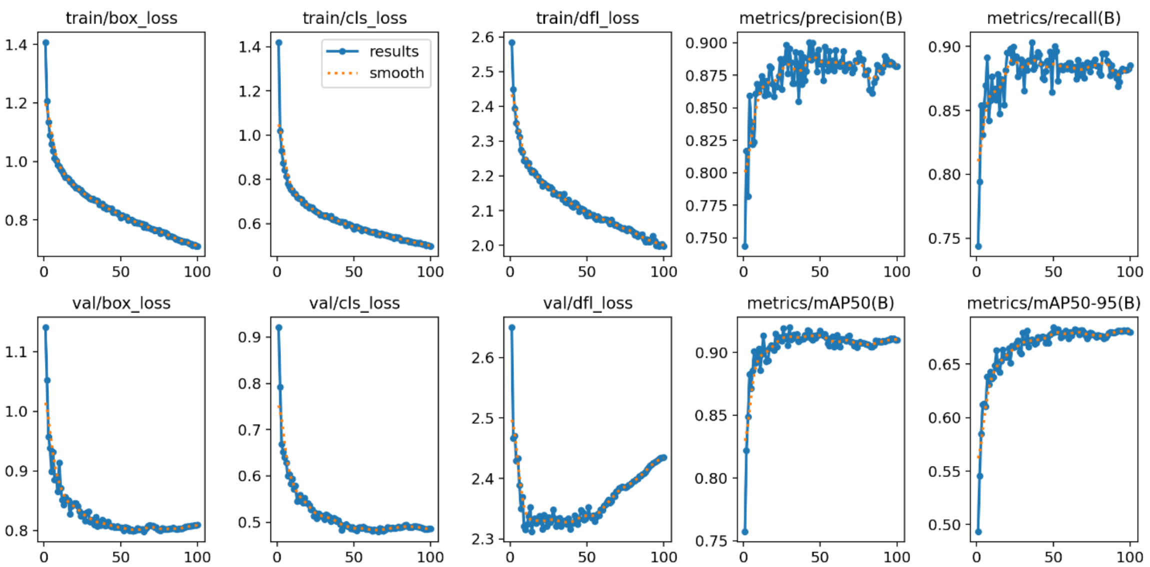


Figure (16) show the training result for the experiment 2

Overall, these results validated the decision to adopt YOLOv8s-OBB, apply strong augmentations, and use a cosine learning rate schedule.

4.3.1 Model Deployment and Real-World Testing

After completing the training phase, we deployed the YOLOv8s-OBB model for real-world testing to validate its performance in actual driving conditions. The objective of this phase was to ensure that the model could accurately detect driver distractions during live operation.

For initial testing, the model was deployed on a laptop connected to the RGB-IR camera positioned inside the car cabin, replicating the setup used during data collection. The model ran in real-time, capturing an image every 30 seconds to analyze the driver's behavior and detect any distractions.

During these driving sessions, the system continuously processed the captured images and displayed the detection results, including bounding boxes and labels for detected objects like hands, face orientation, mobile phones, and steering wheel. This allowed us to visually verify whether the model correctly identified distractions such as hands off the steering wheel, using a mobile phone, or talking to passengers.

4.3.2 Real-World Testing

After deploying the **YOLOv8s-OBB model** on a **laptop** with the **RGB-IR camera**, we conducted several **real-world driving sessions** to validate the system's performance under **actual conditions**. The camera was mounted inside the car cabin, and the model captured **one image every 30 seconds**, analyzing each for potential driver distractions. This section presents **examples from these tests** and discusses the **model's performance** for each scenario.

Example 1: Night Driving – Mobile Phone Detection

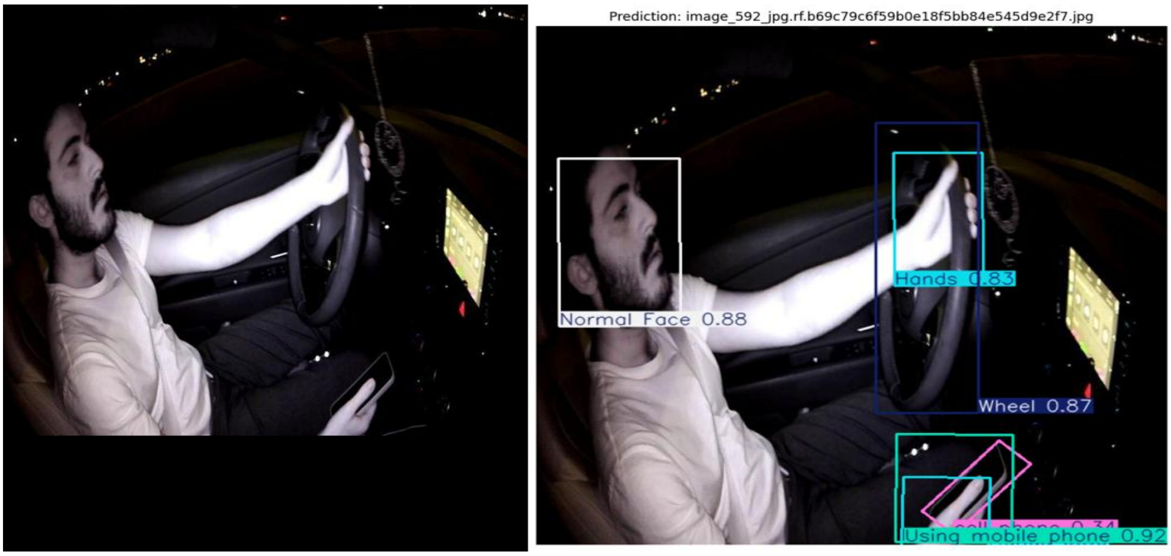


Figure (17) Real-world testing at night showing the original image (left) and the detection output (right).

- In this scenario, the driver is holding a **mobile phone** in the right hand while the left hand is on the **steering wheel**.
- The **model successfully detected**:
    - **Normal Face** with a confidence of **88%** (driver focused forward).
    - **Hands** on the steering wheel with **83%** confidence.
    - **Steering wheel** with **87%** confidence.
    - **Using mobile phone** with **92%** confidence, identifying the distraction correctly.

This example demonstrates the **model's robustness in night driving conditions**. Despite **low-light environments**, the **IR camera** and **YOLOv8s-OBB model** accurately detected the **driver's hand**, **steering wheel**, and **mobile phone usage**. This confirmed the system's capability to identify distractions even when lighting is limited.

Example 2: Night Driving – IR Image with Hands-on-Wheel Detection

Figure (18) Real-world testing at night showing the original IR image (left) and the detection output (right).

In this scenario, the system was tested during night driving using the IR (infrared) camera. As seen in the original frame, the infrared imaging provides clear visibility of the driver’s hands, face, and steering wheel, despite the absence of external lighting. This demonstrates the effectiveness of the IR setup in capturing crucial driver behavior during low-light conditions.

The model successfully detected:

- Normal Face with confidence of 86%, indicating the driver is focused forward.
- Both hands on the steering wheel, with confidences of 82% and 84%.
- Steering wheel with 91% confidence.

Discussion:

This example highlights the model’s strong performance under night-time conditions using IR imaging. The model correctly identified the driver's hands on the wheel, which is crucial for distraction assessment. The high detection confidence across all objects confirms that the YOLOv8s-OBB model, combined with IR input, can reliably operate in challenging lighting environments, ensuring accurate distraction detection both during the day and at night.

Example 3: Daytime Driving – Talking on the Phone Detection

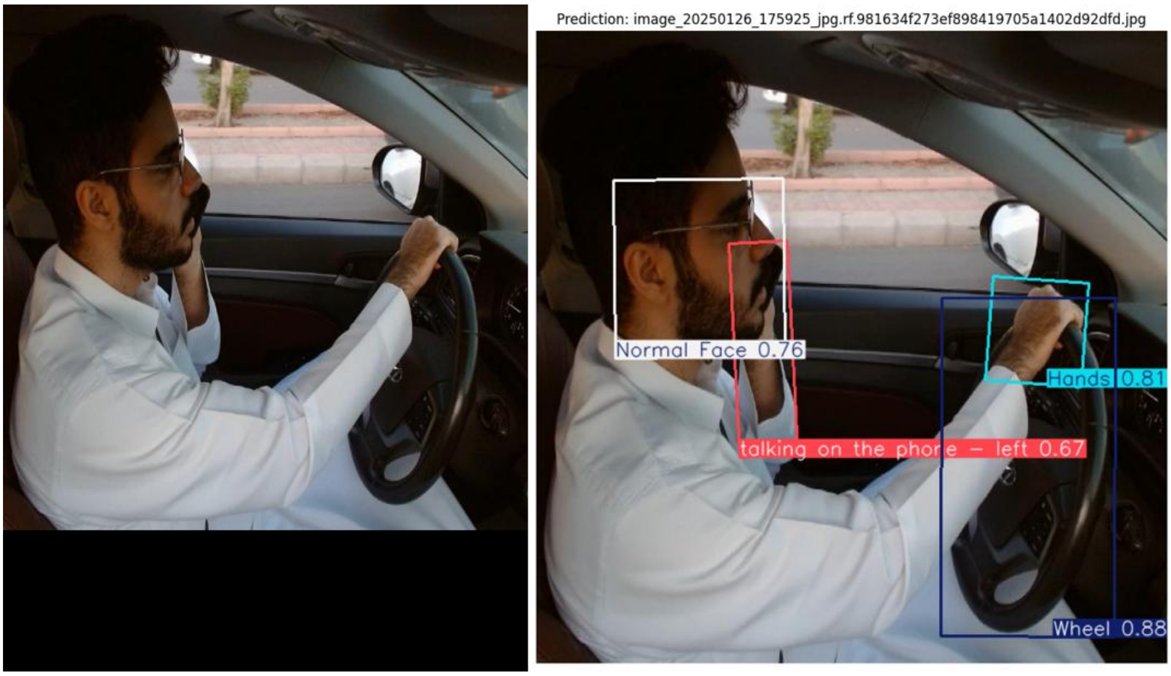


Figure (19) Real-world testing during daytime showing the original image (left) and the detection output (right).

In this scenario, the driver is engaged in talking on the phone (left hand) while driving during the daytime. The model successfully detected:

- Normal Face with 76% confidence.
- Talking on the phone – left with 67% confidence.
- Hands on the steering wheel with 81% confidence.
- Steering wheel with 88% confidence.

This example highlights the model's ability to identify distractions even in bright daytime conditions. Despite the overlapping bounding boxes between the face and the phone, the model accurately detected the talking on the phone – left class. The confidence score (67%) for the phone detection was lower compared to other classes, which suggests that further training data or augmentation could enhance performance for this class. Nevertheless, the YOLOv8s-OBB model consistently recognized the hand-wheel overlap and flagged the distraction event.

As demonstrated through the presented examples, the YOLOv8s-OBB model proved capable of detecting driver distraction classes with good accuracy across various lighting conditions (daytime and nighttime) and in different car cabins. The model consistently identified critical objects such as hands, steering wheel, face orientation, and mobile phone usage, ensuring reliable distraction detection in real-world scenarios. These tests validated the system's robustness and adaptability, confirming its readiness for embedded deployment in diverse driving environments.

4.4.1 Embedded Deployment on Jetson Nano

After testing the model's in real-world testing on a laptop, the next step was to deploy the system on the Jetson Nano 4GB Developer Kit for embedded operation. The Jetson Nano provides the required computational power for running deep learning models while maintaining low power consumption, making it ideal for in-vehicle environments.

4.4.2 Jetson Nano Software Setup

1. **JetPack Installation:**

   The Jetson Nano was flashed with NVIDIA JetPack SDK, which includes essential libraries such as:

   - CUDA (GPU acceleration)
   - cuDNN (deep learning primitives)
   - TensorRT (optimized inference engine)

2. **Python Environment Setup:**
   - Configured a Python 3 virtual environment to manage dependencies and avoid conflicts.
   - Installed PyTorch with CUDA support for GPU-accelerated inference.

3. **YOLOv8 and Required Libraries Installation: Within the virtual environment,**
   - Ultralytics YOLOv8 framework for running the trained model.
   - OpenCV for image processing and video capture.
   - PyTorch for deep learning inference.

4. Testing:

After completing the installation of the Jetson Nano operating system and all Python library dependencies, we proceeded to test the system performance by deploying the trained YOLOv8s-OBB model and running inference tests.

Table (7) Table displaying the inference times (in seconds) for various images processed by the YOLO model.

Image	Inference Time (seconds)
1	38.7
2	8.88
3	1.16
4	0.14
5	0.14

We initially tested the system by feeding it one image to evaluate the inference time. The first prediction took approximately **40 seconds**, which was unexpectedly high for real-time applications. To further investigate, we ran a batch of five consecutive images through the model. The recorded inference times were as follows:

As shown in Table 7, the initial image incurred a high inference time due to the model loading process on Jetson Nano's GPU. The system requires additional time to initialize the model and allocate GPU resources during the first inference. However, once the model was fully loaded, the subsequent images were processed significantly faster, achieving inference times of under 1 second per frame, with the last two images processed in just **0.14 seconds**.

```
python3 -c '
import time
from ultralytics import YOLO

model = YOLO("yolov8s_OBB.pt")  # Load model once
img_path = "test.jpg"

# Warm-up run
model(img_path, imgsz=320, half=True)

# Perform inference multiple times and measure duration
for i in range(5):
    start = time.time()
    results = model(img_path, imgsz=320, half=True)
    duration = time.time() - start
    print(f"Inference {i + 1}: {duration:.2f} seconds")
'
```

Figure (20) Terminal output displaying YOLO model inference times and warnings.

This behavior confirms that the Jetson Nano, after model initialization, can sustain real-time performance, meeting the project requirement of less than 1 second per frame. The initial delay is a known characteristic of running deep learning models on embedded systems, where model loading can be resource-intensive, but inference is efficient after setup.

4.4.3 Software Challenges and Solutions

During the setup process, we encountered several software compatibility issues related to CUDA support on the Jetson Nano. Specifically, not all versions of JetPack, PyTorch, and CUDA are mutually compatible, which caused difficulties in enabling GPU acceleration for running the YOLOv8 model.

We initially attempted to install multiple versions of PyTorch and CUDA to find the combination that successfully enabled CUDA support on the Jetson Nano. Some versions either lacked CUDA compatibility or failed to utilize the GPU hardware, leading to slow inference speeds.

4.5.1 Distraction Detection Algorithm

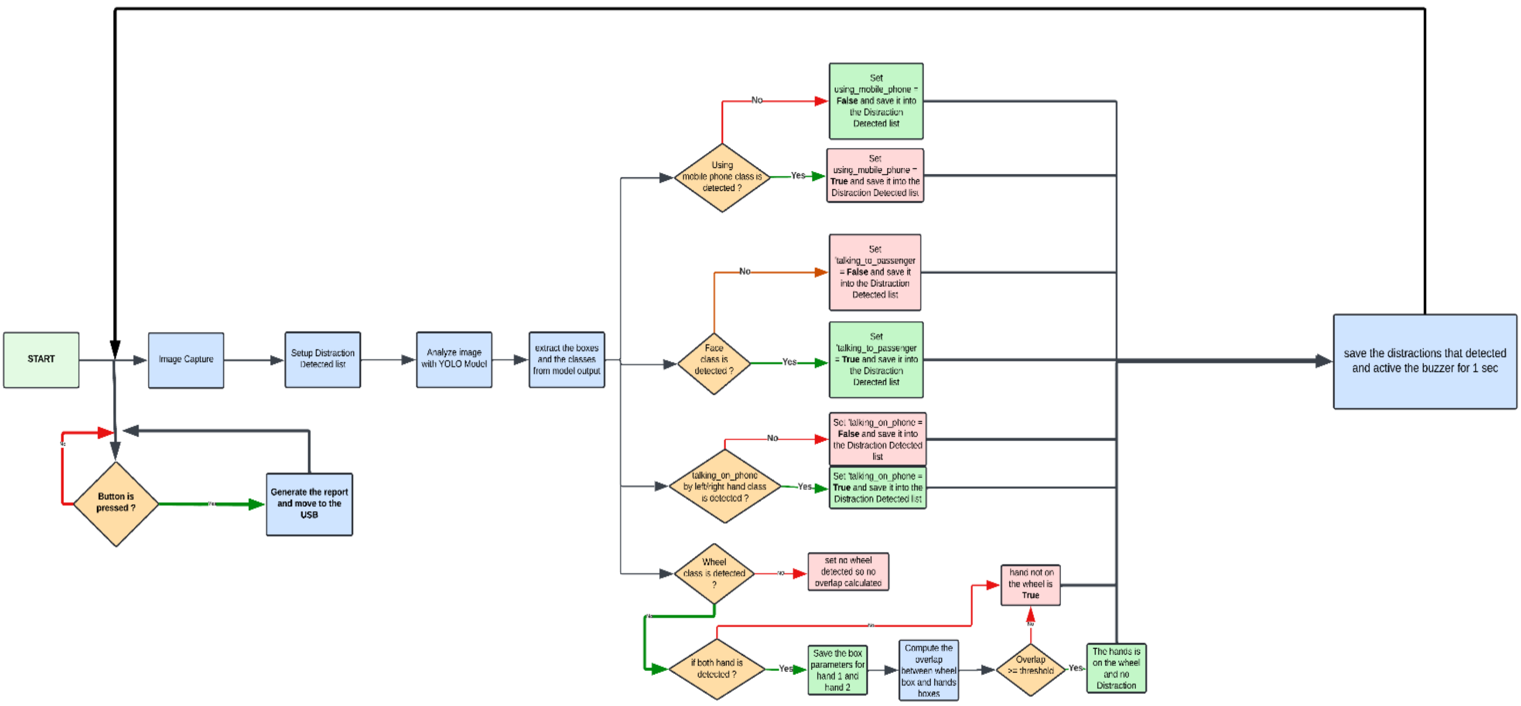


Figure (21) Flowchart showing the distraction detection process using YOLO model analysis.

The distraction detection algorithm integrates YOLOv8s-OBB (Oriented Bounding Box) with post-processing logic to evaluate driver distractions. The model identifies key objects such as hands, steering wheel, mobile phone, and face orientation while the algorithm further analyzes these detections to infer driver behavior and detect specific distractions.

The system focuses on four types of distractions, each identified through distinct detection strategies:

1. Using Mobile Phone:

- Detected if the YOLOv8-OBB model identifies an object classified as mobile phone use.

2. Talking on the Phone (Left/Right):

- Detected if the model identifies a hand holding a phone on either side of the face:
  - Class 6 → Talking on the phone (left hand).
  - Class 7 → Talking on the phone (right hand).

3. **Talking to Passenger:**
    - Detected based on face orientation.
4. **Hands Not on the Steering Wheel (Indirect Distraction):**
    - Detected through calculate the overlap between the hands and the steering wheel:

The detection process consists of **three main stages**:

4.5.2 Stage 1: Image Capture and Inference

- The system **captures an image** from the driver cabin using the capture_image() function.
- If the camera fails to open or capture a frame, an **error is raised**, and the system halts until the next attempt.
- The captured image is processed by the **YOLOv8s-OBB model**, which outputs object detections with **oriented bounding boxes (OBBs)**.
- OBBs contain the object's **position, size, and rotation angle**, allowing robust detection of objects (e.g., hands or mobile phones) in various orientations.

4.5.3 Stage 2: Distraction Analysis Logic

The **Distraction_Detection()** function evaluates the YOLOv8-OBB detections and determines the presence of distractions based on object relationships:

- **Direct Distractions**:
    - Using Mobile Phone → If class 3 is detected, set using_mobile_phone = True.
    - Talking on the Phone (Left/Right) → If class 6 (left) or class 7 (right) is detected, set talking_on_phone_left/right = True.
    - Talking to Passenger → If class 0 (face turned sideways) is detected, set talking_to_passenger = True.
- Indirect Distraction (Hands Not on Wheel):
    - The algorithm first checks if the steering wheel (class 4) is detected:
        - If no steering wheel is detected, no hand-wheel overlap is calculated, and a "no wheel detected" flag is raised.
    - If at least one hand (class 1) is detected:

- The algorithm calculates the overlap percentage between each hand bounding box and the steering wheel bounding box.
  - If the overlap is below a set threshold, the hand is considered not on the wheel.
  - If both hands are either missing or not sufficiently overlapping, the system flags hands_not_on_wheel = True.

To determine the appropriate hand-wheel overlap threshold, we collected a dataset of 200 images where the driver was holding the steering wheel correctly with both hands. For each image, we computed the overlap percentage between the hands and the steering wheel using the system's overlap calculation function. After analyzing these results, we calculated the average overlap, which was approximately **48%.** This value was chosen as the optimal threshold to distinguish between proper hand placement and potential distraction scenarios, ensuring accurate detection of hands not on the wheel.

- **Hand-Wheel Overlap Calculation**:
  - obb_to_polygon(): Converts OBBs into polygon shapes for overlap analysis.
  - hand_overlap_with_wheel(): Computes the **intersection area** between each hand and the steering wheel.

4.5.4 Stage 3: Logging and Output

- The system maintains a text file (distraction_save.txt) to track distraction events for reporting:
  - Using mobile phone.
  - Talking on the phone (left/right).
  - Talking to passenger.
  - Hands not on the wheel.
- After each inference, the algorithm updates the distraction records based on the current detection results, you can see an example of the text file that will save the distraction records in figure 22.

```
2025-04-27 18:42:15
10 // using mobile phone
4 // talking on the phone left/right
5 // talking to the passenger
1 // not holding the steering wheel
```

Figure (22) the text file that saves the distraction records

4.5.5 Algorithm Flow Summary

1. Capture an image from the driver's cabin.
2. Run YOLOv8-OBB inference to detect objects (hands, wheel, phone, face).
3. Analyze detections:
   - Check for **direct distractions** (phone use, passenger interaction).
   - Check for **steering wheel detection**.
   - If the wheel is detected, computing hand-wheel overlaps for indirect distractions.
4. Log distraction events into a persistent file and generate feedback by the Buzzer.
5. Repeat the process continuously.

In the meantime, if the user or the fleet manager push the button, the report will generate automatically by a separated code and saved into the USB FLASH DRIVE that attached to the Jetson nano.

4.5.6 Report Generator

The system includes an automated report generation feature designed to summarize distraction events detected during each driving session. This process leverages several key tools:

- **pdfkit:** A Python library used to generate PDF files from HTML templates**.**
- **wkhtmltopdf**: An external tool that converts HTML content into PDF format**.**
- **BeautifulSoup:** A Python library used to parse and modify the HTML template dynamically.

During operation, the system continuously logs distraction events into a text file (destraction_save.txt). This file records the counts of each distraction type (e.g., mobile phone use, talking to passengers, hands not on the wheel) along with the session start timestamp.

When the user or fleet manager presses the designated push button, the system triggers the report generation process:

1. The system reads data from the distraction log file.
2. It dynamically populates a predefined HTML template with:
   - The start and end times of the driving session.
   - A summary table showing the number of occurrences for each distraction type.
3. The populated HTML is converted into a PDF report using pdfkit and wkhtmltopdf.
4. The generated report is automatically saved to any connected USB drives, ensuring easy access for fleet managers or drivers.

Once the report is generated and saved, the system clears the log file and resets the distraction counters, marking the start of a new driving session. This ensures that each report corresponds to a specific session, providing clear and organized records of driver behavior over time. In figure 23, you can see an example of the report that will generate when the push button is pressed.

DRIVER DISTRACTIN DETECTION SYSTEM

Distraction Report

Company: KAU

Start Date: 2025-04-22

Start Time: 17:37:34

End Date: 2025-04-26

End Time: 00:20:14

Summary of Distraction Types

Distraction Type	Number of distractions
Holding mobile phone against his/her ear	2 Times
Talking to passengers	6 Times
Not holding the steering wheel	2 Times
Holding mobile phone in hands	16 Times

Contact Info: KAU@gmail.com | +966 555 555 555

Page 1

Figure (23) shows the distraction report

4.6.1 Algorithm Testing on Jetson Nano

To test the distraction detection algorithm in a controlled scenario, we performed a test by manually passing a single image through the system. The objective was to assess the algorithm's ability to detect distractions and analyze hand-wheel overlap on the Jetson Nano.

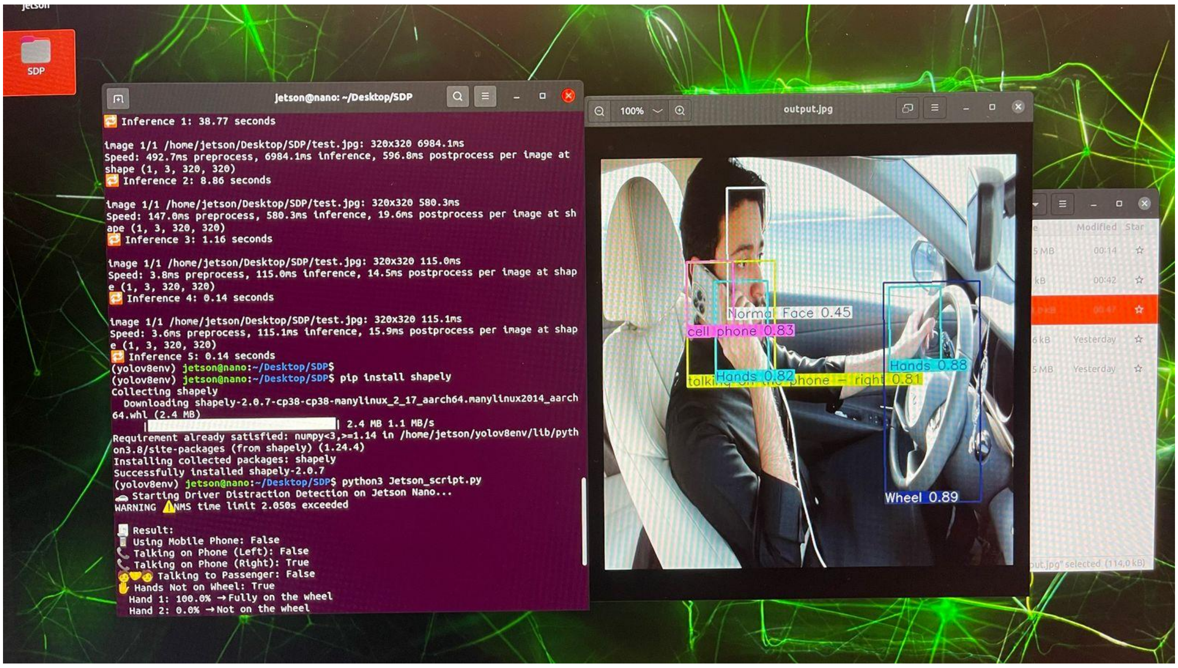


Figure (24) Testing the distraction detection algorithm on Jetson Nano. The left terminal displays inference times, and the right window shows the detection output with bounding boxes and confidence scores.

As shown in **Figure 24**, the system processed the **input image** and successfully detected the following:

- Normal Face with a confidence of 45%.
- Cell phone detected near the left hand with 83% confidence.
- Talking on the Phone (Right) classified as True, while Talking on the Phone (Left) was False.
- Two hands detected:
    - Hand 1: 82% overlap with the steering wheel → classified as Fully on the wheel.
    - Hand 2: 0% overlap with the steering wheel → classified as Not on the wheel.

The system also reported hands not on the wheel as True due to one hand being off the wheel, and talking to a passenger as True, inferred from face orientation.

4.6.2 System Hardware Setup in Car Cabin

To implement the Driver Distraction Detection System in a real-world car cabin environment, we assembled a set of integrated hardware components designed for real-time operation, robust performance, and driver feedback. The system is carefully engineered to ensure consistent functionality under the varying conditions of a moving vehicle. The following outlines the key components and their roles within the system:

The system is powered directly from the car’s 12V DC supply through a car lighter adapter, which feeds into a DC-DC converter (buck converter). This converter stabilizes the output to 5V at 4A, providing sufficient power to operate the NVIDIA Jetson Nano (4GB), the core processing unit. The Jetson Nano runs the YOLOv8s-OBB model, performing real-time object detection and distraction analysis, processing the input images, and generating output based on the detection logic.

For capturing driver images, the system employs an Arducam 1080p Day/Night Vision USB Camera. This camera is strategically positioned inside the car cabin to continuously monitor the driver's behavior. Its day/night vision capability ensures clear image capture in a wide range of lighting conditions, from bright daylight to low-light night driving scenarios.in addition, this camera has an auto switching feature from RGB mode to IR mode. To provide immediate auditory feedback to the driver upon detecting a distraction, an active buzzer is connected to one of the Jetson Nano's GPIO pins. This buzzer is configured to emit a beep lasting one second whenever a distraction event is identified, such as hands not on the steering wheel or mobile phone usage. This feedback mechanism helps alert the driver promptly to correct unsafe behavior.

To ensure stable and optimal placement of the camera within the vehicle cabin, we designed a custom 3D-printed camera mount. This mount was specifically engineered to be installed above the passenger side, providing a clear and unobstructed view of the driver’s face and hands. Its compact and modular design enables quick installation, easy repositioning, and robust performance under different driving conditions.

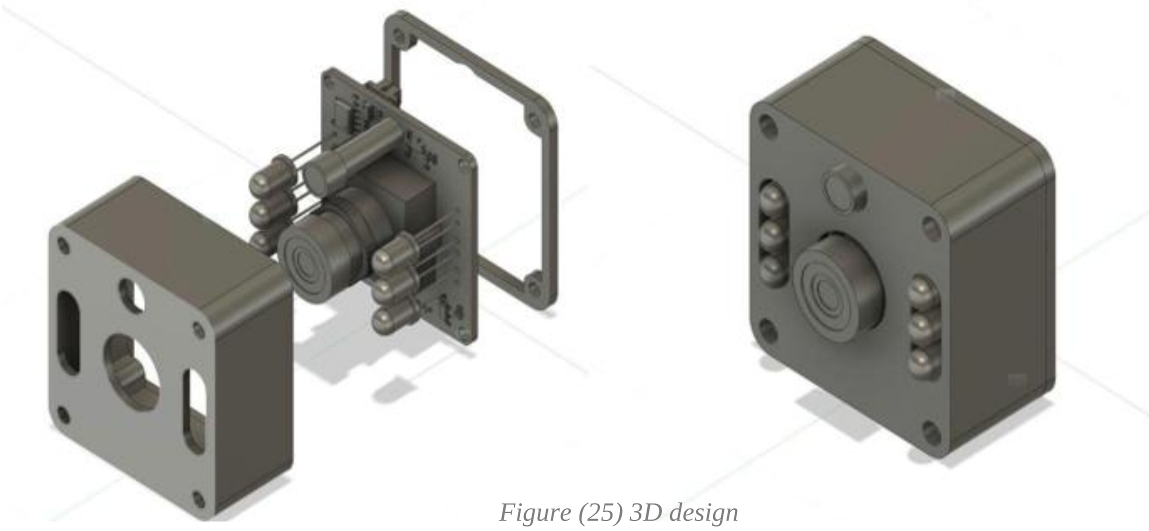


Figure (25) 3D design

Key Features of the Camera Mount:

- Protective Housing:

A snug-fitting enclosure designed for the camera module and its infrared (IR) LEDs, protecting them from dust, vibrations, and external impacts.

- Secure Mechanical Attachment:

The design includes mechanical features that allow the mount to be firmly attached to the vehicle structure, ensuring stability during operation.

- Compact Form Factor:

The mount's slim design makes it ideal for installation in tight spaces, such as above the passenger seat, without obstructing the driver’s view or interfering with vehicle aesthetics.

- Modular Design:

The assembly is easy to put together, disassemble, and reposition if needed, providing flexibility for adjustments or maintenance.

- Precision Fit:

Custom-designed for the specific camera module used in this project, with precise cutouts for the camera lens and IR LEDs, ensuring proper alignment and functionality.

• Optimal Placement Angle:

The camera is angled strategically to ensure full coverage of the driver’s face and hands while remaining unobtrusive in the vehicle cabin.

The following figures illustrate the camera housing:

• Figure 25 (Left): Exploded view of the camera and its protective housing, showing individual components.

• Figure 25 (Right): Assembled view of the mounted camera, highlighting its compact and integrated appearance.

This mounting solution ensures both ease of installation and durability, providing reliable performance for continuous driver monitoring.

Additionally, the system includes a reporting mechanism via a push button that is connected to the Jetson's GPIO pins, allows the driver or user to manually trigger the generation of a distraction report. This report summarizes the detected distraction events logged during the driving session, offering a detailed record of driver behavior for later analysis. Together, these components form a cohesive hardware setup that enables continuous monitoring, real-time feedback, and detailed reporting within the car cabin, ensuring a comprehensive approach to driver distraction detection.

1. Power Supply:

- **Car Lighter Adapter**: Provides **12V DC** from the vehicle.
- **DC-DC Converter (Buck Converter)**: Steps down the car's **12V** to a stable **5V, 4A** output.
- This supplies sufficient power to the **Jetson Nano**, ensuring reliable operation under automotive conditions.

2. Main Processing Unit:

- **NVIDIA Jetson Nano (4GB)**:

- Acts as the **core processing unit**, running the **YOLOv8s-OBB model** and handling inference, distraction detection, and output generation.

3. Camera Module:

- **Arducam 1080p Day/Night Vision USB Camera**:
    - Positioned inside the car cabin to capture real-time video frames of the driver.
    - The day/night vision feature with auto switching ensures consistent performance in varying lighting conditions.

4. Feedback Mechanism:

- **Active Buzzer**:
    - Connected to one of the Jetson Nano's GPIO pins.
    - Provides auditory feedback when a distraction event is detected (e.g., hands not on the wheel, phone use).
    - Configured to **beep for 1 second** per distraction event.

5. Reporting Mechanism:

- Push Button:
    - Connected to Jetson Nano's GPIO pins.
    - When pressed, it triggers the system to generate a distraction report, summarizing the events logged during the session.

- This allows manual intervention by the user to retrieve a report at any time.

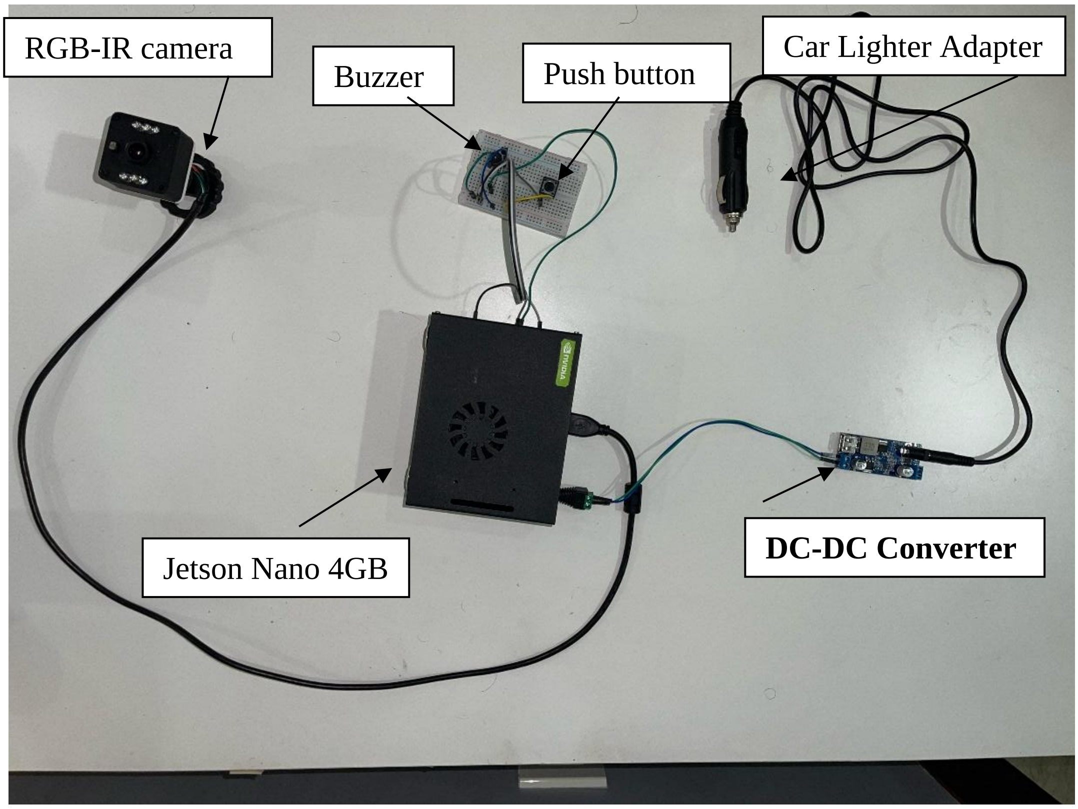


Figure (26) shows the distraction report

Figure (27) shown the camera setup in the car cabin

After completing the hardware setup, we began running the Driver Distraction Detection System inside the car cabin. To ensure everything was operating correctly, we connected a small portable screen to the Jetson Nano. This allowed us to visualize the system output in real-time and verify that the distraction detection algorithm was functioning as intended.

As shown in Figure 27, the system successfully detected the driver's distractions during the driving session. The connected display provided a clear view of the annotated images produced by the YOLOv8s-OBB model, showcasing the detected objects such as hands, steering wheel, mobile phone, and face orientation. This real-time feedback confirmed that the system could accurately identify distractions like mobile phone use, talking to passengers, and hands not on the wheel.

In Figure 28, you can see a sample of the annotated images captured during this driving session. These images include bounding boxes and labels for detected objects, which serve as visual proof of the system's performance.

This setup helped us validate the detection pipeline and ensured the system could operate reliably in a real driving environment.

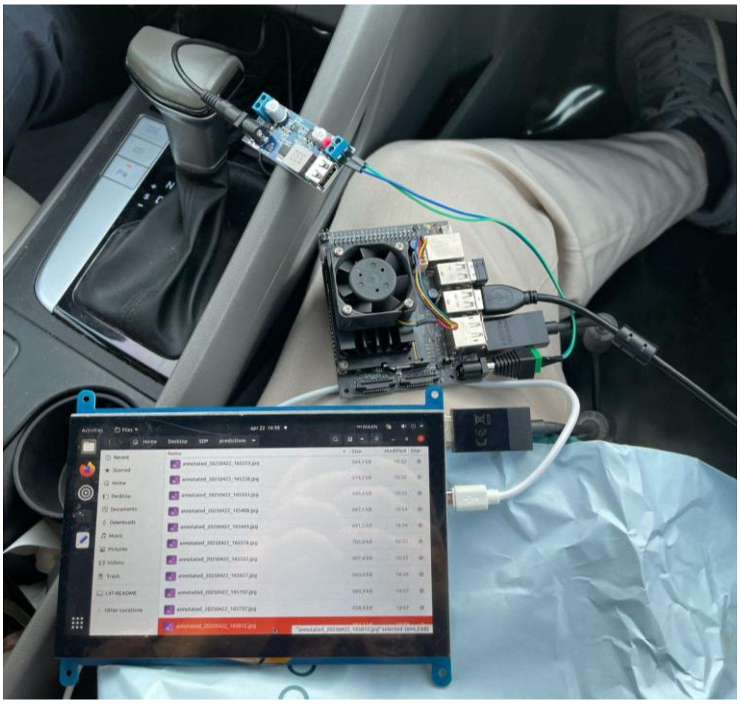


Figure (28) a picture for the system while it is running

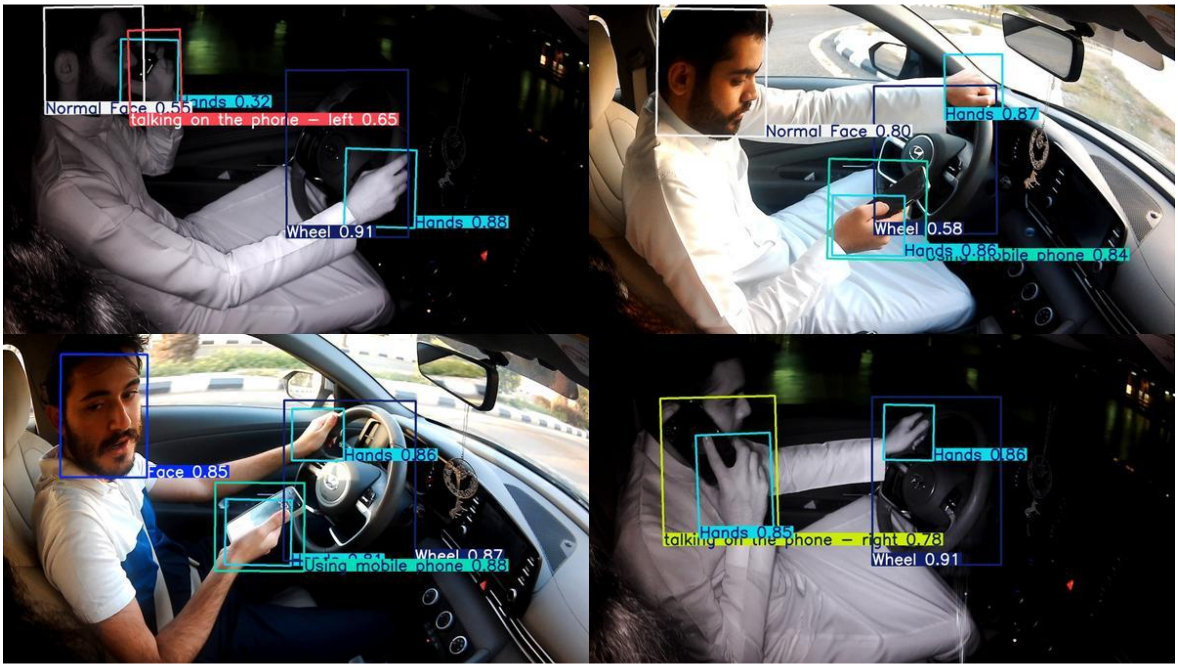


Figure (29) Sample annotated images from the driving session showing distraction detection results.

CHAPTER – 5 VALIDATION EXPERIMENTS

5.1 Validation of Distraction Detection (Four Types):

Experiment Objective:

The objective of this experiment is to validate the system's capability to detect the four specified types of driver distractions: holding a mobile phone in the hands, holding a mobile phone against the ear, talking while looking at a passenger, and not holding the steering wheel.

Background Information:

Accurate detection of these four distractions is a fundamental requirement for the effectiveness of the driver distraction detection system. The system utilizes a Convolutional Neural Network (CNN) model deployed on the NVIDIA Jetson Nano platform. Reliable recognition of these behaviors is essential for providing timely warnings to drivers and for supporting the generation of accurate performance reports for fleet management applications.

Work Plan:

The validation procedure involved collecting a set of 200 images, contains one or more of the distractions type. The selected images were independent of the training dataset to ensure unbiased evaluation of the model's generalization capability. Also, Furthermore, the images were captured from different individuals to test the system's ability to detect distractions across varying subjects and driving behaviors. These images were processed using the trained model running on the Jetson Nano, and the predicted classifications were compared with the actual distraction types to assess the detection performance.

Tools Used:

- NVIDIA Jetson Nano
- Arducam Day-Night Vision Camera
- Pre-trained driver distraction detection model

Collected Data:

The system was tested on images corresponding to the four distraction types, each captured from different individuals. The model's predictions were as follows:

- **Distraction Type:** Holding mobile phone in hands
  Prediction Result: Correct
- **Distraction Type:** Holding mobile phone against ear
  Prediction Result: Correct
- **Distraction Type:** Talking while looking at passenger
  Prediction Result: Correct
- **Distraction Type:** Not holding the steering wheel
  Prediction Result: Correct.

Table (8) accuracy of distraction

Distraction	accuracy
Using mobile phone	**0.87**
Talking on the phone (right)	**0.88**
Talking on the phone (left)	**0.88**
Talking while looking at passenger	**0.83**
Not holding the steering wheel	**0.90**

And here is some samples from the data that we tested the model on:

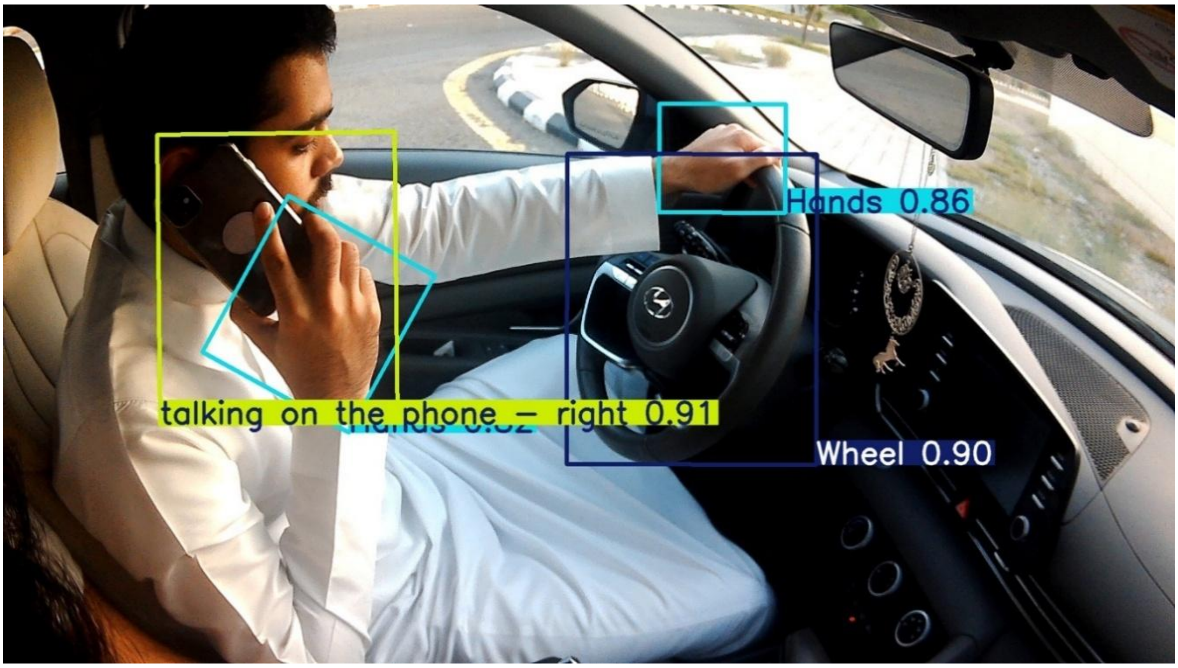


Figure (30) Distraction 1: talking on the phone on the right side.

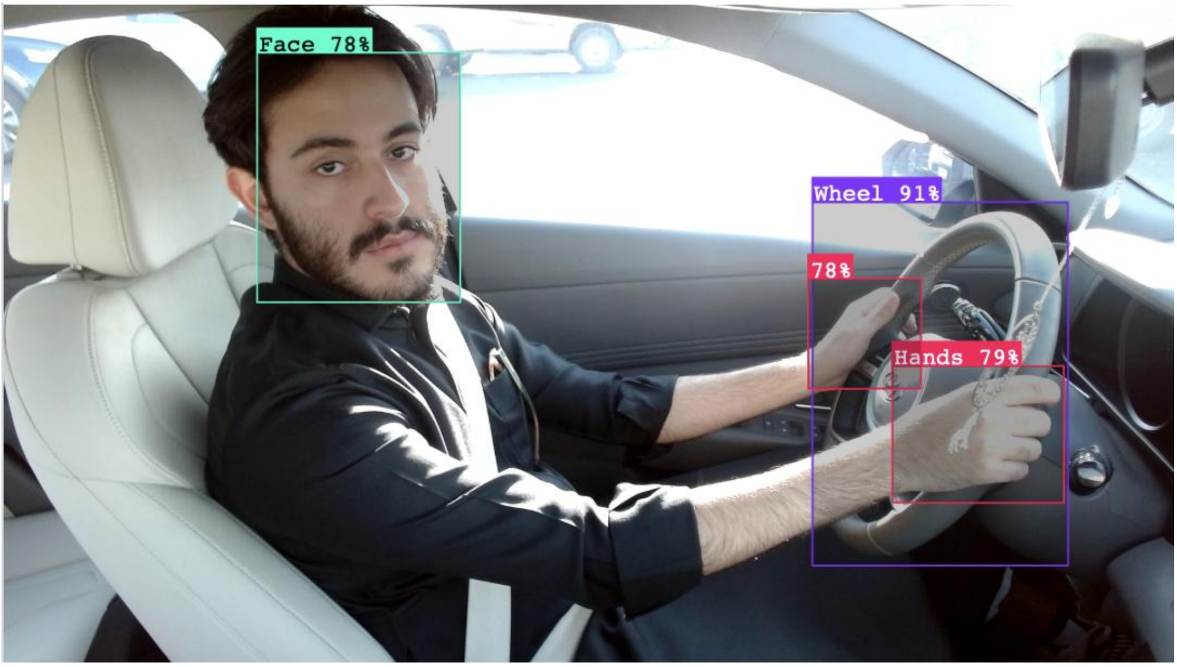


Figure (31) Distraction 1: Distraction 2: looking or talking with the passenger (not looking at the road)

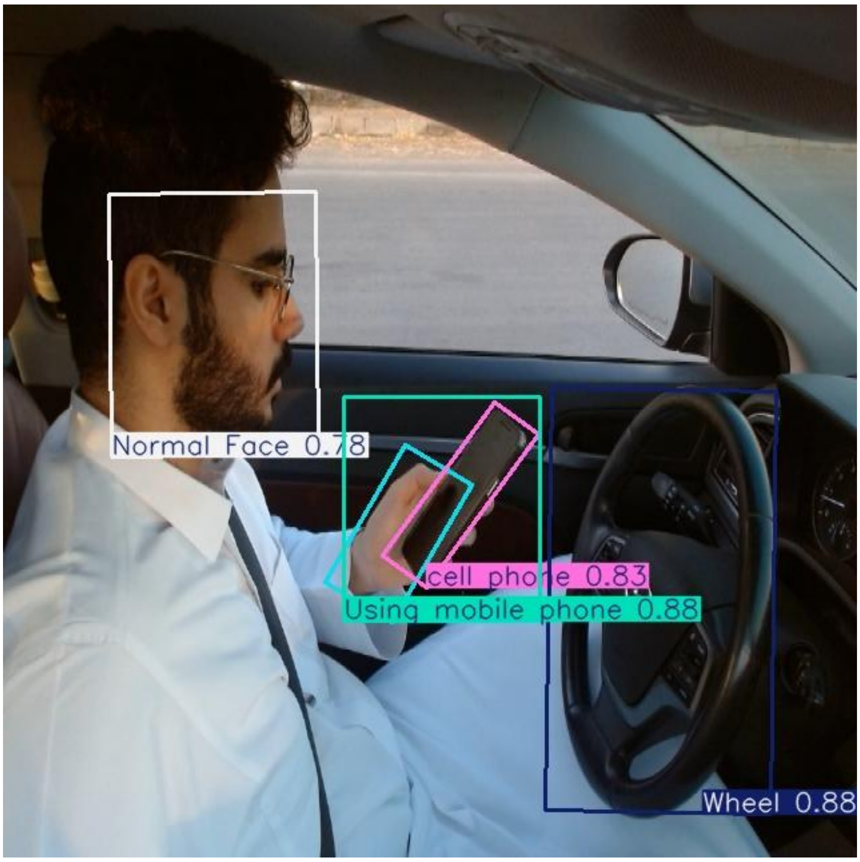


Figure (32) Distraction 3: using mobile phone

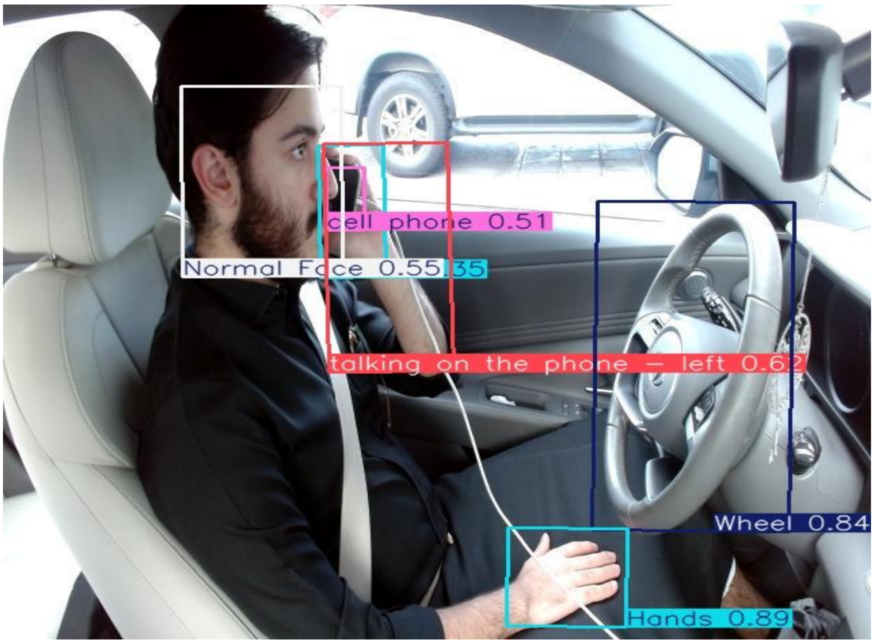


Figure (33) Distraction 4: talking on the phone on the left side

Figure (34) Distraction 5: not holding the steering wheel (detecting the hands and wheel)

5.2 Validation of Detection Accuracy (≥80%):

Experiment Objective:

The primary objective of this validation experiment is to verify that the developed driver distraction detection system achieves a minimum detection accuracy of 80%, as specified in the Product Design Specifications (PDS). Ensuring a high level of detection accuracy is essential for the credibility and effectiveness of the system, as it must reliably distinguish between distracted and non-distracted driving behaviors under a variety of operational conditions.

Achieving this level of performance is crucial not only for issuing timely alerts to the driver but also for providing accurate session summaries for fleet managers and safety evaluators. Successful validation against this objective would confirm the system's readiness for real-world deployment and its ability to contribute meaningfully to the improvement of road safety.

Background Information:

Detection accuracy is one of the most critical evaluation metrics for any driver monitoring system. A system with low accuracy could fail to detect distraction events, leading to missed alerts and potential accidents, or could incorrectly classify safe behaviors as distractions, causing unnecessary alerts and driver frustration. Thus, achieving a high and reliable detection accuracy is pivotal for the system's adoption and effectiveness. In the context of this project, the distraction detection model is based on a Convolutional Neural Network (CNN) trained to identify specific distraction behaviors, including holding a mobile phone, talking on the phone, and not holding the steering wheel properly.

According to the PDS, a minimum detection accuracy of 80% is required to meet the system's acceptance criteria. This threshold ensures that the system provides a strong balance between sensitivity (detecting true distraction events) and specificity (minimizing false alarms), thereby maintaining trust and usability for both drivers and fleet management organizations.

Work Plan:

To comprehensively validate the system's detection accuracy, a systematic evaluation was carried out using the validation portion of the dataset. Approximately 800 images, not previously exposed to the model during training, were utilized for this assessment. These images cover a range of distraction scenarios as well as normal driving conditions, thus providing a diverse and challenging test set for the system. The performance evaluation was based on widely recognized machine learning metrics, including:

- **Precision**: The ratio of correctly predicted distraction instances to all predicted distraction instances.
- **Recall**: The ratio of correctly predicted distraction instances to all actual distraction instances.
- **Mean Average Precision at 0.5 IoU (mAP@0.5)**: A comprehensive metric assessing both detection quality and localization accuracy.

Furthermore, detailed per-class performance metrics were computed to analyze the system's ability to detect each specific type of distraction individually. Additional performance visualization tools, including the Recall-Confidence curve, Precision-Recall curve, Precision-Confidence curve, F1-Confidence curve, and normalized confusion matrix, were generated to provide deeper insights into the system's strengths and areas for potential improvement.

During the evaluation, the "cell phone" class was excluded from the final analysis, as the operational focus of the system is on detecting "holding a mobile phone" rather than generic mobile phone presence.

Collected data:

The evaluation of the model on the validation dataset yielded the following overall performance metrics:

- **Overall Precision:** 0.886
- **Overall Recall:** 0.892
- **Overall mAP@0.5:** 0.917

Table (9) Per-Class Metrics

Distraction Type	Precision	Recall	mAP@0.5
using mobile phone	0.871	0.854	0.859
Talking on the phone (left)	0.884	0.865	0.951
Talking on the phone (right)	0.887	0.900	0.878
Hands	0.950	0.949	0.971
wheel	0.987	0.992	0.991
Face	0.839	0.883	0.991

Table 8 presents the per-class detection performance for the four main targeted distractions. The system achieved a precision of 87.1% and a recall of 85.4% for detecting holding a mobile phone. For detecting talking on the phone while looking left and right, the precision and recall values exceeded 88%, with mAP@0.5 values close to 0.95. Similarly, for detecting proper hand placement on the steering wheel, the system achieved the highest performance. These results indicate consistent and reliable detection capability across all critical distraction types, meeting and exceeding the expected performance standards.

The confusion matrix is a table that compares the model's predicted classes with the actual true classes. It shows how often the system correctly classifies each distraction type and where errors occur. A strong diagonal line in the matrix, as seen in Figure 34, indicates that most predictions match the true labels.

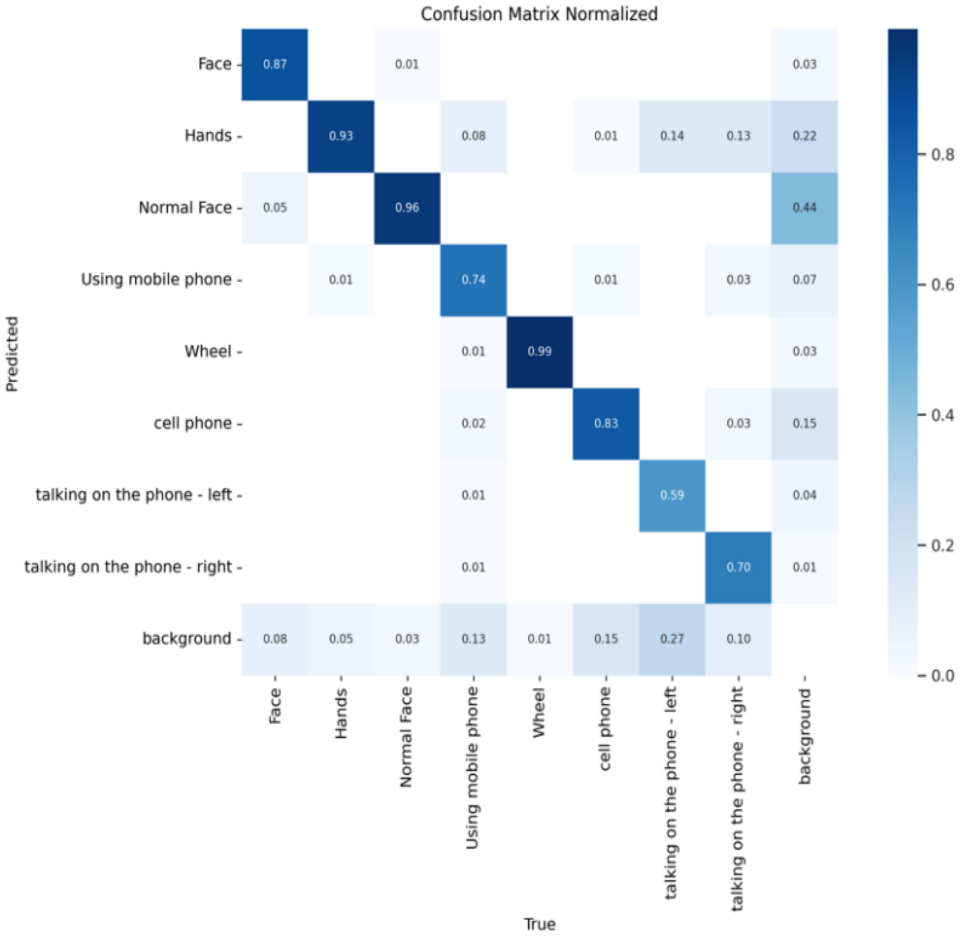


Figure (35) Confusion matrix

The precision-recall (PR) curve, shown in Figure 35, plots precision against recall at different classification thresholds. Precision measures the proportion of correct positive predictions, while recall measures the proportion of actual positives that were correctly identified. A PR curve that stays high across a wide range of recall values, as observed in this experiment, indicates that the system is effective at both detecting distractions and minimizing false alarms.

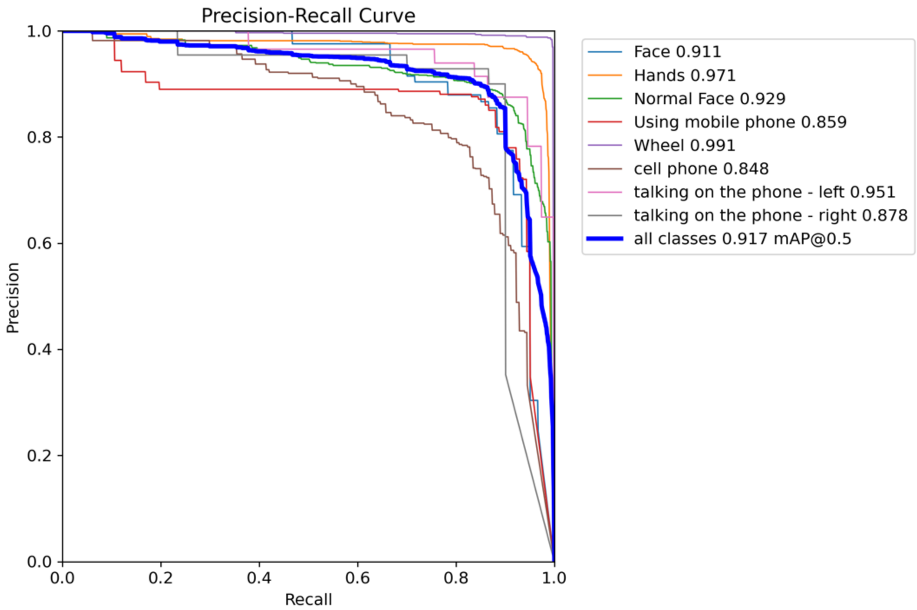


Figure (36) Precision and recall curve

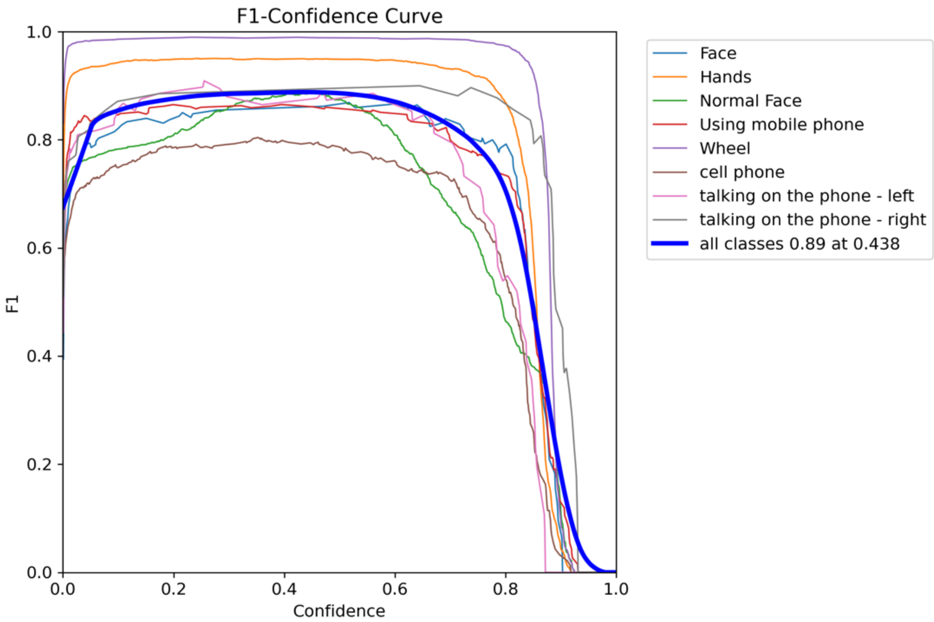


Figure (37) F1 curve

The F1 score curve, presented in Figure 36, shows how the F1 score varies across different confidence thresholds. The F1 score is the harmonic mean of precision and recall, providing a single value that balances both metrics. A high F1 score peak (around 0.89) reflects that the system achieves strong precision and recall simultaneously, ensuring reliable distraction detection without sacrificing accuracy or sensitivity.

Data Analysis and Interpretation:

The overall results confirm that the distraction detection model achieves an overall precision of 88.6%, an overall recall of 89.2%, and an overall mAP@0.5 of 91.7%, all of which exceed the required 80% minimum accuracy threshold.

Additionally, the per-class performance metrics, summarized in Table 5.1, indicate that each individual distraction class achieved precision, recall, and mAP@0.5 values above 80%, demonstrating consistent high-level performance across all target behaviors.
The system's classification performance is visualized in the Normalized Confusion Matrix (Figure 34), which shows strong diagonal dominance, indicating that most predictions were correctly classified with minimal confusion between classes.

The Precision-Recall Curve (Figure 35) illustrates the balance between precision and recall across different confidence thresholds, confirming that the model maintains high precision even as recall increases. Finally, the F1 Score vs Confidence Threshold Curve (Figure 36) highlights that the F1 score reaches a peak of approximately 0.89, indicating a strong overall balance between precision and recall.

Collectively, these metrics and visualizations provide strong evidence that the developed driver distraction detection system meets and exceeds the required accuracy specifications, thereby successfully validating the second must.

5.3 Validation of Model Inference Time for Timely Alert Generation

Experiment Objective:

The objective of this validation is to confirm that the model's inference time is sufficiently short to allow for distraction detection and auditory alert generation within the required 60-second interval.

Background Information:

For the auditory alert system to function as intended, the time required for the model to process an image and detect a distraction must be significantly less than 60 seconds. This ensures that once a distraction occurs, the system can promptly analyze the driver's behavior and trigger an alert within the specified time frame. Excessive inference time could result in delayed alerts, reducing the system's effectiveness in preventing distracted driving incidents.

Work Plan:

To evaluate the system's processing speed, a series of inference tests were conducted on the Jetson Nano using a pre-trained YOLO model. The steps included:

1. Loading the distraction detection model onto the Jetson Nano.
2. Running inference on a test image five consecutive times.
3. Recording the duration required for each inference.
4. Observing any differences between the first and subsequent inference times.

Tools Used:

- NVIDIA Jetson Nano
- Pre-trained YOLOv8 distraction detection model
- Python-based inference timing script

Collected data:

Table (10) inference duration

Inference number	Inference Time (seconds)
1	38.77
2	8.86
3	3.16
4	0.14
5	0.14

Data Analysis and Interpretation:

The results, illustrated in table 9, indicate that after the initial model loading, subsequent image processing times are consistently well below one second. The first inference required approximately 38.77 seconds due to the time needed to load the model into memory, which is a one-time initialization event. After this initialization, all remaining inferences completed in less than one second. This confirms that the system has ample processing time to detect distractions and issue an auditory warning within the 60-second window, satisfying the real-time operational requirement of the third must.

5.4 Validation of Session Data Saving and Report Generation

Experiment Objective:

The objective of this experiment is to validate that the system correctly saves session data during operation, generates an organized report summarizing the types and frequencies of detected distractions, and allows the retrieval of the report through external storage such as a USB drive.

Background Information:

For effective fleet management and driver monitoring, it is essential that the system not only detect distraction events in real-time but also record and summarize these events at the end of each driving session. According to the Product Design Specifications (PDS), the report must be comprehensive, accurate, and easily accessible. Ensuring proper data storage and external retrieval capabilities is crucial for system usability and reliability in real-world deployment.

Work Plan:

To validate the data saving and report generation functionalities, the following procedure was followed:

1. Simulate a typical driving session containing various distraction events.
2. Allow the system to operate normally, recording detected distractions during the session.
3. Upon session completion, insert a USB storage device into the system's designated port.
4. Verify that the system saves a report file containing the session data to the USB.
5. Open and review the report to confirm the accuracy and organization of the recorded information.

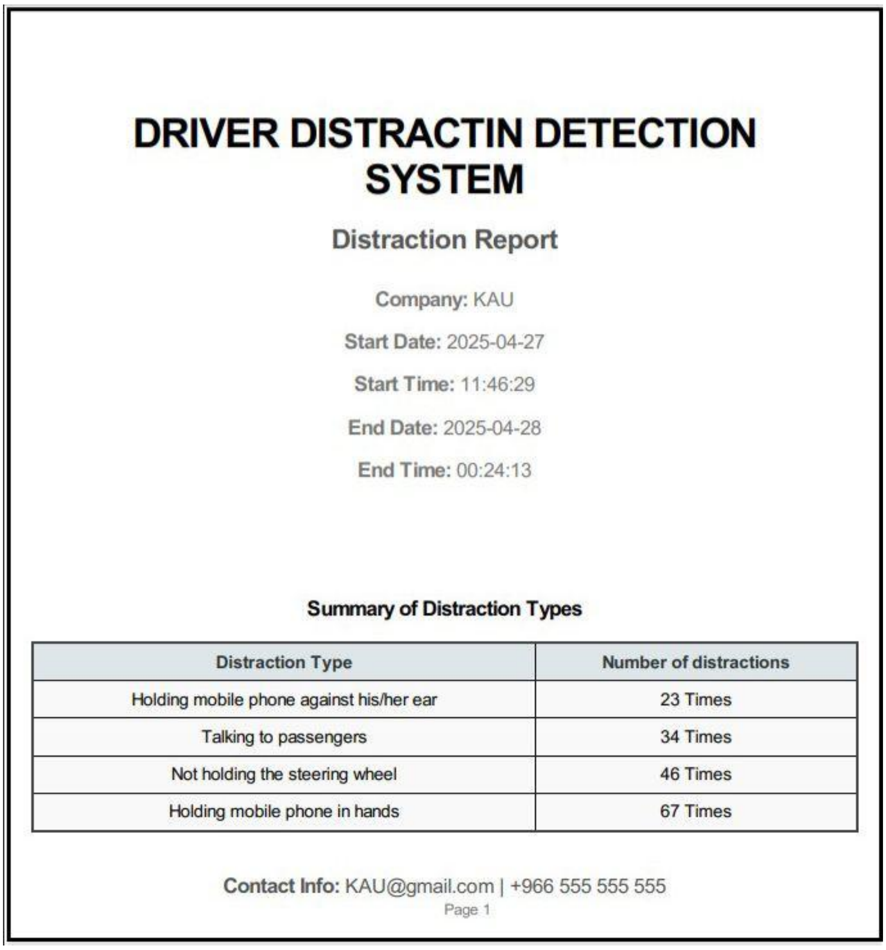
Tools Used:

- NVIDIA Jetson Nano
- Pre-trained driver distraction detection model
- USB flash drive
- Computer for report file access and verification

Collected Data:

The generated report included:

- The company name, start and end date/time of the session.
- A timestamped record for each detected distraction event.
- A summary table listing each distraction type along with the number of occurrences.



DRIVER DISTRACTIN DETECTION SYSTEM

Distraction Report

Company: KAU

Start Date: 2025-04-27

Start Time: 11:46:29

End Date: 2025-04-28

End Time: 00:24:13

Summary of Distraction Types

Distraction Type	Number of distractions
Holding mobile phone against his/her ear	23 Times
Talking to passengers	34 Times
Not holding the steering wheel	46 Times
Holding mobile phone in hands	67 Times

Contact Info: KAU@gmail.com | +966 555 555 555

Page 1

Figure (38) PDF report sample

Data Analysis and Interpretation:

The results demonstrate that the system successfully recorded and summarized distraction events into a structured and readable report format as seen in figure 37. The report accurately reflects the types and frequencies of distractions observed during the session and includes essential session metadata, such as start and end times. Furthermore, the report was correctly saved onto the USB storage device and was easily accessible on a computer without requiring specialized software.

5.5 Validation of Ease of Installation

Experiment Objective:

The objective of this experiment is to validate that the driver distraction detection system can be installed easily and quickly into standard vehicles without the need for specialized tools, major modifications, or professional installation services.

Background Information:

Ease of installation is a critical requirement for the system's practical deployment, particularly for fleet operators and end-users who may not have technical expertise. According to the Product Design Specifications (PDS), the system must be designed for rapid and simple installation while maintaining secure and reliable operation. To achieve this, a custom 3D-printed mount for the camera was developed to facilitate easy and adjustable attachment across different vehicle models.

Work Plan:

To evaluate the ease of installation, the following procedure was followed:

1. Prepare the full system components: Jetson Nano, camera with 3D-printed mount, buzzer, cables, and adhesive supports.
2. Attempt installation of the system into multiple different vehicles without specialized tools.
3. Assess the adaptability of the camera mount and the overall simplicity of the installation steps.

Tools Used:

- Standard mechanical toolkit (screwdriver, adhesive mounts)
- 3D-printed adjustable camera mount
- Jetson Nano and other system components
- Test vehicles (multiple car models)

As you see the figure 38, here are the design of the camera mount. And , as shown in figure 39, the design has been printed and mounted with the camara.

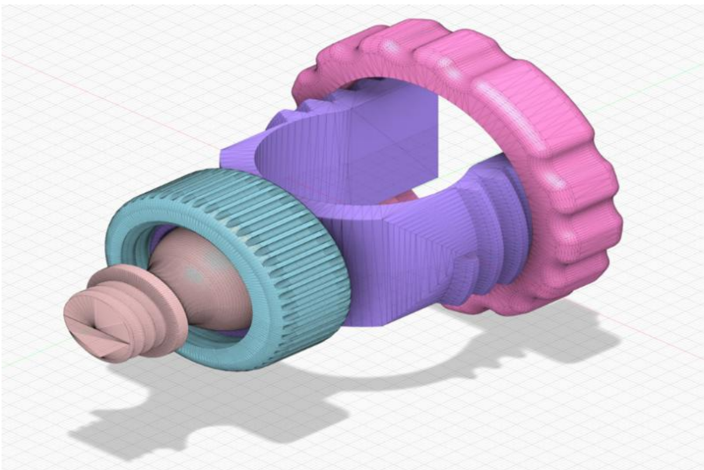


Figure (39) 3D design for the camera mount

Figure (40) Camera mount installed in the car

Collected Data:

Pictures documenting the installation process across different vehicles which took less than 3 minutes are shown in **Figure 40 and 41.**

Figure (41) Jetson nano with the buzzer and the button

Figure (42) the system installed in a car

Data Analysis and Interpretation:

The installation process was completed successfully in less than 3 minutes across multiple car models, without requiring specialized tools, vehicle alterations, or professional assistance. The 3D-printed mount for the camera significantly enhanced the ease and adaptability of the installation. Thus, the system fully satisfies the fifth must by being easily, quickly, and reliably installable in a variety of vehicle environments.

5.6 Validation of Vehicle Power Source Compatibility

Experiment Objective:

The objective of this experiment is to validate that the driver distraction detection system can operate reliably using the standard 12V vehicle power source, meeting the requirement for easy integration into typical car electrical systems.

Background Information:

The Product Design Specifications (PDS) require that the system be powered directly from the vehicle's 12V electrical outlet (the cigarette lighter socket). To ensure compatibility, a voltage regulation system is necessary to convert the 12V input to the 5V required by the Jetson Nano and associated peripherals. Reliable power delivery is essential to guarantee stable operation of the distraction detection system during vehicle operation.

Work Plan:

To validate the power source compatibility, the following steps were followed:

1. Connect a car adapter to the 12V vehicle outlet.
2. Route the 12V output from the car adapter into a DC-DC voltage regulator module.
3. Regulate the voltage output from 12V to 5V using the voltage regulator.
4. Power the Jetson Nano and system components using the 5V regulated output.
5. Observe system stability and performance during powered operation inside the vehicle.

Tools Used:

- 12V car adapter (cigarette lighter type)
- DC-DC voltage regulator (12V to 5V step-down converter)
- Vehicle (test car)

Collected Data:

The setup successfully delivered stable 5V power to the Jetson Nano system, allowing normal system operation. No power interruptions, voltage drops, or system resets were observed during testing.

Figure (43) the system's power Connections

Data Analysis and Interpretation:

The test results demonstrate that the system can be reliably powered using the standard 12V vehicle outlet as seen in figure 42, with proper voltage regulation down to 5V for the Jetson Nano and peripherals. The system operated stably under real conditions inside the vehicle without requiring external power sources or additional modifications. Thus, the system fully satisfies the sixth must by being compatible with standard vehicle electrical systems through the use of a car adapter and a voltage regulation circuit.

5.7 Validation of Operation in Different Lighting and Temperature Conditions:-

Experiment Objective:

The objective of this experiment is to validate that the driver distraction detection system can operate effectively under varying lighting conditions (day and night) and withstand typical temperature variations encountered inside vehicles.

Background Information:

Driver monitoring systems must be robust to changing environmental conditions to be effective in real-world deployment. Vehicles experience a wide range of lighting conditions throughout the day, and cabin temperatures can rise significantly, especially in hot climates.

The system was specifically designed to address these challenges:

- The Arducam Day-Night Vision camera is equipped with an infrared (IR) sensor, allowing for effective image capture during both daytime and nighttime conditions.
- The critical hardware components, including the camera and the Jetson Nano, are enclosed in protective covers to minimize the effects of heat exposure and to ensure stable system performance.

Work Plan:

To validate the system's ability to handle lighting and temperature variations, the following steps were conducted:

1. Test the camera's ability to capture images under different lighting conditions (bright daylight, dim lighting, and complete darkness).
2. Operate the system during daytime hours inside a vehicle exposed to sunlight and elevated cabin temperatures.
3. Monitor system stability, processing performance, and detection accuracy during these varying conditions.
4. Record observations on system overheating, image quality, and detection reliability.

Tools Used:

- Arducam Day-Night Vision Camera with IR capability
- Jetson Nano enclosed in a protective case
- Vehicle (test car) exposed to different lighting and temperature environments

Collected Data:

Example day and night images captured by the camera can be seen in Figure 43 and Figure 44.

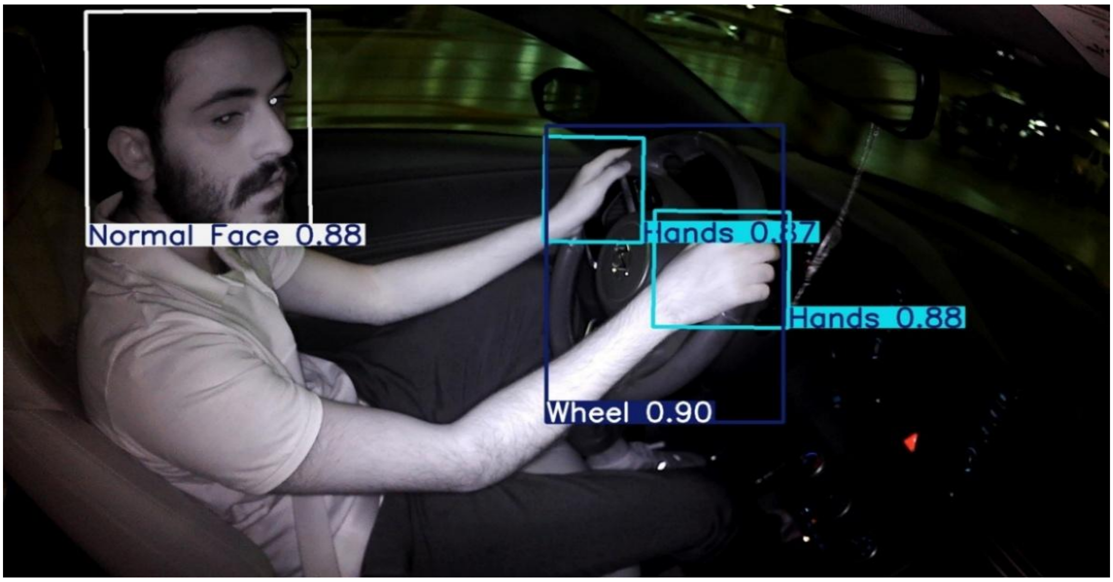


Figure (44) image taken at night

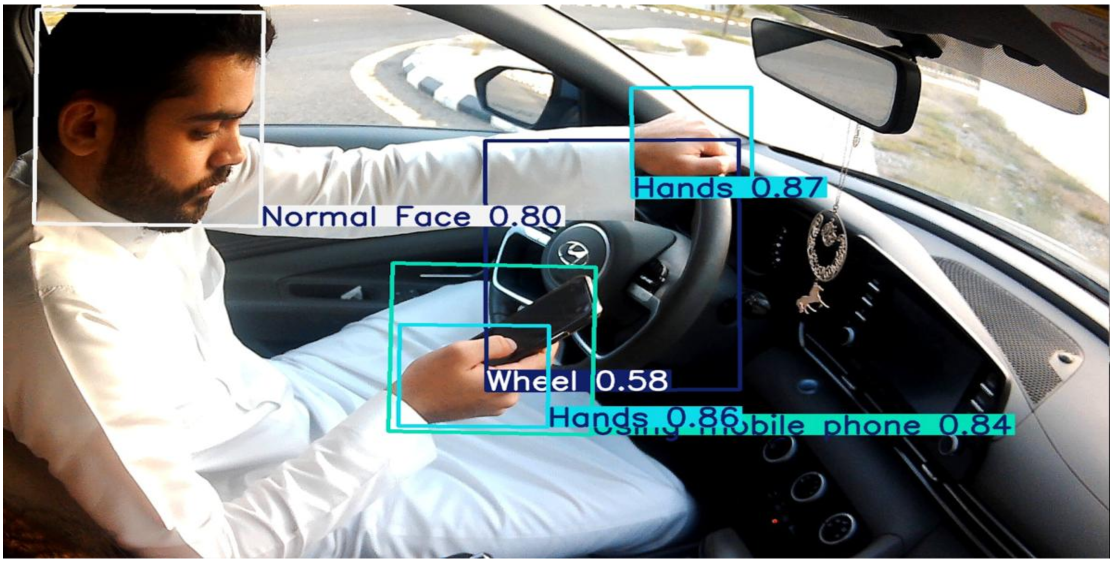


Figure (45) image taken at day

Figure (46) The metal case for the jetson

You can also see the metal case of the jetson nano in figure 45.

Data Analysis and Interpretation:

The results demonstrate that the system effectively captures high-quality images and maintains accurate distraction detection performance under various lighting conditions, including low-light and nighttime scenarios, thanks to the integrated IR sensor.

Additionally, during daytime operation inside the vehicle with elevated temperatures, the system components remained stable and fully operational. The use of protective covers for the camera and Jetson Nano contributed significantly to preventing overheating and ensuring system longevity.

CHAPTER – 6 DISCUSSION AND CONCLUSION

6.1 EVALUATION OF SOLUTION

The proposed driver distraction detection system was evaluated based on the customer's design requirements, which included the detection of four key distractions: holding mobile phone in hands, holding mobile phone against his/her ear, talking to passengers, not holding the steering wheel. The solution successfully meets the customer's "musts," including an 80% accuracy rate for distraction detection, the ability to warn the driver with auditory feedback, and the capability to generate session reports for later retrieval via external storage.

The validation experiments conducted during testing confirmed the system's reliability in detecting the primary distractions under various driving conditions, including day/night and diverse weather scenarios. Additionally, the system's compact design allowed easy installation, ensuring it does not obstruct the driver's view or interfere with vehicle controls, meeting the customer's constraints. While the system met most of the requirements, the accuracy of detection in more complex scenarios, such as detecting passenger conversations without additional contextual factors, could be further improved.

6.2 IMPACT OF SOLUTION

The solution's impact can be evaluated from several perspectives:

- **Global Impact**: On a global scale, distracted driving is a major cause of road accidents, contributing to fatalities and injuries worldwide. The system addresses this critical issue by providing real-time feedback to drivers, thereby reducing the likelihood of accidents caused by distractions. It can be integrated into public and private transportation systems, such as fleet management, contributing to overall road safety.
- **Social Impact**: Socially, the system promotes safer driving habits, raising awareness about the dangers of distractions. It can also be integrated into driver education programs, encouraging responsible driving behavior among young and inexperienced drivers.
- **Environmental Impact**: By improving road safety and reducing accidents, the solution indirectly helps reduce the environmental impact of road incidents, such as fuel wastage due to accidents, and supports the reduction of the carbon footprint associated with traffic congestion.

- **Economic Impact**: Economically, the system can reduce the costs associated with road accidents, including medical expenses, vehicle repairs, and insurance premiums. For businesses relying on fleet management, the system helps prevent delays, vehicle downtime, and the loss of valuable assets.
- **Safety Impact**: The system's real-time alerts provide drivers with immediate warnings, significantly enhancing their awareness and response times, thus improving overall road safety. Continuous monitoring can help reduce accidents caused by driver distraction, which is especially beneficial for commercial drivers operating under time-sensitive conditions.

6.3 FUTURE WORK

While the current implementation of the driver distraction detection system is effective, there are several areas for improvement:

1. **Increased Detection Accuracy**: Although the system currently meets the 80% accuracy requirement, future improvements will focus on expanding the dataset and enhancing labeling quality to provide more diverse and accurately annotated training data. These enhancements will help in further improving the model's detection accuracy, ensuring more reliable performance across various driving scenarios
2. **Real-time Feedback Expansion**: The addition of visual or haptic feedback in conjunction with auditory alerts could provide drivers with more diverse methods of notification, ensuring that the alerts are noticeable even in noisy environments.
3. **Enhanced Distraction Detection**: Future work could focus on expanding the types of distractions detected, including drowsiness, smoking, eating/drinking, or interacting with the navigation system. This would broaden the system's application, making it more comprehensive for a wider range of distractions.
4. **Cloud Integration for Fleet Management**: For businesses, integrating the system with a cloud-based platform could allow real-time monitoring and analysis of driver behavior, enabling fleet managers to intervene immediately if a distraction is detected.
5. **Customization and User Interface**: Future improvements will focus on developing a comprehensive interface for fleet managers, enabling them to monitor driver behavior, analyze distraction events, and customize alert preferences based on operational requirements. This enhancement will make the system a powerful tool for fleet management, supporting safety oversight, driver performance evaluation, and data-driven decision-making across the fleet.

6.4 CONCLUSION

The driver distraction detection system addresses a critical safety issue in modern transportation by effectively identifying key driver distractions such as mobile phone usage, hands-off-the-wheel behavior, and conversations with passengers. The solution not only meets the customer’s design requirements but also provides significant global, social, and economic benefits. By reducing distractions, it helps prevent accidents, promotes safer driving habits, and supports businesses in improving their fleet management.

The project has successfully demonstrated that real-time detection and alerts can significantly enhance driving safety. Despite its success, there is still room for improvement, especially in terms of increasing detection accuracy and expanding the types of distractions detected. However, the current prototype represents a substantial step toward creating smarter, safer driving environments, and its further development will undoubtedly contribute to reducing the risk of accidents caused by distracted driving.

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APPENDIX – A: EVALUATORS COMMENTS

evaluators' comments: -

Table (11) evaluators' comments

First presentation		
NO.	**comments**	**Correction of errors**
1	Goals cannot be part of the Problem Statement.	This error was in the presentation only
2	Why continuous warnings when there are no problems?	It was amended on the fourth page (4) in must, the third number (3).
3	It should not be a portable but fixed system. It should rather be an easily installable system.	We'll focus on designing a fixed, easily installable system rather than a portable one.
4	In MUSTS, you mentioned monitoring talking to passengers for safety; however, it is even more crucial to monitor talking while looking at the passengers.	We changed the must to include Monitoring talking while looking at the passengers
5	A block diagram provides a high-level visual representation of the system architecture. It highlights the components, their interactions, and data flow. In your block diagram, you included functionalities. Replace them with components instead.	We adjusted the block diagram to include components instead of functionalities.
6	Captions for tables are placed above the table (typically left aligned).	The caption positions have been changed to the top and left side for all tables
7	In your PUGH'S METHOD, explain the criteria used and justify the scores assigned to each alternative based on how well they meet those criteria.	We added an explanation about the criteria, and we justified the scores
8	Figure (11) is too small.	We made it bigger and more clear

APPENDIX – B: EFFECTIVE TEAM INTERACTIONS

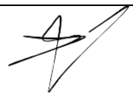
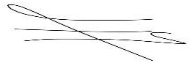
Table (12) Team Information's

Photo	 **Member #1**	 **Member #2**	 **Member #3**
Name	**Jawad Maimani**	**Zyad Alzhrani**	**Abdullah Alghamdi**
ID	**2136574**	**2138321**	**2136513**
Phone Number	**+966 56 185 0070**	**+966 59 331 1087**	**+966 53 517 5737**
Email Addresses	M #1 :- jamaimani0001@stu.kau.edu.sa M #2:- zsaadalzhrani@stu.kau.edu.sa M #3:- Aabdullahalghamdi0027@stu.kau.edu.sa		
Specialty	**Electrical Engineer (Computer)**	**Electrical Engineer (Computer)**	**Electrical Engineer (Computer)**
Role	**Team Leader, Meeting coordinator, and Microcontroller expert**	**AI expert,Design the circuit**	**Expert in both AI and softwareprogramming**
Responsibilities	**Lead the project, organize team meetings, and ensure progress tracking. Design and program the microcontroller systems for the project.**	**Develop AI models for distraction detection. Design the circuits required for system functionality**	**Integrate AI models with the software framework. Develop the software interface and handle system testing**

Meeting Minutes- 1

Date:	2024/9/3
Team:	14
Project Title:	Driver Distraction System

Attendees:

Member 1:	Jawad Maimani	Signature:	
Member 2:	Zyad Alzhrani	Signature:	
Member 3:	Abdullah Alghamdi	Signature:	
Advisor:	Dr. Muhammad Shehzad Hanif	Signature:	
Customer:	________________	Signature:	________________

Agenda:

Obtaining general ideas and information about the project

Discussion Points:

General information about the project

Follow-up of the Last Meeting:

Decisions Taken:

Talking about the team’s skills and our experiences in AI

Actions to do before next meeting:

Reading about the project and getting a general idea about it.

Meeting Minutes- 2

Date:	2024/9/10
Team:	14
Project Title:	Driver Distraction System

Attendees:

Member 1:	Jawad Maimani	Signature:	
Member 2:	Zyad Alzhrani	Signature:	
Member 3:	Abdullah Alghamdi	Signature:	
Advisor:	Dr. Muhammad Shehzad Hanif	Signature:	Shehzad
Customer:	______	Signature:	______

Agenda:

1:- Get a general idea about the project

2:- Talk about Must and want

Discussion Points:

1:- We saw old project files

2:- View files on old research on similar ideas

Follow-up of the Last Meeting:

Decisions Taken:

Many useful files that show us a general idea about the project and how it works, as well as clarification of details in the project, through which we were able to get a general idea about must and want.

Actions to do before next meeting:

Prepare and obtain general information about the project. Writing the background, writing must and want and discussing it with the doctor.

Meeting Minutes- 3

Date:	2024/9/17
Team:	14
Project Title:	Driver Distraction System

Attendees:

Member 1:	Jawad Maimani	Signature:	
Member 2:	Zyad Alzhrani	Signature:	
Member 3:	Abdullah Alghamdi	Signature:	
Advisor:	Dr. Muhammad Shehzad Hanif	Signature:	Shehzad
Customer:	______________________	Signature:	______________

Agenda:

Talking about the problem definition we wrote and making edits

Discussion Points:

Editing things we wrote

Follow-up of the Last Meeting:

We wrote the Problem Definition and need the doctor’s advice to see if it is correct

Decisions Taken:

Amending the Problem Definition and adding modifications to it. We talked about writing Background. He also said that you should look for projects like yours.

Actions to do before next meeting:

Amending the things that the doctor talked about in Problem Definition and his book Background.

Meeting Minutes- 4

Date:	2024/9/24
Team:	14
Project Title:	Driver Distraction System

Attendees:

Member 1:	Jawad Maimani	Signature:	
Member 2:	Zyad Alzhrani	Signature:	
Member 3:	Abdullah Alghamdi	Signature:	
Advisor:	Dr. Muhammad Shehzad Hanif	Signature:	Shehzad
Customer:	____________________	Signature:	____________

Agenda:

1:-Display amendments to the Problem Definition and must and want. 2:-Display what we wrote in the background.

Discussion Points:

1:- The amendment to the problem definition that we wrote and the amendment to the must and want we wrote. 2:- Editing the background.

Follow-up of the Last Meeting:

wrote the background and edited the problem definition.

Decisions Taken:

Amendments to everything we wrote, such as the background, the problem definition, and the must and want.

Actions to do before next meeting:

We amend all the amendments that the doctor informed us of and send the latest amendments to the doctor for approval before sending the report.

Meeting Minutes- 5

Date:	2024/10/8
Team:	14
Project Title:	Driver Distraction System

Attendees:

Member 1:	Jawad Maimani	Signature:	
Member 2:	Zyad Alzhrani	Signature:	
Member 3:	Abdullah Alghamdi	Signature:	
Advisor:	Dr. Muhammad Shehzad Hanif	Signature:	
Customer:	______________________________	Signature:	____________________

Agenda:

Talk about what we did in the first presentation

Discussion Points:

Talk about the feedback provided (we wrote it before grading)

Follow-up of the Last Meeting:

Decisions Taken:

Correcting the mistakes we made in the report and presentation

Actions to do before next meeting:

Take a look at alternative projects

Meeting Minutes- 6

Date:	2024/10/27
Team:	14
Project Title:	Driver Distraction System

Attendees:

Member 1:	Jawad Maimani	Signature:	
Member 2:	Zyad Alzhrani	Signature:	
Member 3:	Abdullah Alghamdi	Signature:	
Advisor:	Dr. Muhammad Shehzad Hanif	Signature:	
Customer:		Signature:	

Agenda:

Get a feedback from the doctor about the robot before handing it over.

Discussion Points:

We will discuss the second report

Follow-up of the Last Meeting:

Decisions Taken:

We discovered, or Dr. Muhammad saw, that all the ALTERNATIVE DESIGNS were wrong, and therefore everything that was done after that would be wrong.

Actions to do before next meeting:

Edit the alternative design and write PUGH’S METHOD and write the BASELINE DESIGN

Meeting Minutes- 7

Date:	2024/10/29
Team:	14
Project Title:	Driver Distraction System

Attendees:

Member 1:	Jawad Maimani	Signature:	
Member 2:	Zyad Alzhrani	Signature:	
Member 3:	Abdullah Alghamdi	Signature:	
Advisor:	Dr. Muhammad Shehzad Hanif	Signature:	
Customer:	______________	Signature:	______________

Agenda:

Reviewing the amendments we made and approving the report.

Discussion Points:

View the modifications. We also modified the Baseline Design and added and modified some texts.

Follow-up of the Last Meeting:

We certainly modified the alternative design as the doctor asked us to, and we also completed the shortcomings.

Decisions Taken:

The doctor showed us the work we had done, and we talked about Baseline Design and Alternative Design, and we adjusted the figures, and we also discussed the tables.

Actions to do before next meeting:

We do the complete work and also research the parts and how they work and understand them.

Meeting Minutes- 8

Date:	2024/11/19
Team:	14
Project Title:	Driver Distraction System

Attendees:

Member 1:	Jawad Maimani	Signature:	
Member 2:	Zyad Alzhrani	Signature:	
Member 3:	Abdullah Alghamdi	Signature:	
Advisor:	Dr. Muhammad Shehzad Hanif	Signature:	Shehzad
Customer:	____________________	Signature:	____________

Agenda:

We show the doctor our progress, looking for cameras, etc

Discussion Points:

The doctor mentioned three things that we should pay attention to or how they work in the project.

Follow-up of the Last Meeting:

We researched how some cameras work and whether they would be Night Vision, and we also researched if there were better types in terms of price.

Decisions Taken:

The doctor stressed to us that we must know three things: the first is about the location of the camera in the car, the second is about the location of the microphone, and the third is to investigate whether the dash cam is a good solution or not.

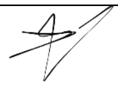
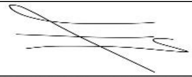
Actions to do before next meeting:

Search for the three points that we explained in the table above

Meeting Minutes- 9

Date:	2024/11/26
Team:	14
Project Title:	Driver Distraction System

Attendees:

Member 1:	Jawad Maimani	Signature:	
Member 2:	Zyad Alzhrani	Signature:	
Member 3:	Abdullah Alghamdi	Signature:	
Advisor:	Dr. Muhammad Shehzad Hanif	Signature:	
Customer:	______________________	Signature:	______________

Agenda:

Discussing the three points, also discussing the comments in the second report, and discussing the grade

Discussion Points:

We will talk about the points and review the mistakes committed in the second report

Follow-up of the Last Meeting:

The three points required of it were researched and discussed with Dr. Muhammad

Decisions Taken:

We discussed the points and the solutions we found, and we also discussed the points that decreased our scores or the comments that required simple modifications.

Actions to do before next meeting:

Correct all errors, and we will hold a final meeting next week and discuss the presentation.

Meeting Minutes- 10

Date:	2025/1/14
Team:	14
Project Title:	Driver Distraction System

Attendees:

Member 1:	Jawad Maimani	Signature:	
Member 2:	Zyad Alzhrani	Signature:	
Member 3:	Abdullah Alghamdi	Signature:	
Advisor:	Dr. Muhammad Shehzad Hanif	Signature:	Shehzad
Customer:	________________	Signature:	________________

Agenda:

Back after the first semester break and start discussing what we will do this semester.

Discussion Points:

We will talk about what we will do this semester.

Follow-up of the Last Meeting:

Decisions Taken:

The first semester's material has been reviewed.

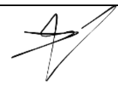
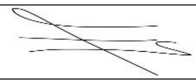
Actions to do before next meeting:

Start the project, take the necessary parts and start implementing it.

Meeting Minutes- 11

Date:	2025/1/28
Team:	14
Project Title:	Driver Distraction System

Attendees:

Member 1:	Jawad Maimani	Signature:	
Member 2:	Zyad Alzhrani	Signature:	
Member 3:	Abdullah Alghamdi	Signature:	
Advisor:	Dr. Muhammad Shehzad Hanif	Signature:	
Customer:	______________________	Signature:	______________

Agenda:

Agree on the material that will be used and that we will take.

Discussion Points:

We decided on the parts we would order, and the parts Dr. Muhammad Bilal had available, and we agreed on the camera we would get from Amazon.

Follow-up of the Last Meeting:

We reviewed what was covered in the first semester and learned about the parts that we will use.

Decisions Taken:

The first semester's We agreed on what we would buy, what we would take from the doctors, and the camera we would take.

Actions to do before next meeting:

Start the project, take the Order items and start working on the project.

Meeting Minutes- 12

Date:	2025/2/18
Team:	14
Project Title:	Driver Distraction System

Attendees:

Member 1:	Jawad Maimani	Signature:	
Member 2:	Zyad Alzhrani	Signature:	
Member 3:	Abdullah Alghamdi	Signature:	
Advisor:	Dr. Muhammad Shehzad Hanif	Signature:	Shehzad
Customer:	______________________	Signature:	______________

Agenda:

We're talking about Concept Session 2 and we talked about some of the pieces.

Discussion Points:

We found out that the camera does not work in night mode. We tried with Dr. Muhammad Bilal and Dr. Muhammad Shahzad, so we had to look for an alternative and found an excellent camera. It will be ordered.

Follow-up of the Last Meeting:

Request leftover items from the last meeting

Decisions Taken:

We talked about the meeting and discussed the camera we would use. We also showed the doctor the things we had requested.

Actions to do before next meeting:

Ordering the camera, we specified and waited for the parts we ordered to arrive.

Meeting Minutes- 13

Date:	2025/3/4
Team:	14
Project Title:	Driver Distraction System

Attendees:

Member 1:	Jawad Maimani	Signature:	
Member 2:	Zyad Alzhrani	Signature:	
Member 3:	Abdullah Alghamdi	Signature:	
Advisor:	Dr. Muhammad Shehzad Hanif	Signature:	Shehzad
Customer:	____________________	Signature:	____________

Agenda:

The camera arrived, we worked on it, showed it to the doctor, and fixed everything.

Discussion Points:

We showed the camera to the doctor and tested it. The night mode was fine and everything was working fine.

Follow-up of the Last Meeting:

The camera arrived and was reviewed with the doctor.

Decisions Taken:

View the camera and view the codes we worked on.

Actions to do before next meeting:

Capture more images and process them with code.

Meeting Minutes- 14

Date:	2025/4/22
Team:	14
Project Title:	Driver Distraction System

Attendees:

Member 1:	Jawad Maimani	Signature:	
Member 2:	Zyad Alzhrani	Signature:	
Member 3:	Abdullah Alghamdi	Signature:	
Advisor:	Dr. Muhammad Shehzad Hanif	Signature:	Shehzad
Customer:	______________________	Signature:	______________

Agenda:

Show the entire project to Dr. Mohammad Shahzad.

Discussion Points:

We presented the project in code and asked the doctor about the robot and discussed its development.

Follow-up of the Last Meeting:

We took many pictures that improved the accuracy of the project with the camera and also used it in more than one car.

Decisions Taken:

We showed the entire project to the doctor with pictures and the entire code and took some advice on the final report.

Actions to do before next meeting:

Complete the Final Report.

APPENDIX – C: USE OF PROJECT MANAGEMENT TECHNIQUES

Table (13) Team Tasks

Name / Title	Type	Assigned	Start Date	End Date	Percent Complete
Senior Project	project	Team 14	8/29/2024	4/16/2025	99%
First Semester	group	Team 14	8/29/2024	11/28/2024	100%
Project Planning	task	Team 14	8/29/2024	9/6/2024	100%
Chapter 1	subgroup	Team 14	9/16/2024	9/26/2024	100%
Problem Definition	task	Jawad	9/16/2024	9/17/2024	100%
Background Information	task	Zyad	9/18/2024	9/20/2024	100%
Problem Statement	task	Abdullah	9/21/2024	9/22/2024	100%
Project Objectives	task	Zyad	9/23/2024	9/24/2024	100%
Product Design Specifications (PDS)	task	Jawad	9/25/2024	9/26/2024	100%
Chapter 2 & 3	subgroup	Team 14	10/7/2024	10/30/2024	100%
Literature Review	task	Team 14	10/7/2024	10/11/2024	100%
Alternative Designs	task	Team 14	10/14/2024	10/18/2024	100%
Alternative comparison	task	Team 14	10/20/2024	10/22/2024	100%
Baseline Design	task	Jawad&Zyad	10/23/2024	10/25/2024	100%
System input/output	task	Abdullah	10/26/2024	10/28/2024	100%
Reviewing	task	Team 14	10/29/2024	10/30/2024	100%
Second Semester	group	Team 14	1/12/2025	5/28/2025	100%
Buy the Components	task	Jawad	1/12/2025	1/15/2025	100%
Build the Driver distraction system	task	Zyad	1/16/2025	2/25/2025	100%
Project assembly	task	Abdullah	2/26/2025	3/17/2025	100%
Test the Driver distraction system	task	Team 14	3/18/2025	4/5/2025	100%
Final Presentation	task	Team 14	4/13/2025	4/16/2025	0%

Gantt Chart:-

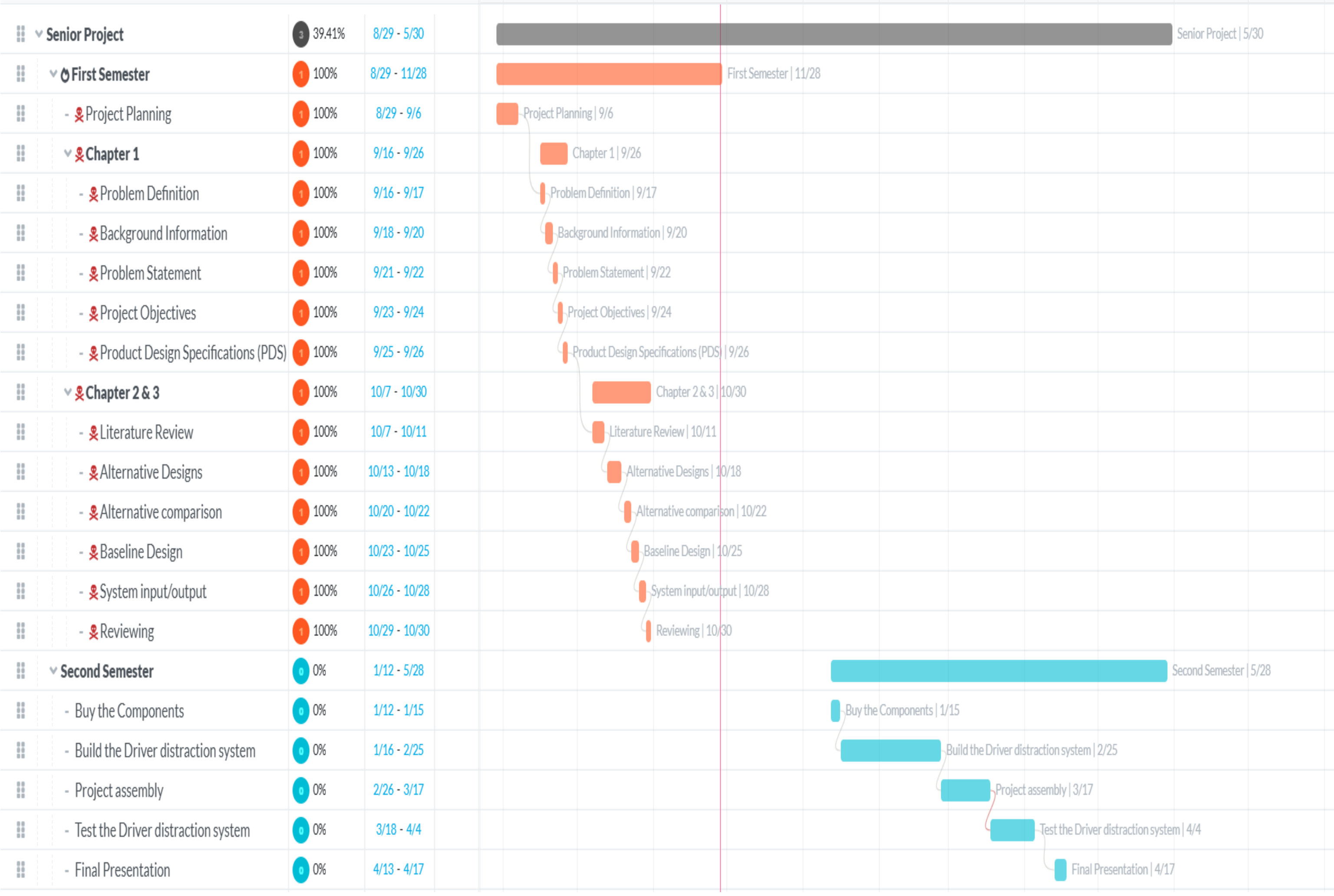


Figure (47) Gantt Chart

APPENDIX – D: RECOGNITION OF ETHICAL AND PROFESSIONAL RESPONSIBILITY

Ethical and Professional Responsibility

Code of Ethics

For this project, the IEEE Code of Ethics is adopted, which emphasizes the following key principles:

- **Public Safety and Welfare**: Engineers must prioritize the safety, health, and welfare of the public in their work. The system we are designing aims to enhance road safety by detecting distracted driving behaviours and issuing real-time alerts, thereby helping to reduce accidents caused by distractions.

- **Confidentiality and Privacy**: Engineers should protect the privacy of individuals and hold paramount their confidentiality. Our system collects sensitive data, such as video and audio recordings of drivers. To align with this ethical responsibility, we will ensure that all collected data is securely stored, anonymized, and used solely for its intended purpose, with access limited to authorized personnel only.

- **Transparency**: We believe in clear communication regarding the functionality of the system and the data collection process. Drivers will be informed of the data being collected, its intended use, and the steps taken to protect their privacy. This will be communicated through clear terms and conditions and a privacy policy.

- **Integrity in Reporting**: The system will be designed to minimize errors and ensure the accuracy of distraction detection. Any issues identified in the system's performance, particularly regarding false positives or negatives, will be addressed promptly. Transparency will be maintained in reporting both the system’s successes and its limitations.

Ethical Issue: Privacy Concerns in Monitoring Driver Behaviour

A major ethical concern related to the project is the privacy and security of the data being collected. The system monitors driver behaviours such as hand positions, eye movements, and conversations. This raises important questions about how the collected data will be handled, stored, and protected. The ethical principle of confidentiality requires that we ensure all personal data is safeguarded against unauthorized access, misuse, or disclosure.

To address these concerns, we will:

1. Implement strong data encryption protocols to protect stored data.
2. Anonymize data whenever possible to avoid the identification of individual drivers.
3. Provide clear communication to users about the data collection process and their rights regarding the information collected.
4. Ensure compliance with relevant data protection regulations (e.g., GDPR, CCPA).

By adhering to these practices, we will ensure that the system maintains the privacy and confidentiality of users while contributing to the overall goal of improving road safety.