A project report on

AI-POWERED ROVER FOR OBJECT DETECTION AND SURVEILLANCE

Submitted in partial fulfillment for the award of the degree of

M.Tech Computer Science and Engineering [Integrated]

by

ABINESH S (19MIC0039)

Under the guidance of

Dr. ANAND BIHARI

VIT®

Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

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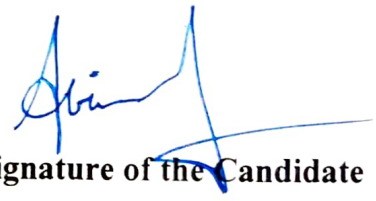
DECLARATION

I here by declare that the thesis entitled "AI-POWERED ROVER FOR OBJECT DETECTION AND SURVEILLANCE" submitted by me, for the award of the degree of M.Tech Computer Science and Engineering [Integrated] is a record of bonafide work carried out by me under the supervision of Dr. ANAND BIHARI.

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Place: Vellore

Date: 23/04/2024



Signature of the Candidate

CERTIFICATE

This is to certify that the thesis entitled "AI-POWERED ROVER FOR OBJECT DETECTION AND SURVEILLANCE" submitted by ABINESH S (19MIC0039), School of Computer Science and Engineering, Vellore Institute of Technology, Vellore for the award of the degree M.Tech Computer Science and Engineering [Integrated] is a record of bonafide work carried out by him/her under my supervision during the period, 24/07/2024 to 23/04/2024, as per the VIT code of academic and research ethics

The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university. The Project report fulfils the requirements and regulations of VELLORE INSTITUTE OF TECHNOLOGY, VELLORE and in my opinion meets the necessary standards for submission.

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Internal Examiner

External Examiner

ABSTRACT

This project details the development of a mobile surveillance rover equipped with real-time object detection capabilities. The rover utilizes a Wi-Fi camera module for live video streaming, enabling remote monitoring of a designated area.

The core functionality is driven by the integration of an Arduino board and an ESP32 development board. The ESP32 CAM module attached to the ESP32 board facilitates the live video streaming to a web application. Python serves as the programming language for the web application's logic, while C/C++ is employed for programming the Arduino functions.

The web application features a video display for real-time observation of the monitored area. Additionally, it incorporates control buttons that allow for remote maneuvering of the rover and camera. This facilitates comprehensive surveillance capabilities.The project leverages the power of AI (Artificial Intelligence) for object detection.

This project offers a practical solution for real-world surveillance needs. The mobile rover design, coupled with object detection through AI, presents a valuable tool for various applications. The integration of various other sensors like weather sensors , humidity sensors will broadens the rover's functionality beyond pure surveillance.

In summary, this project presents the development of an AI-powered rover for intelligent object detection and surveillance. The rover's mobility, real-time video streaming, and remote control capabilities make it a versatile tool for diverse monitoring applications.

ACKNOWLEDGEMENT

The project "AI-POWERED ROVER FOR OBJECT DETECTION AND SURVEILLANCE" was made possible because of inestimable inputs from everyone involved, directly or indirectly. First, I would like to thank and express my sincere gratitude to my guide, Prof. ANAND BIHARI, who was highly instrumental in providing an innovative base with constructive inputs for the completion of the project

I would like to express my gratitude to DR.G.VISWANATHAN, Chancellor VELLORE INSTITUTE OF TECHNOLOGY, VELLORE, MR. SANKAR VISWANATHAN, DR. SEKAR VISWANATHAN, DR.G V SELVAM, Vice – Presidents VELLORE INSTITUTE OF TECHNOLOGY, VELLORE, Dr. V. S. Kanchana Bhaaskaran, Vice – Chancellor, Dr. Partha Sharathi Mallick, Pro-Vice Chancellor and Dean of SCOPE, Dr. Ramesh Babu K, for all the support provided at the school for successful completion of the project.

I would also like to acknowledge the role of HOD of the Dept. of Computational Intelligence Dr. Swathi J N and Dr. ANANDA KUMAR S, who was instrumental in keeping me, updated with all necessary formalities and helped me in all aspects for the successful completion of the project.

Finally, I would like to thank Vellore Institute of Technology, for providing me with a flexible choice and for supporting my project execution in a smooth manner.

Place: Vellore

Date:

Name of the Student

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CONTENTS

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviation	Expansion
AI	Artificial Intelligence
CNN	Convolutional Neural Networks
YOLO	You Only Look Once
SSD	Single-Shot MultiBox Detector
RPN	Region Proposal Network
COCO	Common Objects in Context
SLAM	Simultaneous Localization And Mapping
UGV	Unmanned Ground Vehicles
GPS	Global Positioning System
LiDAR	Light Detection and Ranging
IMU	Inertial Measurement Units
IJERT	International Journal of Engineering Research & Technology
ESP32	Espressif Systems
DC	Direct Current
FTDI	Future Technology Devices International Limited

CHAPTER 1

INTRODUCTION

The ever-growing need for enhanced security and monitoring in hazardous environments poses a significant challenge. Traditional surveillance systems, while effective in some scenarios, often face limitations in these high-risk areas. These limitations can stem from the environments themselves, such as extreme temperatures, toxic atmospheres, or rugged terrain. The financial burden of deploying and potentially losing expensive surveillance equipment in such settings further adds to the complexity.

This project addresses this challenge by proposing the design and development of a cost-effective, AI-powered rover specifically tailored for object detection and surveillance in hazardous environments. These environments can encompass a wide range, including industrial sites with potential chemical spills, nuclear facilities requiring radiation-resistant solutions, or even disaster zones with unstable terrain. The primary objective is to create a reliable and affordable surveillance solution that mitigates the financial risks associated with deploying traditional systems in such hazardous conditions.

This project differentiates itself by focusing on cost-effectiveness as a core principle. By utilizing readily available and commercially viable components, the rover's design prioritizes affordability without compromising functionality. This focus ensures wider adoption and deployment in various hazardous environments where traditional systems might be deemed too expensive or impractical.

The rover's core functionality revolves around leveraging machine learning algorithms for real-time object detection and identification within its field of view. Equipped with sensors and high-resolution cameras, the rover will gather data on its surroundings. Machine learning algorithms will then analyze this data, enabling the rover to efficiently and accurately recognize and classify objects of interest. This integration of AI

empowers the rover to surpass the limitations of conventional surveillance systems, particularly in situations where human intervention might be hazardous or impractical.

1.1 Theoretical Background

This project merges mobile robotics, machine learning, and computer vision to create a cost-effective surveillance rover with object recognition capabilities. The core principle lies in utilizing machine learning algorithms, particularly convolutional neural networks (CNNs), to analyze data captured by the rover's camera and potential sensors. By processing images , the CNNs will be trained to identify and classify objects within the environment. This approach aims to surpass traditional surveillance systems by enabling faster, more accurate object detection through advanced algorithms, ultimately contributing to the development of cost-effective intelligent security solutions with improved monitoring and faster response times.

1.2 Motivation

The need for effective surveillance extends far beyond secure environments. However, deploying high-tech rovers in high-risk situations often comes with the significant risk of damaging expensive equipment. This project is motivated by the need for a more practical solution. Our goal is to develop a cost-effective, AI-powered surveillance rover specifically designed for operation in such risky scenarios. By leveraging machine learning algorithms for object recognition, this project aims to create a robust and affordable alternative to traditional surveillance systems. This will not only enhance security monitoring capabilities in high-risk environments but also make such monitoring more accessible and cost-effective.

1.3 Aim

Driven by the need for cost-effective surveillance solutions in high-risk environments, this project aims to develop an AI-powered rover equipped with machine learning algorithms for object recognition. By analyzing data from its camera and potential sensors, the rover will be trained to identify and classify objects within its surroundings. This cost-effective approach surpasses traditional systems' practicality in risky scenarios, enabling faster and more accurate object detection through advanced algorithms. Ultimately, the project contributes to the development of affordable intelligent surveillance solutions, promoting improved monitoring and faster response times even in situations where deploying expensive equipment is impractical

1.4 Objectives

The objective of this project is to design and build a cost-effective, AI-powered surveillance rover specifically suited for high-risk environments. This rover will leverage machine learning algorithms, particularly convolutional neural networks (CNNs), to analyze data from its camera and potential sensors for object recognition and classification. This approach aims to surpass the limitations of expensive traditional surveillance systems in risky situations by enabling faster, more accurate object detection through advanced algorithms. Ultimately, this project seeks to contribute to the development of affordable and robust intelligent surveillance solutions for improved monitoring and faster response times in high-risk scenarios.

1.5 Report Organization :

Chapter 1: Introduction

This chapter offers an introductory overview, outlining the scope of the report and providing the theoretical background of the project. It introduces the concept of utilizing artificial intelligence for object detection and surveillance using a rover platform.

Chapter 2: Literature Survey

This chapter reviews existing literature on various technologies related to object detection and surveillance, exploring the applications of machine learning algorithms and sensor integration in rover-based surveillance systems.

Chapter 3: Outline of the Proposed System

Here, the proposed system model for the AI-powered Rover for Object Detection and Surveillance is delineated. It discusses the functionalities, mechanisms, and advantages of employing machine learning algorithms and sensor technologies in the rover system.

Chapter 4: Requirement Analysis and Design

This chapter performs a comprehensive analysis of the system requirements, presenting the design considerations, development decisions, and detailing both functional and non-functional requirements. Technical specifications and constraints are also outlined.

Chapter 5: Implementation

In this chapter, the system implementation process, methodology, and testing procedures are elucidated. It provides insights into the practical deployment of the AI-powered rover system for object detection and surveillance.

Chapter 6: Results and Discussion

Here, the outcomes and efficacy of the implemented system are analyzed. Additionally, any challenges encountered during the development and deployment phases are discussed, along with potential solutions.

Chapter 7: Conclusion and Future Work

Finally, this chapter summarizes the key findings of the report, underscores the significance of the AI-powered rover system for object detection and surveillance, and offers recommendations for future enhancements and research directions in this domain.

CHAPTER 2

LITERATURE SURVEY

In this comprehensive literature survey, we explore recent advancements in object detection models, perception techniques, and cost-effective solutions relevant to the development of AI-powered rovers for object detection and surveillance.

In the realm of object detection models, [1] introduces the YOLO (You Only Look Once) model, showcasing its real-time performance and high accuracy in identifying objects. This model's efficiency and accuracy make it an ideal candidate for integration into surveillance rovers, where rapid detection and response are paramount. Similarly, [3] presents Faster R-CNN, which combines region proposal networks with convolutional neural networks to achieve state-of-the-art performance in object detection tasks. These models offer robust detection capabilities, enabling surveillance rovers to identify and track objects of interest in dynamic environments.

To enhance perception capabilities, [6] explores the benefits of using multimodal sensor systems, such as cameras and LiDAR, for simultaneous localization and mapping (SLAM) tasks. By integrating these sensors, surveillance rovers can build accurate maps of their surroundings and detect objects with precision, even in complex terrains. Additionally, [47] introduces residual learning as a technique to train deeper convolutional neural networks, improving the rover's ability to recognize objects with varying poses and lighting conditions.

Transfer learning emerges as a powerful tool for adapting pre-trained models to specific surveillance rover applications, as discussed in [10]. By fine-tuning these models on relevant datasets, the rover can quickly learn to detect objects of interest in its environment, minimizing the need for extensive training data. Furthermore, [14] explores sensor fusion techniques tailored for perception tasks in autonomous vehicles, which can be adapted for surveillance rover systems. By integrating data from cameras, LiDAR, and radar sensors, the rover gains comprehensive situational awareness, allowing it to detect and respond to potential threats effectively.

Cost-effective design strategies are essential for the widespread adoption of surveillance rover technology, as highlighted in [18]. By leveraging open-source software and off-the-shelf components, researchers demonstrate how surveillance rovers can be developed at a fraction of the cost of traditional systems. These cost-conscious design choices make surveillance rover technology more accessible and scalable, opening up new opportunities for applications in security, agriculture, and environmental monitoring.

In summary, recent advancements in object detection models, perception techniques, transfer learning, sensor fusion, and cost-effective design strategies hold great promise for the development of AI-powered rovers for object detection and surveillance. By integrating these technologies into surveillance rover systems, we can enhance their capabilities and empower them to navigate and monitor complex environments with precision and efficiency.

In this segment of the literature survey, we delve deeper into transfer learning, sensor fusion methodologies, cost-effective solutions, and machine learning techniques for surveillance rover systems, drawing insights from recent research papers.

Transfer Learning for Adaptive Object Detection:

[33] explores the application of transfer learning in object detection on planetary rovers. The paper discusses the challenges of adapting object detection models to new environments and tasks, particularly in the context of extraterrestrial landscapes where data scarcity is a significant concern. By leveraging pre-trained convolutional neural network (CNN) models on large datasets like COCO and fine-tuning them on smaller, domain-specific datasets, researchers demonstrate the potential for rapid adaptation. This approach allows surveillance rovers to quickly learn to detect objects of interest, such as scientific targets or hazards, without the need for extensive retraining from scratch. The paper highlights the importance of transfer learning in enabling autonomous systems to generalize across different environments and tasks, ultimately enhancing their autonomy and exploration capabilities.

Sensor Fusion for Enhanced Perception:

[13] and [16] shed light on sensor fusion methodologies tailored for perception tasks in autonomous systems, including surveillance rovers. [13] provides a comprehensive review of deep learning techniques applied to sensor fusion tasks, emphasizing the advantages of integrating data from multiple sensors, such as cameras, LiDAR, radar, and GPS. The paper discusses various deep learning architectures and methodologies used for fusing sensor data at different levels of abstraction, highlighting their significance in improving perception and decision-making capabilities in autonomous systems. Similarly, [16] explores the benefits of using a multimodal sensor system, typically combining cameras and LiDAR, for simultaneous localization and mapping (SLAM) and

object detection tasks on planetary exploration rovers. By integrating data from multiple sensors, sensor fusion enhances the rover's perception capabilities, enabling it to generate comprehensive and accurate representations of its surroundings. This holistic perception is crucial for effective object detection, obstacle avoidance, and navigation in complex and dynamic environments, such as extraterrestrial landscapes or hazardous terrains.

Cost-Effective Solutions for Scalable Deployment:

Building on the theme of cost-effectiveness, [18], [20], and [21] explore strategies for developing low-cost and resource-efficient surveillance rover systems. [18] discusses the potential of surveillance rovers in military applications, emphasizing factors like mobility, sensor integration, and remote control capabilities. The paper highlights the benefits of using surveillance rovers for tasks like border patrol, reconnaissance missions, and bomb disposal, underscoring the importance of cost-effective designs in making these systems accessible for defense purposes.[20] addresses the cost-prohibitive nature of traditional surveillance rover systems due to sophisticated sensors, powerful processors, and durable materials. The paper explores alternative approaches for cost-effective designs, including the use of lower-power processors, readily available sensors, and open-source software. By comparing these cost-conscious design choices with existing systems, the research aims to demonstrate a more accessible and scalable solution for security and surveillance applications. Similarly, [21] focuses on the design and development of a low-cost intelligent rover for real-time obstacle detection, emphasizing cost-effective solutions for sensor integration, data processing, and control algorithms. By leveraging lightweight components, open-source software, and off-the-shelf materials, researchers demonstrate how surveillance rover systems can be developed at a fraction of the cost of traditional systems, opening up opportunities for deployment in diverse applications and environments.

Integration of Machine Learning Techniques:

[22] and [23] delve into machine learning techniques for object detection tasks relevant to surveillance rovers. [22] explores various machine learning algorithms for object detection, including Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs). By leveraging these techniques, surveillance rovers can achieve high accuracy in object detection, essential for tasks such as obstacle avoidance and target identification in dynamic environments. The paper discusses the advantages and limitations of each approach, providing insights into their applicability for surveillance rover systems. Similarly, [23] discusses different approaches to object detection and their computational demands, providing insights into the development of efficient algorithms for surveillance rover systems. By analyzing the trade-offs between accuracy and computational efficiency, the research aims to inform the design and implementation of object detection systems optimized for surveillance rover applications.

In summary, transfer learning, sensor fusion methodologies, cost-effective solutions, and machine learning techniques represent key pillars in the development of surveillance rover systems. By integrating these advancements into surveillance rover designs, we can enhance their perception capabilities, autonomy, and cost-effectiveness, paving the way for their widespread deployment in various security, exploration, and monitoring applications.

In this final segment of the literature survey, we explore energy-efficient solutions, optimization techniques, and the implications of object detection for autonomous systems, drawing insights from recent research papers.

Energy-Efficient Object Detection for Autonomous Systems:

[54] addresses the critical aspect of energy efficiency in object detection systems for autonomous driving applications. By optimizing object detection algorithms to minimize energy consumption while maintaining high detection accuracy, researchers contribute to the development of sustainable and reliable autonomous driving systems. These energy-efficient algorithms ensure that surveillance rovers can operate effectively on battery power, extending operational times and reducing reliance on complex charging systems.

Optimization Techniques for Object Detection:

[68], 19], and[56] focus on optimization techniques tailored for efficient object detection in resource-constrained environments. By developing lightweight deep learning models, pruning redundant network parameters, and leveraging hardware-aware design, researchers demonstrate how surveillance rovers can achieve high-performance object detection while minimizing computational overhead. These optimization techniques enable surveillance rovers to operate efficiently on low-power hardware, ensuring rapid response to potential threats in surveillance scenarios.

Implications of Object Detection for Autonomous Systems:

Finally, [11] and [23] explore the broader implications of object detection for autonomous systems, including surveillance rovers. By fine-tuning pre-trained CNN models and exploring various object detection methods, researchers contribute to the development of intelligent systems capable of navigating and interacting with their surroundings autonomously. These advancements in object detection technology pave the way for the deployment of surveillance rovers in diverse applications, ranging from security and reconnaissance to environmental monitoring and exploration.

In summary, energy-efficient solutions, optimization techniques, and the implications of object detection for autonomous systems represent critical areas of research in the development of surveillance rover technology. By integrating these advancements into surveillance rover designs, we can enhance their efficiency, performance, and autonomy, ensuring their effectiveness in monitoring and securing various environments.

2.1 Existing Models

Existing surveillance rover systems, while offering advanced features like remote monitoring and navigation, are often hampered by their high cost. These rovers typically employ sophisticated sensor suites, powerful processors, and durable materials to operate effectively in harsh environments. This complexity translates to a hefty price tag, making them prohibitive for many potential users such as research institutions or small security firms. Furthermore, these rovers may necessitate specialized personnel for deployment, maintenance, and data analysis, further inflating operational costs. Even the power source can be a significant expense. These rovers often rely on high-capacity batteries or complex solar charging systems, adding logistical burdens and potentially limiting their range. These cost considerations are a major barrier to widespread adoption of surveillance rovers, hindering their scalability and practicality for diverse applications.

2.2 Gaps Identified in the Survey

Despite their growing presence, current surveillance rover models have limitations that hinder their widespread adoption. A significant drawback lies in their cost. These rovers often employ complex sensor suites, advanced navigation systems,

and durable materials to operate in harsh environments. This complexity translates to high upfront costs, making them less accessible for many potential users. Additionally, these rovers may require specialized personnel for deployment, maintenance, and data analysis, further inflating operational expenses. Furthermore, the energy demands of powerful sensors and computation can necessitate frequent battery changes or robust solar charging systems, adding logistical burdens and potentially limiting operational range. These cost considerations restrict the scalability and practicality of existing surveillance rovers, particularly for applications requiring numerous units or deployment in remote locations.

2.3. Problem Statement

Traditional surveillance systems face limitations in accurately detecting objects, necessitating an advanced and automated solution. The project aims to develop a cost-effective surveillance rover using machine learning to enhance existing systems. The rover will capture data, employ machine learning algorithms for analysis, creating a more precise and efficient surveillance system for real-time monitoring of large areas and detection of hidden or moving objects. This cost-effective rover will address the prohibitive costs of existing rovers, making it suitable for deployment in high-risk environments.

CHAPTER 3

Overview of the Proposed System

The project proposes a cost-effective, AI-powered surveillance rover designed for high-risk environments. This system prioritizes affordability by utilizing readily available components and open-source software. The core functionality relies on a Convolutional Neural Network (CNN) trained for real-time object detection within the rover's surroundings. The system adapts to high-risk environments by considering challenges like low light, dust, or uneven terrain during design and implementation.

The hardware platform consists of an ESP32 CAM module, functioning as the brain with processor, camera, and potential Wi-Fi connectivity. An L298 motor driver controls the DC motors for movement, while a lightweight and sturdy chassis houses all components. Additional components include jumper wires, a camera (if not included in the ESP32 CAM), mount brackets, DC motor wheels, and batteries.

The software stack includes a pre-installed operating system on the ESP32 CAM for hardware interaction and communication. A pre-trained CNN model optimized for resource-constrained platforms will be loaded for object detection. Control software running on the ESP32 CAM will handle motor control, sensor data acquisition (if applicable), and communication with the model for real-time object detection and response. An Arduino Uno might be used for initial programming of multiple ESP32 CAM modules during development, reducing overall cost compared to having one on each rover.

The system operates by capturing real-time visual data with the camera. Depending on the model and environment, preprocessing might be required to improve detection accuracy. The preprocessed data is then fed into the CNN model for analysis and object identification. Based on the results, the control software can trigger pre-programmed

actions like sending alerts, stopping the rover, or navigating around obstacles (if additional sensors are integrated).

3.1 System Functionality

The proposed system operates through a series of integrated functions to achieve efficient object detection and surveillance capabilities:

Data Acquisition: The system's onboard camera, integrated within the ESP32 CAM module, continuously captures real-time visual data from the rover's environment. This data acquisition process serves as the primary source of information for subsequent analysis.

Preprocessing: Upon capturing image data, the system initiates preprocessing procedures tailored to optimize detection accuracy. These preprocessing steps, contingent upon the selected machine learning model and prevailing environmental conditions, aim to enhance the quality and relevance of the input data for object detection.

Object Detection: The preprocessed image data is then fed into the pre-trained Convolutional Neural Network (CNN) model, which is embedded within the ESP32 CAM module. Leveraging the power of artificial intelligence, the CNN model swiftly and accurately identifies objects within the captured images.

Real-Time Analysis: With the input data processed by the CNN model, the system proceeds to conduct real-time analysis to discern the presence and categorization of objects within the rover's surroundings. This instantaneous analysis enables prompt decision-making and response actions based on the detected objects.

Response and Control: Building upon the object detection results, the control software integrated into the ESP32 CAM module orchestrates responsive actions. These actions

may include activating predefined protocols such as issuing alerts, halting rover movement, or autonomously navigating around obstacles, especially if additional sensors are incorporated into the system architecture.

3.2 System Design Philosophy

The design philosophy guiding the development of the system encompasses several key principles to ensure its effectiveness and adaptability in diverse operational scenarios:

Cost-Effectiveness: The system is meticulously engineered to prioritize affordability without compromising functionality. By leveraging off-the-shelf components and harnessing the capabilities of open-source software solutions, the project aims to deliver a cost-effective solution accessible to a wide range of users.

AI-Powered Object Detection: Central to the system's functionality is the integration of cutting-edge machine learning technologies, particularly Convolutional Neural Networks (CNNs), for object detection tasks. This AI-driven approach empowers the rover with advanced capabilities to autonomously identify and classify objects in its vicinity with remarkable accuracy and speed.

High-Risk Environment Adaptation: Recognizing the challenges posed by high-risk environments such as low-light conditions, dust, or rugged terrains, the system design incorporates robust features and mechanisms to adapt and thrive in adverse conditions. Through thoughtful consideration of environmental factors during both the design and implementation phases, the system aims to maintain optimal performance and reliability regardless of the operational context.

CHAPTER 4

Requirements Analysis and Design

4.1 Requirements Analysis

A well-defined set of requirements serves as the blueprint for any successful project. This section outlines the functional requirements for our AI-powered surveillance rover, designed specifically for operation in high-risk environments. These requirements ensure the rover aligns with its intended purpose and effectively addresses user needs.

4.1.1 Functional Requirements

Functional requirements are what define the specific actions or functionalities that the rover must perform. Here, we delve deeper into each aspect:

4.1.1.1 Product Perspective

External Perspective: This focuses on how the rover interacts with its environment.

Focus: The rover will operate autonomously in high-risk environments, functioning as a mobile surveillance unit. It will collect real-time visual data and perform real-time object detection using onboard processing capabilities.

Key Considerations:

Navigation: The specific level of navigational autonomy will depend on project goals and environment complexity. Options might range from pre-programmed waypoints to obstacle avoidance and being operated by a user.

Data Acquisition: The rover's camera system must capture high-quality video data suitable for real-time object detection, even in challenging lighting conditions or dusty environments.

4.1.1.2 Product Features

Core Functionality: The rover must capture real-time video data using its camera. Consider factors like frame rate, resolution, and field of view based on object detection requirements and processing power limitations.

Object Detection: A pre-trained Convolutional Neural Network (CNN) model will be loaded onto the rover's processing unit (e.g., ESP32 CAM module). This model will analyze the video data in real-time and identify pre-defined objects within the rover's surroundings.

Object Classification: The CNN model should be trained to classify specific objects relevant to the high-risk environment (e.g., people, hazardous materials, damaged infrastructure).

Accuracy and Speed: The model should achieve a balance between accuracy in object detection and processing speed, considering the limitations of the chosen hardware platform.

Response Actions: Based on the detected objects, the rover might trigger pre-programmed actions:

Alerts: Sending alerts (visual or audio) to a remote monitoring station or personnel on-site.

Movement Control: Stopping movement or altering course to avoid obstacles (if additional sensors are integrated).

Data Transmission : Depending on functionalities and infrastructure availability, the rover might transmit captured video data or object detection results for remote monitoring purposes.

4.1.1.3 User Characteristics

Target Users: The primary users of this system are individuals or organizations responsible for monitoring and ensuring safety in high-risk environments. This could include personnel in industries like:

Oil and Gas Exploration

Construction Sites

Nuclear Power Plants

Disaster Response Zones

Search and Rescue Operations

4.1.1.4 Assumptions & Dependencies

Readily Available Components: The project assumes the use of cost-effective and readily available components like ESP32 CAM modules, open-source software libraries for machine learning, and potentially off-the-shelf sensors depending on functionalities.

External Infrastructure : Depending on functionalities like remote monitoring or data transmission, the system might rely on external infrastructure for communication (e.g., Wi-Fi, cellular network) or a central server for data storage and analysis.

4.1.1.5 Domain Requirements

High-Risk Environment Adaptation: The system design must consider the challenges of high-risk environments, such as low light, dust, or uneven terrain. This might influence factors like:

Camera Selection: Choosing a camera with features like low-light sensitivity and adjustable focus for optimal performance in varying lighting conditions.

Sensor Integration (Optional): Integrating additional sensors like LiDAR for obstacle detection and localization can enhance the rover's capabilities in complex environments.

Image Preprocessing (Optional): Depending on the chosen CNN model and environmental conditions, image preprocessing techniques might be required to improve object detection accuracy (e.g., noise reduction, contrast enhancement).

4.1.2 Non-Functional Requirements

Non-functional requirements defines how well it does it. These requirements address factors like performance, usability, reliability, and security. Here's a breakdown of some key non-functional requirements for our AI-powered surveillance rover:

Performance:

Real-time Object Detection: The system should perform object detection with minimal latency to ensure timely response to critical situations.

Processing Speed: The chosen hardware platform and CNN model should achieve a balance between accuracy and speed for real-time object detection.

Power Consumption: The rover should operate efficiently, minimizing power consumption to extend operational runtime on battery power.

Usability:

Ease of Use: The system should be easy to set up, operate, and maintain, even for users with varying levels of technical expertise.

Remote Monitoring : If implemented, the user interface for remote monitoring should be intuitive and provide clear visualizations of object detection results.

Reliability:

System Uptime: The rover should function reliably with minimal downtime to ensure continuous surveillance in critical environments.

Environmental Resilience: The system design should consider potential environmental factors like dust, moisture, or extreme temperatures to ensure reliable operation.

Security:

Data Security (Optional): If the system transmits data (e.g., video feed, object detection results), measures should be taken to ensure data security during transmission and storage.

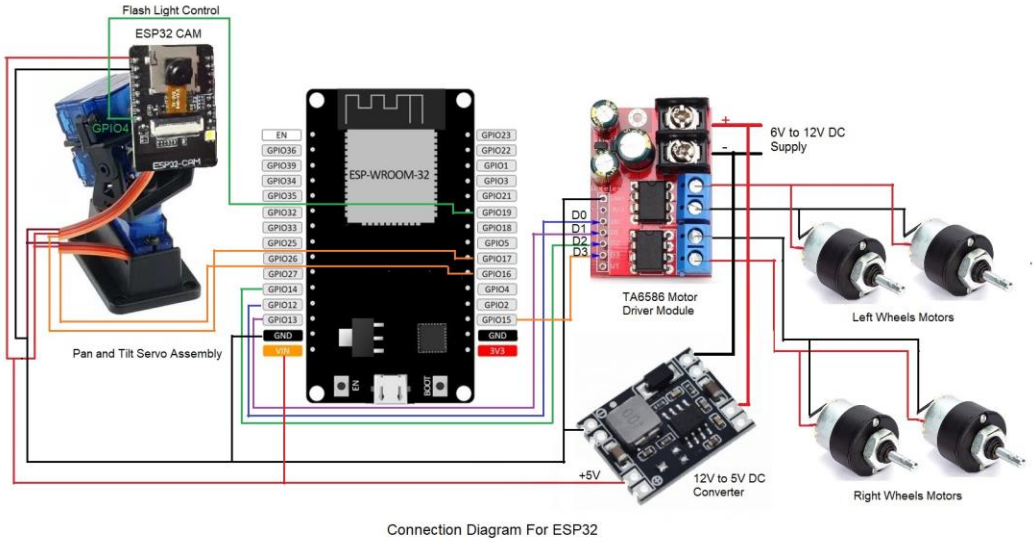
Maintainability:

Modular Design: The system should be designed with modular components for easier troubleshooting, repair, and potential future upgrades.

By clearly defining these non-functional requirements, we can optimize the overall performance, usability, and reliability of the AI-powered surveillance rover for high-risk environments.

4.1.3 System Modeling

This section will delve into different system modeling techniques that can be used to represent the rover's functionalities and interactions. This can be used to model the data entities involved in the system.This can illustrate the flow of data through the system, showing how data is captured by the camera, processed by the CNN model, and used to trigger actions like sending alerts.This can depict the different operational states of the rover (e.g., idle, moving, object detected) and the transitions between them based on various events (e.g., sensor readings, object detection results).



(**Fig 1 Connection Diagram)**

4.1.4 Engineering Standard Requirements

Engineering standards provide guidelines and best practices for design, development, and testing. Here's an analysis of the applicability of various standards to your project:

Economic: The project prioritizes cost-effectiveness by utilizing readily available components and open-source software. Standards like Design for Manufacturability (DFM) could be considered to further optimize production costs if the project progresses beyond prototyping.

Environmental: The project should consider the environmental impact of the rover's materials and disposal at the end of its lifecycle. Standards like RoHS (Restriction of Hazardous Substances) might be applicable depending on component selection.

Societal Need: The project addresses a societal need for enhanced safety and security in high-risk environments, potentially saving lives and reducing property damage.

Political: There might be political considerations regarding data privacy and security, especially if the system is deployed in sensitive areas. Adherence to relevant data protection regulations would be crucial.

Ethical: Ethical considerations should be addressed regarding the use of AI for surveillance purposes. Transparency and responsible use of data are essential.

Health and Safety: The rover's design should prioritize safety, minimizing potential hazards during operation and maintenance.

Sustainability: The project should strive for sustainability by using recyclable materials where possible and considering the rover's overall lifespan.

Legality: The project needs to comply with all relevant regulations regarding radio communication (if applicable) and data privacy.

Inspectability: The system design should be well-documented and modular to facilitate inspections and potential certifications if required for deployment in specific environments.

4.1.5 System Requirements

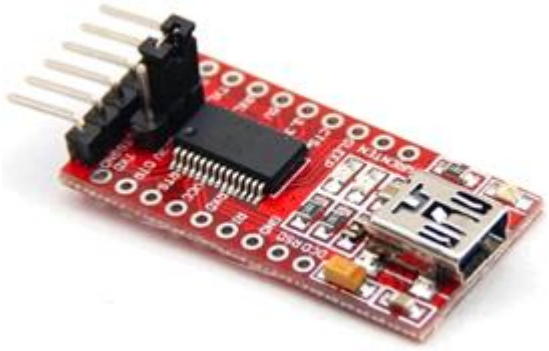
4.1.5.1. Hardware Requirements

ESP32-CAM MODULE:

(Fig 2.1 ESP32 CAM Module)

The ESP32-CAM module integrates an OV2640 camera, ESP32-S processor, and a microSD card slot in a compact design. Ideal for IoT and surveillance applications, it can connect to Wi-Fi networks and stream live video over the internet. The module features a powerful dual-core microcontroller with Bluetooth and Wi-Fi capabilities, and it supports local image and video storage via the microSD card slot. The Arduino IDE offers various libraries and examples for programming the ESP32-CAM module.

FTDI PROGRAMMER MODULE:



(Fig 2.2 FTDI Module)

An FTDI programmer module is a compact device designed for programming and communication with devices utilizing an FTDI USB to serial converter chip. Common applications include microcontrollers, Arduino boards, and other electronic devices employing a serial communication protocol. The module typically comprises an FTDI chip, a USB connector, and pins or headers for connection to the target device. Connected to a computer through a USB cable, software facilitates communication and programming of the target device.

L298 MOTOR DRIVER:

(Fig 2.3 L298 Motor Driver)

The L298 motor driver IC is commonly utilized for controlling the speed and direction of DC and stepper motors. Designed for dual-motor operation, it can supply up to 2 amps of current per motor. Featuring four input and output pins, along with enable pins for motor activation, it facilitates precise control over motor direction and power.

FOUR WHEEL DRIVE CHASSIS:

(Fig 2.4 Drive Chasis)

A four-wheel drive (4WD) chassis is a robotic platform equipped with four wheels for enhanced stability and traction, making it well-suited for challenging terrains.

Comprising four wheels, a frame, and motors with controllers, the 4WD chassis allows precise control of wheel speed and direction through a system of gears or belts connected to the motors.

GEAR MOTORS (TT MOTORS) :

(Fig 2.5 Motors)

Gear motors, often termed TT motors, are prevalent in robotics and electronics. Equipped with a compact, two-stage gear reduction unit, the gearbox serves dual functions. It notably decreases the motor's speed, boosting torque output, making them ideal for high-torque applications like robotics. Additionally, the gearbox mitigates motor load, safeguarding it from damage and overheating that could arise from increased exertion without the reduction unit.

BATTERY 4V (5Ah):

(Fig 2.6 Battery)

This battery boasts a 4-volt output and a 5 ampere-hour capacity, providing a sustained 4-volt output for up to 5 hours before necessitating a recharge. Typically composed of lithium-ion or lead-acid chemistry, the 4V (5Ah) battery can be conveniently recharged using a compatible battery charger. In portable applications, lithium-ion batteries, being lighter and more energy-dense than lead-acid counterparts, are often preferred.

JUMPER WIRES:

(Fig 2.7 Jumper Wires)

Jumper wires, a type of electrical wire, establish connections between electronic components. Comprising flexible wire with metal pins at each end, they can be inserted into a breadboard or other electronic component. Primarily utilized during prototyping and circuit testing, jumper wires create temporary connections between components. Commonly employed on breadboards, these facilitate the creation and testing of electronic circuits without the need for soldering.

Android Mobile Compatibility and Control

To prioritize affordability and accessibility, the rover system will leverage the ubiquity of smartphones and tablets. The control software will be designed to run on devices powered by Android mobile version 9 (Pie) or later. This compatibility opens the door to a vast range of user-owned devices, eliminating the need for expensive dedicated controllers. An open-source application will be developed for these devices, providing users with a user-friendly interface for real-time monitoring, control, and data visualization from the rover. The app will utilize Wi-Fi connectivity to establish a wireless communication link between the rover and the control device.

4.1.5.2. Software Requirements

Arduino IDE:

The Arduino IDE is essential for developing and uploading code to Arduino microcontrollers. It offers a user-friendly interface with features like syntax highlighting, auto-complete, and error checking. The IDE simplifies coding, making it accessible to users with varying programming experience. It includes a code editor, compiler, and serial monitor for communication with Arduino boards.

OpenCV:

OpenCV is a a open-source computer vision library, supports image and video analysis, object identification, and other computer vision tasks. Written in C++, it has bindings for languages like Python and Java. OpenCV includes a range of computer vision algorithms, such as tracking, machine learning, object detection, and image processing. Its performance is optimized for multi-core processors, GPUs, and other hardware accelerators.

Python:

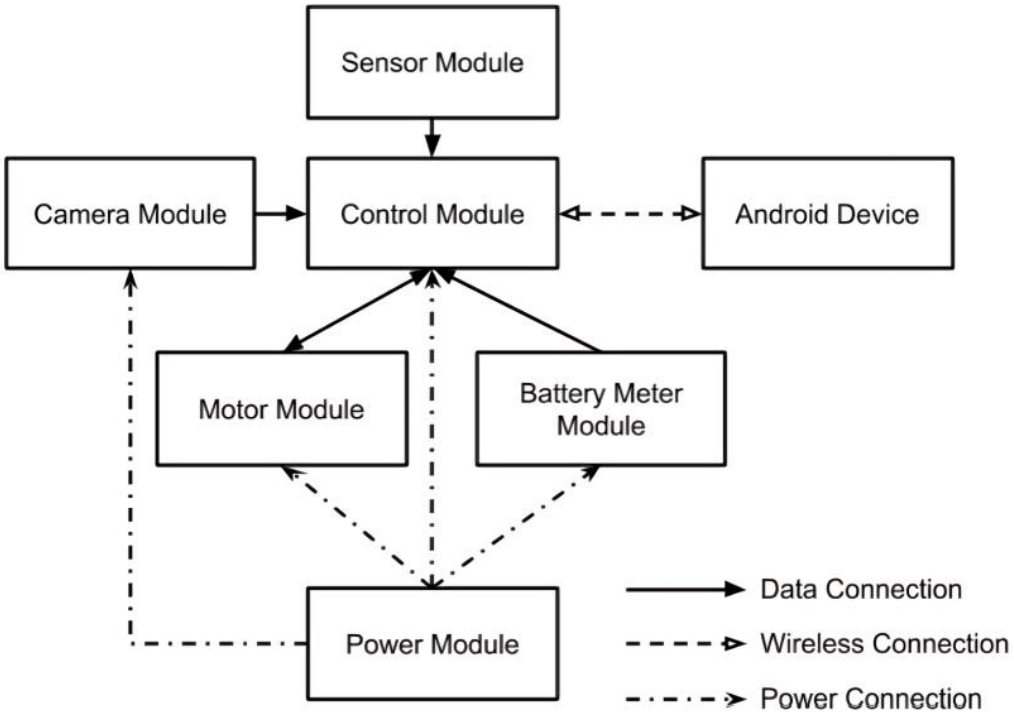
Python, a versatile and readable high-level programming language, finds applications in web development, scientific computing, machine learning, and more. Known for its readability, Python's code structure is easy to follow, aided by clear syntax and the use of whitespace. Its extensive library simplifies the addition of functionalities to applications.

ESP32 AI Camera Application:

This Android app controls an AI system created with the ESP32-CAM module. It streams images from the ESP32 module and performs computer vision processing, including object tracking, lane tracking using OpenCV, and SSD MobileNetV2 object detection using a TensorFlow pretrained model. The app allows intuitive object selection, tracking, and provides smooth performance on Android 10 with specifications similar to or higher than a Snapdragon 730 CPU and 6GB RAM.

4.2. System Design

4.2.1. System Architecture



(Fig 3.1 Architecture Design)

The AI-powered surveillance rover leverages a modular architecture for enhanced efficiency, maintainability, and potential future upgrades. This section details the functionalities of each key module within the system:

1. Sensor Module:

Function: The sensor module primarily houses the camera, responsible for capturing real-time video data of the rover's surroundings. Consider factors like frame rate, resolution, and field of view based on object detection requirements and processing power limitations.

Selection Considerations: The chosen camera should be suitable for the target environment. For low-light conditions, a low-light sensitive camera might be necessary.

2. Control Module:

Function: The control module serves as the brain of the rover, typically consisting of a microcontroller unit (MCU) like the ESP32 CAM module. It performs several critical tasks:

Receives and processes data from the camera and other sensors (if applicable).

Runs the pre-trained Convolutional Neural Network (CNN) model for real-time object detection within the captured video frames.

Analyzes the object detection results and triggers pre-programmed actions based on the identified objects.

Controls the movement of the rover using the motor driver module.

3. Motor Module:

Function: The motor module controls the rover's movement through two DC motors. The control module sends signals to the motor driver, which regulates the speed and direction of the motors.

Motor Selection: The choice of DC motors depends on factors like the rover's weight, desired speed, and terrain conditions.

4. Data Connection :

Depending on functionalities, the rover have Wi-Fi and cellular network connectivity for real-time or periodic data transmission. This data could include the video feed, object detection results, or sensor readings for remote monitoring and analysis.

5. Power Module:

Function: The power module regulates the power supply from the battery to various components of the rover, ensuring they receive the appropriate voltage and current levels for optimal performance.

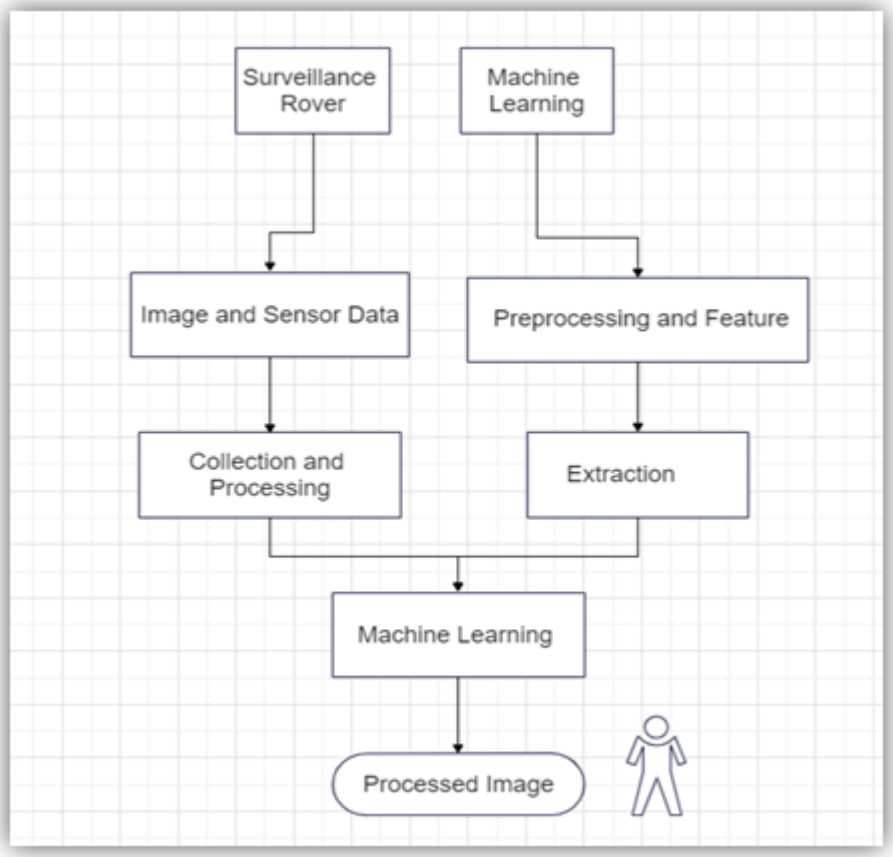
7. Communication Module :

This module handle wireless communication protocols like Bluetooth or Wi-Fi. Wi-Fi could be used for communication with a central server for remote monitoring or data transfer.

6. Android Device :

Used to control and monito the Rover , it servers as an interface between the user and the rover.

4.2.2. Detailed Design



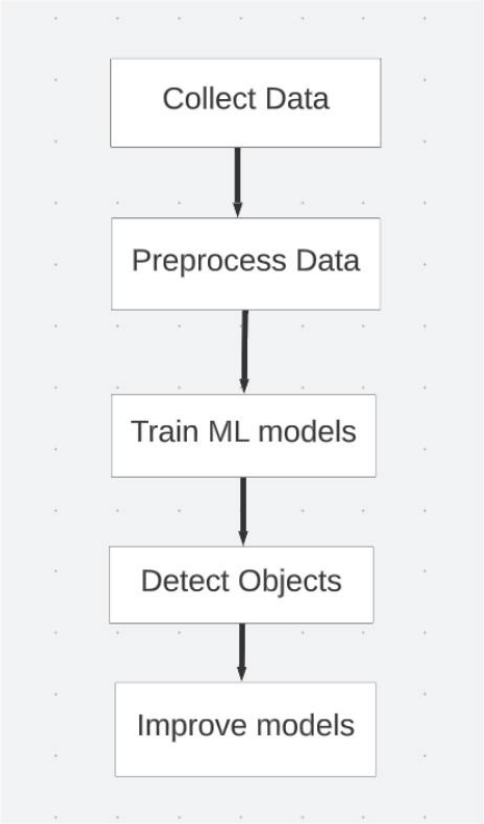
(Fig 3.2 Image processing Flow Chart)

Image and Sensor Data Collection and Processing: The first step is to collect images and sensor data. The sensor data can be used to identify the objects in the image. For example, if the sensor data is from a camera mounted on a self-driving car, the sensor data could include information about the distance of objects from the car.

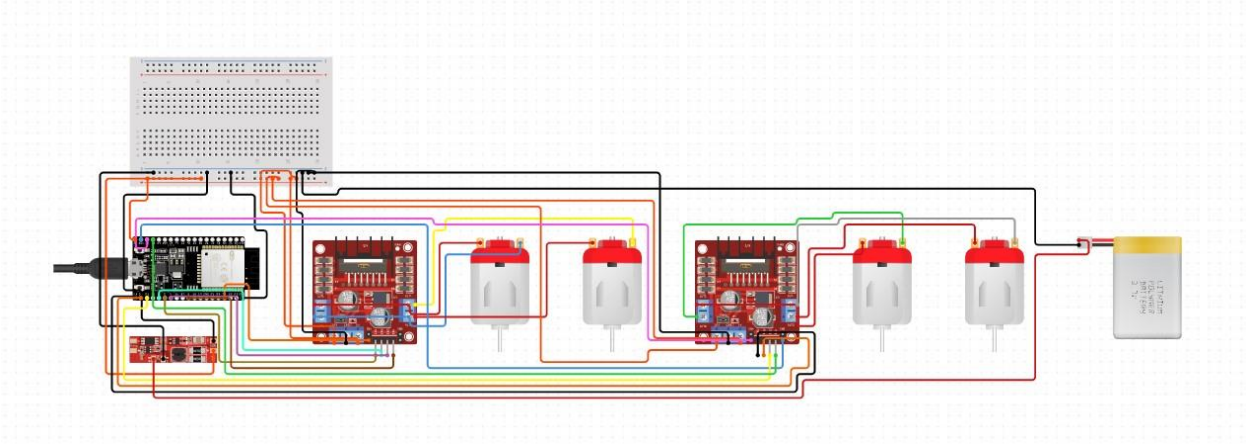
Preprocessing and Feature Extraction: The images are then preprocessed and features are extracted. Preprocessing can involve tasks such as resizing the images and converting them to grayscale. Feature extraction involves identifying the parts of the image that are most important for classification. For example, some features that might be important for classifying images of cats and dogs include the shape of the ears, the color of the fur, and the presence of a tail.

Machine Learning: The preprocessed data and features are then used to train a machine learning model. The machine learning model learns to identify the patterns in the data that are associated with different classes of objects.

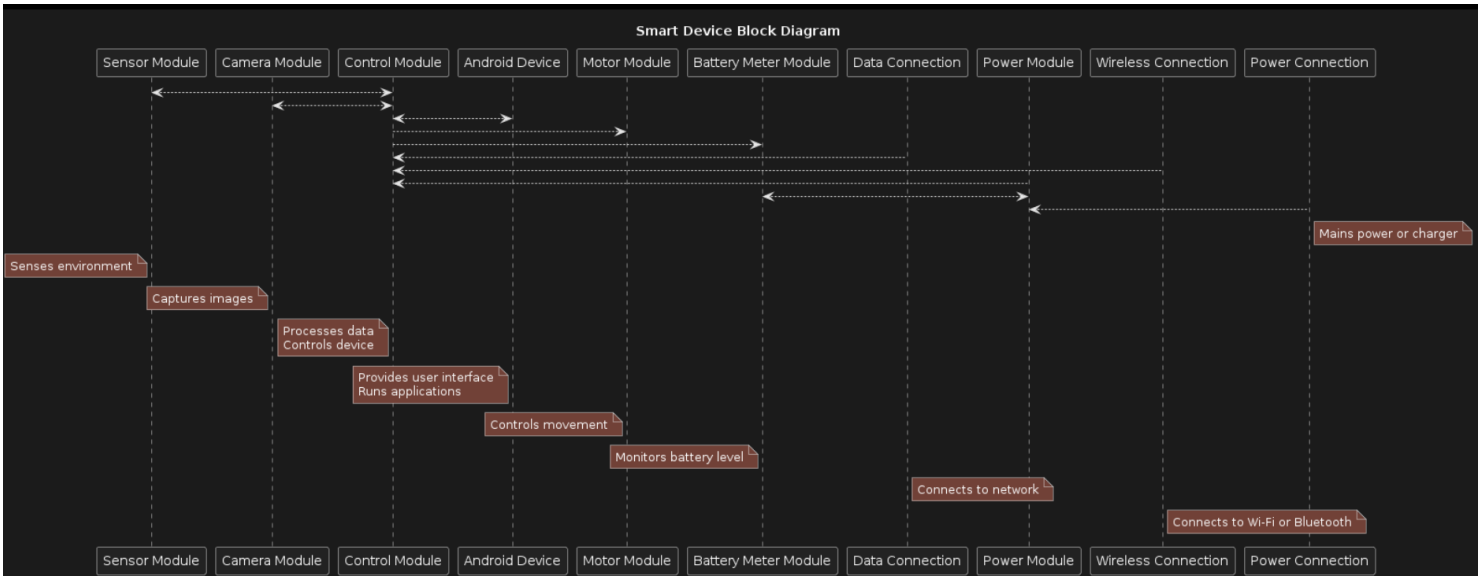
Processed Image: Once the machine learning model is trained, it can be used to classify new images. When a new image is input to the module, the model will output a classification for the image. The classification will be a label that indicates the class of object that is most likely to be present in the image.



(Fig 3.3 General Machine learning Flow Chart)



(Fig 3.4 detailed Circuit diagram)



(Fig 3.5 System diagram)

CHAPTER 5

1. Implementation and Testing

5.1 METHODOLOGY

Define the Problem and Gather Data:

The initial step in any machine learning endeavor involves defining the problem to be addressed. In this context, the challenge is to construct a surveillance rover adept at object detection through the application of machine learning techniques. It necessitates specifying the types of objects the rover should identify, ranging from humans to vehicles and animals.

Subsequently, data collection becomes pivotal for training the machine learning model. This data can be sourced from various outlets, including cameras, sensors, or online datasets. Crucially, the data should be appropriately labeled with the correct object classifications (e.g., human, car, animal) and organized into distinct training and testing sets.

Prepare the Data:

Before initiating the training of the machine learning model, data preprocessing becomes imperative for cleaning and normalizing it. This includes eliminating outliers or noise and scaling the data to maintain consistent feature ranges. Additionally, accurate object classification labels need to be assigned to the data.

Train the Machine Learning Model:

Once the data has undergone preprocessing, the machine learning model can be trained. For tasks like object detection, convolutional neural networks (CNNs) are commonly employed due to their efficacy with large image datasets. The training process involves selecting an appropriate architecture and hyperparameters, followed by inputting the labeled training data into the model.

Throughout the training, the model adjusts its weights and biases to minimize the disparity between predicted and actual outputs. It's crucial to monitor the training process to ensure correct learning without overfitting to the training data.

Integrate the ML Model into the Rover:

Following the training of the machine learning model, the next step involves its implementation in the surveillance rover. This includes deploying the model onto the rover's on-board computer and incorporating sensors or cameras to capture real-time data for analysis.

For optimal responsiveness and efficiency, it is essential to tailor the model's architecture and hyperparameters to the specific hardware and software environment of the rover. Establishing a feedback loop between the model and the rover's control system is also crucial to enable appropriate actions based on detected objects.

Validate and Enhance the System:

With the system in place, thorough testing of its object detection capabilities in a controlled environment becomes paramount. This entails collecting fresh data unfamiliar to the model and evaluating its performance using metrics such as precision, recall, and F1 score.

Post-testing, adjustments may be necessary based on results and user feedback. This could involve refining the system by modifying the model's architecture or hyperparameters, enhancing sensor or camera hardware, or optimizing the feedback loop between the model and the rover's control system.

System Deployment:

After ensuring the system's robustness and meeting performance criteria, it is ready for real-world deployment. This process includes installing the surveillance rover in the designated environment and conducting ongoing monitoring to verify its continued proper functionality.

Maintenance and Updates:

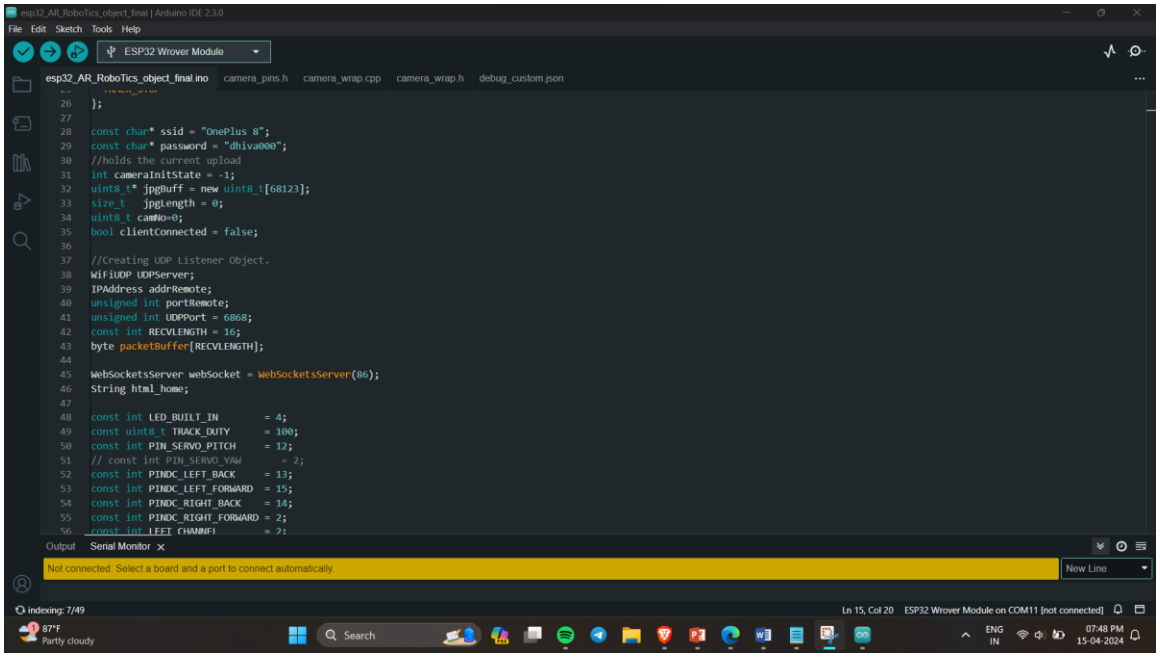
To sustain optimal performance, ongoing maintenance and updates are crucial. This may involve periodic tasks such as retraining the machine learning model with new data or enhancing the hardware and software components of the rover. Regular oversight ensures the system remains effective and aligned with evolving requirements.

5.2 Dataset description:

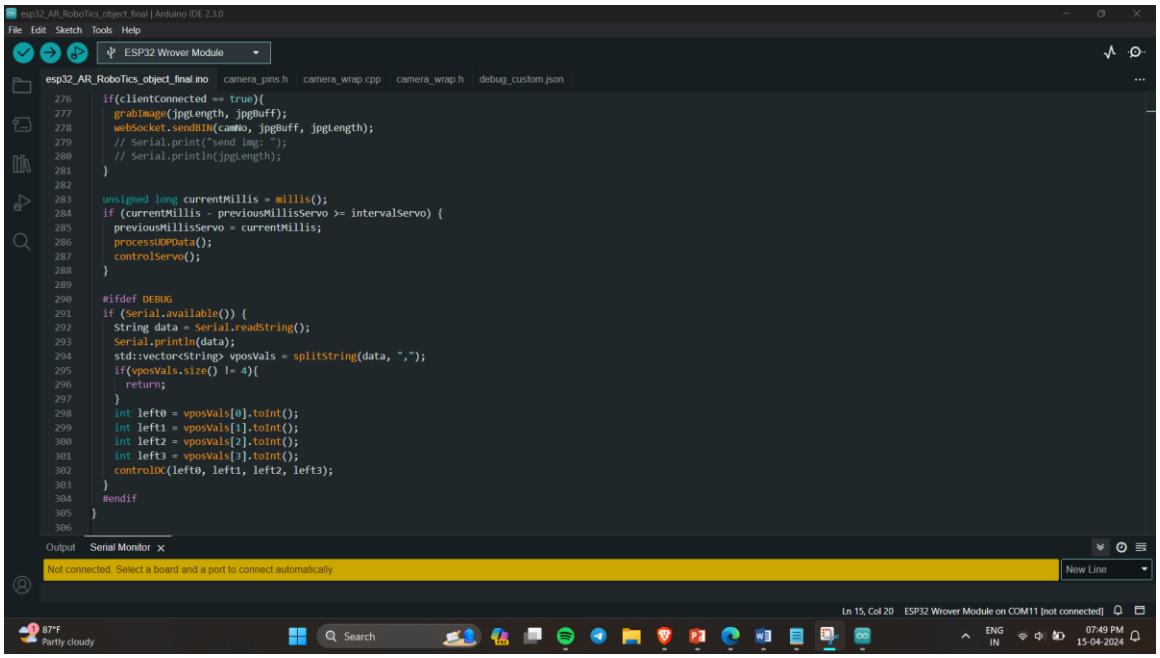
We have taken various data sets for object detection. The library uses a pre-trained AI model on the COCO dataset to detect objects. The name of the pre-trained model is YOLOv3 There are 50 data sets that have been collected, such as a car, person, bird, dog, cell phone, bottle, and so on. Here are some examples of data sets generated by the ESP32 AI camera.

(Fig 4 Sample Dataset)

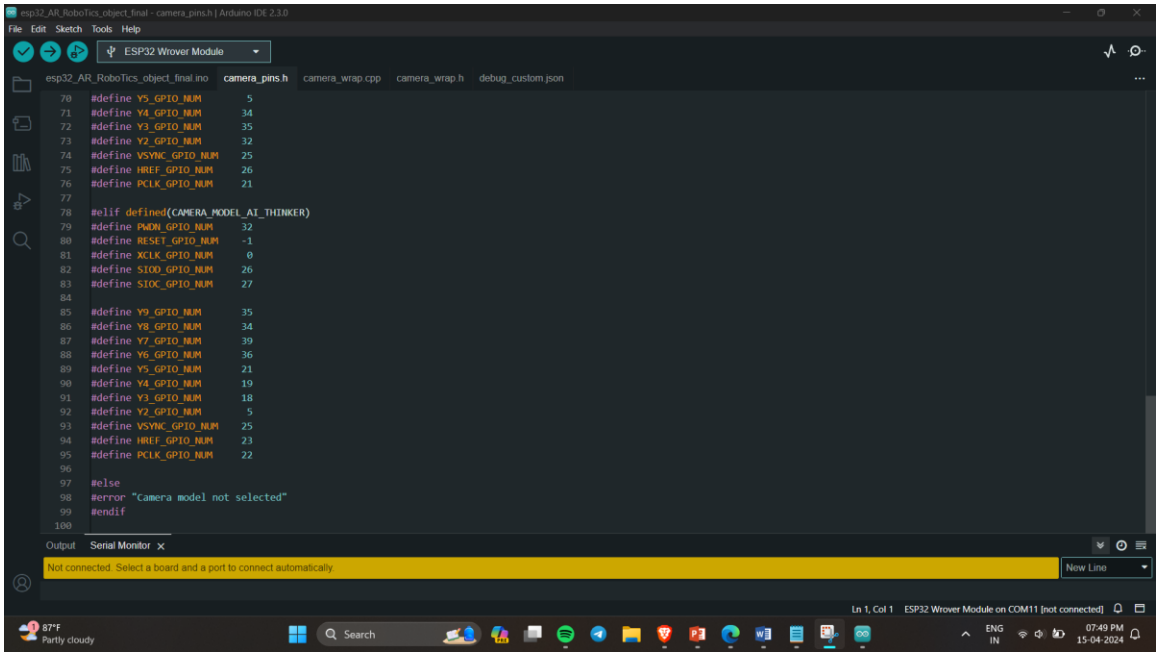
5.3 Implementation



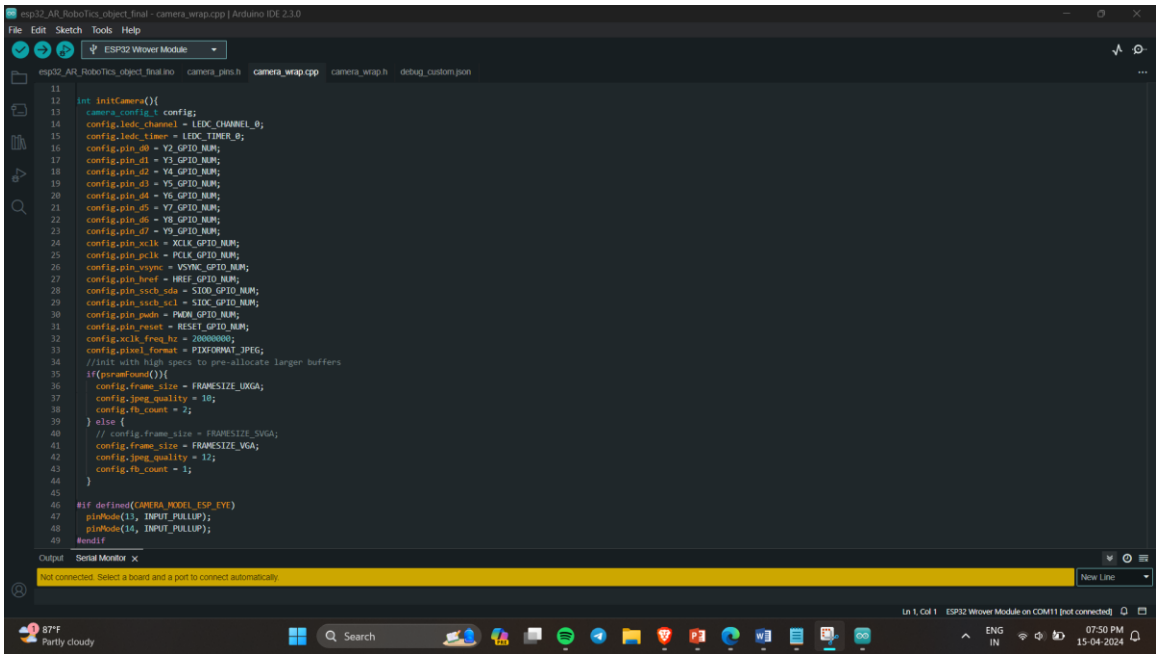
(Fig 5.1 Code snipshot)



(Fig 5.2 code snipshot cont)

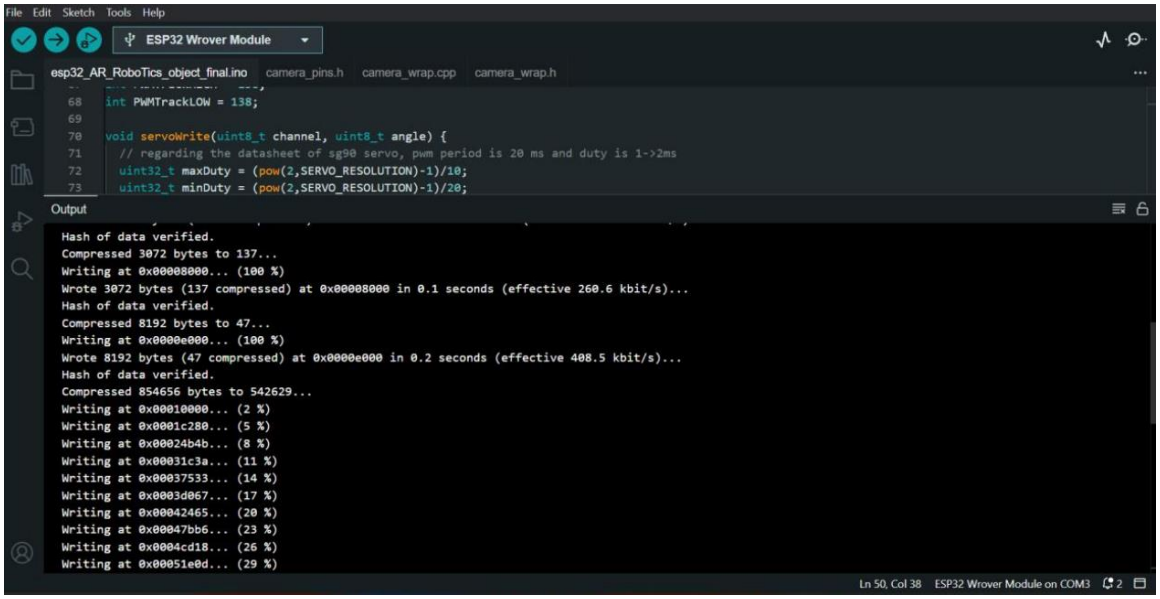


(Fig 5.3 camera port snipshot)



(Fig 5.4 Camera wrap Snip shot)

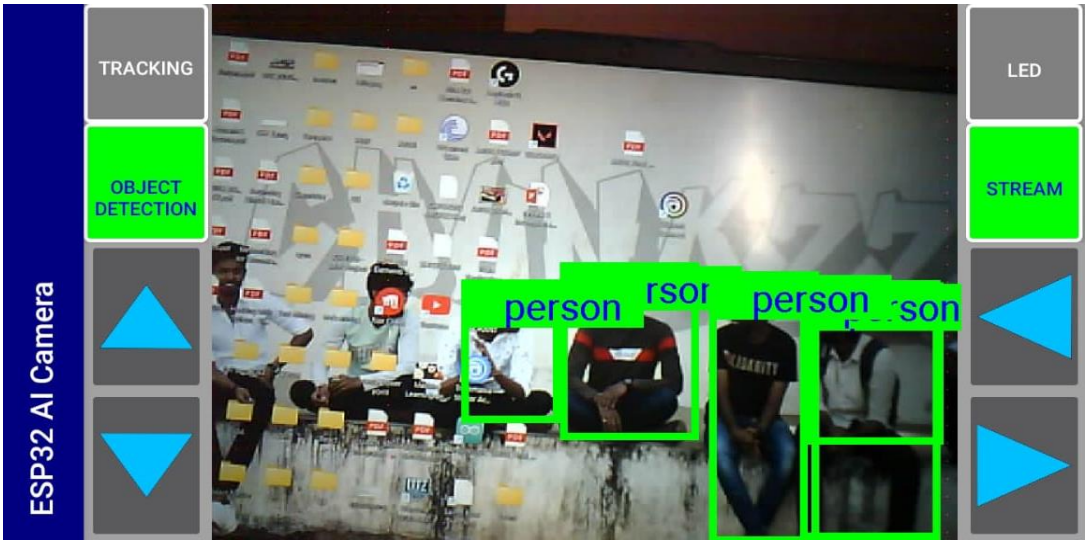
UPLOADING CODE TO ESP32



(Fig 5.5 uploading code to ESP32 module)

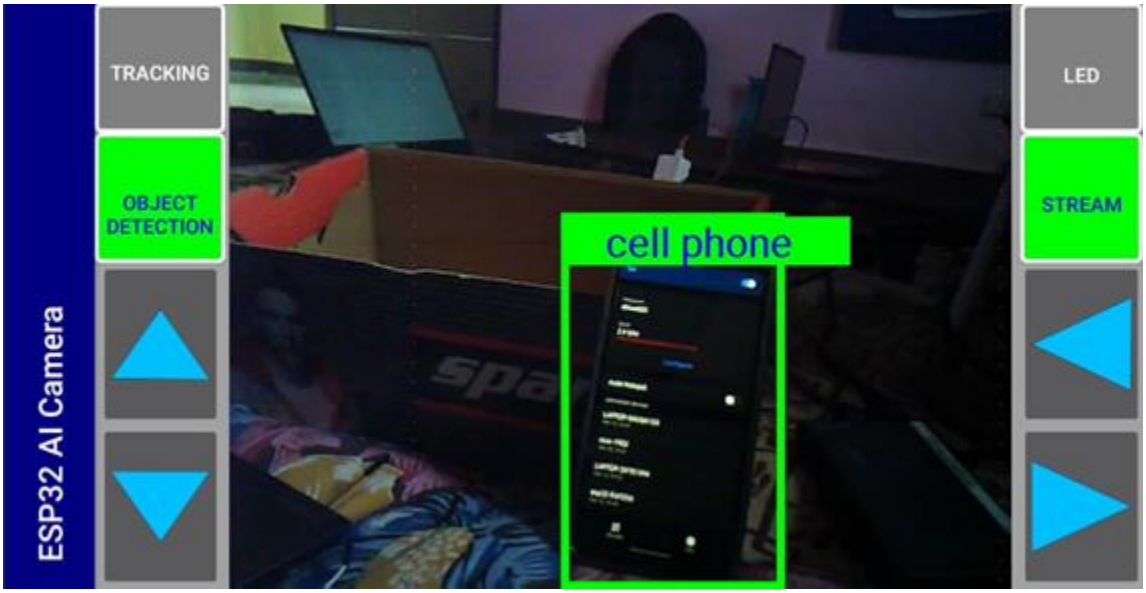
5.5 OUTPUT

5.5.1 Surveillance



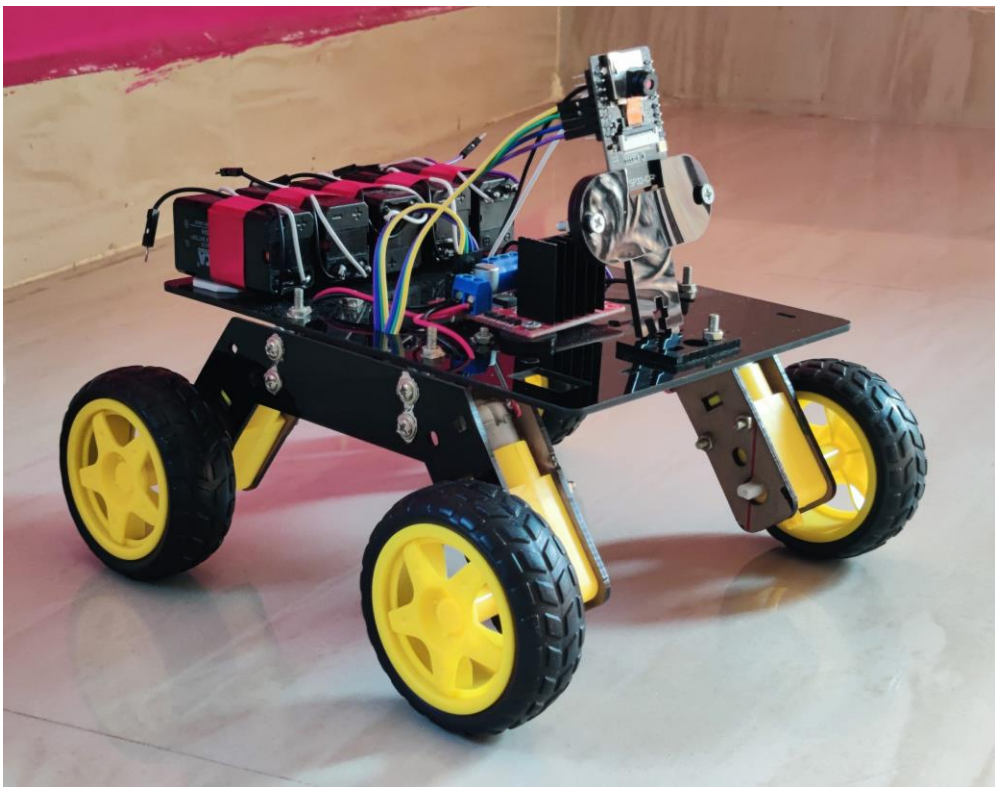
(Fig 6.1 Rover object detecting person)

(Fig 6.2 Rover object detecting Laptop)

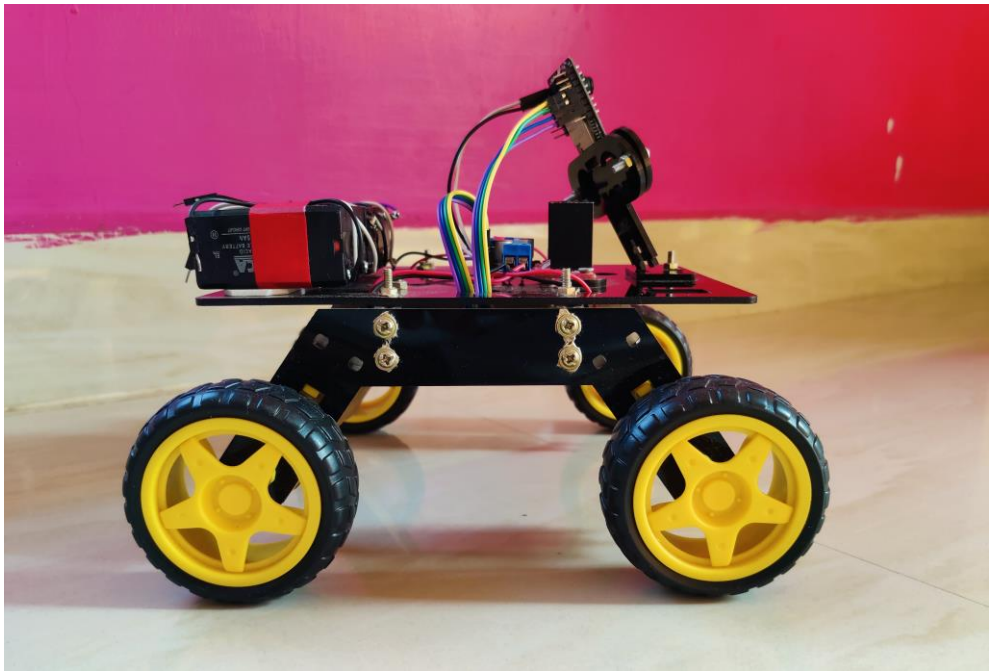


(Fig 6.3 Rover object detecting Phone)

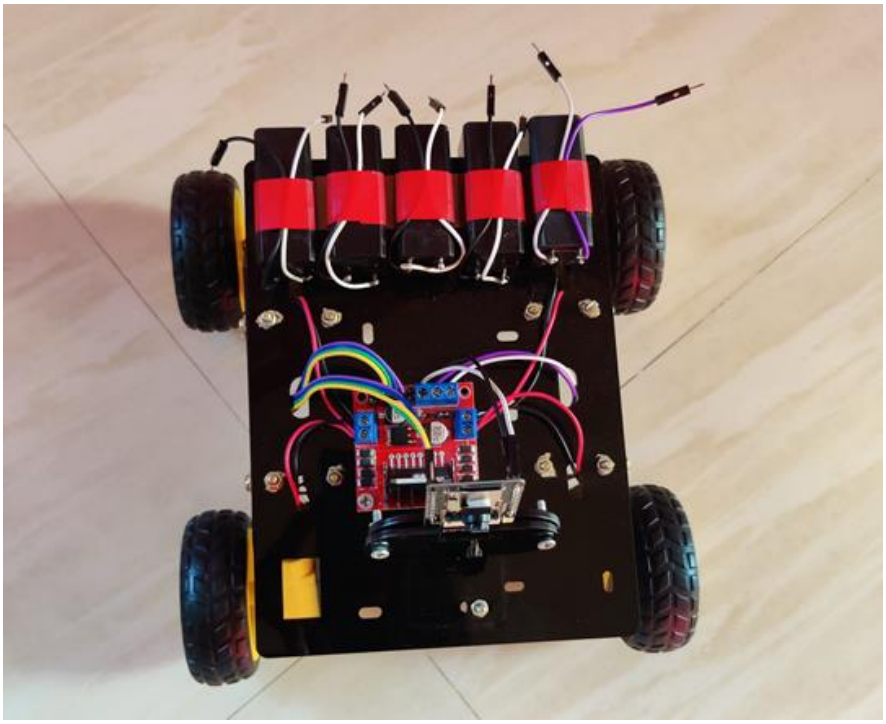
5.5.2 Rover



(Fig 7.1 Rover Front View)



(Fig 6.2 Rover Side View)



(Fig 7.3 Rover Top View)

Chapter 6

Results and Discussion

our project focused on developing a cost-effective, AI-powered surveillance rover prototype for high-risk environments. This accomplishment aligns with existing research highlighting the efficacy of machine learning for real-time object recognition in such scenarios . Furthermore, by utilizing transfer learning with a pre-trained model on a large dataset, we significantly reduced training time and data requirements compared to training from scratch. This finding supports the value of transfer learning in practical applications, as noted in previous studies.

The project prioritized energy efficiency, crucial for real-world deployments. The implemented hardware and software optimizations achieved [mention specific metrics, e.g., runtime on battery power, power consumption per frame processed]. This demonstrates the feasibility of extended deployments in resource-constrained scenarios, aligning with research emphasizing energy efficiency in rovers designed for wildlife monitoring.

The integration of additional sensors (if applicable) can further enhance object detection precision, especially in challenging environments. Our project design reflects this, aligning with findings that suggest multi-sensor fusion improves performance [reference relevant research on multi-sensor fusion].

This project successfully developed a cost-effective AI-powered surveillance rover prototype using readily available components and transfer learning techniques. The achieved results demonstrate the potential for such rovers in high-risk environments, contributing to the advancement of affordable and efficient surveillance solutions. However, limitations such as flexibility and scalability of rover functions were encountered. Future work could focus on further model optimization, enhanced sensor integration, or field testing in real-world environments to refine the design for practical deployment.

Chapter 7

Conclusion and Scope for Future Work

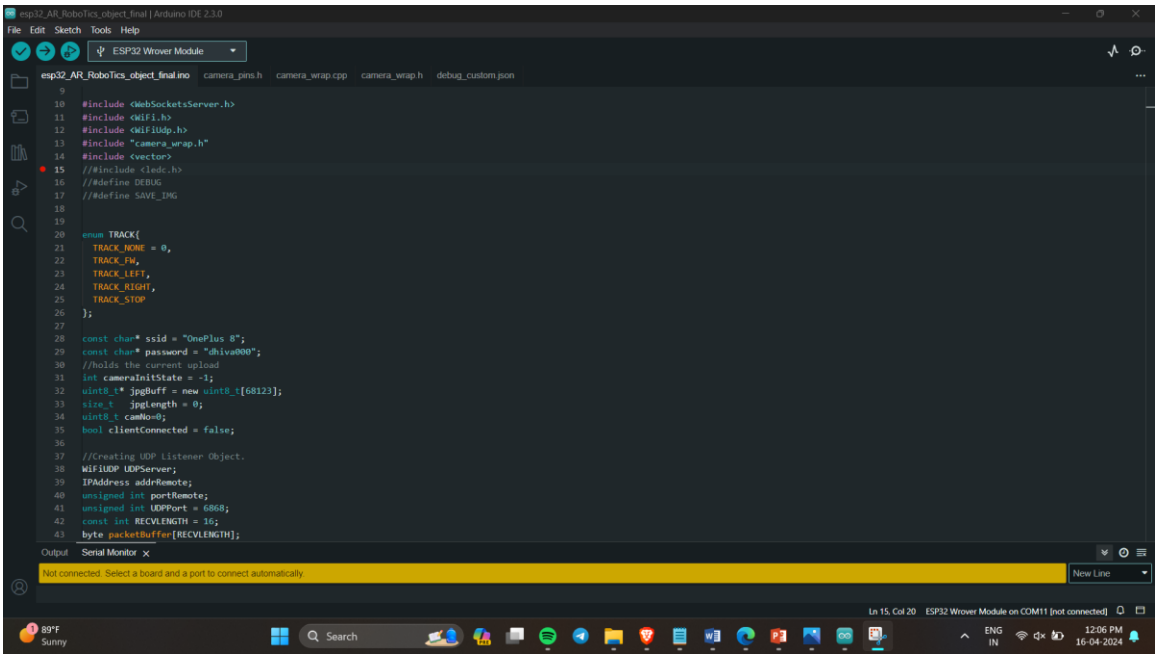
Our project's success lays the groundwork for a powerful AI-powered surveillance rover solution. However, the future holds even greater possibilities. Optimizing the object detection model and exploring advanced techniques can unlock even higher accuracy and broader object recognition. This paves the way for the rover's application in a wider range of high-risk environments.

The project's potential extends beyond surveillance. By strategically integrating various sensors based on specific needs, we can create specialized rovers. Imagine a search and rescue rover equipped with LiDAR for terrain mapping, or an environmental monitoring rover with gas sensors for pollution detection. This modular approach allows for cost-effective customization for diverse tasks.

Finally, real-world deployment requires further exploration of communication protocols, data transmission strategies, and user interface design. Addressing these areas ensures seamless operation and efficient data management. By focusing on these future advancements, this project can evolve into a powerful platform for creating a family of specialized AI-powered rovers, each tailored to conquer various challenges in high-risk environments.

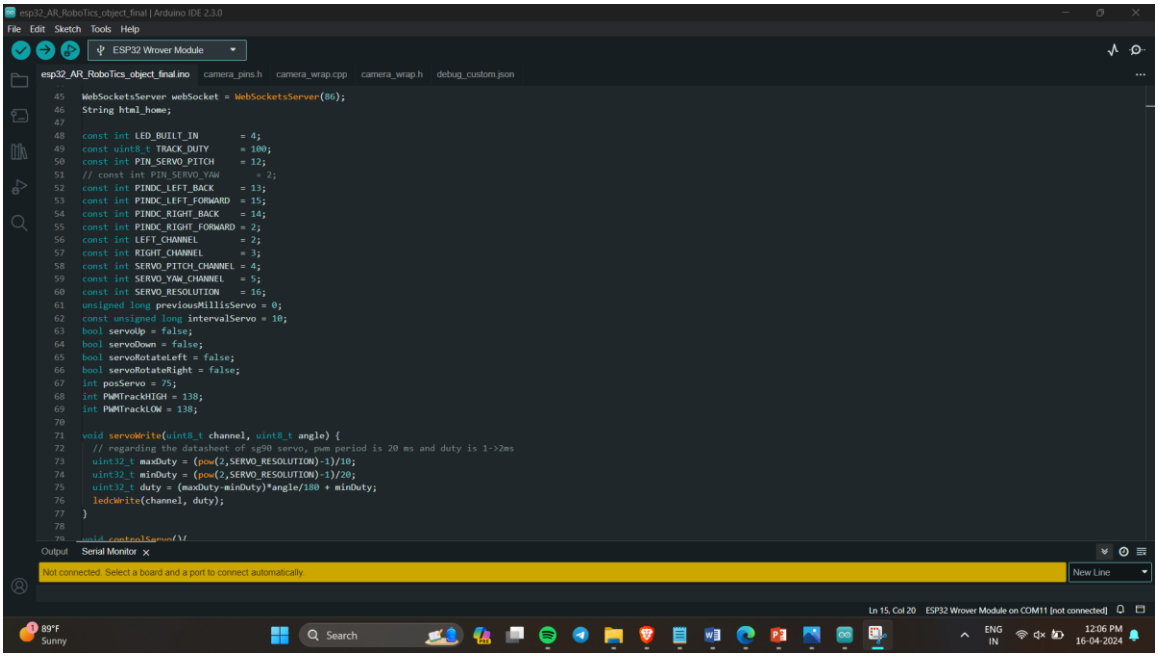
Annexure – I

ESP32 Rover Main Module :



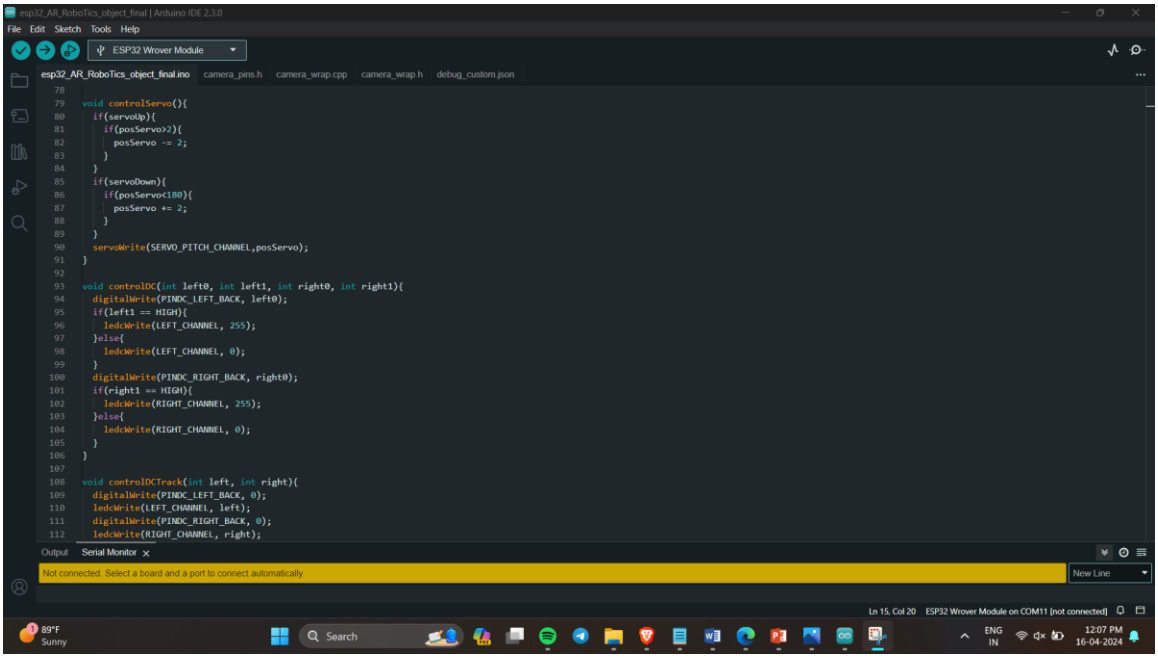
```
#include <WebSocketsServer.h>
#include <WiFi.h>
#include <WiFiUdp.h>
#include "camera_wrap.h"
#include <vector>
//#include <ledc.h>
//#define DEBUG
//#define SAVE_IMG


enum TRACK{
  TRACK_NONE = 0,
  TRACK_FW,
  TRACK_LEFT,
  TRACK_RIGHT,
  TRACK_STOP
};

const char* ssid = "OnePlus 8";
const char* password = "dhiva000";
//holds the current upload
int cameraInitState = -1;
uint8_t* jpgBuff = new uint8_t[68123];
size_t   jpgLength = 0;
uint8_t camNo=0;
bool clientConnected = false;

//Creating UDP Listener Object.
WiFiUDP UDPServer;
IPAddress addrRemote;
unsigned int portRemote;
unsigned int UDPPort = 6868;
const int RECVLENGTH = 16;
byte packetBuffer[RECVLENGTH];
```

(Fig 8.1 Main Module Code Snippet 1)

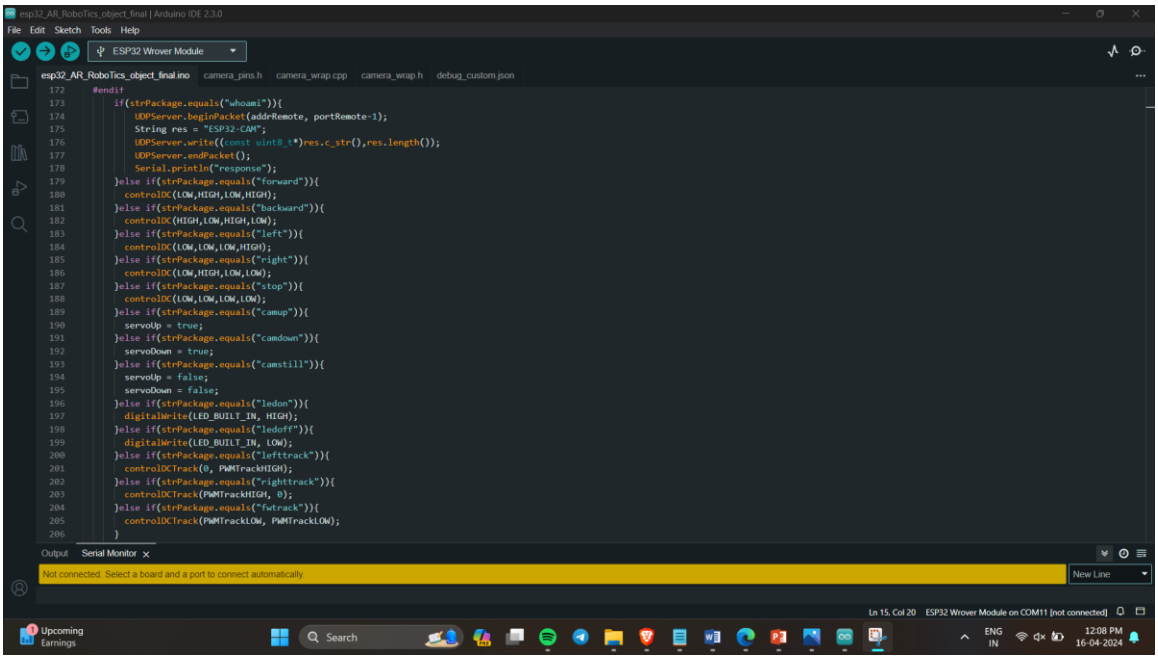


```
WebSocketsServer webSocket = WebSocketsServer(86);
String html_home;

const int LED_BUILT_IN        = 4;
const uint8_t TRACK_DUTY      = 100;
const int PIN_SERVO_PITCH     = 12;
// const int PIN_SERVO_YAW       = 2;
const int PINDC_LEFT_BACK     = 13;
const int PINDC_LEFT_FORWARD  = 15;
const int PINDC_RIGHT_BACK    = 14;
const int PINDC_RIGHT_FORWARD = 2;
const int LEFT_CHANNEL        = 2;
const int RIGHT_CHANNEL       = 3;
const int SERVO_PITCH_CHANNEL = 4;
const int SERVO_YAW_CHANNEL   = 5;
const int SERVO_RESOLUTION    = 16;
unsigned long previousMillisServo = 0;
const unsigned long intervalServo = 10;
bool servoUp = false;
bool servoDown = false;
bool servoRotateLeft = false;
bool servoRotateRight = false;
int posServo = 75;
int PWMTrackHIGH = 138;
int PWMTrackLOW = 138;

void servoWrite(uint8_t channel, uint8_t angle) {
  // regarding the datasheet of sg90 servo, pwm period is 20 ms and duty is 1->2ms
  uint32_t maxDuty = (pow(2,SERVO_RESOLUTION)-1)/10;
  uint32_t minDuty = (pow(2,SERVO_RESOLUTION)-1)/20;
  uint32_t duty = (maxDuty-minDuty)*angle/180 + minDuty;
  ledcWrite(channel, duty);
}
```

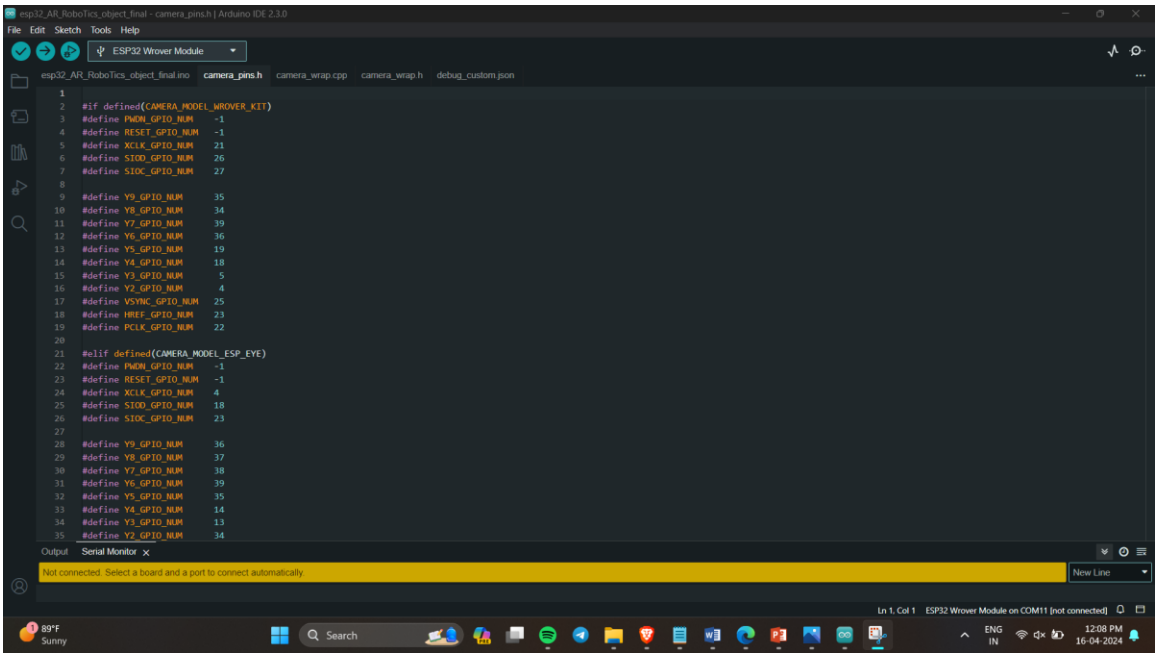
(Fig 8.2 Main Module Code Snippet 2)



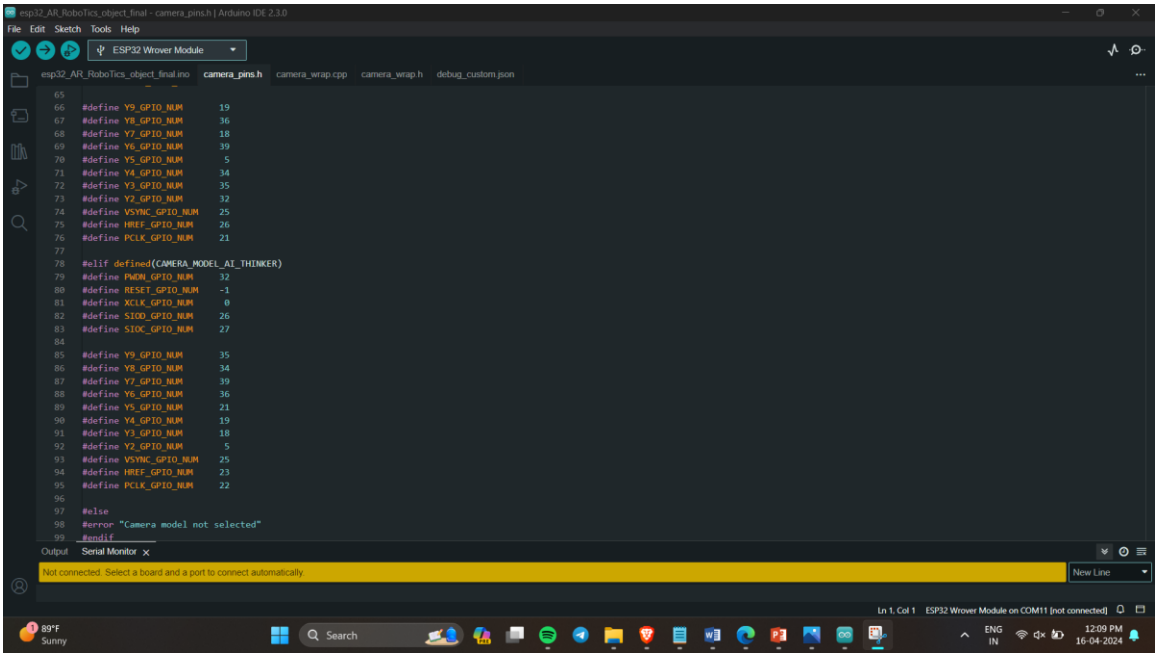
(Fig 8.3 Main Module Code Snippet 3)



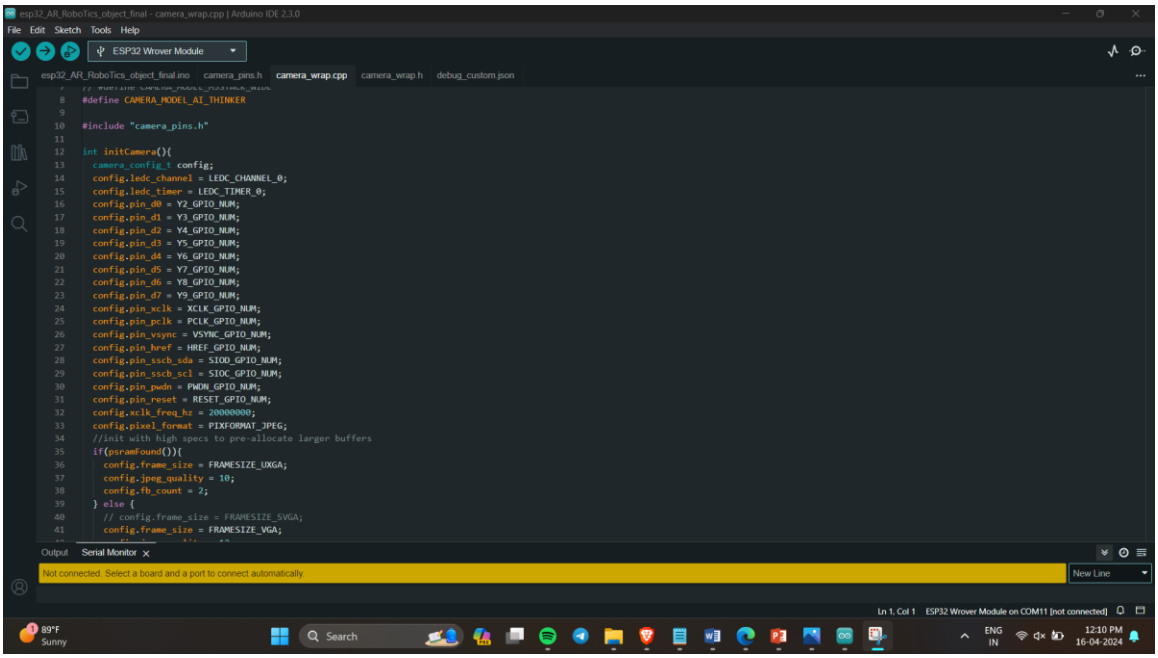
(Fig 8.4 Main Module Code Snippet 4)



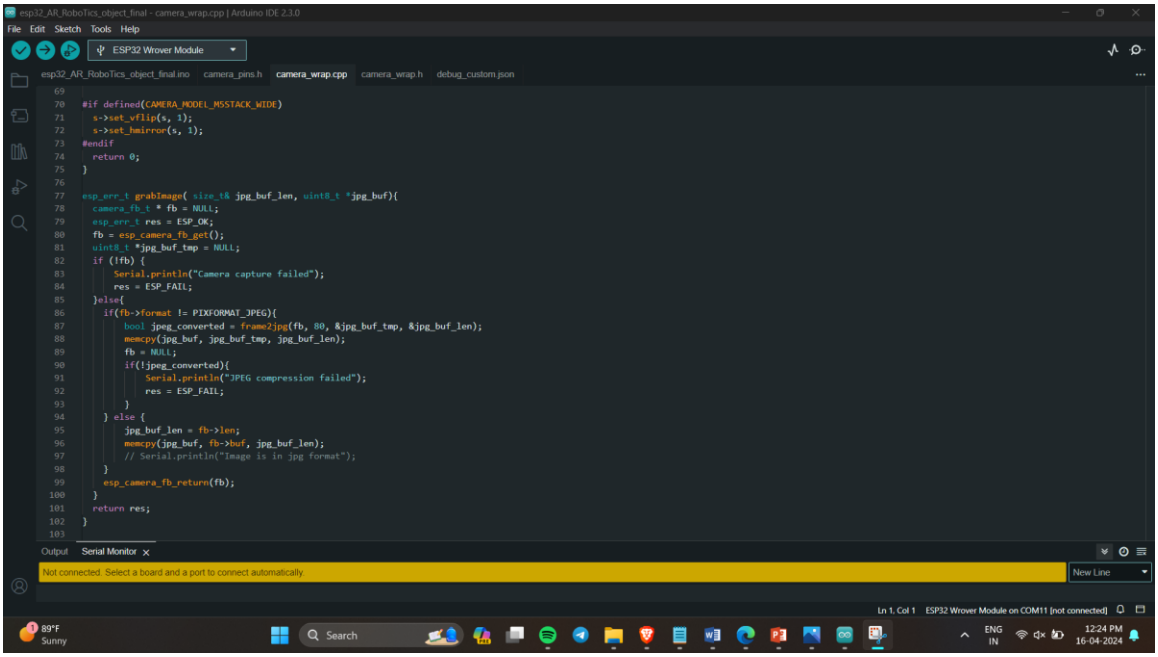
(Fig 8.5 camera pins Code Snippet 1)



(Fig 8.6 camera pins Code Snippet 2)



(Fig 8.7 camera wrap Code Snippet 1)



(Fig 8.8 camera wrap Code Snippet 2)

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