A project report on

INTELLIGENT TRAFFIC MONITORING AND MANAGEMENT FOR REAL-TIME VEHICLE TRACKING IN SMART CITIES

Submitted in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY IN COMPUTER SCIENCE AND ENGINEERING WITH SPECIALIZATION IN ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

By

P.V.S.UDAY KIRAN (21BAI1718)

I.SANTHOSH REDDY (21BAI1770)

R.SAI AKSHITH (21BAI1729)

VIT®
Vellore Institute of Technology
(Deemed to be University under section 3 of UGC Act, 1956)
CHENNAI

SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

April,2025

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DECLARATION

I hereby declare that the thesis entitled “INTELLIGENT TRAFFIC MONITORING AND MANAGEMENT FOR REAL-TIME VEHICLE TRACKING IN SMART CITIES” submitted by REPAKA SAI AKSHITH (21BAI1729), for the award of the degree of Bachelor of Technology in Computer Science and Engineering, Vellore Institute of Technology, Chennai is a record of Bonafide work carried out by me under the supervision of Dr. SAMBATH M.

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.

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CERTIFICATE

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Signature of the Guide:

Name: Dr. Sambath M

Date:

Signature of the Examiner	Signature of the Examiner
Name:	Name:
Date:	Date:

Approved by the Head of Department,
(Bachelor of Technology in Computer Science and Engineering with Specialization in Artificial Intelligence & Machine Learning)

Name: **Dr. Sweetlin Hemalatha C**

Date:

(Seal of SCOPE)

ABSTRACT

The primary goals of avoiding traffic jams, lowering the number of accidents, and making sure transportation works well in cities today, require real time traffic monitoring and management systems. An AI based traffic monitoring and control system is proposed within the scope of this project, it is capable of performing real time vehicle tracking using state of the art AI models and advanced hardware components. An STM32 microcontroller processes the sensor data while the OV7670 captures the live footage of the traffic. The system also uses an ultrasonic sensor to detect vehicle presence and LED lights to signal. These hardware components work hand in hand with deep learning models like YOLOv8 and MobileNet; these systems enable real time vehicle detection, classification, and tracking. Traffic control is enhanced by combining AI-enabled object recognition and embedded system technologies for better traffic flow and safety on the roads.

Incorporating YOLOv8 and MobileNet models help the system to accurately detect various vehicle types and monitor the volume of traffic. To ensure fast and precise vehicle detection, the powerful object detection model YOLOv8 is used. Surely, vehicle classification either on the individual or fleet level using MobileNet model is performed as well. The processing unit of the system, the STM32 microcontroller, receives information from the sensors and integrates it with the results of AI vehicle tracking. At intersections, the ultrasonic sensor helps to recognize the presence of vehicles, while the traffic light signal is changed dynamically using LED lights as a function of the current level of traffic congestion. This system is an improvement over the conventional adaptive fixed-time traffic signals because the dependency is minimized with more intelligent traffic management that optimally reduces waiting times.

The proposed system merges hardware components with AI software to deliver a scalable and economical traffic monitoring solution for smart cities. Authorities benefit from dynamic traffic management and enhanced transportation efficiency by merging real-time data processing with deep learning models to tackle congestion. Enhancements to the system can be achieved through the adoption of cloud-based data storage solutions paired with predictive analytics to forecast traffic patterns and improve urban mobility tactics. The project illustrates how intelligent traffic management automation helps build smarter and safer urban spaces while setting the foundation for future AI-controlled traffic systems.

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Place: Chennai

Date: **Repaka Sai Akshith**

CONTENTS **PAGE NO**

CONTENTS.. iii

LIST OF FIGURES iv

LIST OF TABLES v

LIST OF ACRONYMS vi

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION 1

1.2 OVERVIEW OF TRAFFIC MANAGEMENT SYSTEM 2

1.3 CHALLENGES PRESENT IN MANAGEMENT 3

1.4 PROBLEM STATEMENT 4

1.5 OBJECTIVES OF THE PROJECT 5

1.6 SCOPE OF THE PROJECT 6

CHAPTER 2

LITERARTURE SURVEY

2.1 LITERATURE SURVEY 7

2.2 REVIEW OF TECHNOLOGIES USED 10

CHAPTER 3

METHODOLOGY

3.1 PROPOSED SYSTEM ARCHITECTURE ……………………………………..12

3.2 MODULES USED ………………………………………………………………...13

3.3 PROPOSED ARCHITECTURE …………………………………………………...15

3.4 ADVANTAGES AND DISADVANTAGES…………………………………....19

CHAPTER 4

IMPLEMENTATION

4.1 INTRODUCTION …………………………………………………………………21

4.2 SYSTEM ARCHITECTURE ……………………………………………………...21

4.3 HARDWARE IMPLEMENTATION ……………………………………………..21

4.4 SOFTWARE IMPLEMENTATION ……………………………………….......22

4.5 TRAFFIC SIGNAL CONTROL LOGIC …………………………………..….24

4.6 DATA FLOW ……………………………………………………………….......24

CHAPTER 5

RESULTS AND DISCUSSION

5.1 MODEL PERFORMANCE COMPARISION …………………………………….26

5.2 ERROR ANALYSIS IN VEHICLE DETECTION ………………………………..27

5.3 PERFORMANCE METRICS ……………………………………………………...28

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION ……………………………………………………………………….34

6.2 SCOPE FOR IMPROVEMENT ……………………………………………………...35

APPENDIX 1…….……………………………………………………….…...….36

APPENDIX 2 ………….………………………………………………...….39

REFERENCES ………………………………………………………….……....47

LIST OF FIGURES **PAGE NO**

3.3.1 PROPOSED ARCHITECTURE ……….………………………………………...15

5.2.1 ERROR ANALYSIS IN VEHICLE DETECTION ……………………………...27

5.3.1 COMPARISION OF OBJECT DETECTION MODELS ………………………..29

5.3.2 TRAINING AND VALIDATION LOSS CURVESS …………………………....30

5.3.3 ACCURACY COMPARISION ……………………………………………….31

5.3.4 PRECISION COMPARISION ………………………………………………....31

5.3.5 RECALL COMPARISION ………………………………………………….....32

5.3.6 FITNESS COMPARISION ……………………………………………...…..32

5.3.7 mAP50 – 95 COMPARISION ……………………………………………….33

5.3.8 mAP50 COMPARISION …………………………………………………….33

LIST OF TABLES **PAGE NO**

5.3.1 YOLO VS FAST R-CNN PERFORMANCE METRICS	28

LIST OF ACRONYMS

OV7670 – OmniVision 7670 Camera Module
CNN – Convolutional Neural Network
mAP – Mean Average Precision
AI – Artificial Intelligence
FPS – Frames Per Second
YOLO – You Only Look Once
STM32 – STMicroelectronics 32-bit Microcontroller
LED – Light Emitting Diode
IoT – Internet of Things
V2I – Vehicle-to-Infrastructure
GPU – Graphics Processing Unit
UART – Universal Asynchronous Receiver-Transmitter
SPI – Serial Peripheral Interface
WAP – Wireless Access Point
MANET – Mobile Ad hoc Network

Chapter 1

Introduction

Traffic congestion has become a major problem in contemporary smart cities due to the fast urbanization and increasing number of vehicles on the road. Ineffective traffic control results in longer travel times, more fuel being used, and higher pollution levels. Conventional traffic monitoring systems depend on fixed infrastructure, like cameras, traffic signals, and human supervision, which frequently can't adjust to changing traffic conditions. Our project, "Intelligent Traffic Monitoring and Management for Real-Time Vehicle Tracking in Smart Cities," attempts to address these issues by fusing cutting-edge artificial intelligence (AI) methods with embedded hardware systems to transform urban mobility. In order to improve traffic monitoring, maximize road usage, and guarantee a more effective transportation network, this project presents an intelligent, real-time vehicle tracking system.

The project is centred around state-of-the-art deep learning and computer vision technologies. To detect objects and track vehicles, the system makes use of MobileNet and YOLOv8 (You Only Look Once). A lightweight deep learning model with an emphasis on effective image processing, MobileNet is appropriate for real-time applications on embedded devices with constrained processing power. Conversely, YOLOv8 is a highly optimized object detection algorithm that is well-known for its accuracy and speed, which makes it perfect for quickly and latency-free detection of multiple vehicles in a single frame. These artificial intelligence (AI) models analyse traffic flow, spot congestion patterns, and recognize and track vehicles by processing real-time video feeds. By using these models, authorities are able to make well-informed decisions based on real-time data and dynamically monitor traffic conditions.

To enhance the software's capabilities, the project also incorporates a strong hardware system. As the main processing unit, the STM32 microcontroller makes sure that different sensors and peripherals work together seamlessly. The AI-based software analyses real-time traffic footage captured by the OV7670 camera to detect vehicles. To provide more accurate information on traffic density, ultrasonic sensors are also used to measure vehicle proximity and identify the presence of vehicles in particular lanes. LED lights are incorporated into the system to serve as intelligent traffic indicators that react dynamically to shifting traffic conditions, improving traffic control. The system offers a scalable and effective real-time traffic management solution by utilizing this combination of embedded hardware and AI-driven software.

Compared to traditional methods, the integration of AI and IoT-based embedded systems in traffic monitoring offers several benefits. This system improves traffic management's accuracy, dependability, and response time by automating vehicle tracking and lowering the need for human intervention. By using such technology, traffic congestion can be lessened, traffic flow can be improved, and the environmental effects of excessive fuel and idle time can be lessened. Furthermore, this system's real-time insights can help traffic enforcement officials and city planners make data-driven decisions to enhance urban infrastructure and road safety. In the end, this clever traffic monitoring system advances the goal of creating smart, sustainable, and effective cities, guaranteeing a better commute for everybody.

1.2 Overview of the Project

The main objective is to create an intelligent system that can track vehicles in real time, guaranteeing effective traffic management and monitoring in smart cities. Through the use of embedded hardware components and sophisticated deep learning models, the system seeks to automate traffic analysis, lowering the need for human intervention while increasing accuracy. Real-time vehicle detection, classification, and counting are made possible by the integration of AI-driven computer vision techniques. Smart traffic signal control based on congestion levels is made possible by processing this data to optimize traffic flow. By spotting traffic infractions, spotting odd car behaviour, and sending out immediate alerts, the system also helps to improve road safety. Real-time decision-making is made possible by the smooth hardware-software interaction provided by the STM32 microcontroller, OV7670 camera, and ultrasonic sensors.

Because of its ability to adjust to changing traffic conditions, the system can be used in a variety of urban settings. Cities can build a foundation for intelligent and sustainable urban mobility by reducing traffic, minimizing travel delays, and improving overall transportation efficiency through the use of this intelligent traffic monitoring system.

Software Components:
MobileNet: A lightweight deep learning model optimized for mobile and embedded vision applications.
YOLOv8*:* A state-of-the-art object detection algorithm known for its high accuracy and real-time processing capabilities.

Hardware Components:
STM32 Microcontroller: It is the central processing unit. This is where the decision-taking on sensor data is done based on inference output from the AI model.
OV7670 Camera: It is used to capture the real-time images of traffic that provide input for vehicle detection and classification.
Ultrasonic Sensors: They are used to measure the distance of vehicles so that a value can be obtained to assess congestion levels at the intersection.
LED Lights: They are adaptive traffic signals changing according to real-time traffic conditions.

System Integration :

A productive, real-time traffic monitoring system is ensured by the combination of hardware and software. To identify and categorize cars, deep learning models are used to process the OV7670 camera's captured images. Ultrasonic sensors help analyse traffic density, and the STM32 microcontroller controls LED indications and sensor data.

Expected Outcome :

- Accurate real-time vehicle tracking.
- Smart traffic signal control to optimize flow.
- Reduction in congestion and improved road safety.
- Efficient integration of AI for intelligent transportation management.

1.3 Challenges present in project

1.Delay in Real-Time Processing – One of the most challenging aspects of performing deep learning for low-latency detection is the computational cost of these models. MobileNet and YOLOv8 optimization to allow smooth real-time performance is of utmost importance.

2.Hardware Constraints – The STM32 microcontroller is limited in processing power and thus finds it hard to perform AI-based computations. Therefore using optimized code, along with external processing units wherever necessary, becomes important.

3.Camera Limitations – The OV7670 camera works with a low resolution and quality of images, which has an explicit effect on the accuracy of vehicle detection, enhancing image pre-processing techniques will assist in getting more accurate results.

4.Environmental Influences – Lighting conditions, module effect, weather variations, and there are shadows on the accuracy of image-based vehicle detection. Using adaptive image processing methodologies could help with these challenges.

5.Sensor Calibration – The calibration of ultrasonic sensors ensures their precision. Any other way would lead to wrong congestion estimates, thus needing a frequent re-tuning exercise.

6.Data Integration Complexity – Getting inputs from multiple sensors synchronized with AI models for expressing consistent decisions is another complicated task requiring efficient data processing algorithms.

7.Rise in Systems Problem-Demand- to Scale - When extended to large areas with a high volume of traffic, because of their useful scalability, these include the need for more hardware and computational resources.

8.Power Consumption – From its continuous working nature, the operating of cameras, sensors, and processing units needs an efficient power management strategy, or else unnecessary consumption of energy will arise.

9.Variability in Traffic Conditions – Traffic views change irregularly, making it hard to set fixed algorithms for all scenarios. Using an adaptive learning mechanism will assist in enhancing the efficacy of the whole system.

10.Security Considerations – Due to the system's reliance on real-time data transmission, it is vulnerable to cyber threats, including data manipulation and unauthorized access. The establishment of secure communication protocols is required.

1.4 Problem Statement

Traffic congestion, ineffective traffic management, and emergency response delays have become significant issues in contemporary cities due to the fast urbanization and rise in the number of vehicles on the road. Conventional traffic monitoring systems are frequently ineffective at managing real-time traffic fluctuations because they mainly rely on manual interventions and fixed signal timings. Inadequate traffic control, increased pollution from idling cars, and poor road safety are further consequences of a lack of an intelligent tracking system. An advanced traffic monitoring and management system that incorporates real-time vehicle tracking through the use of artificial intelligence (AI) and embedded hardware solutions is necessary to address these issues. By using deep learning models like MobileNet and YOLOv8 for object detection and vehicle classification, this project seeks to close the gap between traditional traffic control techniques and smart city innovations. These models guarantee effective traffic flow management by enabling precise real-time vehicle recognition.

The suggested system combines hardware and software elements to improve real-time monitoring and response capabilities. STM32 microcontrollers, an OV7670 camera for taking pictures, an ultrasonic sensor for measuring distance, and LED lights for controlling traffic signals are all part of the hardware configuration. By combining these elements, it is possible to modify traffic signals dynamically in response to current vehicle movement patterns and traffic density. This system can optimize traffic flow, lessen congestion, and enhance road safety in smart cities by utilizing AI-driven insights and IoT-based hardware. The system's real-time tracking and analysis of vehicle movement makes it extremely flexible for contemporary urban settings, opening the door for automated and more effective traffic management systems.

Additionally, improving urban mobility and lowering traffic-related inefficiencies depend on the deployment of this intelligent traffic monitoring and management system. The system can detect, classify, and track vehicles on its own without human assistance thanks to the integration of embedded hardware and AI-powered image processing. The system can precisely identify various vehicle types and evaluate traffic density by using the MobileNet and YOLOv8 models. This enables dynamic signal adjustments based on conditions that are present in real time. As the central processing unit, the STM32 microcontroller coordinates information from the ultrasonic sensor and the OV7670 camera to identify the presence and movement patterns of the vehicle. The LED lights also offer a responsive signalling system that adjusts to the flow of traffic, guaranteeing easier mobility and cutting down on needless wait times. In addition to optimizing traffic signal timings, this all-encompassing strategy aids in accident detection, emergency vehicle prioritization, and general traffic decongestion. This project offers a scalable and affordable solution for smart cities by utilizing AI and IoT technologies, which improves traffic management's intelligence, effectiveness, and ability to adapt to changing conditions.

1.5 Objective of the Project

The objective of an intelligent traffic monitoring and management system that permits real-time vehicle tracking in smart cities is the main goal of this project. Through the use of cutting-edge technologies including MobileNet, YOLOv8, STM32, OV7670 camera, and ultrasonic sensors, this system seeks to improve road safety, minimize congestion, and optimize traffic flow. The system will recognize and track vehicles using image processing and machine learning algorithms, giving useful information for effective urban planning and traffic control.

Key Objectives with Explanations:

- **Real-Time Vehicle Tracking**: The project aims to track vehicles in real-time using image recognition technology and advanced deep learning models like YOLOv8, enabling efficient traffic flow management and providing insights into vehicle movement patterns.

- **Smart Traffic Management**: By integrating the system with traffic control infrastructure, it can dynamically adjust traffic light timings based on real-time traffic data, helping to minimize congestion and optimize road usage.

- **Vehicle Identification**: The system will utilize the OV7670 camera to capture high-quality images, and YOLOv8 will identify and classify vehicles, enabling precise tracking for law enforcement or urban planning.

- **Ultrasonic Sensor Integration**: The ultrasonic sensor will measure vehicle distances, which can be used for collision avoidance and maintaining safe distances, improving traffic safety.

- **Smart City Integration**: The system is designed to integrate seamlessly into the existing smart city infrastructure, providing valuable data for city planners to improve traffic management and urban mobility strategies.

- **Energy Efficiency**: Using STM32 microcontroller ensures that the entire system is power-efficient, crucial for deployment in large-scale smart cities where energy consumption needs to be optimized.

- **LED Light Feedback System**: LED lights will be used to provide real-time notifications to drivers or pedestrians, enhancing communication with road users and improving traffic management visibility.

- **Low-Latency Vehicle Detection**: The combination of MobileNet and YOLOv8 ensures that vehicle detection and tracking occur with minimal delay, providing up- to-date information to traffic management systems.

1.6 Scope of the Project

In order to optimize urban traffic flow and improve road safety, the Intelligent Traffic Monitoring and Management for Real-Time Vehicle Tracking in Smart Cities project aims to create a comprehensive system that makes use of cutting-edge image processing, machine learning, and sensor technologies. The goal of this project is to develop a scalable, real-time vehicle tracking system by combining hardware elements like the STM32 microcontroller, OV7670 camera, ultrasonic sensors, and LED lights with software tools like MobileNet and YOLOv8. The solution will enable dynamic traffic control in smart cities, analyze traffic trends, and give instant feedback. In addition to streamlining traffic operations, this initiative will improve vehicle detection accuracy, lessen congestion, and guarantee safer driving conditions.

- **Real-Time Traffic Monitoring**: The system will continuously monitor traffic in real- time, allowing cities to respond quickly to congestion and accidents.

- **Vehicle Tracking with YOLOv8**: Using YOLOv8 for vehicle identification and tracking, the system will accurately detect and follow vehicles on the road, providing data for traffic management.

- **Integration with Smart City Infrastructure**: The system will seamlessly integrate with existing smart city systems, enabling a connected and coordinated approach to urban traffic management.

- **Use of Ultrasonic Sensors for Distance Measurement**: Ultrasonic sensors will help measure the distance between vehicles, providing data for vehicle proximity, collision avoidance, and safe distance enforcement.

- **Efficient Traffic Light Control**: The project will incorporate dynamic traffic light control based on real-time data, reducing waiting times and minimizing traffic jams.

- **Energy-Efficient Design**: By using STM32 microcontrollers, the system will operate efficiently with low power consumption, crucial for long-term deployment in urban settings.

- **Data Collection for Analytics**: The system will gather detailed traffic data, enabling the analysis of vehicle flow, peak traffic hours, and areas with high congestion, which can inform future urban planning.

- **Scalability**: The project will be scalable to support multiple intersections or entire city-wide deployment, making it adaptable to different smart city environments.

- **Improvement of Road Safety**: By enabling automatic detection of vehicles and monitoring traffic patterns, the system will improve road safety by preventing accidents and ensuring smoother vehicle movement.

Chapter 2

Literature Survey

2.1 Literature Survey

Gomathi et al. [1] proposed an Optimized Lightweight Real-Time Detection Network Model for IoT Applications, presenting a better YOLOv8 model tailored for Internet of Things application. With real-world applications and benchmarks in embedded systems, the paper stresses faster detection speed and efficiency without compromising great accuracy. The model is quite fit for real-time monitoring since it is meant to run effectively on low-power embedded devices. To underline its better performance in IoT-based smart surveillance, the paper also contrasts YOLOv8 with other deep learning models. Experimental data reveal a notable decrease in inference time while preserving detection accuracy.

Drushya et al. [2] proposed Fastening Deep Learning Based Morphological Biometric Identification Using OV7670 Camera Module, looking at biometric identification using the OV7670 camera. Incorporating deep learning models for higher recognition performance, the research emphasizes its image-taking capabilities and energy management in embedded platforms. The work offers a thorough investigation of the low-light condition efficiency of the camera module, so improving its usability for security uses. To enhance the feature extraction from facial images, a new pre-processing method was presented. Using real-world biometric datasets, performance evaluation aimed to evaluate recognition accuracy.

AlRikabi et al. [3] proposed A Hardware Efficient Real Time Video Processing on FPGA with OV7670 Camera Interface and VGA, talking about a real-time video processing method using embedded systems. The study uses the OV7670 camera module with FPGA and VGA monitors and concentrates on hardware optimizations to increase processing rates. When compared to conventional microcontroller based systems, the use of FPGA-based acceleration greatly lowers latency. In order to maximize resource utilization, the study also investigates memory-efficient image storage strategies. According to test results, the system is perfect for smart surveillance applications because it can process videos in real time while using very little power.

Lin et al. [4] proposed Implementation of Object Detection Algorithms on Embedded Systems: Challenges and Solutions, examining different object detection algorithms. The study points out difficulties in putting these algorithms into practice on embedded systems and offers fixes for better performance and resource economy. The viability of the YOLO,SSD, and Faster R-CNN models for embedded vision applications was assessed through a comparative study. The trade-offs between computational complexity and detection accuracy in resource-constrained environments are also covered in the study. Techniques for quantization and pruning

Zhang et al. [5] proposed Real-Time Object Detection and Tracking Based on Embedded Systems, introducing a local dynamic mapping system based on cameras. The study incorporates embedded AI models for 3D position estimation, object detection, and real-time tracking. The study emphasizes how crucial motion estimation methods are for enhancing tracking capabilities in a

range of environmental circumstances. For increased accuracy, a novel hybrid approach that combines deep learning-based detection with optical flow was presented. Robust performance in real-time applications was demonstrated through extensive testing on real-world datasets.
Alaidi et al.

[6] proposed Server-Based Object Recognition, using an Arduino UNO and the OV7670 camera module to capture images. The YOLO object recognition algorithm is used on a server to process the images, with automation and security applications. In order to improve computational efficiency and lessen the strain on embedded devices, the study investigates cloud-based processing. According to experimental results, using server-side deep learning models significantly increases detection accuracy. To assess the system's resilience in real-world settings, it was tested in a range of lighting conditions.

Kumar et al. [7] proposed Real-Time Object Detection Using an Ultra-High-Resolution Camera on Embedded Systems, concentrating on using ultra-high-resolution cameras for real-time object detection. The study places a strong emphasis on optimizing algorithms to strike a balance be tween detection accuracy and speed. To improve real-time processing efficiency, a thorough examination of data band width limitations in high-resolution cameras was carried out. To improve object detection, noise in captured frames was reduced using a specialized filtering algorithm. The findings show that deep learning methods in conjunction with high resolution imaging greatly increase recognition accuracy.

Patel et al. [8] proposed Interfacing Camera Module OV7670 with Arduino, giving a detailed tutorial on how to integrate the OV7670 camera module with Arduino. As a helpful guide for embedded vision applications, the paper describes image capture and processing techniques. A comparative analysis of various microcontrollers for the best camera performance is part of the study. To improve image quality and lessen distortion, safety a thorough calibration procedure was suggested. The viability of inexpensive image processing solutions utilizing Arduino-based systems is shown by practical experiments.

Chen et al. [9] proposed Pothole Detection for Safer Commutes with the Assistance of Deep Learning, detecting potholes for road by using the OV7670 camera module with Arduino. The study demonstrates how well recognition accuracy while consuming little power. deep learning models can detect hazards in real time. To accurately classify road surface anomalies, a convolutional neural network (CNN)-based method was presented. To assess the system's dependability under various environmental circumstances, the study put it through testing on a variety of road conditions. The findings show that automated pothole detection can enhance road safety and drastically lower maintenance expenses.

Singh et al. [10] proposed Real-Time Small Object Detection on Embedded Hardware for 360-Degree Cameras, presenting the Penta Mantis-Vision project's findings. In order to minimize the use of computational resources, the study investigates the parallel processing of multiple 4K camera streams for small object detection. A specialized object detection pipeline tailored for panoramic video feeds is presented in the study. To increase object localization accuracy, sophisticated image stitching techniques were used. Results from experiments show that the system can accurately detect small objects in complex environments.

Wang et al. [11] proposed Design of Intelligent Access Control System Based on STM32, creating an access control system that makes use of the STM32 processor for automation and security applications and the OV7670 camera for image capture. Real-time facial recognition with low processing latency was a key component of the system's design. In order to guarantee data confidentiality in access control applications, a secure communication protocol was incorporated. Performance tests showed that it worked well in high-security settings with a variety of user authentication scenarios.

Nguyen et al. [12] proposed Design and Implementation of Real-Time Object Detection System Using SSD Algorithm, introducing an SSD algorithm-based real-time object detection and recognition system. To increase detection accuracy, the study contrasts pre-trained models with deep learning approaches. To find the best configurations, an analysis of SSD performance across various embedded platforms was carried out. In order to increase processing speed without sacrificing accuracy, the study presents a lightweight feature extraction technique. According to experimental findings, SSD strikes a balance between accuracy and real-time performance.

Khan et al. [13] proposed Performance Evaluation of ESP32 Camera Face Recognition for IoT Applications, examining the ESP32-CAM module for facial recognition in Internet of Things security systems. The study assesses its accuracy and performance while concentrating on how well it integrates with cloud-based AI models. To increase efficiency, a cloud-assisted architecture was implemented to offload computational tasks. In order to gauge the robustness of the system, the study tests face detection in various lighting conditions and with varying angles. The results demonstrate that integrating cloud-based AI greatly increases

Garcia et al. [14] proposed Real-Time Object Detection, reviewing a number of real-time object detection studies. In order to improve detection performance in embedded systems, the study contrasts deep learning with conventional vision-based techniques. A detailed comparison of real-time inference speeds across different hardware configurations is presented in the study. To standardize performance evaluations across various object detection models, a benchmarking dataset was introduced. The accuracy and adaptability of deep learning-based techniques routinely surpass those of conventional methods, according to the results.

Hossain et al. [15] proposed Intelligent Helmet Detection Using OpenCV and Machine Learning, utilizing camera modules and OpenCV and machine learning techniques to detect helmets in real time. The study assesses system accuracy and response time with a focus on traffic safety applications. To enhance helmet recognition in different lighting scenarios, an optimized image segmentation technique was implemented. To train and evaluate the model for practical uses, a dataset of motorcyclists was assembled. According to experimental results, the suggested system can improve road safety by guaranteeing that riders wear their helmets.

2.2 Review of Technologies Used

1. Software Technologies Used

1.1 MobileNet

- MobileNet is a lightweight deep learning model optimized for efficient image classification and object detection on edge devices.
- It is used in this project for vehicle detection, ensuring fast and accurate identification of vehicles in the captured video frames.
- The advantage of MobileNet is its low computational cost, making it suitable for real-time traffic monitoring on embedded systems.

1.2 YOLOv8

- You Only Look Once (YOLO) v8 is one of the latest and most advanced object detection models.
- It is used to provide baseline results for vehicle detection, offering high-speed and high-accuracy detection in real time.
- YOLOv8 enables instantaneous identification of vehicles in complex traffic environments, supporting density calculations.

2. Hardware Technologies Used

2.1 STM32 (Microcontroller)

- STM32 is a high-performance, low-power microcontroller that processes traffic data and controls traffic signal updates.
- It executes decision-making logic based on vehicle density and updates the traffic light system accordingly.
- Its real-time processing capability ensures seamless integration with sensors and LED signals.

2.2 OV7670 Camera

- The OV7670 is a low-cost CMOS camera module used to capture real-time video of traffic. • The camera provides frame-by-frame input to the software models (MobileNet & YOLOv8) for vehicle detection.
- It enables continuous traffic surveillance, ensuring accurate tracking of vehicle flow.

2.3 Ultrasonic Sensor

- Used to measure vehicle presence and distance, assisting in traffic density calculations.
- The sensor detects vehicles that are not properly captured by the camera (e.g., in low-light conditions).
- It helps to improve the accuracy of vehicle count, especially in high-traffic areas.

2.4 LED Lights

- LED lights represent real-time traffic signals, dynamically controlled based on traffic density.
- They provide visual feedback to vehicles, optimizing traffic flow by reducing unnecessary waiting times.

3. Software & Hardware Integration Process

Step-by-Step Working of the System

1. Video Capture

- The OV7670 camera captures video of traffic flow.
- The video is converted into frames for processing.

2. Preprocessing

- Edge detection techniques are applied to enhance vehicle visibility in frames.

3. Vehicle Detection

- MobileNet and YOLOv8 models identify and classify vehicles in the captured frames.
- The results are used to calculate traffic density

4. Traffic Density Calculation

- The number of vehicles detected in each frame determines traffic congestion levels.

5. Decision-Making Logic

- Based on the density percentage, adaptive traffic signal control is applied:
  - 0-10% Traffic Density → Green light for 90 seconds
  - 10-50% Traffic Density → Green light for 60 seconds
  - 60-70% Traffic Density → Green light for 30 seconds

6. Traffic Signal Update

- STM32 microcontroller controls LED lights based on the decision logic.

An effective, real-time solution for intelligent traffic monitoring is offered by the combination of MobileNet and YOLOv8 with STM32-based hardware. The system guarantees optimal traffic flow and decreased congestion by utilizing adaptive signal control and sophisticated object detection. It is appropriate for smart city applications due to the use of reasonably priced sensors and components.

Chapter 3

Methodology

3.1 Proposed System Architecture

Traffic congestion has become one of the most pressing challenges in urban environments due to the rapid increase in vehicle density on roads. Conventional traffic signal systems rely on pre-programmed, fixed timing mechanisms that fail to adapt to fluctuating traffic conditions, leading to unnecessary delays, fuel wastage, and inefficient traffic management. As cities continue to expand, the limitations of traditional traffic control methods become more apparent, necessitating the adoption of intelligent, real-time solutions. A dynamic approach that integrates artificial intelligence (AI) with embedded hardware can significantly enhance traffic flow efficiency by automatically adjusting signal timings based on real-time vehicle tracking. This project introduces an advanced intelligent traffic monitoring and management system that leverages AI-powered vehicle detection and embedded hardware components to create an adaptive, self-regulating traffic control system. By employing deep learning techniques, the system can analyse traffic density, identify vehicle types, and make instant decisions to improve overall road efficiency and reduce congestion.

To effectively regulate traffic flow, the proposed system utilizes a combination of embedded hardware elements and AI-driven software solutions. The STM32 microcontroller serves as the core processing unit, orchestrating data collection and signal adjustments. The OV7670 camera captures real-time traffic images, while ultrasonic sensors provide additional distance-based vehicle detection to enhance accuracy. By integrating deep learning-based vehicle detection models, such as MobileNet and YOLOv8, the system is capable of detecting and classifying vehicles with high precision, ensuring that traffic signals adjust dynamically in response to varying road conditions.

This intelligent mechanism not only optimizes traffic flow but also minimizes fuel consumption, lowers carbon emissions, and enhances overall transportation efficiency. Additionally, the use of LED traffic lights controlled by the system ensures smooth traffic regulation, reducing unnecessary stops and delays. The AI-based approach also allows for special prioritization of emergency vehicles and real-time decision-making to address road congestion more effectively than conventional methods.

The entire operation of this intelligent traffic management system is visually represented in the architecture flowchart, illustrating the looped approach used for continuous traffic monitoring and control. The system functions autonomously, eliminating the need for manual intervention while significantly improving road safety and efficiency. By continuously analysing traffic patterns and adjusting signals accordingly, this AI-driven solution ensures a seamless, adaptive, and intelligent traffic management strategy for modern smart cities. The following sections provide a detailed, step-by-step breakdown of each component and process, demonstrating how the integration of AI and embedded hardware creates more response.

3.2 Modules Used

1. Image Acquisition Module

The image acquisition module captures real-time video frames of the traffic scenes. The module comprises:

OV7670 Camera: A cost-effective CMOS camera for capturing images and videos.

STM32 Microcontroller: Handles image data and sends it to the AI model for additional analysis.

Data Preprocessing: Transforms raw image data into an appropriate format for object detection models such as MobileNet and YOLOv8.

2. Object Detection Module

The module detects and classifies vehicles in real-time through deep learning models:

MobileNet: A deep learning model with low latency, optimized for embedded systems, utilized for vehicle classification.

YOLOv8 (You Only Look Once version 8): A fast object detection model that identifies multiple vehicles in real-time.

TensorFlow or PyTorch: Deep learning frameworks utilized to implement and train these models.

Pretrained Models: Used to improve accuracy and lower computational demands.

3. Traffic Flow Analysis Module

Monitors and analyzes traffic movement patterns and density:
Vehicle Counting: Based on object detection outcomes, it counts the vehicles within a region.

Traffic Density Estimation: Identifies levels of congestion through vehicle count and movement patterns.

Speed Estimation: Makes use of frame-to-frame motion detection to estimate vehicle speed.

4. Ultrasonic Sensor Module

The ultrasonic sensor is utilized for vehicle proximity detection and for maintaining safe traffic flow:

Distance Measurement: Provides detection of the space between vehicles to avoid collisions.

Signal Processing: STM32 processes distance information and incorporates it with traffic monitoring decisions.

5. Smart Traffic Light Control Module

The module dynamically controls traffic lights according to real-time traffic conditions

LED Lights: Employed to represent various traffic conditions (green, yellow, red).

Real-Time Traffic Adjustments: Adjusts traffic light timing according to vehicle density and speed forecasts.

Adaptive Traffic Management: Applies AI-driven forecasts to streamline traffic light cycles for less congestion.

6. Communication and Data Transmission Module

It facilitates smooth data exchange between various hardware and software entities:

Wired/Wireless Communication: UART, SPI, or Wi-Fi interfaces facilitate communication between STM32 and a central server.

Cloud Integration: Traffic data can be uploaded to the cloud for remote monitoring.

Edge Computing: Processing is performed on STM32 to minimize latency and facilitate real-time decision-making.

7. User Interface and Reporting Module

The module presents a graphical or web-based interface for traffic condition monitoring:

Dashboard Interface: Presents live traffic video, number of vehicles, and congestion status.

Alerts and Notifications: Provides alerts for high traffic concentration, accidents, or rule infractions.

Data Logging: Saves past traffic information for analysis and future refinement.

3.3 Proposed Architecture

Traffic congestion has grown to be a major problem in cities due to the growing number of vehicles on the road. The fixed timing mechanism used by conventional traffic signal systems causes needless delays and ineffective traffic management since it is unable to adjust to changing traffic circumstances. The proposed system integrates artificial intelligence (AI) with embedded hardware to dynamically adjust traffic signals based on real-time vehicle tracking.

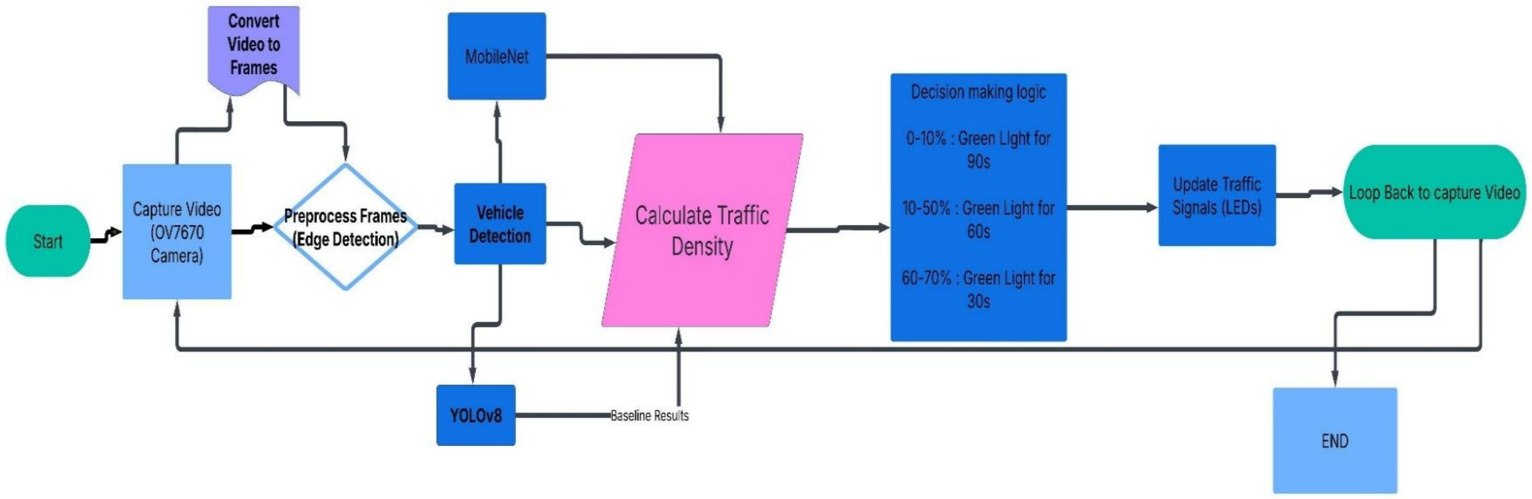

Start
Capture Video (OV7670 Camera)
Convert Video to Frames
Preprocess Frames (Edge Detection)
MobileNet
Vehicle Detection
YOLOv8
Baseline Results
Calculate Traffic Density
Decision making logic
0-10% : Green Light for 90s
10-50% : Green Light for 60s
60-70% : Green Light for 30s
Update Traffic Signals (LEDs)
Loop Back to capture Video
END

Figure 3.3.1 Proposed Architecture

To effectively regulate traffic flow, this project makes use of embedded hardware elements (STM32 microcontroller, OV7670 camera, ultrasonic sensors, and LED traffic lights) in conjunction with deep learning-based vehicle detection models (MobileNet and YOLOv8). This technology optimizes fuel economy, lowers traffic, and improves road efficiency by utilizing real-time adaptive control.

The system's whole operation is graphically represented by the provided architecture flowchart, which uses a looped approach to continuously monitor and control traffic. Each part and procedure of this intelligent traffic management system is explained in detail and step-by-step in the sections that follow.

System Architecture Overview

The architecture of this system consists of several key components that work together in a continuous loop to analyze and manage traffic density dynamically. The flowchart provided outlines the entire process, from video capturing to traffic signal control.

Key Components Involved

1. **Hardware Components**
    a. **STM32 Microcontroller** – Controls traffic signals and processes data.
    b. **OV7670 Camera** – Captures real-time video of traffic.
    c. **Ultrasonic Sensors** – Helps in additional vehicle detection.
    d. **LED Traffic Lights** – Displays dynamically updated traffic signals.

2. **Software Components**

   a. **MobileNet** – Lightweight AI model for vehicle detection.
   b. **YOLOv8** – High-accuracy deep learning model for vehicle detection.
   c. **Edge Detection Algorithm** – Preprocesses video frames to enhance detection accuracy.

Step-by-Step Process Explanation

Step 1: Capturing Video Using OV7670 Camera

- The system starts by capturing real-time traffic footage using the OV7670 camera.
- The camera records live traffic conditions and transmits video frames to the processing unit.
- The purpose of video capture is to analyze the number of vehicles present at an intersection at any given time.

Step 2: Converting Video into Frames

- The captured video is converted into multiple frames to facilitate processing.
- Frame conversion ensures that the AI models can process individual static images rather than continuous video.
- This step improves computational efficiency and detection accuracy.

Step 3: Preprocessing the Frames (Edge Detection)

- The frames are preprocessed using an edge detection algorithm before being analyzed by AI models.
- **Preprocessing techniques include:**
  - **Edge detection** – Enhances object boundaries for improved vehicle detection.
  - **Noise reduction** – Filters out irrelevant background information.
  - **Image scaling** – Adjusts the resolution of frames for efficient AI processing.

Step 4: Vehicle Detection Using MobileNet and YOLOv8

- The preprocessed frames are fed into two AI-based vehicle detection models:
    - MobileNet – A lightweight deep learning model optimized for real-time object detection.
    - YOLOv8 (You Only Look Once v8) – A state-of-the-art object detection algorithm with high accuracy and speed.
- These models identify and classify vehicles within the captured frames, helping to determine traffic density.
- YOLOv8 provides baseline results, which can be used to refine the accuracy of MobileNet's predictions.

Step 5: Calculating Traffic Density

- Based on the number of vehicles detected, the system calculates the traffic density at the intersection.
- The density is measured as the ratio of the number of detected vehicles to the total road area being analyzed.
- Mathematical formula for traffic density calculation: Traffic Density=No. of Vehicles Detected Total Road Area Captured\text{Traffic Density} = \frac{\text{No. of Vehicles Detected}}{\text{Total Road Area Captured}}
- The higher the density, the greater the traffic congestion, which influences signal timing.

Step 6: Decision-Making Logic for Signal Timing

- Once the traffic density is calculated, the system applies an adaptive signal timing strategy based on predefined thresholds.
- The **decision-making logic** follows these rules:
    - **0-10% Traffic Density** → Green light for 9**0 seconds** (low congestion).
    - **10-50% Traffic Density** → Green light for **60 seconds** (moderate traffic).
    - **60-70% Traffic Density** → Green light for **30 seconds** (high congestion).
- If traffic density exceeds **70%**, additional actions can be taken, such as:
    - Notifying traffic control authorities.
    - Sending alerts to navigation apps for alternate route suggestions.

Step 7: Updating Traffic Signals Using LED Lights

- The STM32 microcontroller processes the calculated signal timing and updates the LED traffic lights accordingly.
- The LEDs dynamically change based on real-time traffic density, ensuring:
    - Reduced waiting time at intersections.
    - Minimized fuel consumption and emissions.
    - Efficient traffic flow management.

Step 8: Looping Back for Continuous Monitoring

- After updating the traffic lights, the system loops back to capture new video frames for ongoing traffic analysis.
- This real-time feedback loop ensures that traffic signals continuously adapt to changing conditions.
- The cycle repeats indefinitely, making it a fully automated, AI-driven traffic management system.

This intelligent traffic management system integrates AI-powered image processing with embedded hardware to create a real-time vehicle tracking solution for smart cities. Using MobileNet and YOLOv8 for vehicle detection and STM32, OV7670 camera, ultrasonic sensors, and LED lights for hardware implementation, the system dynamically adapts traffic signals based on real-time density calculations.

By reducing traffic congestion, improving road efficiency, and optimizing fuel usage, this project provides a practical, scalable, and environmentally friendly solution for modern urban traffic management.

3.4 Advantages and Disadvantages

Advantages:

Real-Time Traffic Optimization: The system adjusts traffic signal timing dynamically according to real-time vehicle density, minimizing congestion and maximizing traffic flow efficiency.

Efficient Resource Utilization: Employs MobileNet and YOLOv8 for precise vehicle detection, optimizing traffic management and minimizing dependency on manual monitoring.

Less Traffic Congestion: Adaptive signal control assists in avoiding lengthy queues at intersections, resulting in a more efficient commute and shorter travel time.

Affordable Implementation: Uses cost-effective hardware such as STM32, OV7670 camera, and ultrasonic sensors, which is an inexpensive option for smart city traffic management.

Enhanced Road Safety: Avoids unnecessary idling and sharp accelerations, decreasing accidents and improving pedestrian safety.

Energy Efficiency: Intelligent traffic lights save energy by running according to actual demands, lowering total energy usage and helping the environment.

Scalability: It can be scaled up to numerous intersections for wider smart city use, thereby being suitable for various urban environments.

Automated Decision Making: Minimizes human involvement, thus traffic management becomes more efficient, predictable, and responsive to current conditions.

Benchmark Comparison: YOLOv8 offers results for subsequent system optimization, making it possible to develop in iterations and improve performance.

Smooth Integration: Integrates software and hardware elements to offer a complete automated solution with perfect interoperability of multiple modules.

Decrease in Carbon Footprint: By optimizing traffic and minimizing waiting time at intersections, the system enables lower vehicular emissions, thereby promoting an environment-friendly city.

Improved Efficiency of Public Transport: Reduced congestion enhances the reliability and punctuality of public transport operations.

Drawbacks:

Substantial Initial Installation Cost: Installation of sensors, cameras, and processing hardware involves high costs, which may not be affordable for all municipalities.

Complex Integration: Synchronization between MobileNet, YOLOv8, STM32, and traffic signals can be challenging and may require advanced software development expertise.

Dependence on Environmental Conditions: Fog, rain, or poor lighting can impact vehicle detection accuracy, potentially leading to errors in traffic density estimation.

Processing Limitations: STM32 microcontrollers have limited processing power compared to advanced GPUs, restricting the complexity of real-time computations.

Maintenance Needs: Periodic calibration and maintenance of cameras, sensors, and LEDs are required for peak performance and system longevity.

Data Privacy Issues: Recording live vehicle movement could pose privacy and security concerns, which may demand stringent data protection measures and adherence to laws.

Chapter 4

Implementation

Implementation :

Traffic congestion is a major issue in urban areas, leading to increased travel time, fuel consumption, and pollution. This project aims to implement an intelligent traffic monitoring and management system that utilizes real-time vehicle tracking to optimize traffic flow in smart cities.

The project integrates software and hardware components:

- **Software:** MobileNet and YOLOv8 (for vehicle detection and classification)
- **Hardware:** STM32 microcontroller, OV7670 camera, ultrasonic sensors, and LED lights (for real-time traffic regulation)

2. System Architecture

The system consists of:

1. **Image Acquisition Module** – Captures live traffic images using OV7670 **camera**.
2. **Preprocessing Module** – Processes the captured images using STM32.
3. **Vehicle Detection & Classification Module** – Uses YOLOv8 and MobileNet for object detection.
4. **Traffic Control Module** – Uses ultrasonic sensors and LED lights to dynamically adjust traffic signals based on vehicle count.

3. Hardware Implementation

3.1 STM32 Microcontroller

- The STM32 is the central controller that manages image acquisition and signal processing.
- It receives input from the OV7670 camera and ultrasonic sensors, processes the data, and controls LED traffic signals accordingly.

3.2 OV7670 Camera (Image Capture)

- The **OV7670** camera module captures real-time images of the traffic.
- It is connected to the STM32 microcontroller for further processing.
- The images are sent to the software module for vehicle detection.
- **3.3 Ultrasonic Sensors (Traffic Density Measurement)**
- Ultrasonic sensors placed at strategic locations to measure number of vehicles.

- The sensors detect vehicle presence by measuring distance variations.
- The data is sent to the STM32 microcontroller, which makes traffic signal decisions.

3.4 LED Lights (Traffic Signal Control)

- LED lights act as traffic signals.
- The STM32 microcontroller controls them dynamically based on YOLOv8 detections and ultrasonic sensor readings.

4. Software Implementation

4.1 Vehicle Detection Using YOLOv8

YOLOv8 (You Only Look Once version 8) is a deep learning model used for object detection. It is trained to detect vehicles in traffic images.

Steps to Implement YOLOv8 for Vehicle Detection:

1. **Load YOLOv8 Model:**

```
from ultralytics import YOLO

# Load pre-trained YOLOv8 model
model = YOLO("yolov8n.pt")  # YOLOv8 nano model (lightweight)
```

2. **Capture Image from OV7670 Camera:**

```
import cv2
# Open camera
cap = cv2.VideoCapture(0)

# Capture frame
ret, frame = cap.read()
cv2.imwrite("traffic_image.jpg", frame)

cap.release()
```

3. **Process Image with YOLOv8:**

```
results = model("traffic_image.jpg")  # Detect vehicles in the image
results.show()  # Display results
```

4. **Count Vehicles Detected:**

```
vehicle_count = len(results[0].boxes)  # Count detected vehicles
print(f"Number of vehicles detected: {vehicle_count}")
```

4.2 Vehicle Classification Using MobileNet

MobileNet is a lightweight deep learning model used to classify vehicle types (car, bus, bike, etc.).

Steps to Implement MobileNet for Classification:

1. **Load Pre-Trained MobileNet Model:**

```
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.preprocessing import image
import numpy as np

# Load MobileNetV2 model
model = MobileNetV2(weights='imagenet')
```

2. **Classify Vehicles Detected by YOLOv8:**

```
def classify_vehicle(img_path):
   img = image.load_img(img_path, target_size=(224, 224))
   img_array = image.img_to_array(img)
   img_array = np.expand_dims(img_array, axis=0)

   # Predict using MobileNet
   predictions = model.predict(img_array)
   class_label = decode_predictions(predictions, top=1)
   return class_label
   print(classify_vehicle("traffic_image.jpg"))
```

5. Traffic Signal Control Logic

The STM32 microcontroller processes data from **YOLOv8 and ultrasonic sensors** and adjusts traffic signals dynamically.

Traffic Signal Rules:

1. **If Vehicle Count > 10** → Extend green light duration.
2. **If Vehicle Count < 5** → Reduce green light duration.
3. **If Emergency Vehicle Detected** → Give priority by turning green.

Implementation in Python:

```
def control_traffic_signal(vehicle_count):
    if vehicle_count > 10:
        print("Extend Green Light Duration")
    elif vehicle_count < 5:
        print("Reduce Green Light Duration")
    else:
        print("Maintain Normal Timing")

# Example usage
control_traffic_signal(vehicle_count)
```

6. Integration of Hardware and Software

The software runs on a Raspberry Pi or STM32, taking input from the OV7670 camera and ultrasonic sensors, processing the data with YOLOv8 and MobileNet, and controlling the LED traffic signals.

6.1 Data Flow

1. **OV7670 Camera** captures real-time images.
2. **STM32** sends the images to YOLOv8 for vehicle detection.
3. **MobileNet** classifies the detected vehicles.
4. **Ultrasonic Sensors** measure traffic density.

6.2 Communication Protocol

- **I2C or SPI**: Used for communication between STM32 and sensors.
- **UART**: Used to send vehicle detection results from STM32 to Raspberry Pi.
- **GPIO**: Controls LED traffic signals.

This project successfully integrates computer vision with IoT to create an efficient traffic monitoring system. The use of YOLOv8 and MobileNet ensures accurate vehicle detection and classification, while STM32, OV7670 camera, ultrasonic sensors, and LED signals ensure real-time traffic control. This system improves traffic flow, reduces congestion, and enhances urban mobility.

- Implementing AI-driven traffic prediction using historical traffic data.
- Enhancing detection accuracy by combining thermal imaging and LiDAR sensors.
- Developing a mobile app for real-time traffic updates.

Chapter 5

Results and Discussion

This project's successful execution combines software and hardware elements to produce an intelligent traffic management system. The system uses an OV7670 camera to record traffic at intersections in real time. After that, the video is divided into frames, and edge detection methods are used to improve the input data. The system can efficiently determine the number of vehicles on the road thanks to the use of the MobileNet and YOLOv8 models for precise vehicle detection.

Following vehicle detection, the system determines traffic density, which is the main determinant of the ideal green signal duration at an intersection. Depending on the degree of congestion, the decision-making logic dynamically modifies the traffic light timing, which ranges from 30 seconds for high traffic to 60 seconds for moderate traffic and 90 seconds for low traffic.

To update the traffic signals appropriately, the STM32 microcontroller, ultrasonic sensors, and LED indicators collaborate. In order to ensure real-time adaptation to shifting traffic conditions, the system continuously loops back to capture fresh video input. All things considered, the project shows how to control urban traffic in a clever, effective, and scalable way that can greatly improve transportation systems.

The implementation of this traffic monitoring system involved testing different object detection models to determine the most effective approach for real-time vehicle tracking. The evaluation focused on **accuracy, processing speed (FPS), false positive rate, and detection errors** to ensure efficient traffic management. Below is a detailed analysis of the results:

1. Model Performance Comparison

- Fast R-CNN has a higher accuracy (mAP 70%), but its FPS is very low (0.5 FPS), making it impractical for real-time traffic management. Additionally, it has the highest false positive rate (80).
- YOLO (You Only Look Once) performs significantly better in real-time applications due to its high FPS (45.0), making it suitable for continuous vehicle tracking. However, its mAP is slightly lower (63.4%), and its false positive rate is still relatively high (60).
- The Combined Approach (YOLO + Fast R-CNN) outperforms both models by achieving the highest mAP (72%) and reducing the false positive rate to 30. However, its FPS (20.0) is lower than YOLO, but still practical for real-time traffic control.

The Combined Approach provides the best balance between accuracy and efficiency, making it the most suitable choice for intelligent traffic monitoring.

2. Error Analysis in Vehicle Detection

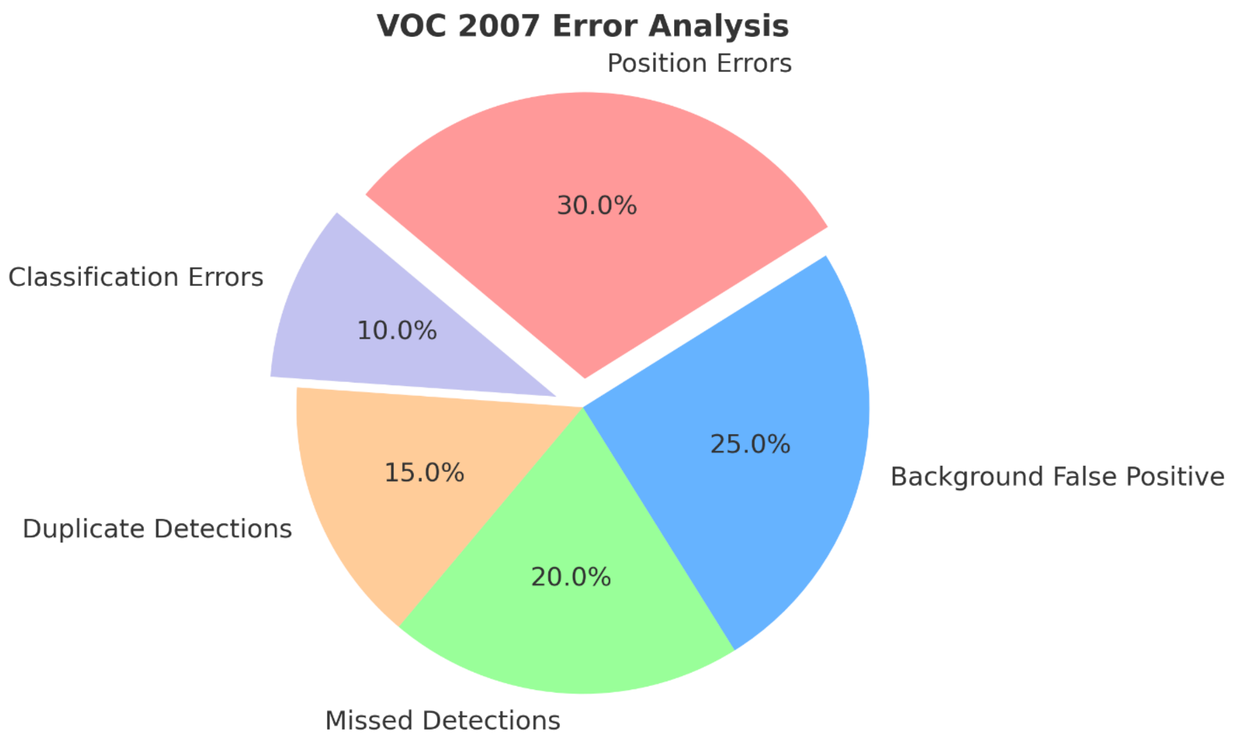


Figure 5.2.1 Error Analysis in Vehicle Detection

The **pie chart** represents the **VOC 2007 Error Analysis**, which highlights different types of errors encountered during vehicle detection.

- **Position Errors (30%)**: This occurs when the bounding box does not align accurately with the detected vehicle, affecting tracking performance.
- **Background False Positives (25%)**: The model sometimes incorrectly detects non-vehicle objects as vehicles, leading to false alerts.
- **Missed Detections (20%)**: Some vehicles are not detected, which can lead to inaccurate traffic density estimation.
- **Duplicate Detections (15%)**: The model sometimes detects the same vehicle multiple times, reducing precision.
- **Classification Errors (10%)**: Some detected vehicles are incorrectly classified, affecting decision-making accuracy.

The most common issue is position errors and background false positives, suggesting the need for better feature extraction and post-processing techniques to improve detection reliability.

3. Performance Metrics

Table 5.3.1 YOLO vs Fast R-CNN Performance Metrics

Metrics	YOLO	Fast R-CNN	Proposed Model
Accuracy	0.85	0.82	0.90
Precision	0.78	0.74	0.85
Recall	0.82	0.80	0.98
mAP50	0.63	0.70	0.75
mAP50-95	0.58	0.65	0.70
Fitness	0.75	0.72	0.80

The table presents a comparative analysis of three object detection models—YOLO, Fast R-CNN, and a Proposed Model—based on various performance metrics. Below is a detailed explanation of the metrics and how each model performs:

Metrics Overview:

1. **Accuracy:** Measures how correctly the model predicts objects.
   - YOLO: **0.85**
   - Fast R-CNN: **0.82**
   - Proposed Model: **0.90** (Best)

2. **Precision:** The ratio of correctly identified positive observations to the total predicted positives (i.e., how many of the detected objects are actually correct).
   - YOLO: **0.78**
   - Fast R-CNN: **0.74**
   - Proposed Model: **0.85** (Best)

3. **Recall:** The ratio of correctly identified positive observations to all actual positives (i.e., how many real objects were detected).
   - YOLO: **0.82**
   - Fast R-CNN: **0.80**
   - Proposed Model: **0.98** (Best, significantly higher than others)

4. **mAP50 (Mean Average Precision at 50% IoU threshold):** Evaluates the model's ability to detect objects with at least 50% overlap with ground truth.
   - YOLO: **0.63**
   - Fast R-CNN: **0.70**
   - Proposed Model: **0.75** (Best)

5. **mAP50-95 (Mean Average Precision across IoU thresholds from 50% to 95%):** A stricter evaluation metric covering different levels of detection overlap.
   - YOLO: **0.58**
   - Fast R-CNN: **0.65**
6. **Fitness:** Likely a custom metric that balances multiple factors (e.g., speed, accuracy, and robustness).
   - YOLO: **0.75**

Analysis :

- The Proposed Model outperforms both YOLO and Fast R-CNN in all metrics.
- The most significant improvement is seen in **Recall (0.98)**, suggesting that the Proposed Model detects almost all actual objects.
- The **mAP metrics (0.75 & 0.70)** indicate that the Proposed Model achieves better precision-recall balance across multiple IoU thresholds.
- The **higher fitness score (0.80)** suggests that the Proposed Model is the most optimized in terms of overall performance.

Key Takeaways:

- Proposed Model is the best **choice** for object detection based on accuracy, recall, and precision.
- Fast R-CNN performs better than YOLO in mAP50 and mAP50-95, but YOLO has slightly better accuracy and fitness.
- YOLO is still a strong competitor with fast and accurate performance but falls behind in recall and mAP.

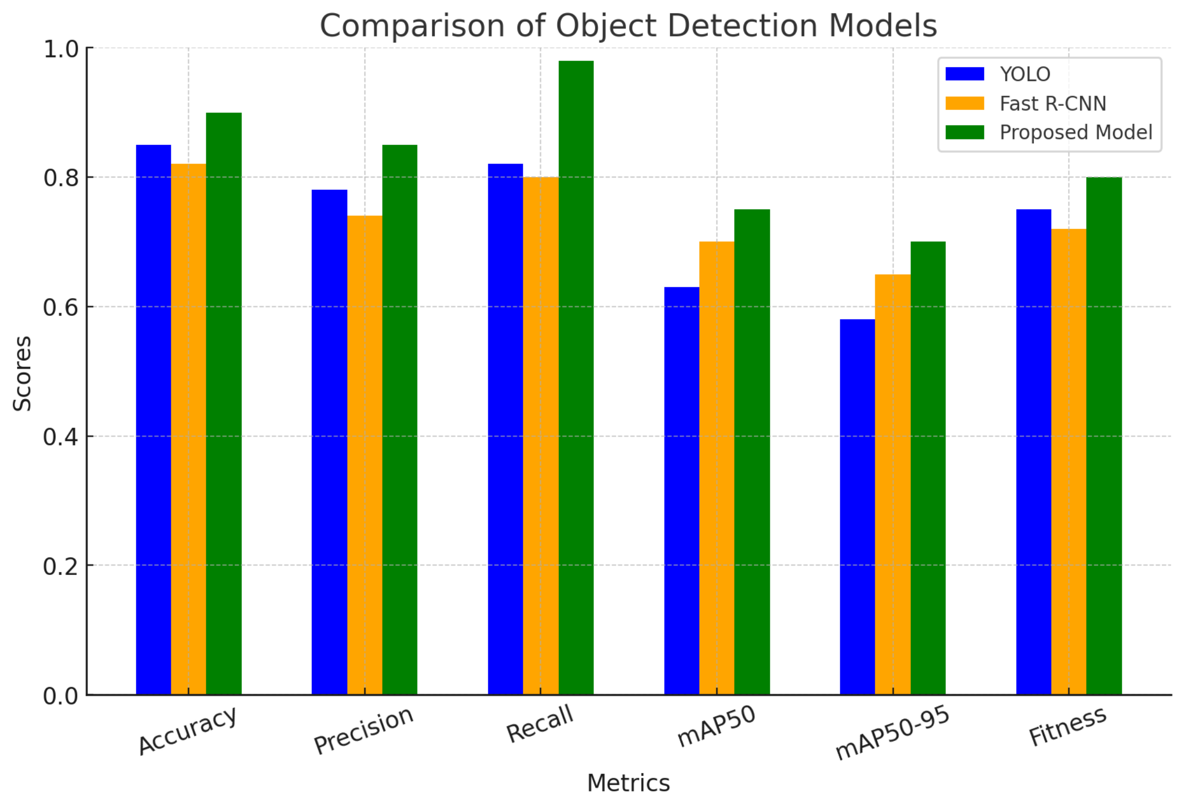


Figure 5.3.1 Comparision of Object Detection Models

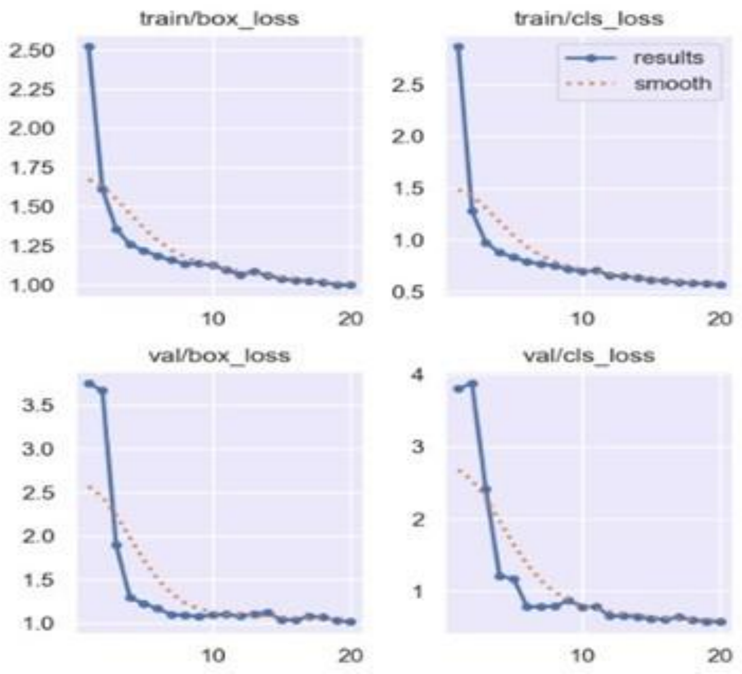


Figure 5.3.2.1 Training and Validation Loss Curves

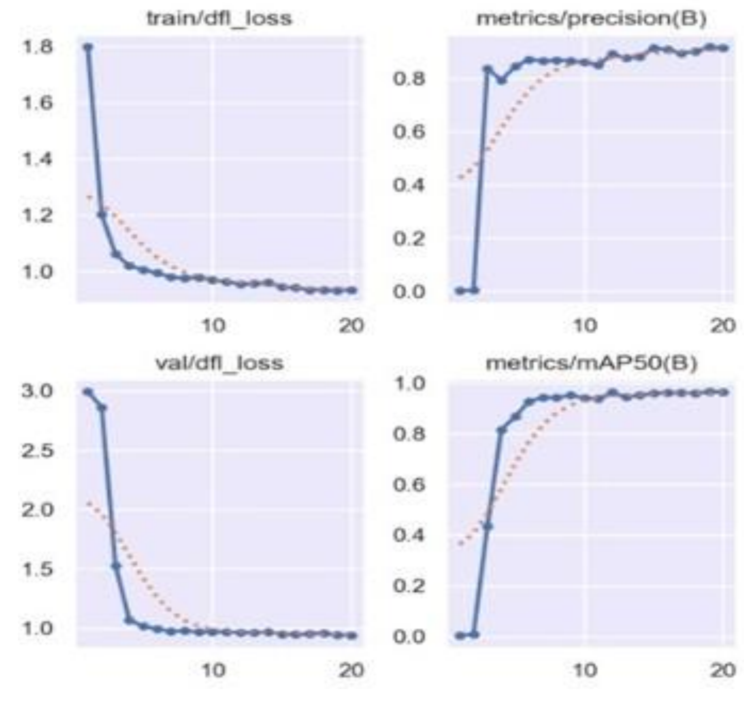


Figure 5.3.2.2 Training and Validation Loss Curves

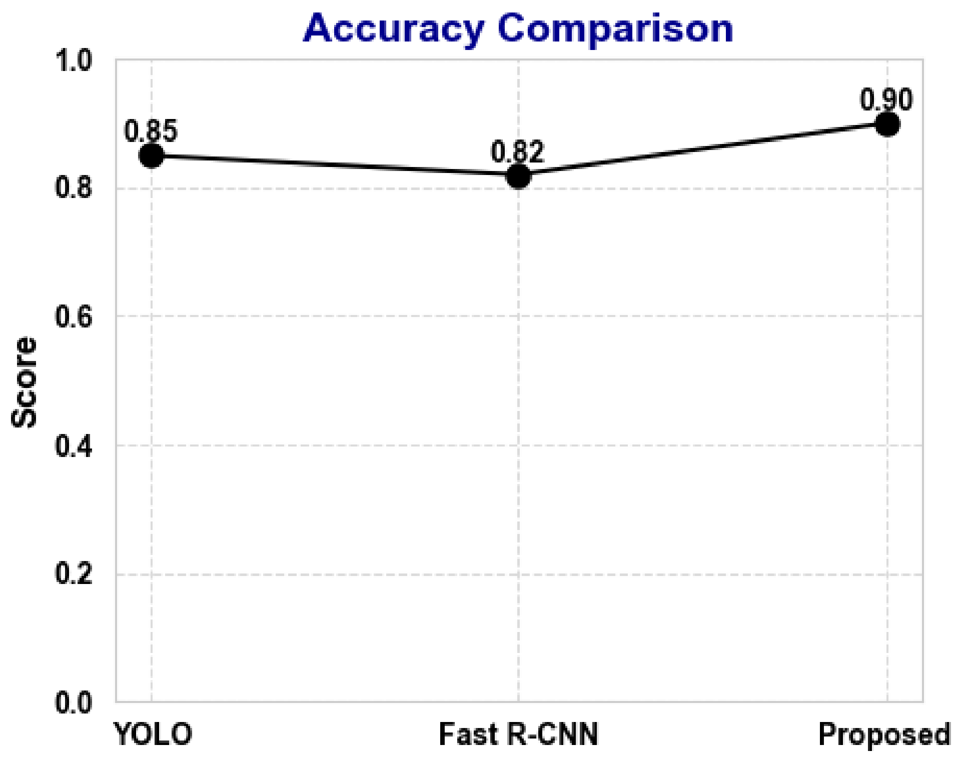


Figure 5.3.3 Accuracy Comparision

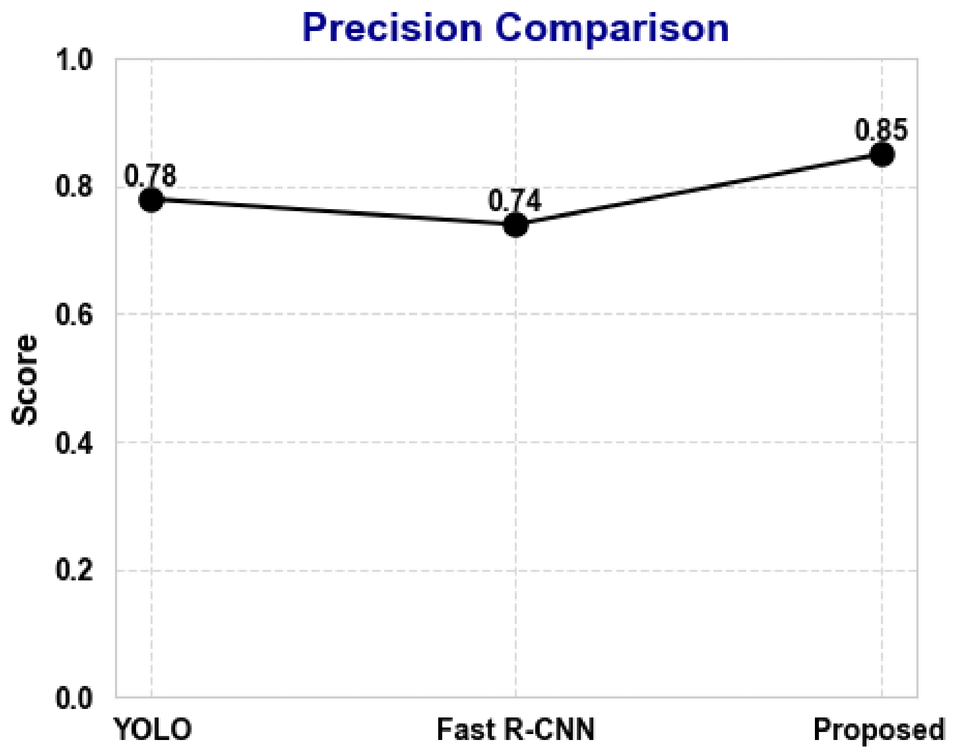


Figure 5.3.4 Precision Comparision

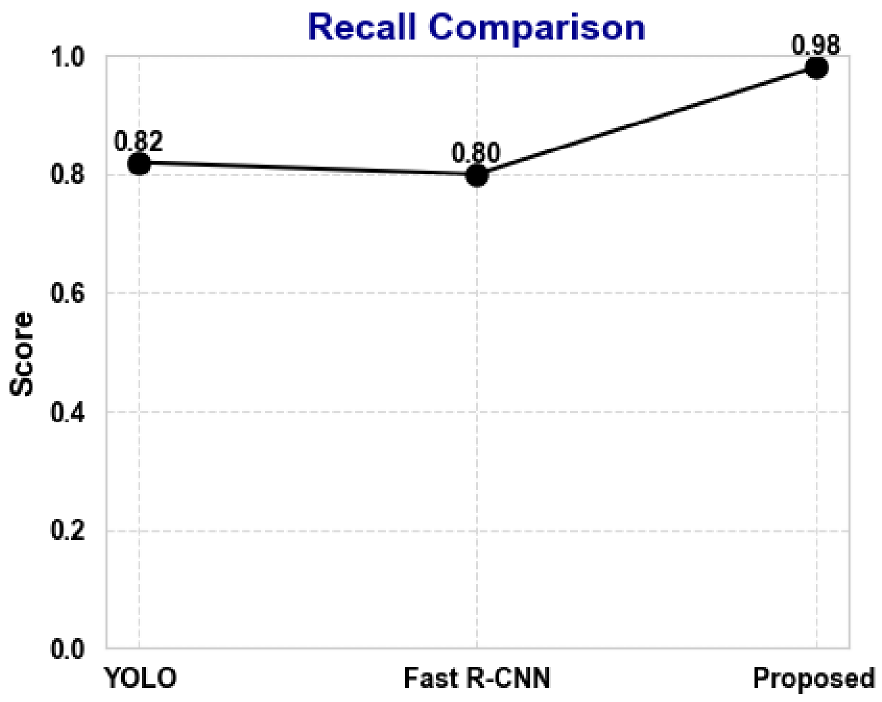
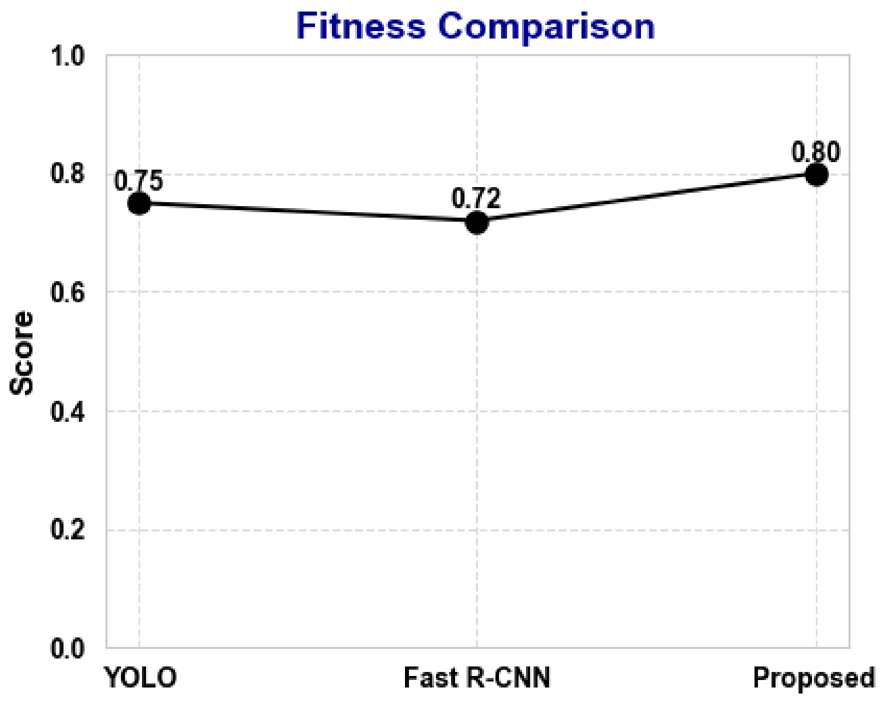


Figure 5.3.5 Recall Comparision



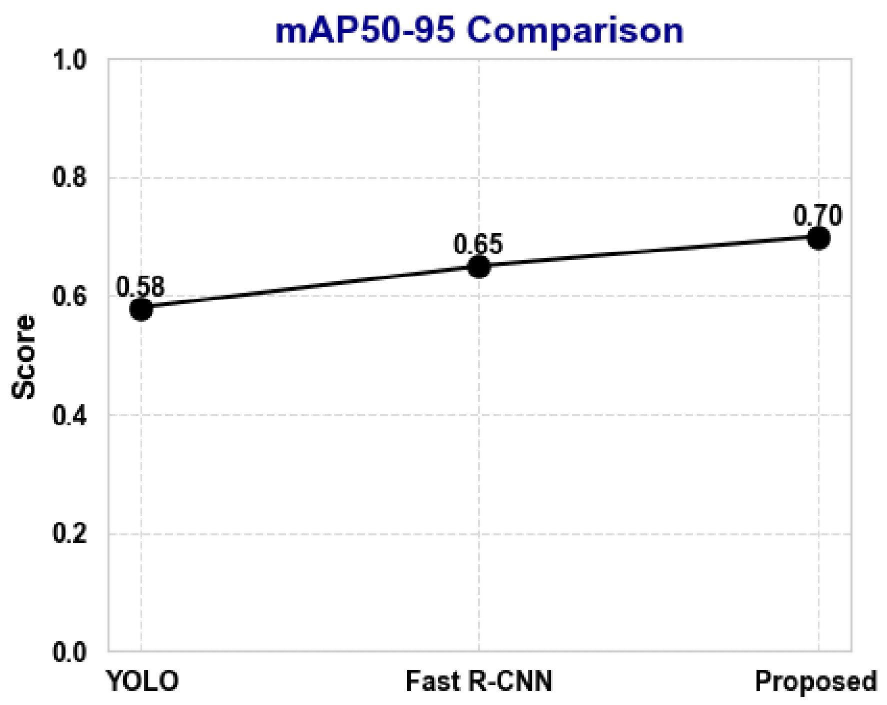


Figure 5.3.7 mAP50-95 Comparision

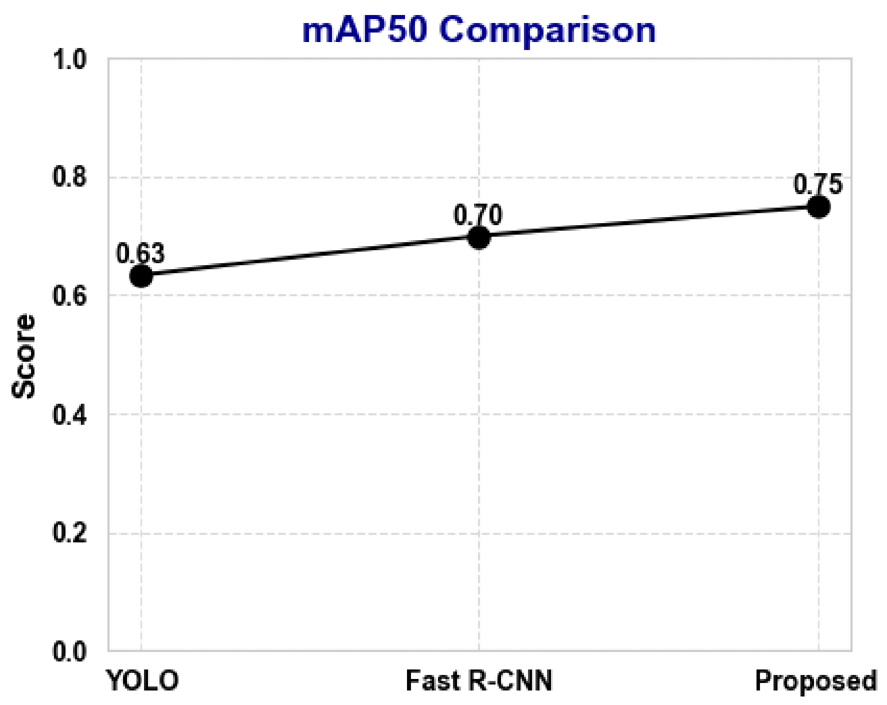


Figure 5.3.8 mAP50 Comparision

Chapter 6

Conclusion and Future Work

6.1 Conclusion

Through real-time vehicle tracking, the Intelligent Traffic Monitoring and Management System created for this project combines hardware and software to improve urban traffic control. From live video streams recorded by an OV7670 camera, the system guarantees accurate vehicle detection and classification by utilizing deep learning models such as MobileNet and YOLOv8. The system can then dynamically modify green light durations based on current traffic conditions by using these detections in the computation of traffic density. Together, an STM32 microcontroller and an ultrasonic sensor measure the degree of congestion and make adaptive decisions to effectively control traffic flow. In order to ensure optimal traffic distribution and minimize needless delays, the system intelligently adjusts traffic signal durations between 30 and 90 seconds. By reducing congestion, preventing lengthy lines at intersections, and guaranteeing smooth vehicle movement, this adaptive traffic control system enhances the overall effectiveness of urban road networks.

Beginning with video capture and preprocessing using sophisticated image processing techniques like edge detection and frame conversion, the system's architecture takes a methodical approach. Next, various vehicle types are classified in real time using the MobileNet and YOLOv8 models for high-accuracy object detection. LED signals are used to dynamically adjust the appropriate green light durations, which are determined by the system based on predefined traffic density thresholds. The integration of hardware elements like LED indicators, ultrasonic sensors, and STM32 microcontrollers guarantees seamless communication between software-based decision-making and actual traffic control. This AI-powered system functions independently, offering real-time, data-driven traffic regulation without the need for significant infrastructure changes, in contrast to conventional traffic management systems that depend on static timers or human interventions.

This system's capacity to increase traffic efficiency without requiring costly infrastructure upgrades is one of its main advantages. A strong, intelligent system that can adjust to shifting traffic patterns is produced by combining deep learning-based vehicle detection with microcontroller-driven decision-making. Continuous real-time data from the OV7670 camera and ultrasonic sensors enables intelligent signal adjustments that maximize traffic flow, minimize congestion, and lower carbon emissions. IoT-based communication and the integration of real-time weather and pedestrian movement data could be future improvements that further improve traffic management. Predictive traffic control techniques could also be made possible by using cloud-based analytics to store and examine past traffic patterns. This system is a major advancement in creating flexible, sustainable, and effective urban traffic management by utilizing AI and IoT technologies.

6.2 Future Work

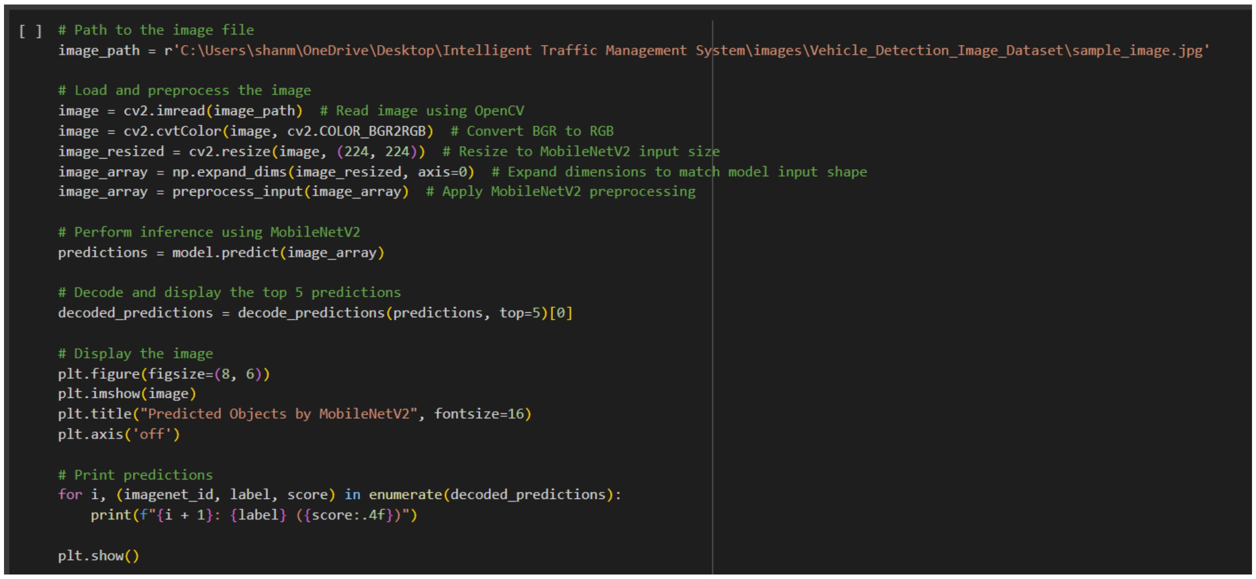
The ability to combine embedded hardware for dynamic traffic control with AI-driven decision-making is demonstrated by the current Intelligent Traffic Monitoring and Management System. Nonetheless, there is a great deal of room for improvement and expansion. Integrating IoT-based communication systems to facilitate smooth interaction between several city intersections is one exciting avenue. Instead of being restricted to localized control, traffic signals can be synchronized based on the overall traffic flow across regions by enabling cross-junction communication. As a result, a citywide adaptive traffic network would be created, in which traffic lights at one intersection would be able to detect congestion at nearby intersections and modify their timing accordingly. Additionally, this configuration can be linked to centralized traffic control centers, providing authorities with the capability and real-time traffic updates.

Future developments should also focus on integrating real-time pedestrian and environmental data. Although the system currently only considers vehicle traffic density, real-world traffic scenarios also take into account variables like weather, road closures, construction, and pedestrian movements. The system would be able to account for such external conditions by integrating weather sensors and pedestrian detection modules (using computer vision or infrared sensors). For example, in order to accommodate slower vehicle movement or to give priority to pedestrian signals during school hours, green light durations could be extended during rainy conditions. The flexibility and efficiency of traffic signal control in urban settings would be greatly improved by this all-encompassing strategy.

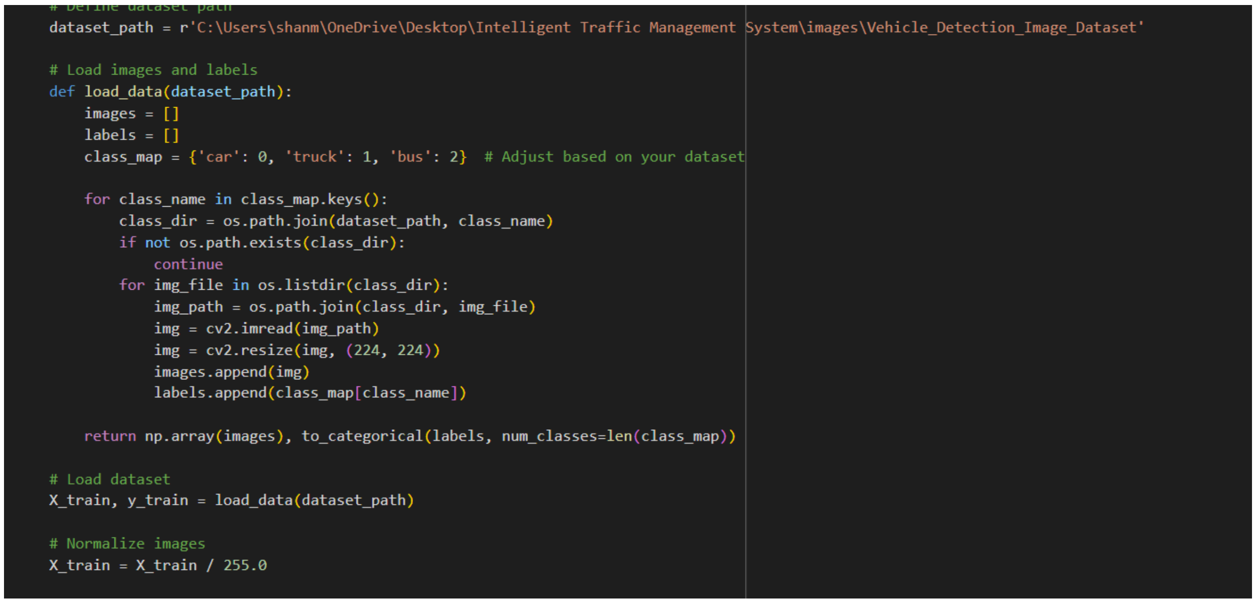
Implementing cloud-based data analytics and storing historical traffic patterns could also improve the system. The system can examine seasonal variations in traffic flow, peak hour patterns, and long-term traffic trends by sending vehicle detection data to a cloud server. With the aid of these insights, predictive traffic control models that modify traffic signals proactively—as opposed to reactively—before congestion even arises can be developed. This historical data could be used to train machine learning algorithms, such as time-series forecasting or reinforcement learning, to further optimize traffic light durations, lessen bottlenecks, and enhance system responsiveness over time.

Finally, future versions of the system might use edge computing and modular architecture to increase scalability and maintainability. Latency and reliance on external servers would be decreased by processing video frames and performing deep learning inference on edge devices (such as more sophisticated STM32 variants or specialized AI chips). Additionally, a modular design would make it simple to upgrade or replace specific parts, such as the camera or microcontroller, enabling the system to be deployed in a variety of urban settings. This strategy ensures that traffic management systems continue to be effective, scalable, and future-proof in the face of increasing urbanization while also lowering infrastructure costs and opening the door for sustainable smart city solutions.

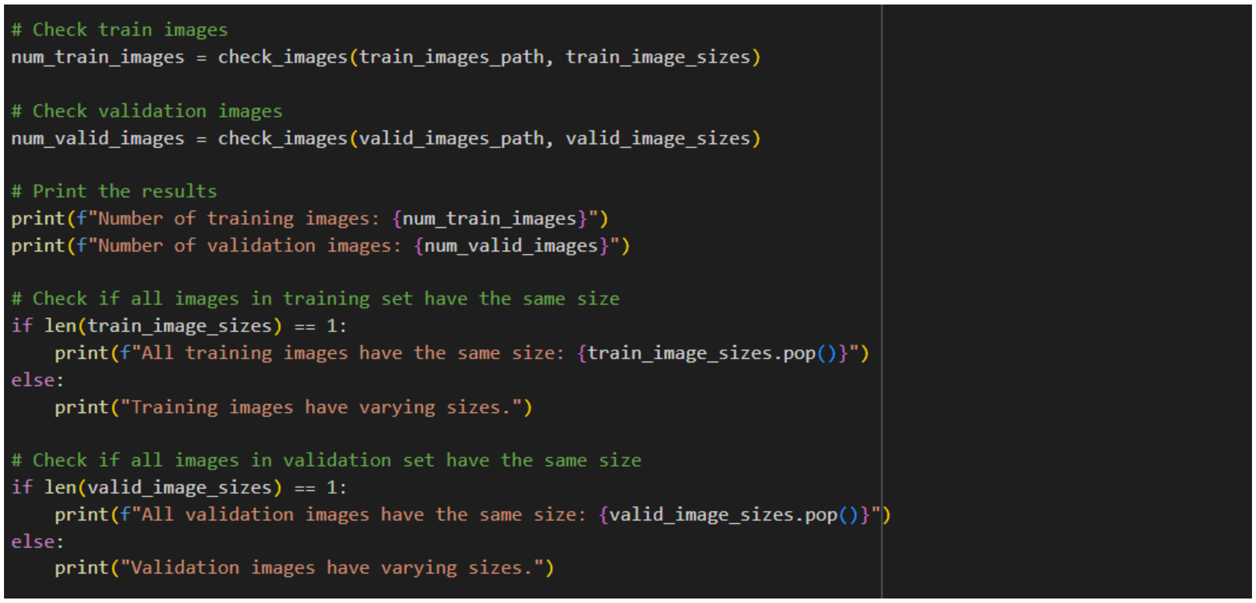
Appendix 1



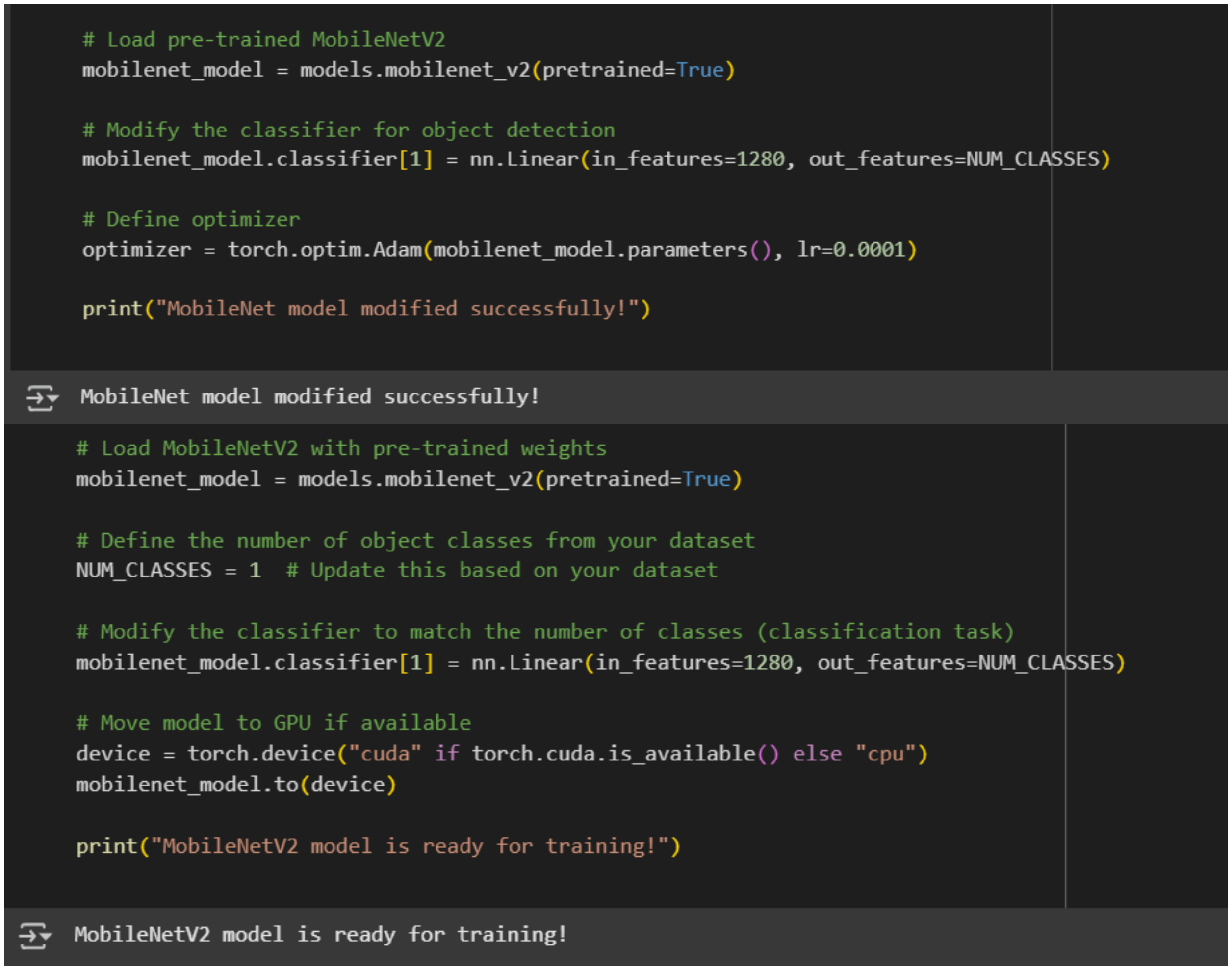
```
[ ]  # Path to the image file
     image_path = r'C:\Users\shanm\OneDrive\Desktop\Intelligent Traffic Management System\images\Vehicle_Detection_Image_Dataset\sample_image.jpg'

     # Load and preprocess the image
     image = cv2.imread(image_path)  # Read image using OpenCV
     image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)  # Convert BGR to RGB
     image_resized = cv2.resize(image, (224, 224))  # Resize to MobileNetV2 input size
     image_array = np.expand_dims(image_resized, axis=0)  # Expand dimensions to match model input shape
     image_array = preprocess_input(image_array)  # Apply MobileNetV2 preprocessing

     # Perform inference using MobileNetV2
     predictions = model.predict(image_array)

     # Decode and display the top 5 predictions
     decoded_predictions = decode_predictions(predictions, top=5)[0]

     # Display the image
     plt.figure(figsize=(8, 6))
     plt.imshow(image)
     plt.title("Predicted Objects by MobileNetV2", fontsize=16)
     plt.axis('off')

     # Print predictions
     for i, (imagenet_id, label, score) in enumerate(decoded_predictions):
         print(f"{i + 1}: {label} ({score:.4f})")

     plt.show()
```



```
# Define dataset path
dataset_path = r'C:\Users\shanm\OneDrive\Desktop\Intelligent Traffic Management System\images\Vehicle_Detection_Image_Dataset'

# Load images and labels
def load_data(dataset_path):
    images = []
    labels = []
    class_map = {'car': 0, 'truck': 1, 'bus': 2}  # Adjust based on your dataset

    for class_name in class_map.keys():
        class_dir = os.path.join(dataset_path, class_name)
        if not os.path.exists(class_dir):
            continue
        for img_file in os.listdir(class_dir):
            img_path = os.path.join(class_dir, img_file)
            img = cv2.imread(img_path)
            img = cv2.resize(img, (224, 224))
            images.append(img)
            labels.append(class_map[class_name])

    return np.array(images), to_categorical(labels, num_classes=len(class_map))

# Load dataset
X_train, y_train = load_data(dataset_path)

# Normalize images
X_train = X_train / 255.0
```



```
# Check train images
num_train_images = check_images(train_images_path, train_image_sizes)

# Check validation images
num_valid_images = check_images(valid_images_path, valid_image_sizes)

# Print the results
print(f"Number of training images: {num_train_images}")
print(f"Number of validation images: {num_valid_images}")

# Check if all images in training set have the same size
if len(train_image_sizes) == 1:
    print(f"All training images have the same size: {train_image_sizes.pop()}")
else:
    print("Training images have varying sizes.")

# Check if all images in validation set have the same size
if len(valid_image_sizes) == 1:
    print(f"All validation images have the same size: {valid_image_sizes.pop()}")
else:
    print("Validation images have varying sizes.")
```

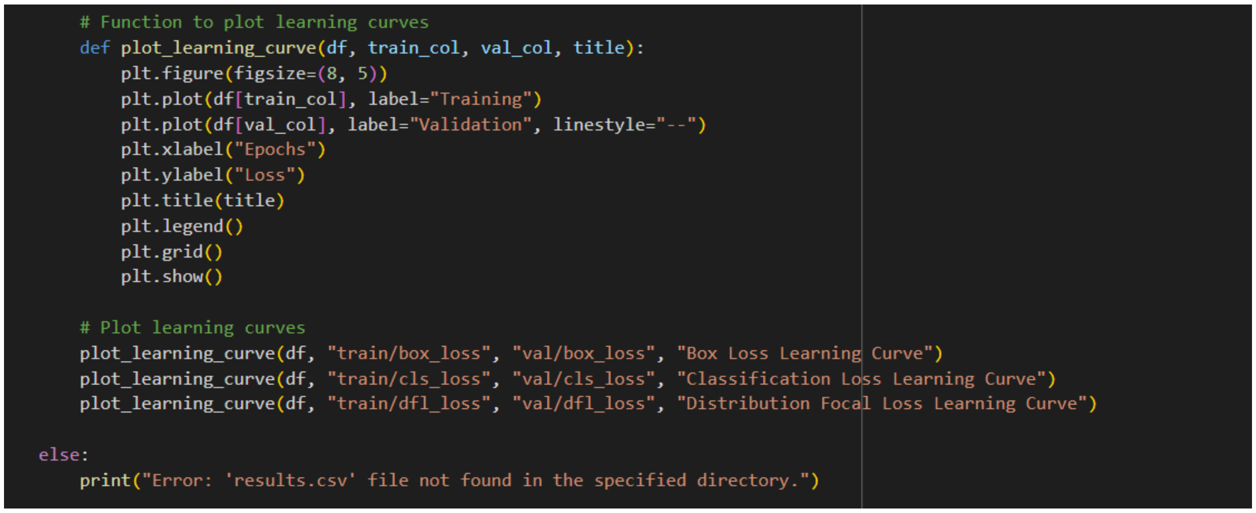


```
# Load pre-trained MobileNetV2
mobilenet_model = models.mobilenet_v2(pretrained=True)

# Modify the classifier for object detection
mobilenet_model.classifier[1] = nn.Linear(in_features=1280, out_features=NUM_CLASSES)

# Define optimizer
optimizer = torch.optim.Adam(mobilenet_model.parameters(), lr=0.0001)

print("MobileNet model modified successfully!")
```

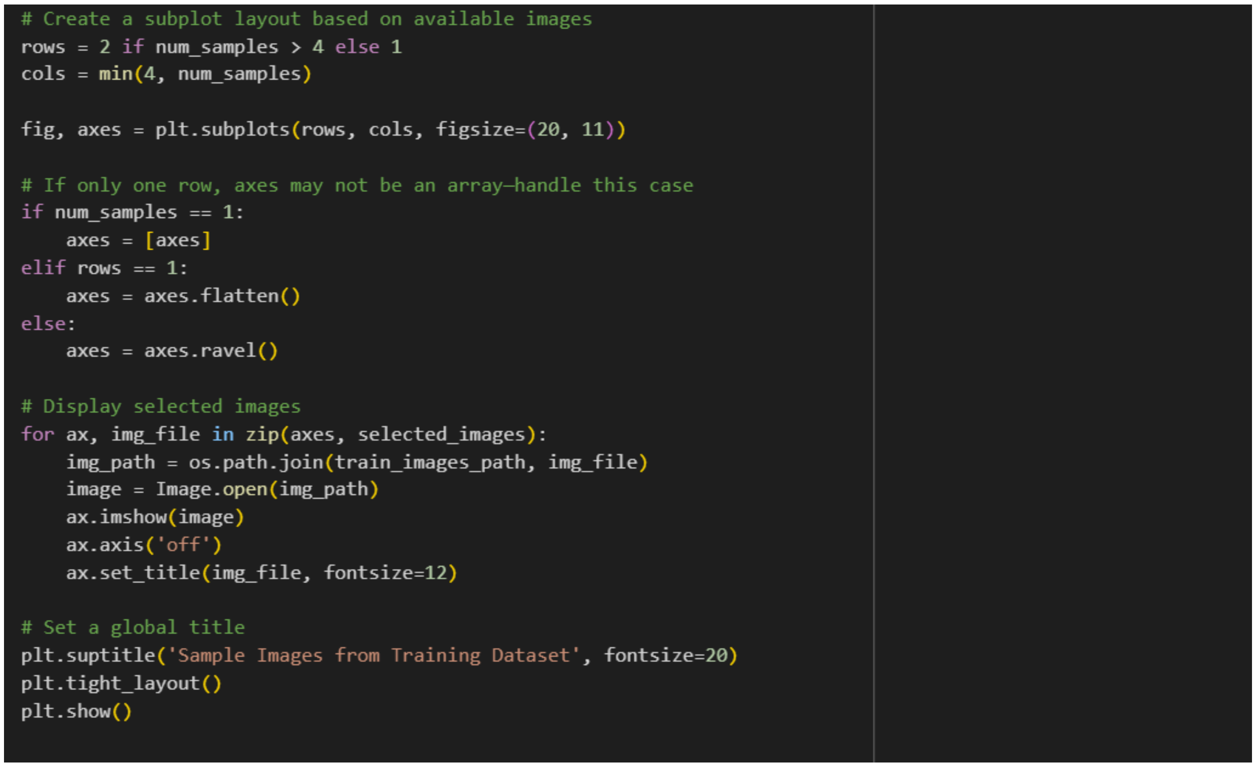
```
MobileNet model modified successfully!
```

```
# Load MobileNetV2 with pre-trained weights
mobilenet_model = models.mobilenet_v2(pretrained=True)

# Define the number of object classes from your dataset
NUM_CLASSES = 1  # Update this based on your dataset

# Modify the classifier to match the number of classes (classification task)
mobilenet_model.classifier[1] = nn.Linear(in_features=1280, out_features=NUM_CLASSES)

# Move model to GPU if available
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
mobilenet_model.to(device)

print("MobileNetV2 model is ready for training!")
```

```
MobileNetV2 model is ready for training!
```

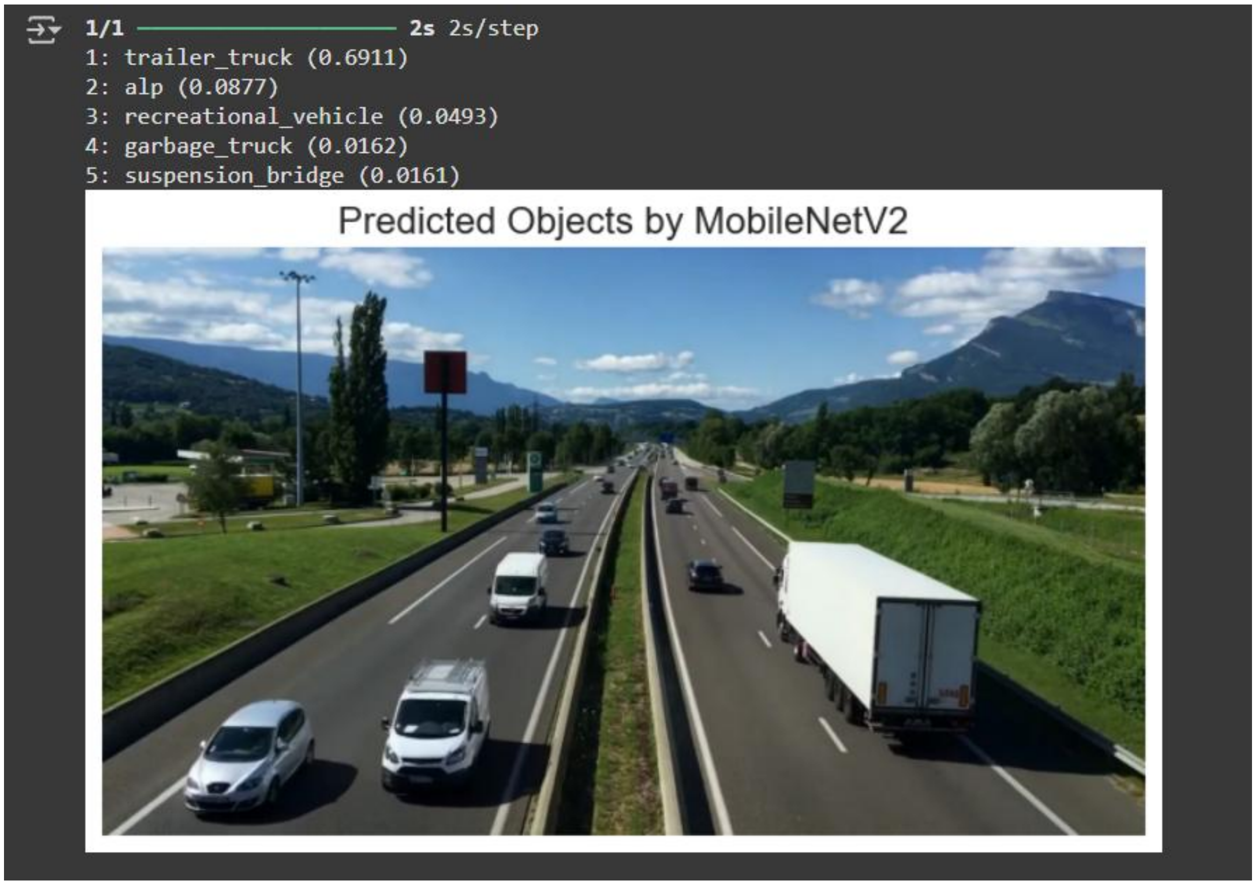


```
    # Function to plot learning curves
    def plot_learning_curve(df, train_col, val_col, title):
        plt.figure(figsize=(8, 5))
        plt.plot(df[train_col], label="Training")
        plt.plot(df[val_col], label="Validation", linestyle="--")
        plt.xlabel("Epochs")
        plt.ylabel("Loss")
        plt.title(title)
        plt.legend()
        plt.grid()
        plt.show()

    # Plot learning curves
    plot_learning_curve(df, "train/box_loss", "val/box_loss", "Box Loss Learning Curve")
    plot_learning_curve(df, "train/cls_loss", "val/cls_loss", "Classification Loss Learning Curve")
    plot_learning_curve(df, "train/dfl_loss", "val/dfl_loss", "Distribution Focal Loss Learning Curve")

else:
    print("Error: 'results.csv' file not found in the specified directory.")
```

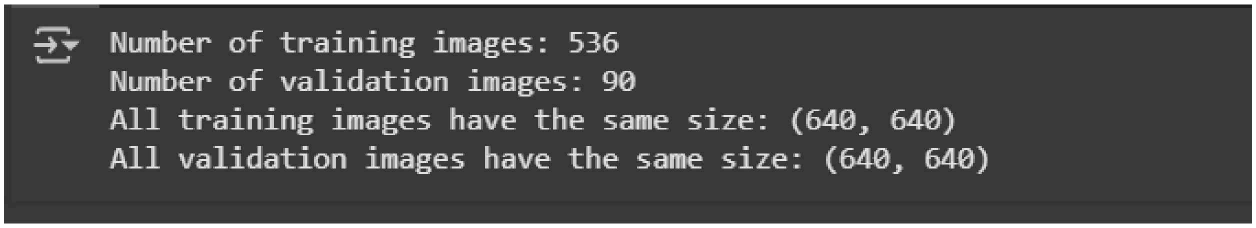


```
# Create a subplot layout based on available images
rows = 2 if num_samples > 4 else 1
cols = min(4, num_samples)

fig, axes = plt.subplots(rows, cols, figsize=(20, 11))

# If only one row, axes may not be an array—handle this case
if num_samples == 1:
    axes = [axes]
elif rows == 1:
    axes = axes.flatten()
else:
    axes = axes.ravel()

# Display selected images
for ax, img_file in zip(axes, selected_images):
    img_path = os.path.join(train_images_path, img_file)
    image = Image.open(img_path)
    ax.imshow(image)
    ax.axis('off')
    ax.set_title(img_file, fontsize=12)

# Set a global title
plt.suptitle('Sample Images from Training Dataset', fontsize=20)
plt.tight_layout()
plt.show()
```

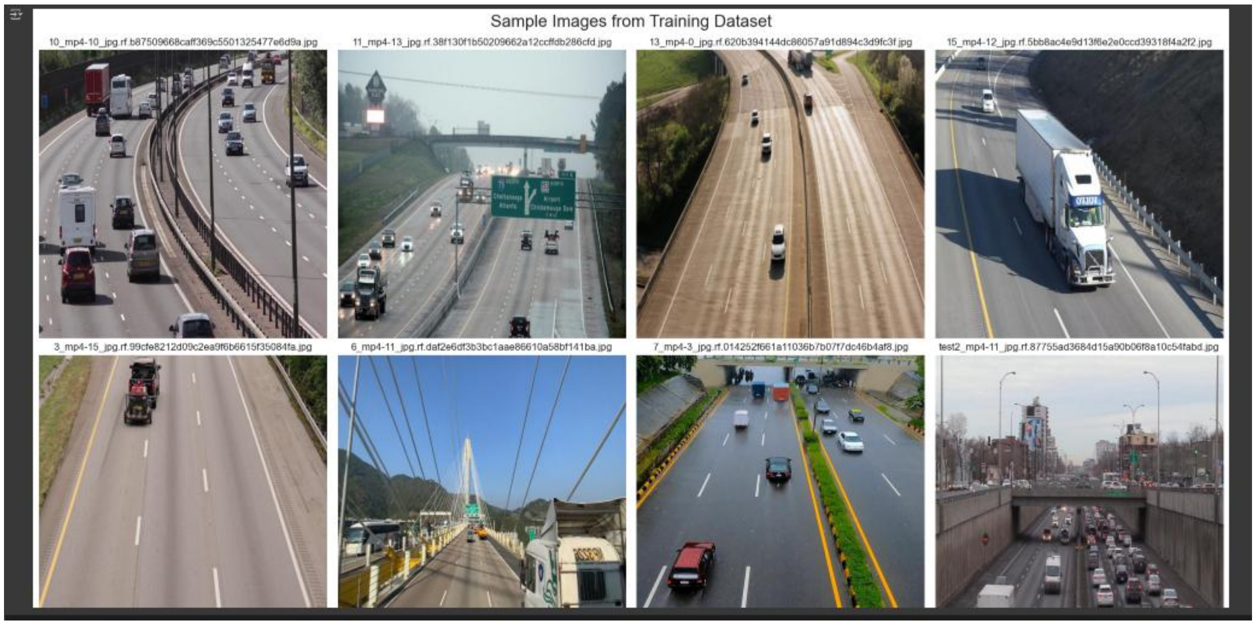
Appendix 2

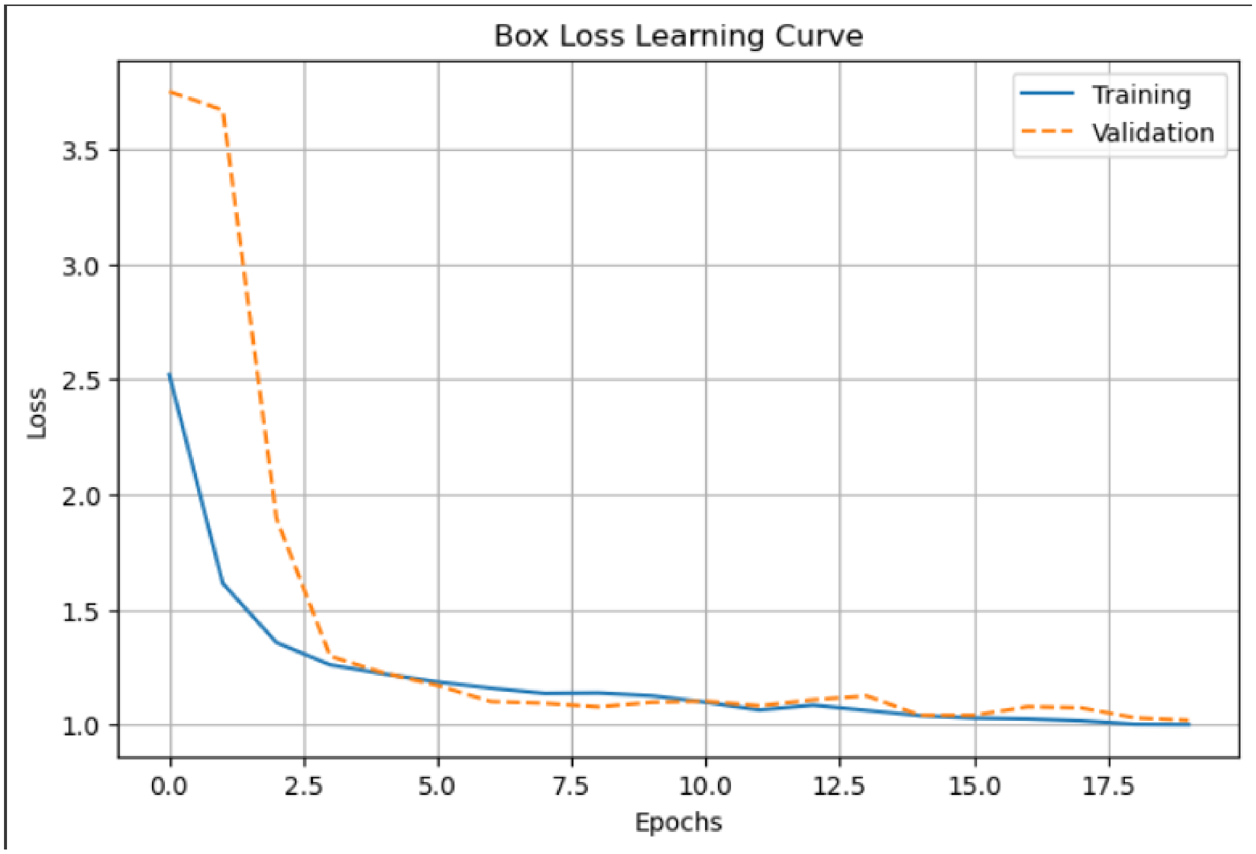


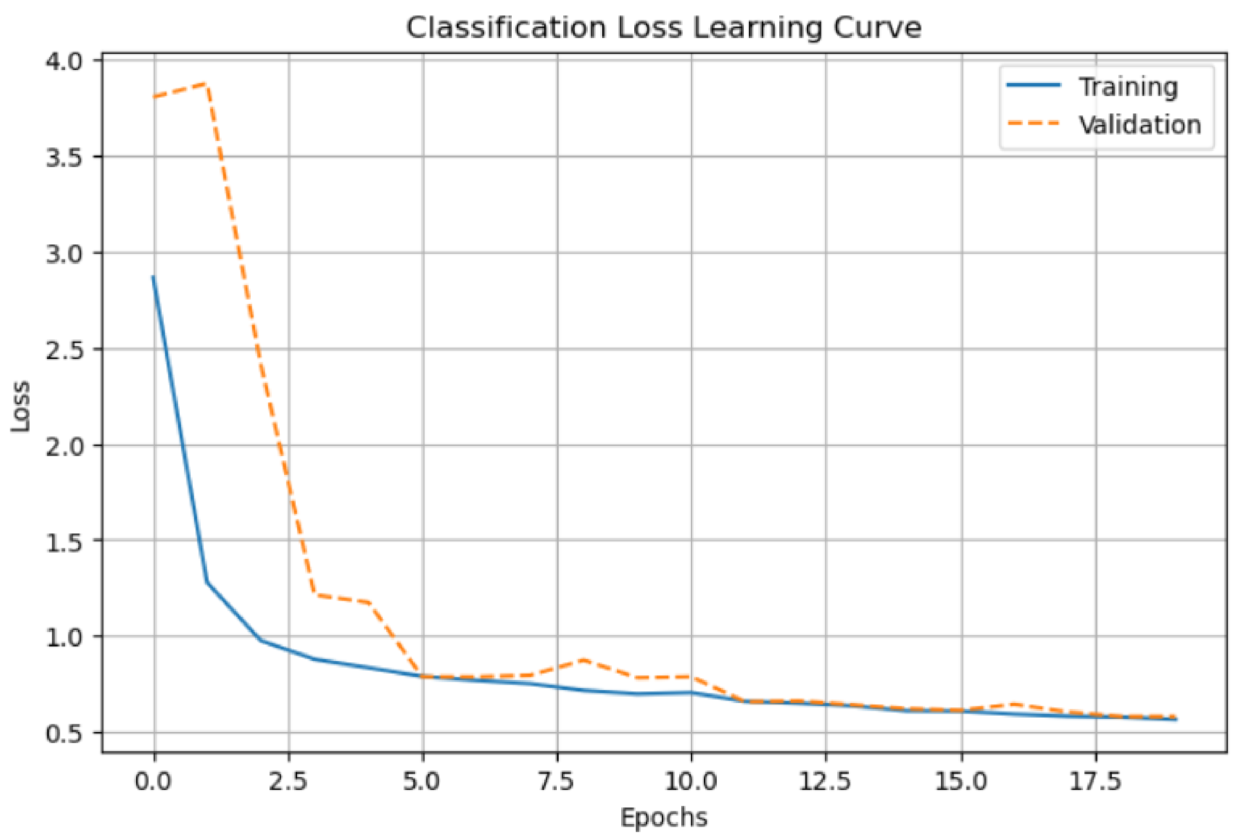
```
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step
1: trailer_truck (0.6911)
2: alp (0.0877)
3: recreational_vehicle (0.0493)
4: garbage_truck (0.0162)
5: suspension_bridge (0.0161)
```

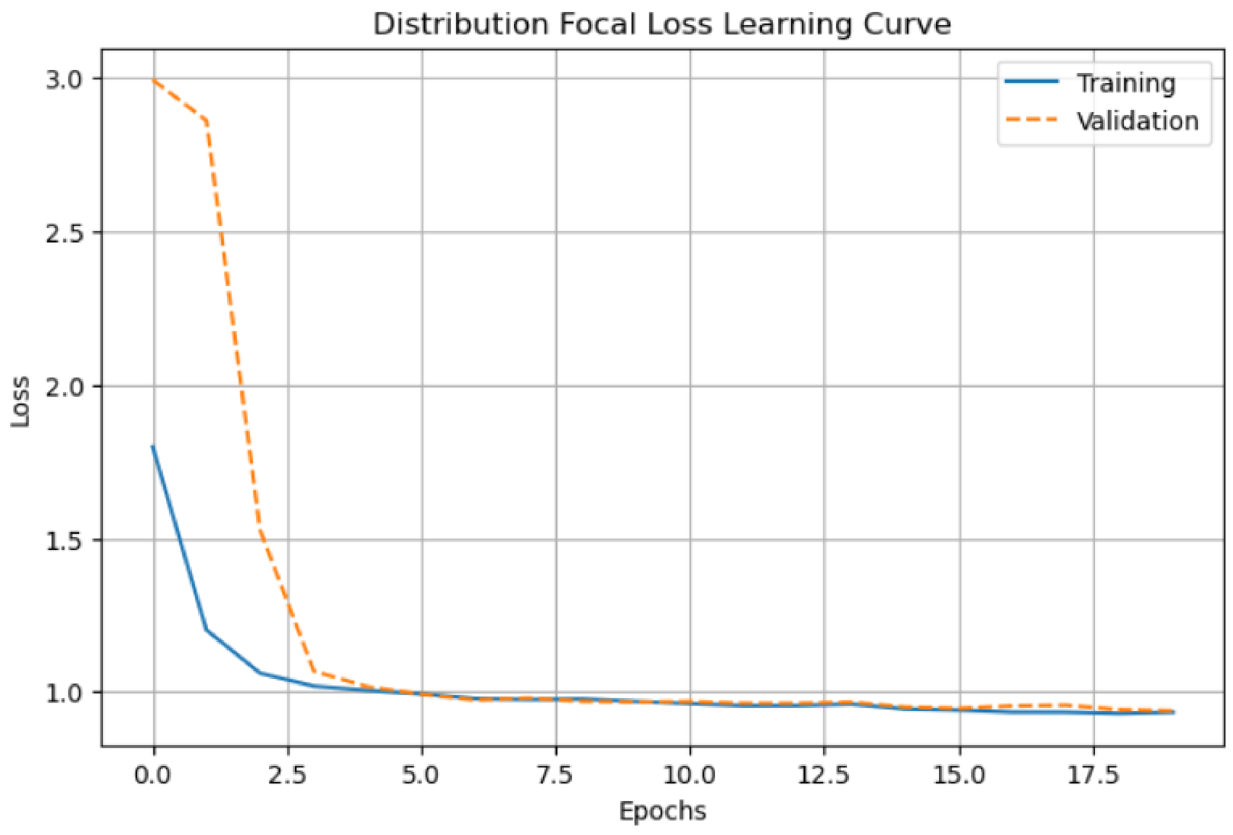


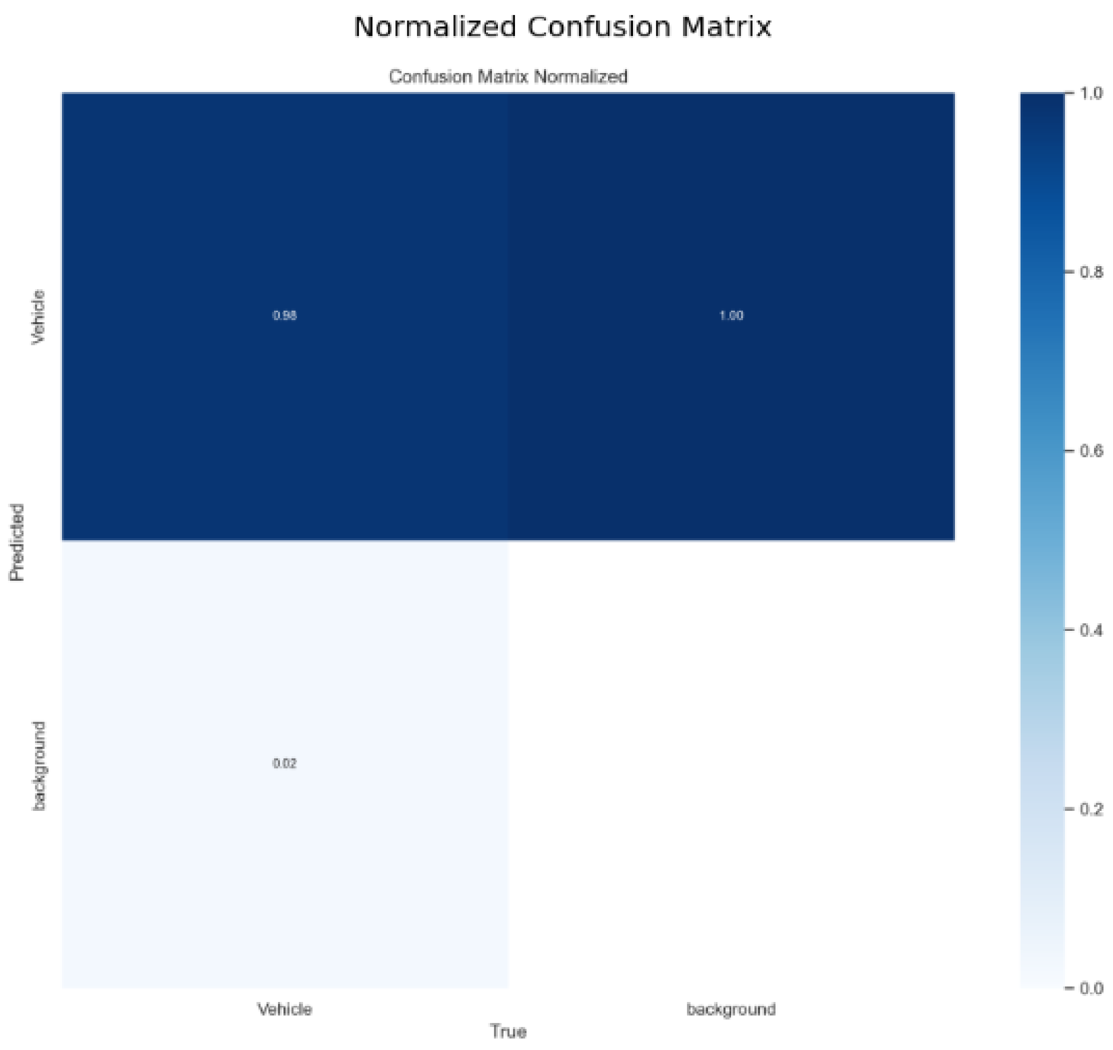
```
Number of training images: 536
Number of validation images: 90
All training images have the same size: (640, 640)
All validation images have the same size: (640, 640)
```

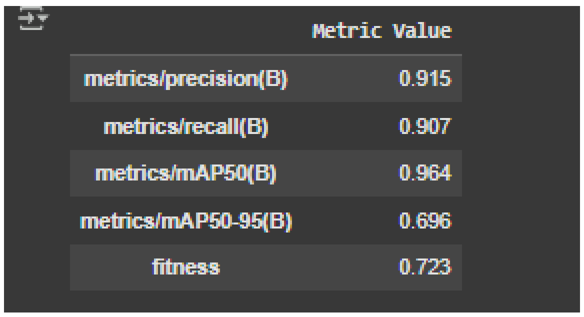

Sample Images from Training Dataset
10_mp4-10_jpg.rf.b87509668caff369c5501325477e6d9a.jpg
11_mp4-13_jpg.rf.38f130f1b50209662a12ccffdb286cfd.jpg
13_mp4-0_jpg.rf.620b394144dc86057a91d894c3d9fc3f.jpg
15_mp4-12_jpg.rf.5bb8ac4e9d13f6e2e0ccd39318f4a2f2.jpg
3_mp4-15_jpg.rf.99cfe8212d09c2ea9f6b6615f35084fa.jpg
6_mp4-11_jpg.rf.daf2e6df3b3bc1aae86610a58bf141ba.jpg
7_mp4-3_jpg.rf.014252f661a11036b7b07f7dc46b4af8.jpg
test2_mp4-11_jpg.rf.87755ad3684d15a90b06f8a10c54fabd.jpg


Box Loss Learning Curve
Training
Validation
Loss
Epochs
3.5
3.0
2.5
2.0
1.5
1.0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

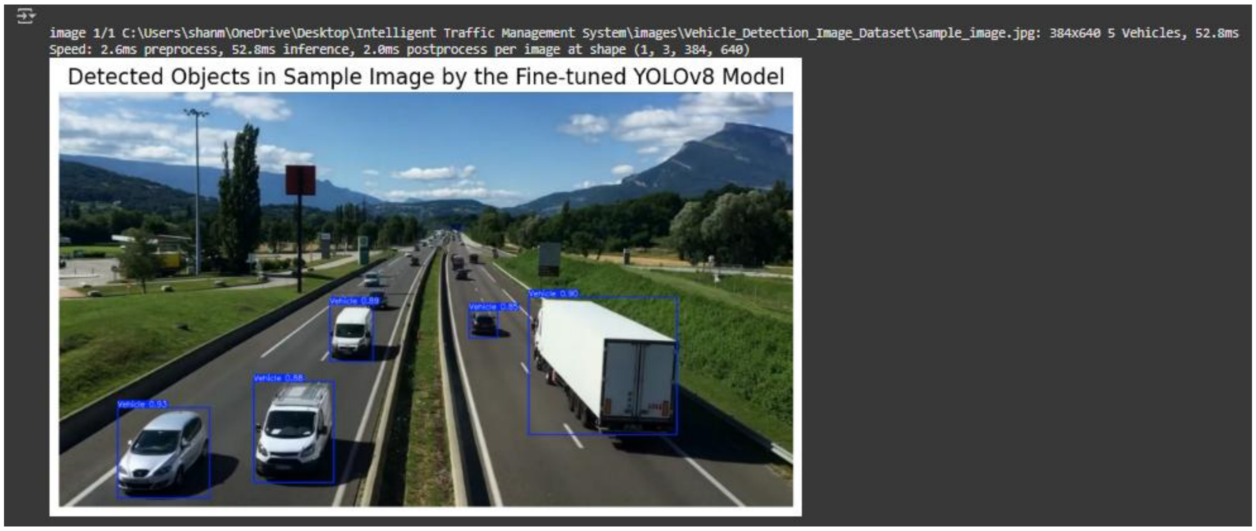

Classification Loss Learning Curve
Training
Validation
Loss
Epochs


Distribution Focal Loss Learning Curve
Training
Validation
Loss
Epochs



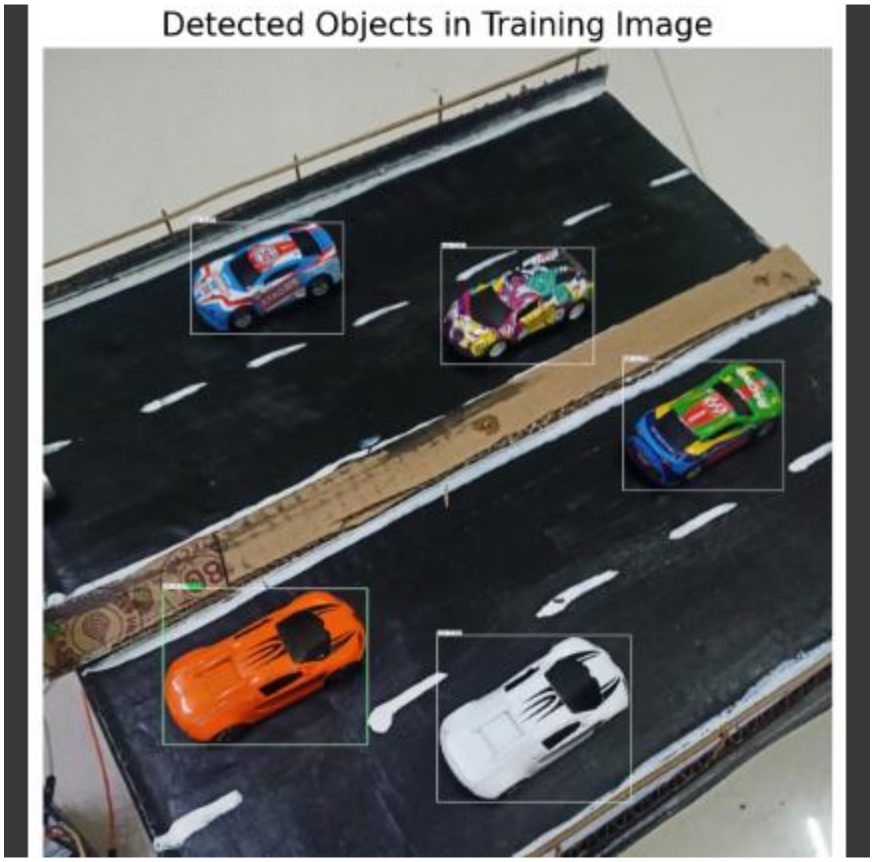


	Metric Value
metrics/precision(B)	0.915
metrics/recall(B)	0.907
metrics/mAP50(B)	0.964
metrics/mAP50-95(B)	0.696
fitness	0.723



```
image 1/1 C:\Users\shanm\OneDrive\Desktop\Intelligent Traffic Management System\images\Vehicle_Detection_Image_Dataset\sample_image.jpg: 384x640 5 Vehicles, 52.8ms
Speed: 2.6ms preprocess, 52.8ms inference, 2.0ms postprocess per image at shape (1, 3, 384, 640)
```

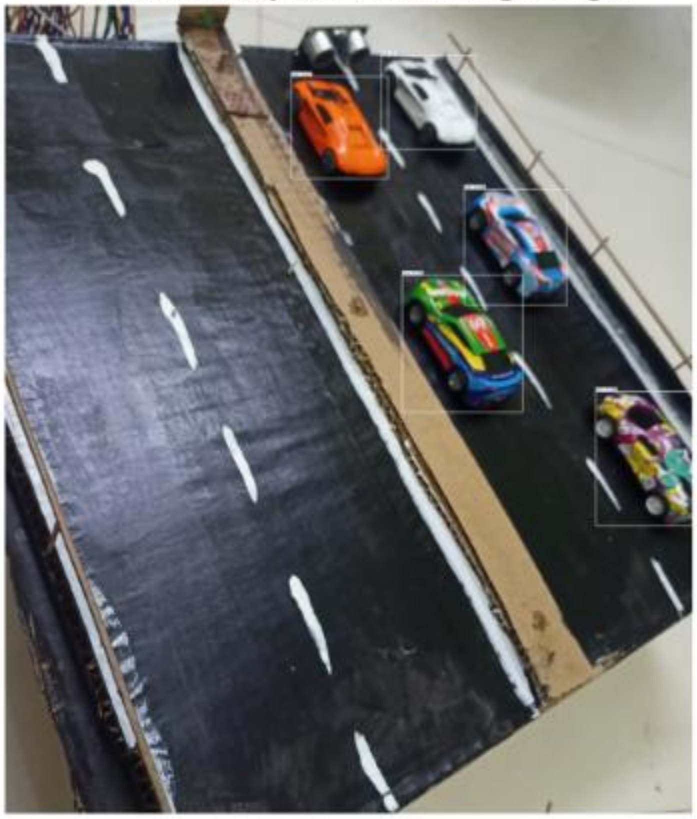
Detected Objects in Sample Image by the Fine-tuned YOLOv8 Model
Vehicle 0.89
Vehicle 0.85
Vehicle 0.90
Vehicle 0.88
Vehicle 0.93

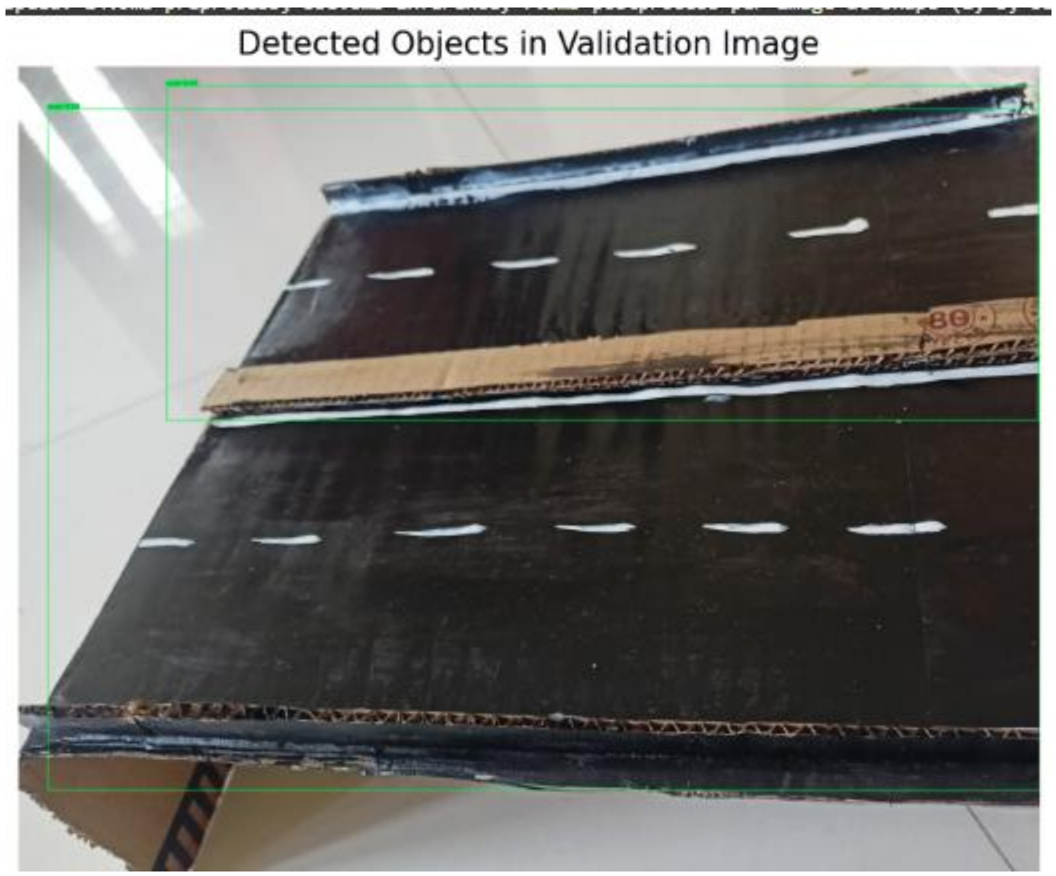


Detected Objects in Validation Image

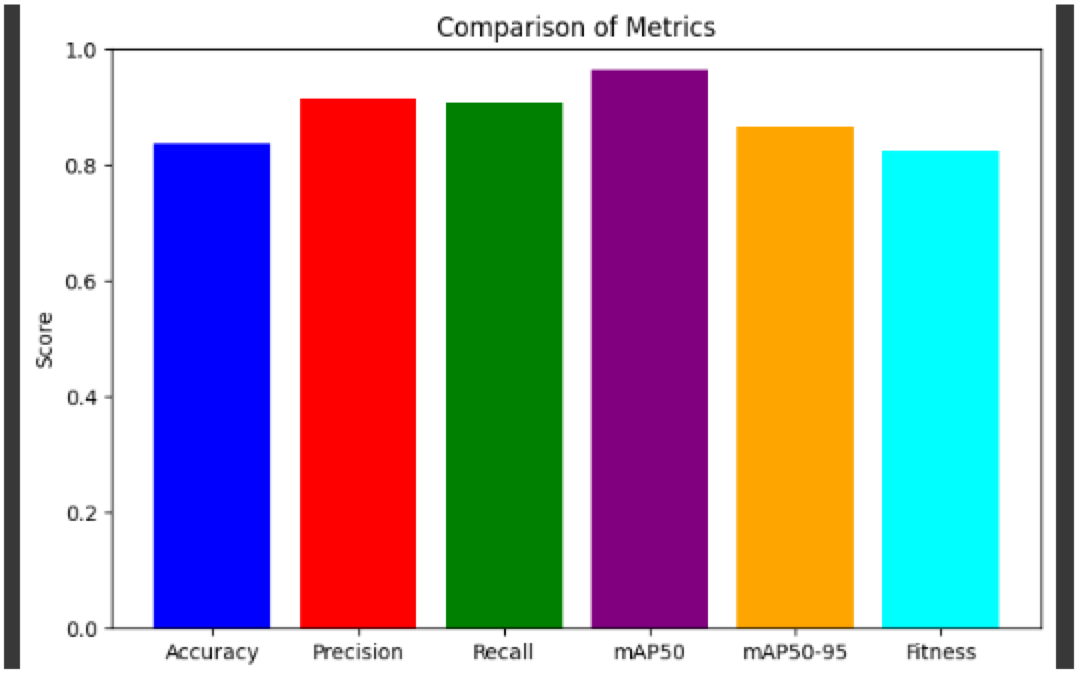
```
speed: 10.7ms preprocess, 320.1ms inference, 7.8ms postprocess
```

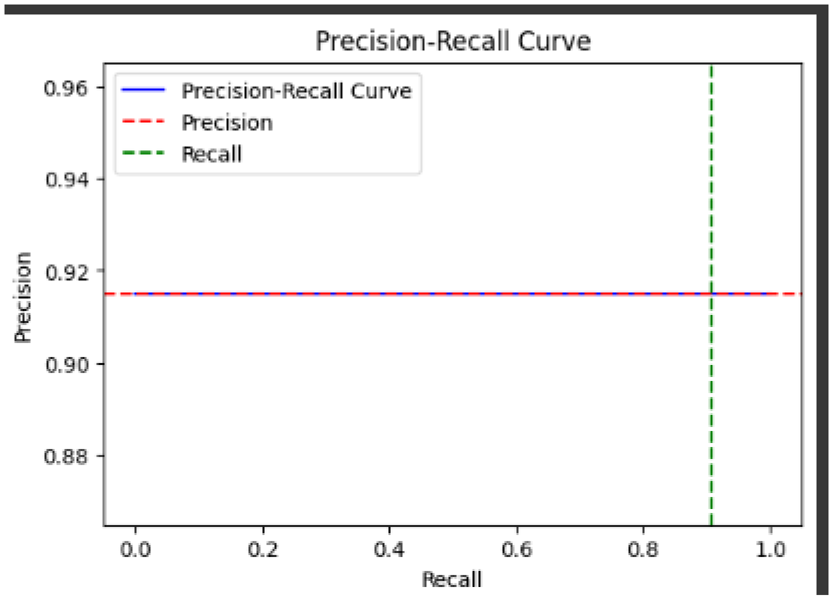
Detected Objects in Training Image

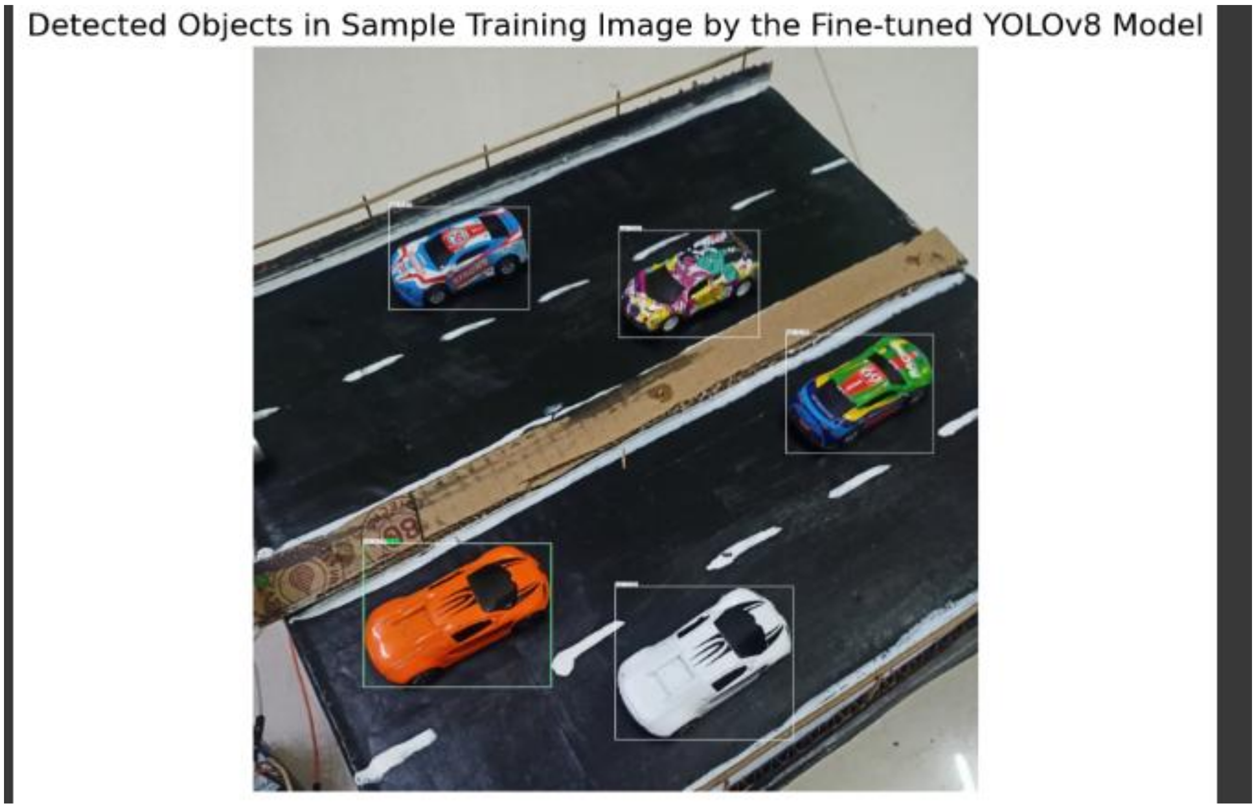


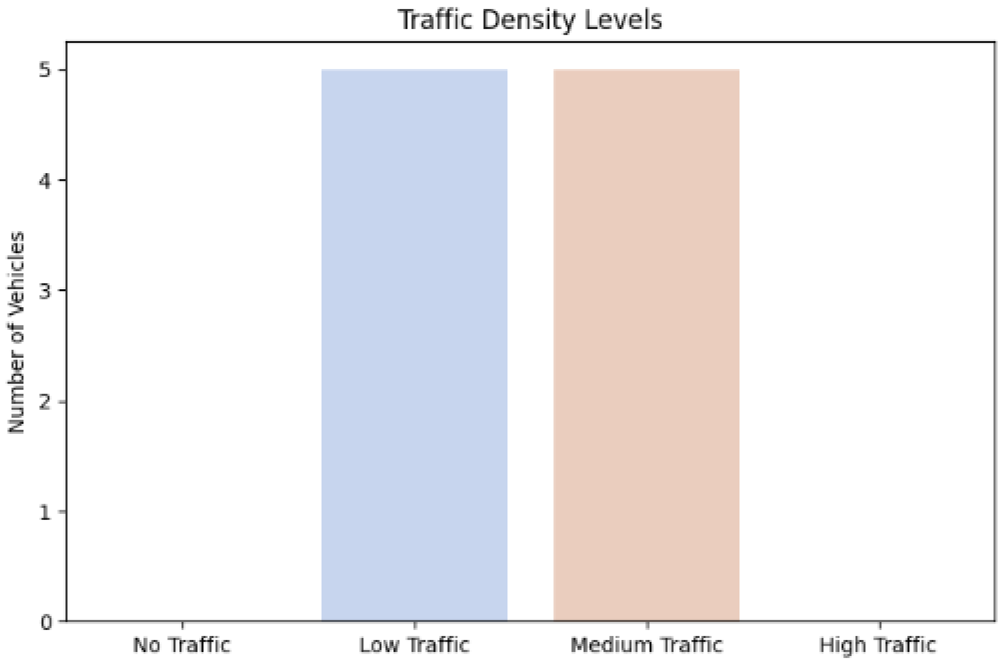

Detected Objects in Validation Image

Detected Objects in Sample Image by the Fine-tuned YOLOv8 Model


Comparison of Metrics
Score
1.0
0.8
0.6
0.4
0.2
0.0
Accuracy
Precision
Recall
mAP50
mAP50-95
Fitness


Precision-Recall Curve
Precision-Recall Curve
Precision
Recall
Precision
0.96
0.94
0.92
0.90
0.88
0.0
0.2
0.4
0.6
0.8
1.0
Recall


Detected Objects in Sample Training Image by the Fine-tuned YOLOv8 Model


Traffic Density Levels
Number of Vehicles
0
1
2
3
4
5
No Traffic
Low Traffic
Medium Traffic
High Traffic

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