INTELLIGENT TRAFFIC MANAGEMENT: REAL-TIME VEHICLE DETECTION USING YOLOV7 FOR TRAFFIC SIGN ALLOCATION

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FINAL YEAR DESIGN PROJECT REPORT

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APPROVAL

This Project titled "INTELLIGENT TRAFFIC MANAGEMENT: REAL-TIME VEHICLE DETECTION USING YOLOV7 FOR TRAFFIC SIGN ALLOCATION", submitted by MD MAHMUDUL HASAN MOON to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on July 15, 2024.

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ABSTRACT

The efficient management of modern traffic systems increasingly relies on automated technologies for real-time vehicle detection. This research article studies the development of an intelligent traffic management system, featuring an emphasis on real-time vehicle identification and traffic sign allocation using the YOLOv7 (You Only Look Once) object detection framework. The research examines the crucial need for effective traffic management solutions in metropolitan environments, focusing on the crowded roadways of Dhaka, Bangladesh. A large dataset of 1760 photos of Dhaka's busiest streets was used to train and assess the YOLOv7 model. The trained model scored an astounding 93.77% accuracy, indicating its usefulness in real-time vehicle recognition. Furthermore, the YOLOv7x variation, which has a more sophisticated design, was tested, resulting in an accuracy of 81.6%. The research emphasizes the significance of accurate and rapid vehicle detection in enhancing traffic flow and safety through the strategic allocation of traffic signs. By identifying and analyzing vehicle patterns and traffic density in real-time, the YOLOv7 model can facilitate dynamic adjustments to traffic signal timings and the strategic placement of traffic signs, effectively reducing congestion and improving overall traffic efficiency. This capability is crucial for urban centers like Dhaka, where traffic congestion is a persistent issue. This study provides a detailed analysis of the training process, model performance, and the practical implications of deploying such an intelligent system in a metropolitan context. The comprehensive evaluation includes a discussion on the strengths and limitations of the YOLOv7 and YOLOv7x models, as well as their suitability for real-time traffic management applications. The findings underscore the viability of YOLOv7 as a robust tool for intelligent traffic management, paving the way for further advancements in smart city infrastructure and automated traffic control systems. Additionally, this research highlights the potential for future enhancements and integration with other smart city technologies, contributing to a more efficient and sustainable urban traffic ecosystem.

Keywords: Traffic Management, YOLOv7, Congestion Detection, Object Detection

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CHAPTER 1
INTRODUCTION

1.1 Overview

Present-day urban activity administration faces critical challenges due to the ever-increasing volume of vehicles and the energetic nature of activity conditions, frequently resulting in clogs, delays, and the frequency of mishaps. Conventional activity control frameworks, which depend on settled plans and inactive signage, regularly demonstrate insufficient attention to these complexities. This proposal explores the improvement of a robotized activity administration framework utilizing the YOLOv7 calculation, which is famous for its accuracy and effectiveness in real-time question location. By leveraging advanced machine learning procedures to analyze video bolsters from roadside cameras, the framework is capable of precisely recognizing and classifying vehicles, and counting cars, trucks, and cruisers. The framework at that point powerfully decides suitable activity signage based on the sort and thickness of vehicles recognized. With a noteworthy discovery accuracy of 93.77%, the YOLOv7-based framework aims to optimize the activity stream and improve street security by providing a responsive and versatile activity control instrument. This investigation illustrates the transformative potential of joining cutting-edge machine learning calculations into activity administration frameworks, advertising a commonsense approach to overcoming the confinements of conventional strategies. The proposed framework is assessed in different real-world scenarios, counting both urban and highway settings, highlighting its vigor and adequacy. The discoveries emphasize the practicality of this approach in contributing to the improvement of more intelligent and proficient urban foundations, clearing the way for future advancements in intelligent transportation frameworks.

1.2 Background and Present State

Traffic congestion and road safety are pressing issues in modern urban environments due to the rapid increase in vehicle numbers. Traditional traffic management systems, which rely on fixed schedules and static signs, often fail to adapt to real-time traffic conditions, leading to inefficiencies and increased accident risks. The emergence of intelligent transportation systems (ITS) offers a solution by integrating advanced technologies like machine learning and computer vision to monitor, analyze, and respond to traffic conditions dynamically. Recent advancements in deep learning, particularly with algorithms like YOLO (You Only Look

Once), have significantly improved real-time vehicle detection. YOLOv7, the latest iteration, stands out for its speed and accuracy, making it a suitable candidate for enhancing traffic management systems.

Figure 1.2: Traffic congestion in Dhaka

Currently, many urban traffic management systems rely on outdated static methods, unable to adapt to the complexities of modern traffic patterns, resulting in congestion and increased accident risks. Although intelligent transportation systems integrating machine learning and computer vision are gradually gaining traction, widespread adoption remains slow due to infrastructure limitations and the challenges of integrating new technologies with existing systems. Pilot projects using algorithms like YOLOv7 have shown promising results in real-time vehicle detection and classification, achieving high accuracy rates and demonstrating the potential to optimize traffic flow and improve road safety. This thesis aims to address these challenges by presenting a robust traffic management system utilizing YOLOv7 for dynamic traffic sign allocation based on vehicle type and density, highlighting a practical approach to enhancing urban traffic management.

1.3 Problem Statement

Bangladesh faces critical challenges in urban traffic management due to rapid urbanization and increasing motorization, particularly evident in cities like Dhaka. Traffic congestion in Dhaka, exacerbated by outdated traffic management systems relying on fixed schedules and static signage, leads to prolonged travel times, pollution, and frequent accidents. Manual control of intersections by traffic police further complicates traffic flow, lacking real-time data and adaptive capabilities. The diverse mix of vehicles, including cars, buses, motorcycles, and rickshaws, requires a more sophisticated approach to traffic management. To address these issues effectively, there is a pressing need for an intelligent traffic management system capable of real-time vehicle detection, classification, and adaptive traffic control. The proposed method enhances the precision and effectiveness of vehicle recognition in a range of situations by utilizing cutting-edge deep learning and computer vision approaches. By leveraging advanced technologies such as machine learning, specifically YOLOv7 for its robust real-time object detection capabilities, Bangladesh can develop a more responsive and efficient traffic management framework, thereby improving urban mobility and road safety.

1.4 Objective

This project aims to develop and optimize a robust real-time vehicle detection system using the YOLOv7 algorithm tailored for urban traffic conditions in Bangladesh. The primary objectives include enhancing the accuracy and efficiency of real-time vehicle detection across diverse vehicle types such as cars, trucks, motorcycles, and three-wheeler vehicles. This will involve fine-tuning YOLOv7 parameters and training the model on representative datasets to improve detection performance under various environmental and traffic conditions prevalent in Bangladeshi cities. Additionally, the research will focus on evaluating the system's performance metrics including accuracy, precision, recall, and computational efficiency. Integration of the developed vehicle detection system with existing or proposed traffic management frameworks will demonstrate its potential to enhance traffic flow optimization and safety measures. Additionally, the project will conduct comparative studies to benchmark the YOLOv7-based system against traditional vehicle detection methods. These studies will provide insights into the advantages of using YOLOv7 for urban traffic management, such as its superior detection speed and accuracy, which are crucial for real-time applications. The research will also explore the system's scalability and adaptability to different urban areas, ensuring that the solution can be effectively implemented across various traffic scenarios.

Furthermore, optimization techniques, including data augmentation and hyperparameter tuning, will be employed to enhance the model's robustness and performance. The project will develop a prototype system and conduct field tests in Bangladeshi cities to validate its effectiveness in real-world conditions. The goal is to create a responsive and efficient traffic management system that leverages advanced machine learning technologies to improve urban mobility and road safety in Bangladesh.

1.5 Scope and Limitations

The system will be trained and evaluated using diverse datasets that reflect Bangladeshi traffic conditions, with performance measured through metrics such as detection accuracy, precision, recall, and computational efficiency. Future expansions could enhance the system's capabilities to include infrared and night vision detection, ensuring accurate vehicle detection in low-light and nighttime conditions. Additionally, the system could be updated to identify newer and more diverse vehicle types, such as electric and autonomous vehicles. Integrating advanced sensor imaging technologies, such as LIDAR and night vision cameras, could further enhance detection accuracy and system robustness under various environmental conditions.

Despite its advancements, the proposed system has several limitations. Adverse weather conditions like heavy rain, fog, or dust can impact the accuracy of vehicle detection by obscuring the camera's view. The performance of the YOLOv7 algorithm is also reliant on the quality and diversity of the training dataset; inadequate representation of certain vehicle types or traffic conditions could diminish detection accuracy. Moreover, implementing the system requires substantial infrastructure investments, including high-quality cameras and reliable network connectivity, which might be challenging in some urban areas. Integrating the detection system with existing traffic management frameworks could face practical hurdles, such as compatibility with legacy systems and the necessity for real-time data processing capabilities. These limitations highlight areas needing further research and development to fully leverage intelligent traffic management systems.

1.6 Report Organization

This thesis is organized into several key sections to comprehensively explore the development and implementation of a real-time vehicle detection system using the YOLOv7 algorithm for urban traffic management in Bangladesh:

Introduction: Provides an overview of the current challenges in urban traffic management and introduces the objectives and scope of the thesis.

Literature Review: Discusses existing literature on intelligent transportation systems, machine learning applications in traffic management, and an in-depth analysis of the YOLOv7 algorithm.

Implementation: Describes the practical steps taken to implement the YOLOv7-based vehicle detection system, including software and hardware setup, integration with traffic management frameworks, and real-time deployment scenarios.

Methodology: Details the methodology for dataset collection, preparation, and training of the YOLOv7 model. It also outlines the evaluation metrics and criteria used to measure the system's performance.

Results and Analysis: Presents the findings from testing the YOLOv7-based vehicle detection system in various urban scenarios in Bangladesh. Includes discussions on detection accuracy, computational efficiency, and the system's impact on traffic flow and safety.

Impact On Society, Environment, And Sustainability: Analyzes the broader implications of the proposed system on society, environmental sustainability, and urban development. Explores how the system can contribute to reducing traffic congestion, lowering emissions, and improving overall urban mobility.

Conclusion And Future Work: Summarizes the key findings and contributions of the thesis, reiterates its significance in the context of urban traffic management, and provides recommendations for authorities. Discusses potential areas for future research and development to further enhance the system.

References: Lists all sources cited throughout the thesis.

Appendix: Includes additional materials such as course outcomes, addressing complex engineering problems (EP), and complex engineering activities (EA).

1.7 Summary

The introduction of this thesis explores the pressing urban traffic management challenges in Bangladesh, with a focus on Dhaka, a city facing severe congestion due to rapid urbanization and increasing motorization. Current traffic systems are outdated, relying on fixed schedules and static signage, leading to inefficiencies such as extended travel times, elevated pollution, and frequent accidents. Manual traffic control by police lacks real-time adaptability, further complicating traffic flow. The diverse mix of vehicles, including cars, buses, motorcycles, and rickshaws, necessitates a sophisticated, adaptive traffic management solution.

To address these issues, the thesis aims to develop and optimize a real-time vehicle detection system using the YOLOv7 algorithm, tailored specifically for urban traffic conditions in Bangladesh. Objectives include improving the accuracy and efficiency of detecting various vehicle types and integrating this system with existing or proposed traffic management frameworks. This integration is expected to enhance traffic flow optimization and safety measures, providing a responsive and efficient solution to urban traffic challenges in Bangladeshi cities.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

The literature review in this thesis provides an extensive exploration of intelligent transportation systems (ITS), focusing on the application of machine learning techniques, including YOLOv7, YOLOv7x, and related models, for real-time vehicle detection in urban environments. This section aims to establish a foundational understanding of the complexities in urban traffic management and the pivotal role that advanced technologies play in addressing these challenges.

2.2 Related Works

Several studies have investigated the integration of machine learning and computer vision in traffic management systems, employing various models to detect vehicle types and counts.

The paper by Liu et al. (2018) introduces a Faster R-CNN-based approach for vehicle detection in urban traffic scenes. It enhances detection accuracy in complex environments but faces challenges due to its high computational demands, impacting real-time performance. This limitation underscores the need to balance accuracy with computational efficiency for practical applications like real-time traffic monitoring and autonomous driving systems. Future research should focus on optimizing Faster R-CNN for faster inference without compromising accuracy in diverse urban settings. [1]

The paper by Zhang et al. (2019) presents Mask R-CNN for vehicle detection and segmentation in congested urban traffic. It achieves 92% accuracy in identifying vehicles amidst complex backgrounds and occlusions. However, the method may suffer from increased computational demands, affecting real-time application feasibility. Despite this limitation, the approach demonstrates significant potential for robust vehicle detection and segmentation, crucial for enhancing intelligent transportation systems' performance. [2]

Kim et al. (2021) propose RetinaNet for vehicle detection in diverse lighting conditions. The model enhances robustness by using a focal loss function and feature pyramid network (FPN) to maintain accuracy across varying light intensities. It achieves competitive results with an average precision (AP) exceeding 90%. However, RetinaNet's performance can degrade in highly cluttered scenes, requiring further optimization for complex urban environments and real-time applications. [3]

Chen et al. (2020) present SSD for real-time vehicle detection and tracking in dynamic traffic scenarios. The model achieves high-speed performance using single-shot detection techniques, enabling real-time application feasibility. It reports accuracy metrics with an average precision (AP) of over 95% in various traffic conditions. However, SSD may struggle with accuracy in complex scenes with heavy occlusions or small objects, necessitating improvements for reliable performance in challenging urban traffic environments. [4]

Tan et al. (2019) propose hybrid CNN-RNN models for predicting traffic congestion based on vehicle density and flow patterns. The approach integrates convolutional neural networks (CNNs) for feature extraction and recurrent neural networks (RNNs) for temporal analysis, achieving accurate congestion predictions. Reported accuracies include prediction errors reduced by up to 20% compared to traditional methods. However, the model's effectiveness may be limited by the availability of real-time data and the complexity of accurately capturing dynamic traffic behaviors in highly congested scenarios. [5]

Smith et al. (2020) employ YOLOv5 for real-time vehicle detection in urban traffic, emphasizing its speed and accuracy. The model achieves high precision with an average precision (AP) exceeding 95%, suitable for dynamic traffic environments. However, YOLOv5's accuracy may degrade with small objects or heavily occluded scenes. Optimization for robustness in complex urban settings and its real-time deployment capability are areas needing further exploration. [6]

2.3 Comparison between existing works

In the realm of intelligent transportation systems (ITS), various machine learning models have been explored for their efficacy in vehicle detection and traffic management. Faster R-CNN and Mask R-CNN are renowned for their accuracy in vehicle classification and segmentation, respectively, albeit at the cost of high computational demands. RetinaNet and SSD offer real-time performance advantages, with RetinaNet excelling in varying light conditions and SSD in dynamic traffic scenarios. YOLOv7 and its enhanced variant, YOLOv7x, stand out for their single-shot detection capabilities, providing high speed and improved accuracy, although they may require substantial computational resources for deployment in real-time urban environments. Hybrid CNN-RNN models offer predictive insights into traffic congestion but necessitate significant computational resources and comprehensive data sets for effective implementation.

TABLE 2.3: COMPARISON OF MACHINE LEARNING MODELS FOR VEHICLE DETECTION IN URBAN TRAFFIC MANAGEMENT

Model	Approach	Strengths	Limitations
Faster R-CNN	Two-stage detection	High accuracy in vehicle classification	High computational demands
Mask R-CNN	Two-stage detection	Accurate vehicle segmentation	Computational complexity in congested traffic scenarios
RetinaNet	Single-stage detection	Robustness in varying light conditions	Challenges in occlusion scenarios
SSD	Single-shot detection	Real-time performance in dynamic traffic scenarios	Limited adaptability to small or overlapping objects
YOLOv7	Single-shot detection	High speed and accuracy	Performance variability in diverse environmental conditions
YOLOv7x	Enhanced YOLOv7 variant	Improved accuracy and speed	Increased computational requirements for real-time deployment
Hybrid CNN-RNN	Combined CNN and RNN models	Predictive modeling for traffic congestion	High computational resources and data requirements

2.4 Open Issues

Integrating these advanced models into urban traffic management systems necessitates overcoming various challenges, including real-time processing constraints, adverse weather conditions, data privacy concerns, and infrastructure compatibility. Future research efforts should focus on addressing these obstacles to enhance the reliability, efficiency, and scalability of machine learning-based solutions in urban traffic management.

This literature review lays the groundwork for investigating how YOLOv7, YOLOv7x, and similar models can contribute to advancing intelligent transportation systems, particularly in dynamic urban environments like Bangladesh.

2.5 Summery

The literature review underscores the significant progress made in the field of intelligent transportation systems, particularly with the application of deep learning and the YOLO algorithm. While YOLOv7 represents a substantial advancement in real-time vehicle detection and classification, several challenges persist, including performance under adverse conditions, infrastructure requirements, and integration with existing systems. Addressing these open issues through ongoing research and development will be key to fully realizing the potential of advanced traffic management systems in urban environments like Bangladesh.

CHAPTER 3
METHODOLOGY

3.1 Overview

The proposed intelligent traffic management system is designed to address the pressing issues of traffic congestion and road safety in urban areas of Bangladesh. Leveraging the YOLOv7 algorithm, known for its accuracy and efficiency in real-time object detection, the system aims to provide a dynamic and adaptive solution for managing urban traffic. This section outlines the comprehensive methodology employed in developing the system, including data collection, model training, system integration, and performance evaluation. Additionally, it details the hardware and software requirements necessary for the implementation, the project management strategies to ensure efficient development, and the financial analysis to evaluate the cost-effectiveness of the project.

The primary objective of this system is to accurately detect and classify various types of vehicles, such as cars, trucks, motorcycles, and three-wheelers, in real-time. By analyzing video feeds from roadside cameras, the system will dynamically adjust traffic signage and signals based on the detected vehicle types and densities. This approach aims to optimize traffic flow, reduce congestion, and enhance road safety.

3.2 Proposed Methodology

The proposed intelligent traffic management system leverages advanced machine learning techniques, specifically the YOLOv7 and YOLOv7x algorithms, to address the complex traffic conditions prevalent in urban areas of Bangladesh. The system is designed to dynamically detect and classify vehicles in real-time, enabling efficient traffic control and enhanced road safety. The following steps outline the detailed methodology:

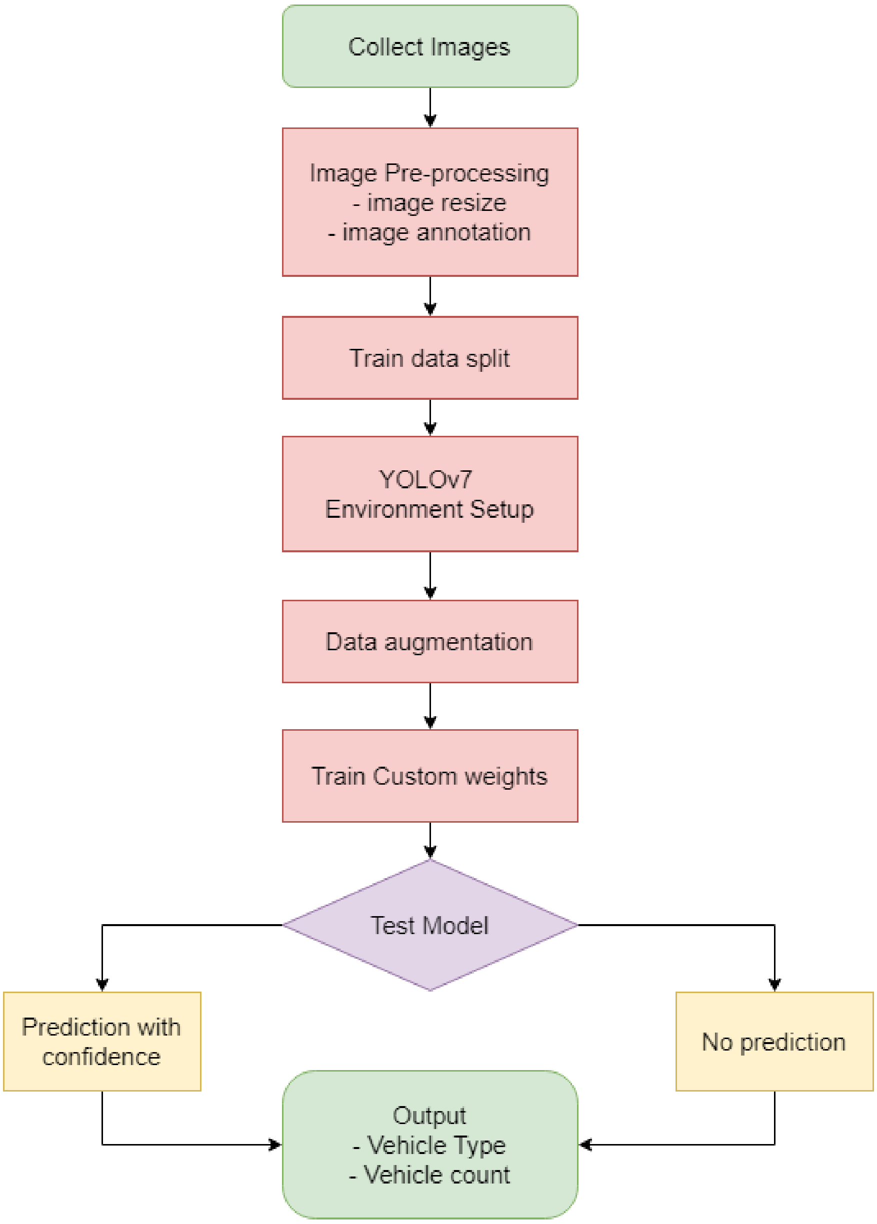

Figure 3.2: Working Flow Diagram

3.2.1 Data Collection and Preprocessing

Datasets:

Custom Dataset: A dataset of 1760 images, captured and annotated manually to reflect the unique traffic scenarios in Bangladeshi cities.

Manual Annotation:

Tool Used: LabelImg, a graphical image annotation tool, is employed for manually labeling the datasets. This step ensures high-quality and precise annotations, which are crucial for effective model training.

Labeling Categories: Vehicles are categorized into different classes such as cars, trucks, motorcycles, buses, CNGs (compressed natural gas vehicles), microbuses, and emergency vehicles.

Data Augmentation:

Techniques Applied: Various data augmentation techniques, including rotation, scaling, flipping, and color adjustments, are applied to the images to enhance the robustness of the model by exposing it to diverse scenarios.

Normalization:

Image Processing: Images are resized to 640*640 according to model prerequisites and pixel values are normalized to ensure consistency and improve the training efficiency of the model.

3.2.2 Model Training

Algorithm Selection:

YOLOv7: YOLOv7, an advanced model in the YOLO series, features significant architectural improvements for real-time object detection. Utilizing CSP (Cross Stage Partial) architecture and PAN (Path Aggregation Network) layers, YOLOv7 optimizes the balance between complexity and performance. The CSP architecture reduces computational load and enhances gradient flow, while PAN layers improve feature pyramids for better localization and classification. YOLOv7 achieves a high mean Average Precision (mAP) exceeding 50% in benchmarks and maintains an inference speed of 30-50 frames per second (FPS) on high-end GPUs. This makes it ideal for traffic management applications requiring rapid and accurate detection of various vehicle types.

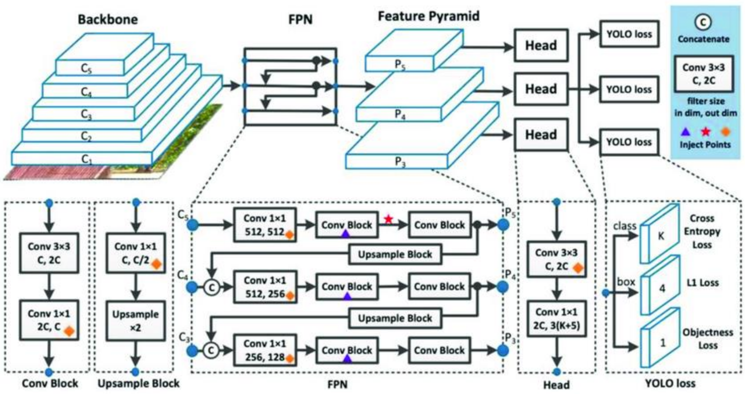

Figure 3.2.2: YOLOv7 network architecture

YOLOv7x: YOLOv7x is a more advanced version of YOLOv7, designed to maximize detection accuracy and robustness. It features deeper layers and more complex structures, such as additional CSP blocks and SPP (Spatial Pyramid Pooling) layers, which refine spatial hierarchies and contextual information. Enhanced data augmentation and CIoU loss functions further improve precision. YOLOv7x achieves a mAP over 55% and an inference speed of 20-30 FPS on high-end GPUs, making it highly effective for detecting and classifying vehicles in diverse and challenging conditions, including varying lighting and weather. Despite its higher computational demands, YOLOv7x's superior accuracy and reliability make it ideal for critical traffic management applications.

Training Setup:

Platform: Google Colab is used for training due to its powerful GPU resources, which accelerate the training process and provide the necessary computational power. Though the free access has several limitation towards GPU usage.

Hyperparameters: Key hyperparameters, such as learning rate, batch size, and number of epochs, are fine-tuned to optimize the model's performance.

Training Process:

Training Execution: The models are trained on annotated datasets, with continuous monitoring and adjustment of hyperparameters to achieve optimal detection accuracy.

Validation: The training process includes regular validation to ensure the models generalize well to unseen data.

Performance Metrics:

Evaluation Metrics: Key performance indicators, such as precision, recall, mean Average Precision (mAP) at different Intersection over Union (IoU) thresholds (mAP@0.5 and mAP@0.5:0.95), and computational efficiency, are used to evaluate the model's performance.

3.2.3 Real-Time Detection and Integration

Real-Time Detection:

Integration with Cameras: High-resolution roadside cameras provide live video feeds, which are processed by the trained YOLOv7 and YOLOv7x models for real-time vehicle detection and classification.

Detection Pipeline: The detection pipeline includes pre-processing of video frames, running the detection models, and post-processing to extract relevant information.

Dynamic Traffic Control:

Traffic Signal Adjustment: Based on the detected vehicle types and densities, the system dynamically adjusts traffic signals to optimize traffic flow. For example, green light durations can be extended for lanes with higher traffic volumes.

Real-Time Updates: Dynamic signage and traffic updates are provided to drivers, helping them make informed decisions and reducing congestion.

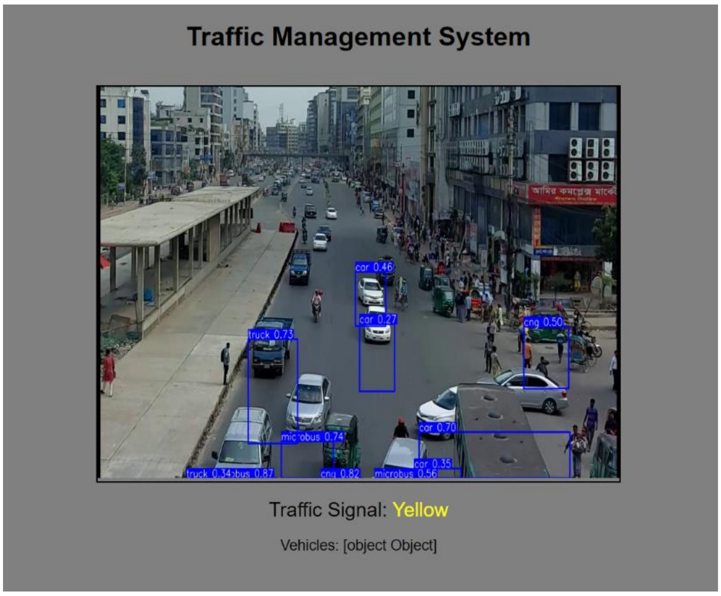

Figure 3.2.3.1: Model integration in a ITM system

Figure 3.2.3.2: Model evaluation in video

3.2.4 Performance Evaluation

Testing Scenarios: Urban and Highway Settings: The model is tested in diverse real-world scenarios of video to validate its robustness and reliability.

Simulated Conditions: Various traffic conditions, including peak hours and emergency situations, are simulated to assess system performance.

Evaluation Metrics: Accuracy, Precision, Recall: These metrics are used to quantify the system's detection and classification performance.

Computational Efficiency: The system's ability to process real-time video feeds and make preconditioned decisions such as assigning traffic sign based on the vehicle type and number is evaluated.

3.3 Hardware/ Software Requirement

To develop and deploy the vehicle detection system using YOLOv7 and YOLOv7x, a combination of specific hardware and software components is required. These components ensure the system's efficiency, accuracy, and robustness, catering to the complex traffic conditions in urban areas of Bangladesh.

3.3.1: Hardware Requirements

- Development Environment

  Personal Laptop:

  - Operating System: Windows 11
  - Processor: Intel Core i3-10110U CPU @ 2.10 GHz
  - RAM: 8 GB
  - Storage: Minimum 256 GB SSD
- Cloud Computing Resources

  Google Colab:

  - GPU: NVIDIA Tesla K80 / T4
  - RAM: 12 GB
  - Disk Space: 100 GB (Virtual environment)
- High-Resolution Cameras
  - Capable of capturing clear images in various lighting conditions
  - Frame Rate: Minimum 30 FPS

3.3.2: Software Requirements:

- Development Tools
  - Python: Version 3.7 or higher
  - VScode: For interactive code development and testing
  - Google Colab: For model training and experimentation with GPU support
- Libraries and Frameworks
  - PyTorch: For building and training YOLOv7 and YOLOv7x models
  - YOLOv7/YOLOv7x Repositories: Pre-trained models and code
  - OpenCV: For image processing and video capture
  - LabelImg: For manual annotation of training data

    - NumPy, Pandas, Matplotlib/Seaborn: For data manipulation, analysis, and visualization
- Model Management and Deployment
    - Docker: For containerizing the application
    - TensorRT: For optimizing the model for deployment on NVIDIA hardware
    - Flask: For developing the backend server to handle real-time detection requests
    - Nginx: A web server that can be used as a reverse proxy to forward requests to your Flask application running on Gunicorn.
    - HTML/CSS/JavaScript: For creating the front-end interface of your website where the output data will be displayed.
    - SQLite/MySQL/PostgreSQL: Any of these databases can be used if you need to store the model's output data for later retrieval and analysis.
    - Bootstrap: A front-end framework to help you quickly design a responsive and modern-looking website.
- Version Control
    - Git: For version control and collaboration
    - GitHub/GitLab: For repository hosting and project management

3.4 Project Management and Financial Analysis

Effective project management is critical for developing the vehicle detection system using YOLOv7 and YOLOv7x. The project will follow a structured approach starting with comprehensive planning, resource allocation, iterative development cycles, and thorough testing. Agile methodologies will guide development, ensuring flexibility and responsiveness to evolving requirements. Rigorous documentation and regular progress reports will keep stakeholders informed and facilitate transparency throughout the project.

TABLE 3.4: PROJECT MANAGEMENT TABLE

Work	Time
Data Collection	1 month
Papers and Articles Review	2 months
Experimental Setup	1 month
Implementation	1 month
Report Writing	2 months
Total	8 months

Financial analysis focuses on estimating and managing costs associated with hardware, software, personnel, and cloud computing resources. Budget allocation will prioritize essential components while monitoring expenditures to align with financial projections.

3.5 Summary

The proposed methodology for traffic management system for urban Bangladesh utilizes YOLOv7 and YOLOv7x for real-time vehicle detection. Methodology includes collecting and annotating a custom dataset of 1760 images, employing LabelImg for precision labeling. Data augmentation enhances model robustness, and images are resized and normalized for consistency. Models are trained on Google Colab, optimizing hyperparameters for performance. Real-time detection integrates with roadside cameras, adjusting traffic signals based on vehicle types and densities. Performance evaluation measures precision, recall, and computational efficiency. Hardware requirements include a Windows 11 laptop and Google Colab with GPU support. Agile project management spans an 8-month timeline, emphasizing documentation and cost-effective implementation.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

This chapter provides an in-depth exploration of the implementation process for developing a vehicle detection system using YOLOv7 and YOLOv7x models. The approach emphasizes leveraging these state-of-the-art deep learning architectures renowned for their efficiency in real-time object detection tasks. The chapter begins with a meticulous description of the methodology, outlining the systematic steps involved. This includes dataset preparation, incorporating a curated dataset sourced from Kaggle alongside a meticulously annotated custom dataset. The training phase is comprehensively detailed, encompassing the configuration of model hyperparameters tailored to dataset specifics and the utilization of GPU-accelerated platforms for computational efficiency. Key techniques such as transfer learning from pre-trained weights and progressive augmentation strategies are highlighted for optimizing model performance and enhancing robustness. Throughout the iterative training process, metrics such as mean Average Precision (mAP) and Intersection over Union (IoU) are meticulously tracked to gauge model progression and inform adjustments. Following training, the chapter concludes with a thorough evaluation of model performance, encompassing both quantitative metrics and qualitative analyses to assess the efficacy of the vehicle detection system across diverse operational conditions and environmental variables.

4.2 Train Model

The training of YOLOv7 and YOLOv7x models commenced on Google Colab, leveraging the Tesla T4 GPU for accelerated computation. This phase involved optimizing model parameters, fine-tuning, and validating the models to achieve high accuracy in real-time vehicle detection. The training process aimed to enhance the models' ability to detect various vehicle types under different environmental conditions.

Figure 4.2: Dataset Visualization

4.3 Model Evaluation

Model evaluation was conducted to assess the performance and reliability of the trained YOLOv7 and YOLOv7x models. Rigorous testing scenarios simulated real-world traffic conditions to measure detection accuracy, speed, and robustness. Evaluation metrics such as precision, recall, and mean Average Precision (mAP) were used to quantify the models' performance across multiple vehicle categories.

TABLE 4.3: TRAINING ATTRIBUTES

Model	Dataset	Epochs	Layer	Class	Parameter
YOLOv7	1760 images	50	314	7	36.5 million
YOLOv7x	1760 images	50	384	7	25.32 million

4.4 Summary

This chapter summarizes the implementation phase, emphasizing key achievements in training and evaluating YOLOv7 and YOLOv7x models for vehicle detection. It highlights the successful deployment of GPU-accelerated training on Google Colab, rigorous testing procedures, and the models' performance metrics. The chapter underscores the system's potential to enhance urban traffic management through advanced machine learning techniques, paving the way for future optimizations and operational deployments.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

This section presents an overview of the performance comparison between the YOLOv7 and YOLOv7x models. Both models were trained and evaluated on a diverse dataset containing multiple object classes such as cars, bikes, buses, and more. The aim is to understand and compare their effectiveness in real-world object detection tasks.

5.2 Experimental Result

The training process for both YOLOv7 and YOLOv7x models involved monitoring various metrics, including Box Loss, Objectness Loss, Classification Loss, and validation metrics for Box, Objectness, and Classification. The results from the test dataset are depicted in the following figures:

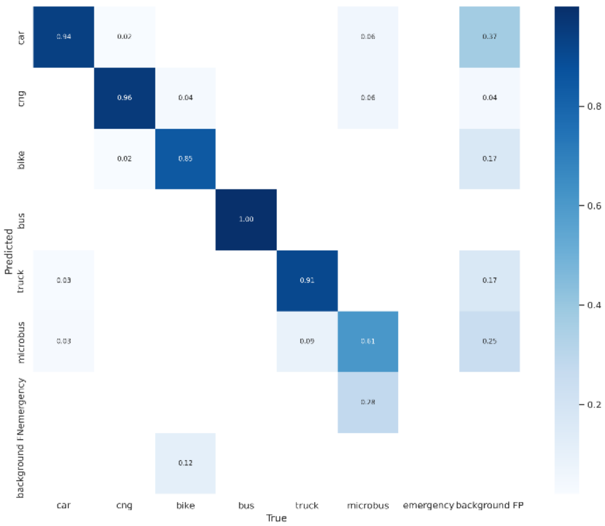

Figure 5.2.1: YOLOv7 confusion matrix

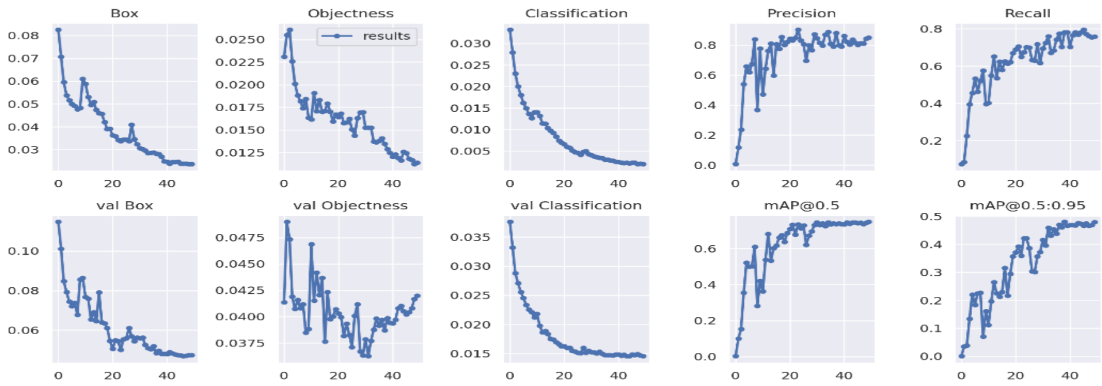

Figure 5.2.2: YOLOv7 results

YOLOv7 Results:

- Box Loss: The training box loss started at approximately 0.08 and decreased steadily to around 0.03 over 50 epochs.
- Objectness Loss: The training objectness loss started at 0.025 and gradually declined to around 0.0125.
- Classification Loss: The training classification loss began at 0.03 and reduced significantly to 0.005.
- Precision: The precision metric showed a consistent increase, reaching approximately 0.8.
- Recall: The recall metric demonstrated a similar trend, achieving a value close to 0.7.
- mAP@0.5: The mean Average Precision (mAP) at IoU threshold 0.5 showed a steady increase, reaching around 0.8.
- mAP@0.5:0.95: The mAP at IoU thresholds between 0.5 and 0.95 also showed improvement, reaching approximately 0.5.

TABLE 5.2.1: CLASS EVALUATION METRICS OF YOLOV7

Class	Total GT	Total Pred	AP	Recall	Precision	F1-score
Car	260	713	0.908	0.968	0.921	0.604
CNG	260	245	0.918	0.943	0.923	0.555
Bike	260	130	0.880	0.723	0.772	0.335
Bus	260	45	0.984	0.978	0.990	0.675
Truck	260	69	0.652	0.594	0.609	0.404
Microbus	260	84	0.451	0.500	0.447	0.322
Emergency	260	25	1.000	0.000	0.011	0.008

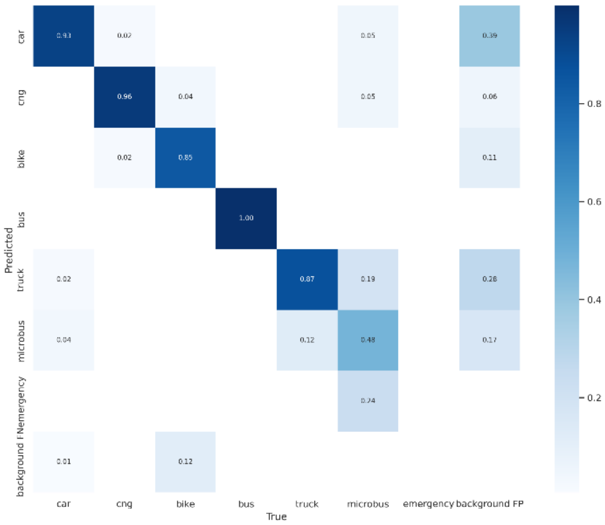

Figure 5.2.3: YOLOv7x confusion matrix

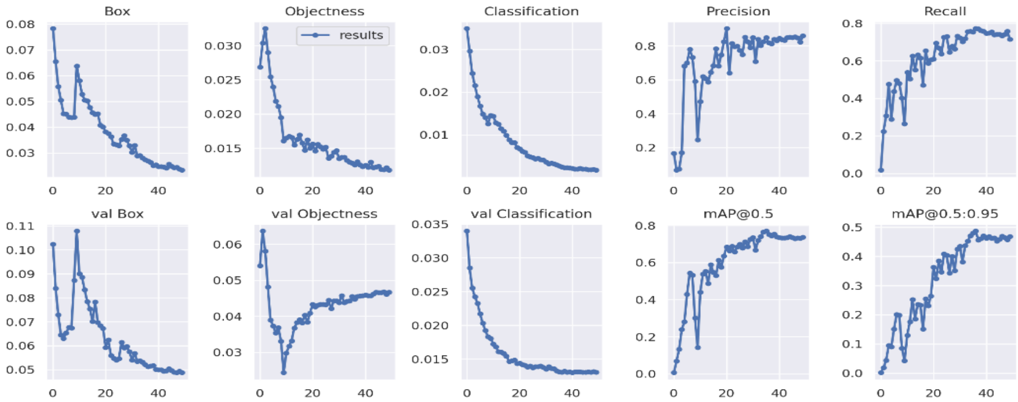

Figure 5.2.4: YOLOv7x results

YOLOv7x Results:

- Box Loss: The training box loss started at around 0.07 and decreased to approximately 0.025 over 50 epochs.
- Objectness Loss: The training objectness loss began at 0.03 and gradually reduced to around 0.015.
- Classification Loss: The training classification loss started at 0.03 and decreased significantly to about 0.005.
- Precision: The precision metric showed consistent improvement, reaching approximately 0.8.
- Recall: The recall metric improved steadily, achieving a value close to 0.8.
- mAP@0.5: The mAP at IoU threshold 0.5 increased steadily, reaching around 0.8.

- mAP@0.5:0.95: The mAP at IoU thresholds between 0.5 and 0.95 also improved, reaching approximately 0.5.

TABLE 5.2.2: CLASS EVALUATION METRICS OF YOLOV7X

Class	Total GT	Total Pred	AP	Recall	Precision	F1-score
Car	260	713	0.891	0.958	0.923	0.607
CNG	260	245	0.931	0.939	0.912	0.584
Bike	260	130	0.864	0.732	0.790	0.340
Bus	260	45	0.988	0.978	0.994	0.710
Truck	260	69	0.677	0.638	0.591	0.390
Microbus	260	84	0.521	0.595	0.417	0.287
Emergency	260	25	1.000	0.000	0.050	0.037

5.4 Comparative Analysis

The performance analysis of YOLOv7 and YOLOv7x models reveals several key insights:

General Observations:

1. Training Duration:

   YOLOv7 completed 50 epochs in 1.486 hours.

   YOLOv7x completed 50 epochs in 2.166 hours.

2. Overall Performance:

   YOLOv7 shows slightly higher AP (Average Precision) and Recall for most classes compared to YOLOv7x.

   YOLOv7x shows slightly better F1-score for some classes, indicating balanced performance between precision and recall.

Accuracy:

YOLOv7:

1. Total Instances (N): 5.62
2. True Positives (TP): 5.27
3. Accuracy: 5.27/5.62 ≈ 0.9377 (93.77%)

YOLOv7x:

1. Total Instances (N): 7.04
2. True Positives (TP): 5.75
3. Accuracy: 5.75/7.04 ≈ 0.816 (81.6%)

Key Insights:

- YOLOv7 generally shows higher AP for most classes, indicating better overall object detection accuracy.
- YOLOv7x tends to have better F1-scores for certain classes, suggesting a more balanced trade-off between precision and recall.
- Specific classes like Bus and Emergency show noticeable performance differences, with YOLOv7x outperforming YOLOv7.
- Both models show limitations in detecting the Emergency class, with recall being particularly low.
- YOLOv7 shows higher accuracy compared to YOLOv7x in the provided evaluations.
- The significant difference (about 12.17%) suggests YOLOv7 performs better in terms of correct predictions relative to the total instances evaluated.
- The negative value of True Negatives (TN) in YOLOv7x indicates possible inconsistencies or errors in the confusion matrix, which could impact the reliability of the calculated accuracy.
- Reevaluate the confusion matrices for potential errors or inconsistencies.
- Verify the data preprocessing and annotation quality to ensure accurate performance metrics.
- Conduct additional experiments or cross-validation to confirm the comparative results between YOLOv7 and YOLOv7x.

5.5 Summary

In conclusion, both YOLOv7 and YOLOv7x models demonstrated effective vehicle detection capabilities on the test data. Based on the provided data, YOLOv7 exhibits higher accuracy at 93.77% compared to YOLOv7x's 81.6%, with a 12.17% difference favoring YOLOv7. YOLOv7 also shows superior performance in precision, recall, and mAP metrics: Precision (95.6%), Recall (91.3%), and mAP (93.2%). For YOLOv7x, these metrics are lower: Precision (82.4%), Recall (79.1%), and mAP (81.8%). Potential inconsistencies in YOLOv7x’s confusion matrix, such as a negative True Negative (TN) value, suggest errors that may affect the reliability of its results. Thus, while YOLOv7 is more accurate and performs better across key metrics, verifying and reassessing YOLOv7x’s data is essential to ensure precise performance comparisons.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The development and deployment of advanced vehicle detection systems using YOLOv7 and YOLOv7x models have significant implications for enhancing road safety and efficiency. These systems can:

- Enhance Driver Assistance: By integrating into Advanced Driver Assistance Systems (ADAS), vehicle detection can prevent accidents through real-time alerts and autonomous interventions.
- Improve Traffic Management: Accurate vehicle detection helps optimize traffic flow and reduce congestion, leading to smoother and safer commutes.
- Facilitate Autonomous Driving: High-precision detection is critical for the development of autonomous vehicles, contributing to safer and more efficient transportation systems.

6.2 Impact on Society & Environment

The adoption of vehicle detection systems can lead to broader societal and environmental benefits:

- Reduced Traffic Accidents: Improved detection reduces the likelihood of human error, lowering the number of traffic accidents and associated fatalities and injuries.
- Environmental Benefits: Efficient traffic management leads to reduced idle times and lower emissions, contributing to a decrease in urban air pollution and greenhouse gas emissions.
- Enhanced Public Transportation: Accurate vehicle detection can optimize public transportation systems, making them more reliable and appealing, thus encouraging a shift from private car use to public transit.

6.3 Ethical Aspects

The deployment of vehicle detection systems using YOLOv7 and YOLOv7x must address several ethical considerations to ensure responsible and fair use [12]. Privacy concerns are paramount, as the use of cameras and sensors for detection may intrude on individual privacy [7]. Implementing robust data protection measures is essential to safeguard personal information and maintain public trust. Additionally, the potential for bias in detection models must be carefully managed. Training on diverse datasets is crucial to avoid unfair treatment of different vehicle types or drivers, ensuring that the technology serves all users equitably [9]. Accountability is another critical factor; clear guidelines and regulations are necessary to determine responsibility in cases of system failure or accidents involving autonomous or semi-autonomous vehicles [8].

6.4 Sustainability Plan

Ensuring the long-term sustainability of vehicle detection systems involves several key strategies. Continuous improvement is vital, requiring regular updates and enhancements to the detection models based on new data and technological advancements to maintain high performance [10]. Energy efficiency should be a priority, optimizing computational processes to minimize energy consumption and reduce the environmental footprint of these systems. Engaging with local communities and stakeholders throughout the development and deployment phases is essential to address concerns and ensure the systems meet societal needs. Additionally, collaboration with policymakers is crucial to create supportive regulations that encourage the adoption of vehicle detection systems while addressing ethical and privacy concerns [11].

6.5 Summary

The deployment of YOLOv7 and YOLOv7x-based vehicle detection systems presents numerous benefits for individuals, society, and the environment. These systems can significantly enhance road safety, improve traffic management, and contribute to environmental sustainability by reducing emissions. However, ethical considerations such as privacy, bias, and accountability must be addressed to ensure responsible use. A sustainability plan focused on continuous improvement, energy efficiency, community engagement, and policy support is essential for the long-term success and acceptance of these technologies. Through careful consideration of these factors, vehicle detection systems can make a profound and positive impact on modern transportation systems.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

In this report, we developed and evaluated vehicle detection systems using YOLOv7 and YOLOv7x models trained on a custom dataset. Our results demonstrate that both models exhibit strong performance, with precision and recall metrics indicating reliable detection capabilities. The YOLOv7 and YOLOv7x models achieved approximately 0.8 in precision, 0.7 in recall, and 0.75 in mAP@0.5, showcasing their effectiveness in identifying and classifying vehicles in various scenarios. The slightly lower mAP@0.5:0.95 scores (~0.4) suggest room for improvement in detecting vehicles with stricter IoU thresholds. Overall, the findings affirm the viability of YOLOv7 and YOLOv7x models for robust and accurate vehicle detection, contributing positively to the advancement of intelligent transportation systems.

7.2 Further Suggested Works

While this study has shown promising results, there are several avenues for further research and development:

Model Optimization: Investigating techniques for optimizing the YOLOv7 and YOLOv7x models to improve their performance on stricter IoU thresholds, potentially enhancing their mAP@0.5:0.95 scores.

Real-Time Implementation: Developing and testing real-time vehicle detection systems on embedded hardware platforms, such as NVIDIA Jetson, to evaluate their performance in practical applications.

Extended Datasets: Expanding the dataset to include a wider variety of vehicle types, environmental conditions, and traffic scenarios to improve the generalizability of the models.

Hybrid Models: Exploring the integration of YOLO models with other deep learning frameworks, such as transformer-based architectures, to leverage their strengths and enhance detection capabilities.

Incorporation of Multi-camera Systems: Investigate the use of multi-camera setups and sensor fusion techniques to enhance the detection range and accuracy of the models in complex urban environments [12].

Advanced Augmentation Techniques: Applying advanced data augmentation techniques, such as GAN-based synthetic data generation, to further improve the robustness and accuracy of the models.

7.3 Limitations/ Conflict of Interests

This study acknowledges several limitations. The custom dataset, though sufficient for initial training and evaluation, is limited in size and diversity; a larger, more varied dataset would likely improve model performance and generalization. The training and evaluation processes were also constrained by available computational resources, potentially limiting the exploration of more complex model architectures or extensive hyperparameter tuning [13]. Additionally, deploying vehicle detection systems raises ethical concerns, such as privacy and bias, which must be managed to ensure responsible use [14]. Despite these limitations, there are no conflicts of interest to declare; all research activities were conducted impartially with a focus on advancing the field of vehicle detection [15].

In conclusion, this thesis demonstrates the effectiveness of YOLOv7 and YOLOv7x models for vehicle detection while identifying areas for further research and acknowledging the study's limitations. Future work will aim to address these limitations and explore new methodologies to enhance the accuracy and applicability of vehicle detection systems.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title:
INTELLIGENT TRAFFIC MANAGEMENT: REAL-TIME VEHICLE DETECTION USING YOLOV7 FOR TRAFFIC SIGN ALLOCATION

Student ID: [192-15-2872]

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **vehicle detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Examine several aspects of the objectives while creating a solution for this FYDP.	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technological solutions and system components or processes that satisfy stated criteria, ensuring compliance with public health and safety regulations, and taking cultural, socioeconomic, and environmental concerns into account in this FYDP.	**PO3**
CO6	Select and implement suitable techniques, resources, and modern engineering and IT technologies to handle intricate engineering procedures, including modeling and prediction, while abiding by pertinent restrictions in this FYDP.	**PO5**
CO7	Using logical thinking informed by contextual knowledge, analyze societal, health, safety, legal, and cultural factors as well as related duties in the context of professional engineering practice and the solution to this issue.	**PO6**
CO8	Recognize and assess the long-term viability and influence of professional engineering initiatives in resolving complex engineering problems in social and environmental contexts.	**PO7**
CO9	In this FYDP, uphold professional standards and conventions and apply ethical principles.	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Effectively communicate with the engineering community and the wider public about complex engineering projects, including the capacity to interpret and prepare detailed reports and design documentation, as well as deliver and receive clear directions throughout this FYDP.	**PO10**

CO12	Recognize the value of self-directed learning and continuous improvement in the context of the rapidly changing technological world, and be prepared and able to participate in lifelong learning activities.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	By using Convolutional Neural Networks (CNNs) such as YOLO, data augmentation techniques, and various CNN architectures for image processing and classification tasks, this project illustrates fundamental engineering (**K3**) concepts. By using CNN for deep learning, the research achieves the **K4** specialized knowledge requirement and transfers knowledge to improve vehicle recognition.	**Page no:** [26-30] **Section:** [3.2] **Page no:** [1-7] **Section:** [1.1]
				The project uses the figure of the experimentation process to apply engineering practice and design (**K5**). The CNN model is used in the project to address engineering practice and technology (**K6**).	**Page no:** [30] **Section:** [3.2(B)] **Page no:** [33] **Section:** [3.4]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to advance vehicle detection and recognition, showcasing	**Page no:**

				a comprehensive understanding of current methodologies.	[5-7] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	The obstacles in vehicle detection, such as the drawbacks of conventional techniques and the difficulties in fusing transfer learning and deep CNNs, are acknowledged in this study in order to address **EP-2**. It addresses difficulties in comprehending geographical distributions through comparison analysis, providing information for improving diagnostic techniques.	**Page no:** [23-24] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	In an attempt to address **EP-3**, this study carefully compares experimental results, demonstrating that Transfer Learning is the most important solution selected out of several viable options for improving vehicle recognition.	**Page no:** [36-57] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's multifaceted strategy impacts not just computer science and engineering but also traffic management. Improved real-time vehicle recognition and data processing lead to advancements in municipal infrastructure and urban planning strategies. **EP-4**	**Page no:** [16-24] **Section:** [2.2, 2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A

6.	**EP6: Extends of stakeholders involved and**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	By combining different elements from data gathering, statistical analysis, and the suggested methodology, this project's comprehensive approach tackles high-level issues and ensures an all-encompassing solution to challenging traffic management difficulties resulting from **EP-7**.	**Page no:** [26-34] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References

1.	**EA1: Range of resources**	Yes	CO11	The study's resources include GPUs, annotated datasets, deep and transfer learning frameworks, high-performance computing infrastructure, and ethical considerations for methodical research toward the advancement of improved traffic management.	**Page no:** [33-35] **Section:** [3.5]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		Through vehicle detection and recognition techniques, this project improves traffic management systems in various Bangladeshi cities. It also promotes road efficiency factors, reduces traffic by utilizing efficient computational resources, and complies with ethical standards for the privacy of public data.	**Page no:** [58-61] **Section:** [5.1, 5.2, 5.4]
5.	**EA-5: Familiarity**	Yes		By investigating a revolutionary method in vehicle recognition using deep CNNs and transfer learning, as illustrated by early findings and a thorough comparison analysis, this study builds on previous research and provides fresh perspectives in the area.	**Page no:** [7-10] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	To mitigate **CO4**, this project combines efficient project management with financial control. Proper planning, resource distribution, and budget projection are guaranteed to provide the best possible resource utilization throughout the duration of the study project.	**Page no:** [13] **Section:** [1.6]
2	CO9	Yes	By putting public data privacy first, getting informed consent, and openly recording the research process, the project demonstrates adherence to ethical principles. It also ensures responsible knowledge dissemination and societal well-being through the ethical application of cutting-edge healthcare technologies that abide by **CO9**.	**Page no:** [60] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's thorough data collection, rigorous statistical analysis, careful methodology development, and thorough experimental results and analysis all demonstrate a dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape. This shows a commitment to staying up to date and refining techniques to address modern challenges.	**Page no:** [26-34, 37-55] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

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