School of

Electronics and Communication Engineering

Minor - II Project Report

on

Smart Traffic Light Control System

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SCHOOL OF ELECTRONICS AND COMMUNICATION ENGINEERING

CERTIFICATE

This is to certify that project entitled **" Smart Traffic Light Control System "** is a bonafide work carried out by the student team of **"Puneet R K - 01FE21BEC101, Pranav P - 01FE21BEC096, Jayapriya A N - 01FE21BEC134, Shreya Nadgir - 01FE21BEC127, Mahati V Phadnis - 01FE21BEC039"**. The project report has been approved as it satisfies the requirements with respect to the mini project work prescribed by the university curriculum for BE (VI Semester) in School of Electronics and Communication Engineering of KLE Technological University for the academic year 2023-2024.

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- The Project Team

ABSTRACT

Traffic congestion in modern cities necessitates innovative management strategies to ensure smooth and efficient movement of vehicles. The Smart Traffic Light Control System (STLCS) addresses this challenge by optimizing intersection traffic flow through dynamic adjustments of traffic light sequences and durations based on real-time vehicle densities at each lane. After each phase, the vehicle densities of the remaining lanes are re-evaluated to determine the next lane to receive a green light. By proportionally distributing the total cycle length according to vehicle densities, STLCS ensures lanes with higher traffic receive more green light time, enhancing overall traffic efficiency. This system results in reduced travel times, lower emissions, and improved road safety. Case studies and simulations have demonstrated STLCS's effectiveness in various urban environments, showcasing its potential to revolutionize traffic management in congested cities.

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Chapter 1

Introduction

Traffic Congestion is a traffic phenomena characterized by slower vehicle speeds, longer trip times and increased queuing of vehicles.
Traffic congestion occurs when the number of vehicles is larger than the capacity of a road or intersection. As a result vehicles pile up, velocity decreases and trip time increases.
Traffic demand often grows over time, thus traffic congestion occur simply because of the inefficient traffic light control system.

1.1 Motivation

The critical need for a Smart Traffic Light Control System arises from the persistent inefficiencies of traditional traffic light systems in congested urban areas, which contribute to longer travel times and heightened environmental pollution. Current systems lack the adaptability to respond to fluctuating traffic conditions, resulting in suboptimal traffic flow and increased emissions. Motivated by the necessity to enhance urban mobility and sustainability, the development of STLCS leverages advanced technologies to provide a dynamic, real-time solution. This system aims to intelligently manage traffic, reduce congestion, and improve overall urban living conditions by ensuring more efficient and eco-friendly transportation networks.

1.2 Objectives

- Implement a robust system to collect and process real-time data from sensors, including vehicle presence, and vehicle counts detection at the intersection.

- Design algorithm capable of analyzing the collected data to dynamically adjust signal timings at intersections, prioritizing efficient traffic flow, reducing congestion, and minimizing travel times.

- Validate the performance of the signal timing adjustment algorithms through simulation and real-world testing, assessing their effectiveness in reducing congestion, minimizing travel times, and improving overall traffic efficiency.

1.3 Literature Survey

1. **Smart Traffic Control System using YOLO ((IRJET))** [4]

   The values will be read frame by frame in the streaming video of roads. Camera sends all the captured input videos to the cloud. The background algorithm filters the video to count the density of vehicles in every lane. Then based on threshold values each lane is prioritized and hence timer is set appropriately. Yolo helps to count vehicle in real-time. Density is counted on the basis of vehicle category.

2. **Deep Learning based smart traffic light system using Image Processing and YOLO** [3]

   Image and video datasets are selected from cameras monitoring traffic. Application of the YOLO v7 object identification technique using a neural network for traffic signal application. Model is trained on dataset comprising photos and videos of India road traffic. At the intersection, a camera will be put in place for the purpose of taking pictures of the lane's real-time traffic. The image processing methods are used to establish the traffic density. Thus, time is assigned for lanes and manage traffic lights based on percentage matching. The time for each lane is determined by the controller based on the percentage match.

3. **A Self-Adaptive Traffic Light Control System Based on YOLO** [5]

   This system is based on computer vision to have a real-time status of the traffic at the intersection. The embedded Controller is then processing the frames using YOLO as a deep CNN. Each lane, a Camera is installed and YOLO is detecting and tracking objects: For each new vehicle, the model is launching a timer to record its waiting time until it leaves the intersection. The controller can then compute vehicles per lane and their waiting time.Based on this real-time information, the system will optimize the green light timer of the next phase to enable maximum number of vehicles to pass safely with minimum waiting time.

4. **Smart Traffic Control System for Dubai: A Simulation Study Using YOLO Algorithm** [1]

   This proposed solution presents an effective approach for managing traffic flow. By utilizing video feeds from CCTV cameras, the system automatically detects the number and types of vehicles, including pedestrians, at the intersection. The AI software then analyzes this information in real-time to determine the efficient way to move traffic through the intersection, optimizing the changing of traffic lights accordingly. To achieve accurate vehicle detection, the system employs YOLO and CNN algorithms. YOLO is used to detect vehicles, people, and pedestrians. On the other hand, CNN is used for image processing, enabling the system to identify traffic congestion and respond appropriately.

5. **Design of a Smart Traffic Signal Control System for Smart City Applications** [2]

   In this paper, a multi-modal smart traffic control system (STSC) for the infrastructure in the smart city is proposed. The major components in the proposed STSC include RSU controller, OBU, signal controller, and cloud center. It supports EVSP, TSP, and R2V message broadcasting. New traffic signal scheme is specially designed for the EVSP, it can inform all the drivers near the intersection when EV is approaching, smoothing the traffic flow and enhancing the safety without extra hardware costs.

1.4 Problem Statement

Develop an Smart Traffic Light Control System to optimize the traffic light control based on real-time traffic conditions, reducing congestion and improving traffic flow in smart cities.

1.5 Application in Societal Context

There are several advantages for society in developing a smart traffic light control system that optimizes traffic light management based on current traffic circumstances. This technology can shorten commutes, increasing productivity and improving urban residents' quality of life by easing traffic congestion and optimizing traffic flow in smart cities.

Enhancing traffic efficiency not only lowers emissions and fuel consumption but also improves air quality, which is vital for public health and environmental sustainability. Furthermore, the system can improve road safety by reducing traffic bottlenecks, which lowers the risk of accidents and guarantees faster passage for emergency vehicles.

By tackling both current traffic issues and long-term urban planning objectives, the Smart Traffic Light Control System aims to produce more livable, effective, and ecologically friendly urban environments.

1.6 Project Planning

The Smart Traffic Light Control System aims to optimize traffic flow based on real-time conditions, reducing congestion and improving efficiency in smart cities. It begins with cameras installed at intersections to capture real-time traffic data, which is then processed by an object detection and counting module to identify and count vehicles. This data is sent to a central controller, which analyzes traffic information and dynamically adjusts signal timings through the traffic signal controller.

Additionally, the controller interacts with a timer and scheduler to ensure traffic signals operate within predefined schedules and adapt to changing traffic patterns throughout the day, maintaining a feedback loop for continuous optimization. The implementation involves installing cameras, developing detection software, setting up the central controller, integrating it with signal controllers, and configuring the timer and scheduler. The system's effectiveness is validated through simulations and real-world testing, aiming to create smarter, more efficient, and sustainable urban environments by addressing traffic congestion challenges effectively.

1.7 Organization of the Report

- **Chapter 1** gives the basic introduction to the project explaining the motivation, objectives and project flow.

- **Chapter 2** is about the system design which includes causal diagram and functional block diagram

- **Chapter 3** is about the conditions of the traffic signals in order to check the vehicle density

- **Chapter 4** is about the implementation and result analysis

- **Chapter 5** is about the conclusion and future scope

Chapter 2

System design

In this Chapter, we list out the interfaces.

2.1 Causal Diagram

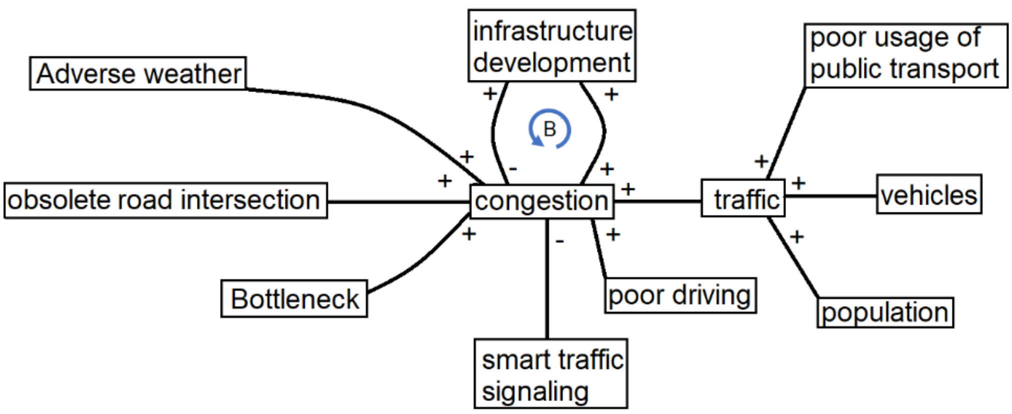

Figure 2.1: Causal Diagram

Figure 2.1 illustrates the various contributors to traffic congestion, including bad weather, outdated intersections, low public transportation usage, population growth, and reckless driving. These factors converge at the central node, congestion, which in turn influences other elements within the system.

Unfavorable weather conditions slow down travel and lead to more accidents, exacerbating congestion. Outdated road intersections, designed and managed inefficiently for current traffic levels, further worsen congestion.

Congestion-related bottlenecks further impede the flow of vehicles. However, infrastructure expansion and intelligent traffic signals can minimize congestion by increasing road capacity and streamlining traffic flow, whereas poorly planned projects may temporarily exacerbate it. Additionally, poor public transportation usage and population growth contribute to traffic congestion by increasing the number of private vehicles on the road. Inadequate driving techniques are also a contributing factor.

2.2 Functional Block Diagram

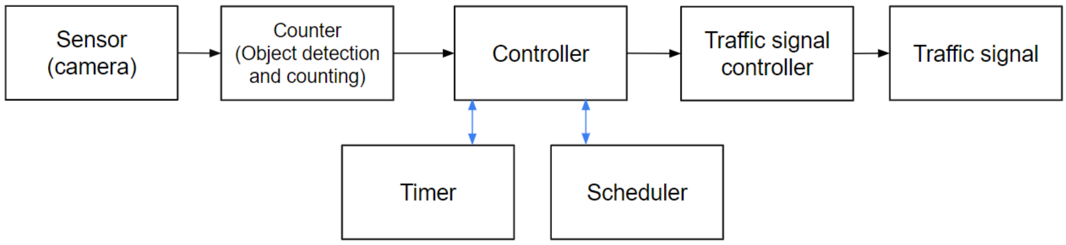

Figure 2.2: Functional Block Diagram

Figure 2.2 illustrates the block diagram of a smart traffic management system. In this system, traffic data is collected in real-time by cameras and processed for object counting and detection. This information is then utilized by a controller to optimize and manage the traffic signals in conjunction with a timer and scheduler. By dynamically adjusting the traffic lights based on current traffic conditions, the ultimate goal is to enhance traffic flow and reduce congestion.

- **Sensor (Camera):** The process starts with a sensor, typically a camera, which is used to capture real-time images or videos of the traffic situation.

- **Counter (Object Detection and Counting):** The captured data from the camera is sent to a counter module, which is responsible for object detection and counting. This module identifies and counts the number of vehicles or pedestrians in the captured images.

- **Controller:** The data from the counter is then sent to a controller. The controller processes this information to make decisions on how to control the traffic signals. It takes into account the current traffic conditions to optimize traffic flow.

- **Timer:** The controller communicates with a timer module. The timer helps in scheduling the duration of traffic signals based on the traffic data received. It ensures that the traffic signals change at appropriate intervals to manage traffic flow effectively.

- **Scheduler:** Alongside the timer, the controller also communicates with a scheduler. The scheduler manages and coordinates the timing and sequence of traffic signals, ensuring they operate in a synchronized manner to minimize traffic congestion.

- **Traffic Signal Controller:** The decisions made by the controller are then sent to the traffic signal controller. This module directly controls the physical traffic signals based on the optimized schedule and timing determined by the controller.

- **Traffic Signal:** Finally, the traffic signal controller operates the actual traffic signals, changing their states (red, yellow, green) to regulate the traffic flow according to the optimized plan.

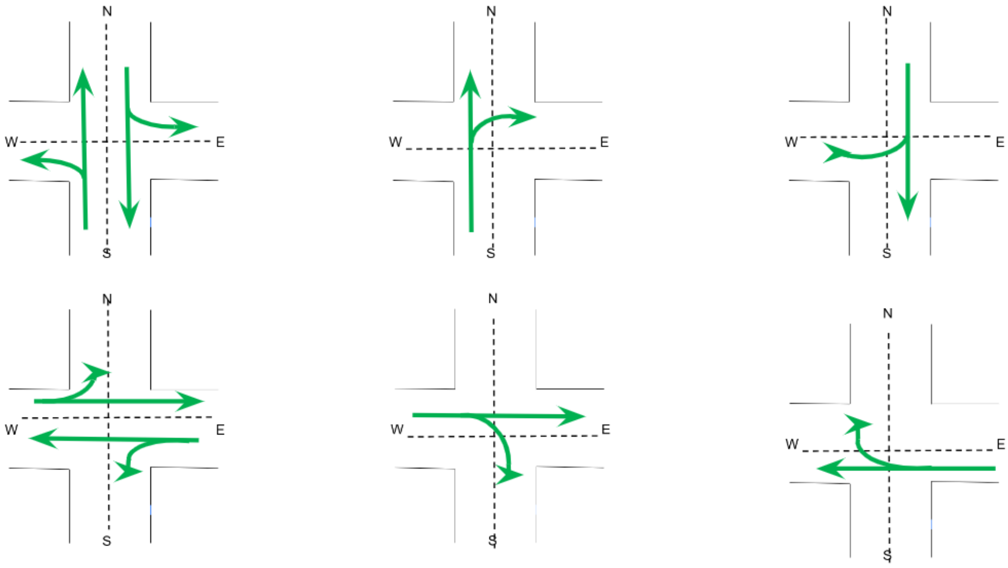

Figure 2.3: Phases of Traffic Signal

Figure 2.3 illustrates the various phases of traffic flow at an intersection -
Allowing cars to travel straight through the intersection in either an east-west or a north-south direction.
Allowing cars to turn left or right at different times from each direction is known as left and right turning.

- **Phase 1**
  - North-South Movement: Vehicles can move straight from South to North and North to South.
  - East-West Turn: Vehicles coming from the East can turn left (North) and vehicles from the West can turn right (South).

- **Phase 2**
  - North-South Movement: Vehicles can move straight from South to North.
  - East Turn: Vehicles from the South can turn right (East).
- **Phase 3**
  - North-South Movement: Vehicles can move straight from North to South.
  - West Turn: Vehicles from the North can turn right (West).
- **Phase 4**
  - East-West Movement: Vehicles can move straight from West to East and East to West.
  - North-South Turn: Vehicles coming from the North can turn left (West) and vehicles from the South can turn right (East).
- **Phase 5**
  - East-West Movement: Vehicles can move straight from West to East.
  - North Turn: Vehicles from the East can turn right (North).
- **Phase 6**
  - East-West Movement: Vehicles can move straight from East to West.
  - South Turn: Vehicles from the West can turn right (South).

- Maximum green light duration: 60 seconds (vehicle density >40)

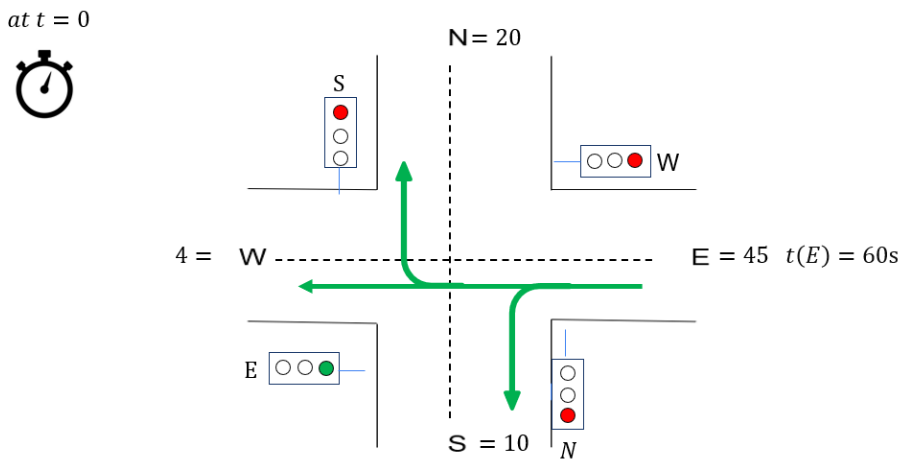

Figure 2.4: Green Signal given to East Lane

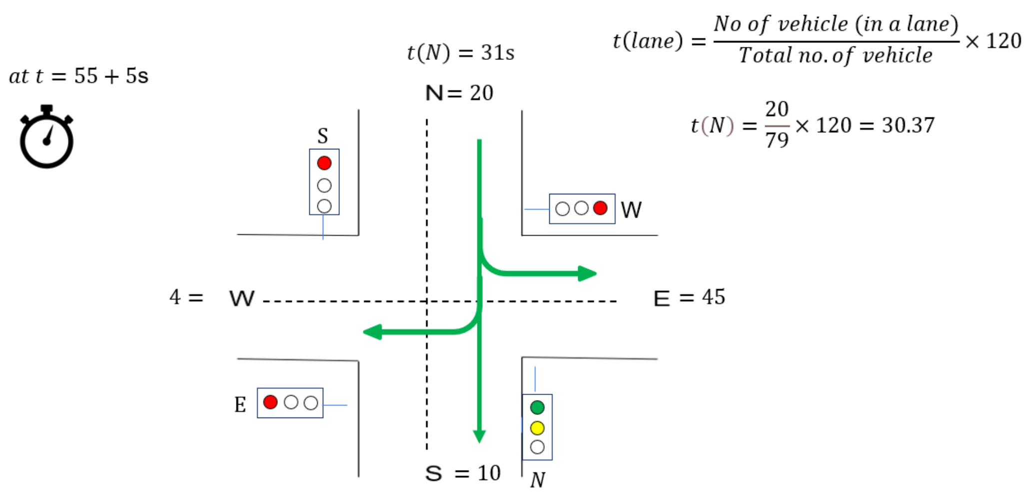

Figure 2.5: Green Signal given to North Lane

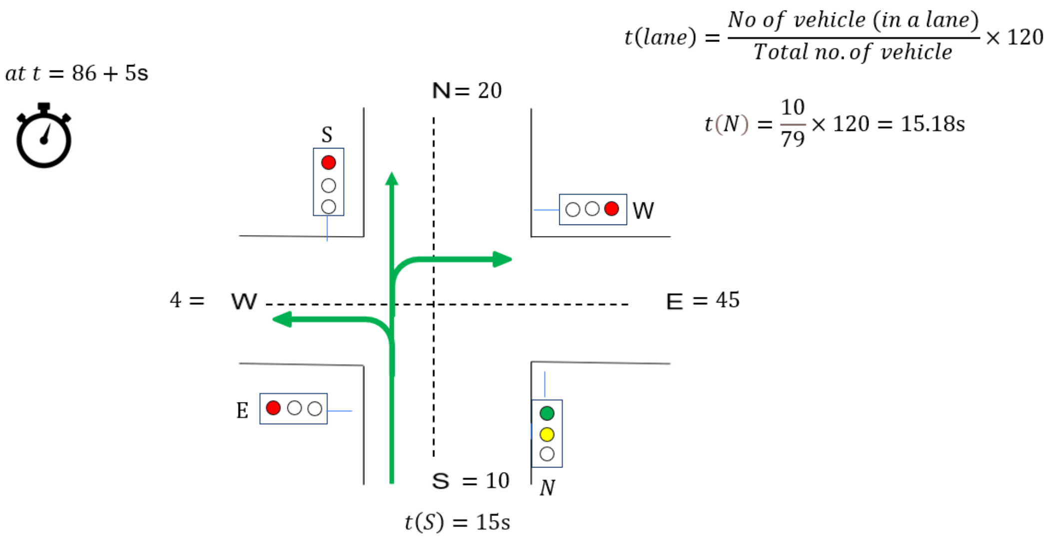

Figure 2.6: Green Signal given to South Lane

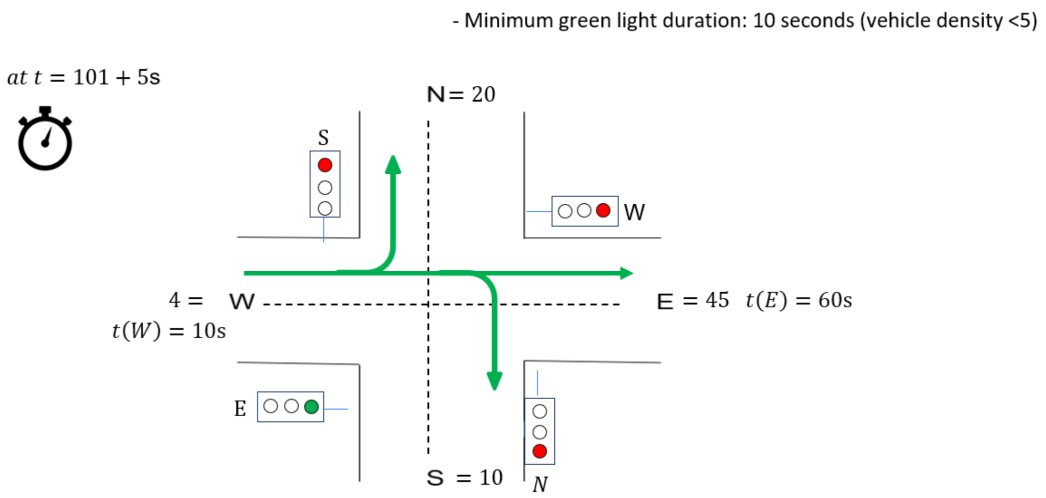

Figure 2.7: Green Signal given to West Lane

Chapter 3

Implementation Details

Following are the implementation details of the Project:-

3.1 Object Detection using YOLO

For Object detection the YOLO V5s model is used to detect six classes - car, motocycle, bus, van, truck, jeepney.

- Architecture Summary - 213 layers, 7225885 parameters
- Epochs - 21
- Python - 3.10.12, torch - 2.3.0+cu121
- Dataset : train - 1330 images, validation - 391 images, test - 188

3.2 Conditions of traffic signals to check the vehicle density

- **Dynamic Scheduling**
  - If no vehicles are present in any lane, the traffic signal will not be scheduled.

- **Priority Based on Density**
  - The lane with the highest vehicle density will be given priority for scheduling.

- **Timing Constraints**
  - Minimum green light duration: 10 seconds (vehicle density < 5)

  - Maximum green light duration: 60 seconds (vehicle density > 40)

- **Single Phase Operation**

- Each lane can be scheduled only once per cycle.

- Suppose a lane has vehicle density=0,then that lane is marked as scheduled after all other lanes have been monitored.

- **Signal components**
  - Each green light duration must include 3 seconds of yellow light and 2 seconds of red light.

- **Re-evaluation after each phase**
  - After the scheduled duration for a lane(e.g, 30 seconds for north lane), the vehicle densities of the remaining lanes will be re-evaluated.

  - The next lane to be scheduled will be chosen based on the updated densities.

- **Indication of next lane**
  - During the yellow and red phases of the current lane, the next lane to be scheduled will receive yellow indication to prepare.

- **Cycle length distribution**
  - The total cycle length will be divided based on the vehicle density.
    The formula is shown below:

$$t(lane) = \left(\frac{No.\ of\ vehicles\ (in\ a\ lane)}{Total\ no.\ of\ vehicles} \right) \times 120 \tag{3.1}$$

Equation 3.1 is used to determine the duration t_{lane} for which the green light should remain on for a specific lane. It ensures that lanes with higher traffic density receive a longer green light duration compared to lanes with fewer vehicles, thereby optimizing traffic flow based on real-time traffic conditions.

Chapter 4

Implementation

The Project has been implemented with the following details:-

4.1 Counting and timing assignment with scheduling

Table 4.1: Traffic signal timing based on vehicle count per lane

Lane	Vehicle count	Time Assigned	Schedule
North	13	22s	3
East	28	47s	2
South	36	60s	1
West	5	10s	4

Table 4.1 outlines a prospective approach to improve traffic flow and alleviate congestion by modifying traffic signal timings based on lane occupancy. In this system, the duration of green lights is dynamically allocated; lanes with higher traffic volumes receive longer green light durations. This strategy ensures that lanes with more vehicles are cleared more quickly, thereby reducing overall wait times and congestion while maintaining a balance between fairness and effectiveness.
To maximize throughput and prevent lane spillover, the timetable prioritizes lanes with higher vehicle volumes. An adaptive traffic control system utilizes real-time data from traffic sensors to dynamically make these adjustments, ensuring swift adaptations to traffic conditions.

4.2 Result Analysis - 1

Figure 4.1 illustrates the training and validation loss metrics of a machine learning model across 21 epochs.

- **Box Loss (train and val):** During training and validation, this metric assesses how accurate the predicted bounding boxes were. The model is getting better at predicting bounding boxes, as seen by the consistent drop in both the training

Figure 4.1: Loss Functions Analysis

(train/box_loss) and validation (val/box_loss) box losses over epochs.

- **Object Loss (train and val):** This statistic assesses how well the model can identify the objects in the environment, object losses show a consistent downward trend indicating that the model is improving with time in terms of object identification.

- **Class Loss (train and val):** This measures the accuracy of the model in classifying the object correctly, both the training and validation class losses decrease, which indicates improvements in the model's classification accuracy.

The results lines (solid blue) and smooth lines (dotted orange) across all graphs demonstrate a consistent trend of decreasing loss values, signifying effective learning and generalization. The close alignment between training and validation loss curves suggests that the model is not overfitting and is likely generalizing well to unseen data.

Overall, the decreasing trends in all six metrics indicate that the model is effectively learning and improving its performance on the tasks of object detection, classification, and localization.

Figure 4.2 and Figure 4.3 illustrates crucial evaluation metrics for a multi-class object detection model: the Precision-Recall Curve and the F1-Confidence Curve.

Precision-Recall Curve:
Figure 4.2 illustrates the Precision-Recall (PR) Curve, showcasing the correlation between precision and recall for individual classes as well as the model's overall performance across all classes. The curves provide insights into the following aspects:

- **Car (0.993):** This class shows a nearly perfect PR curve, indicating excellent performance with high precision and recall.

- **Motorcycle (0.964):** This class also performs very well, with high values for both precision and recall, though slightly lower than the car class.

- **Bus (0.104):** The bus class has a very poor PR curve, indicating low precision and recall, and suggesting that the model struggles to detect buses accurately.

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- **Van (0.878):** The van class shows good performance with a high PR curve, though not as high as cars and motorcycles.

- **Truck (0.875):** This class also shows good performance with high precision and recall.

- **Jeepney (0.221):** The jeepney class has a low PR curve, indicating poor performance in detecting jeepneys.

F1-Confidence Curve:
Figure 4.3 displays the F1-Confidence Curve, illustrating how the F1 score changes across various confidence thresholds for individual classes and overall. The analysis of this curve is as follows:

- **Car:** The F1 score for the car class is high across most confidence levels, indicating that the model consistently performs well in detecting cars.

- **Motorcycle:** This class also maintains a high F1 score across different confidence thresholds, similar to the car class.

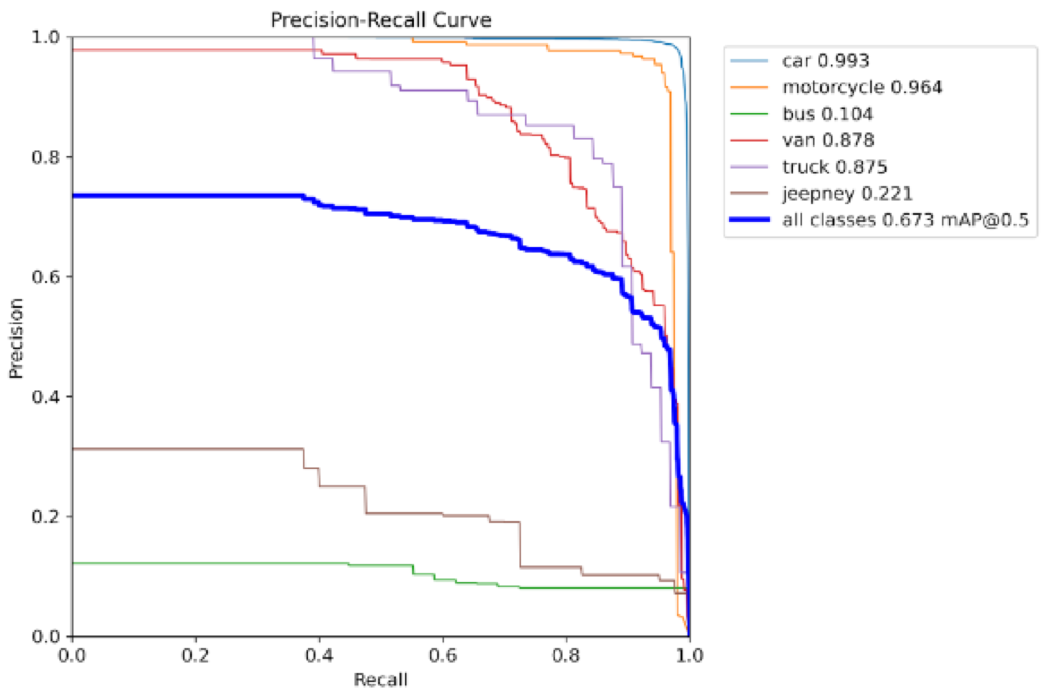

Figure 4.2: Precision-Recall Curve Analysis

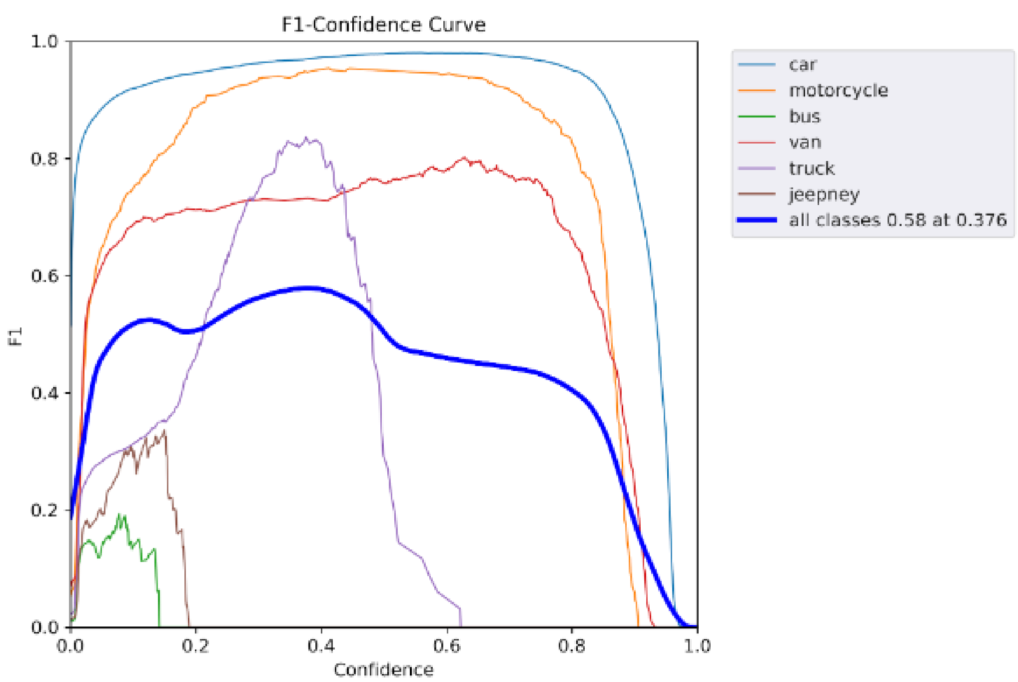

Figure 4.3: F1-Confidence Curve Analysis

- **Bus:** The bus class has a very low F1 score, consistent with its poor PR curve, indicating the model's difficulty in detecting buses.
- **Van:** The van class shows a good F1 score, indicating reliable detection performance.
- **Truck:** This class has a high F1 score, showing consistent performance across different confidence levels.
- **Jeepney:** The jeepney class has a low F1 score, similar to its PR curve performance, indicating poor detection capability.

4.3 Result Analysis - 2

Classes: The classes in the confusion matrix are car, motorcycle, bus, van, truck, jeepney, and background.

Interpretation

Diagonal Elements: These elements represent the correctly classified instances for each class.
For example:

- The model correctly classified 99 percent of the cars as cars.
- The model correctly classified 97 percent of the motorcycles as motorcycles.
- The model correctly classified 78 percent of the vans as vans.

Off-Diagonal Elements: These elements represent the correctly misclassified instances for each class.
For example:

- 24 percent of the cars were misclassified as motorcycles.
- 11 percent of the cars were misclassified as buses.
- 17 percent of the cars were misclassified as trucks.
- 65 percent of the cars were misclassified as background.
- 5 percent of the motorcycles were misclassified as background.
- 66 percent of the buses were misclassified as cars.
- 55 percent of the buses were misclassified as vans.
- 72 percent of the buses were misclassified as trucks.

Figure 4.4: A confusion matrix illustrating the performance of a multi-class classification model for vehicle types. Darker shades signify higher counts or normalized counts of predictions, with the diagonal cells representing correct predictions and off-diagonal cells indicating misclassifications

- 17 percent of the buses were misclassified as background.
- 44 percent of the trucks were misclassified as vans.
- 13 percent of the trucks were misclassified as background.
- 1 percent of the background was misclassified as cars.
- 3 percent of the background was misclassified as motorcycles.
- 1 percent of the background was misclassified as vans.

Figure 4.4 illustrates a confusion matrix that offers a comprehensive visual depiction of the model's performance, showcasing its strengths as well as areas where enhancements are needed.

4.4 Result Analysis - 3

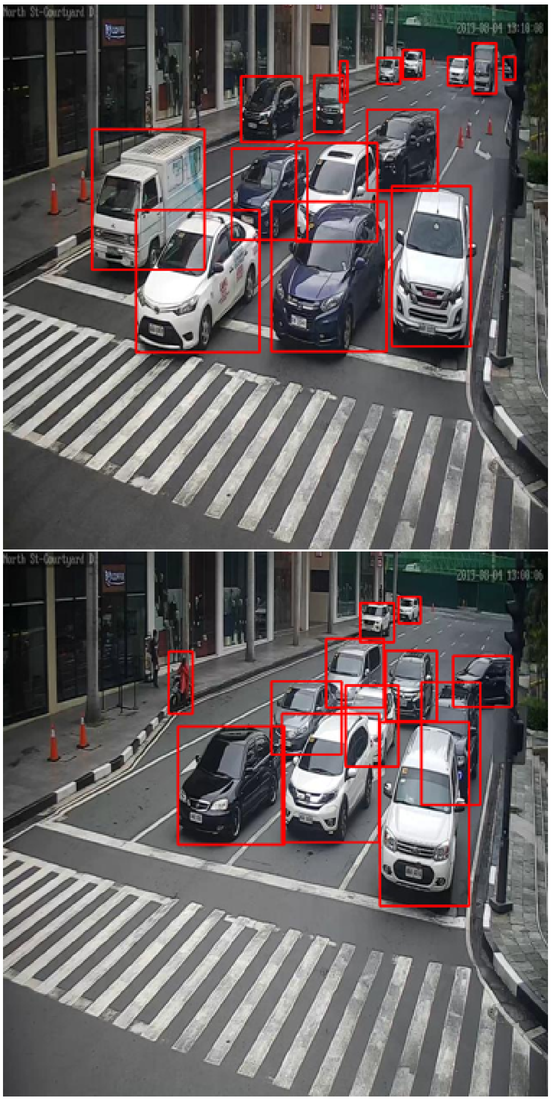

Figure 4.5: Vehicle Detection at an Urban Intersection

Figure 4.5 showcases the implementation outcomes, displaying images derived from a vehicle detection system deployed at an intersection. These images are most likely generated by a camera-based traffic monitoring configuration, where individual vehicles are identified and delineated by red rectangles, signifying successful detection.

Figure 4.6: Real-time Vehicle Detection and Classification at an Intersection

Figure 4.6 showcases the effective deployment of a vehicle detection and classification system at an intersection. Each frame within the image grid depicts a moment in real-time traffic monitoring, showcasing accurate detection and classification of vehicles. This display highlights the high efficiency of the vehicle detection and classification system, which serves as an essential component of an intelligent traffic management system.

The system possesses the capability to significantly enhance traffic flow and alleviate congestion in metropolitan areas, as demonstrated by its accuracy, real-time processing, and comprehensive data collection capabilities. This solution plays a key role in advancing smarter and more efficient city traffic management over time by optimizing traffic signal control according to real-time conditions.

Chapter 5

Conclusions and Future scope

Our research successfully implemented an advanced system that collects and analyzes sensor data to detect and count vehicles at intersections. The system is designed to dynamically adjust signal timings to optimize traffic flow, thereby minimizing travel times and alleviating congestion. We validated the effectiveness of our signal timing adjustment algorithms through comprehensive simulations and real-world testing, demonstrating their potential to enhance traffic efficiency.

Our Smart Traffic Signal Control System significantly reduces traffic congestion and improves overall traffic flow in urban areas by optimizing traffic signal control based on real-time traffic conditions. This achievement not only fulfills our objectives but also highlights the transformative potential of such technologies in traffic management within smart cities.

Future work on this project will entail applying the algorithm to actual embedded devices to guarantee effective real-time processing on boards such as Arduino or Raspberry Pi. The system will respond more quickly to real-world situations if real-time traffic datasets from cameras and Internet of Things sensors are integrated.

For increased accuracy, the system will be expanded to handle bigger cities and integrate a greater variety of sensors, such as GPS and meteorological information. While direct communication between automobiles and traffic signals is made possible by V2X communication, sophisticated machine learning and artificial intelligence approaches will improve predictive capacities.

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