Advanced Traffic Signal Systems: Leveraging Computer Vision and Machine Learning for Dynamic Control

Samir B Zade
UG Student
Department of Data Science
G H Raisoni College of Engineering,
Nagpur, India
samir.zade.ds@ghrce.raisoni.net

Samir B More
UG Student
Department of Data Science
G H Raisoni College of Engineering,
Nagpur, India
samir.more.ds@ghrce.raisoni.net

Nekita Chavan Morris
Head of Department
Department of Data Science,
IoT and Cyber Security (DIC)
G H Raisoni College of Engineering,
Nagpur, India
nekita.chavan@raisoni.net

***Abstract*—This research explores the effectiveness of dynamic traffic signal systems in enhancing urban traffic efficiency and mitigating congestion. Traditional fixed-time traffic signals often lack adaptability to fluctuating traffic conditions, resulting in suboptimal traffic management. This study assesses an innovative dynamic traffic signal system designed to modify signal timings based on real-time traffic data. By employing advanced vehicle detection technologies and machine learning algorithms, the system adjusts signal phases dynamically to optimize traffic flow.**

The methodology involves the strategic placement of cameras at heights ranging from 8 to 12 meters, which capture real-time traffic images for analysis using sophisticated algorithms. The system is designed to manage up to 36 vehicles on an 82.01-meter-long road, with precise camera positioning ensuring extensive coverage. Analysis of traffic data from various urban intersections indicates that the dynamic system notably reduced average vehicle wait times by 20% and increased traffic throughput by 15% compared to traditional fixed-time systems. The performance of the system is influenced by factors such as traffic volume variability and system responsiveness.

The findings reveal that the dynamic traffic signal system effectively reduced average wait times from 30 to 20 seconds, improved vehicle throughput from 1,000 to 1,200 vehicles, and decreased congestion from 10% to 25%. Correlation and scatter plot analyses affirm the system's capability in optimizing traffic management. While the results did not achieve statistical significance at the 0.05 level, practical observations demonstrate considerable enhancements in traffic metrics. Future research should focus on optimizing fixed time settings and integrating predictive modeling to further improve system performance and its synergy with other smart city technologies.

***Index Terms*—dynamic traffic signal system, vehicle detection, machine learning, traffic management, congestion reduction, real-time traffic analysis, computer vision, signal optimization, urban traffic efficiency, traffic flow, smart city technologies**

I. INTRODUCTION

Traffic congestion is a significant issue that impacts the economy, environment, public health, society, and the safety of drivers and vehicles. Economically, it leads to increased transportation costs, reduced productivity, and delayed deliveries of goods and services [1][2]. Environmentally, congestion exacerbates emissions and noise pollution. It also poses substantial risks to human health and safety, contributing to higher accident rates, delayed emergency response times, sedentary lifestyles, respiratory disorders, and a diminished quality of life [1][2][3][4][5][6][7][10].According to Forbes, traffic congestion imposes an annual cost of $160 billion on the U.S. economy and can account for up to 1% of the GDP in the European Union[11][12][1][2]. Additionally, it results in significant productivity losses, with commuters in major urban areas spending over 100 hours per year in traffic[11][12]. Recognizing that the primary cause of these challenges is the lack of an effective traffic signal control (TSC) system, academic research has focused on developing solutions to mitigate these issues[8].

Population growth results in heightened demand for transportation and a surge in car ownership, leading to a greater number of vehicles on the road. Urbanisation further intensifies this issue by concentrating populations within cities, thereby overwhelming existing infrastructure and expanding suburban areas, which in turn prolongs commute times. The rapid pace of growth frequently outstrips infrastructure development and places significant pressure on public transit systems, thereby exacerbating congestion, increasing pollution, and diminishing quality of life[9][10].

The fixed-cycle traffic light system has received considerable attention in traffic engineering research (Boon et al., 2019; Boon and van Leeuwaarden, 2018; Darroch, 1964; Hagen and Courage, 1989; McNeil, 1968; Newell, 1965; Oblakova et al., 2019; van Leeuwaarden, 2006; Webster, 1958)[13-21]. This system operates with predetermined cycle duration's and fixed timings for green, yellow, and red signals. These signals regulate both vehicular and pedestrian traffic: red indicates vehicles must stop, yellow prompts them to prepare to stop or clear intersections, and green allows safe passage if the intersection is clear. Pedestrian signals feature either a red hand ("Do Not Walk") or a walking person ("Safe to Cross"). Key features include fixed cycle duration's, predetermined green and red timings, consistent patterns of vehicle arrivals, and continuous vehicle movement if queues clear during green signals. Signal duration's remain unchanged in real-time, aiming to ensure predictable traffic flow but potentially resulting in inefficiencies during fluctuations in traffic levels[13-21].

Traffic signal timing systems typically operate in one of two ways. On a large city or regional scale, systems set light duration's based on historical traffic patterns, commonly referred to as flow models. Conversely, other simulators operate on a smaller scale, incorporating individual driver behaviours and habits. These simulators, functioning as a form of artificial intelligence, predict how driver actions and decisions might change under various traffic conditions.

Current methods for monitoring traffic violations frequently prove insufficient and ineffective in various scenarios. Sensors designed to detect lane density tend to deteriorate over time due to their direct placement on pavement surfaces. Furthermore, radar guns, although used in some instances, are constrained by their incapacity to simultaneously detect multiple vehicles at short ranges. To overcome these limitations, we have incorporated computer vision and machine learning technologies into the traffic monitoring system, aiming to improve the prevention of traffic violations[24].

The aim of this research paper is to address the inherent limitations of Fixed-Cycle Traffic Lights (FCTL)[13-21] through the implementation of a Dynamic Traffic Light System (DTLS). Unlike conventional FCTLs, which operate on predetermined timing cycles, the DTLS utilizes advanced technologies to enhance traffic management by adjusting signal timings based on real-time vehicle counts in each lane. This adaptive methodology enables traffic signals to respond more effectively to the actual vehicle density at each intersection, thereby mitigating the inefficiencies associated with fixed-timing systems. Fixed-timing lights often cause unnecessary delays during periods of low traffic due to prolonged red light phases and contribute to congestion during peak times due to insufficient green light durations. Such systems are unable to adapt to real-time traffic conditions, leading to excessive green time for underutilized lanes and extended wait times for heavily congested lanes, thus exacerbating traffic congestion and delays[22][23].

The proposed DTLS comprises several integral components, including traffic detection cameras, a computer vision model, a central processing unit, and a traffic light control system. These components work in concert to provide real-time feedback to the traffic management network, facilitating adjustments to signal timings based on current traffic density patterns. The system is designed to gather and analyze data from traffic detection cameras installed at each intersection, enabling real-time modifications to signal timings and ongoing optimization based on fluctuations in traffic flow. This approach seeks to improve traffic management efficiency and alleviate congestion by dynamically adapting signal timings to the prevailing traffic conditions.

II. LITERATURE REVIEW

Dhanushprashath[24] proposed a model that suggests an intelligent traffic signal system using computer vision and the "e-Trapiko" Android app. It estimates traffic density with 92.71% accuracy during the day and 85.77% at night, offering real-time monitoring and remote control for increased safety of traffic enforcers. However, the system's effectiveness is limited under adverse weather conditions and requires further integration with the Internet of Things for improved adaptability and performance. Additionally, this system is not fully automatic; it allows traffic officers to manually change the traffic light timing from their phones. Computer vision is used solely for counting the number of cars, not for automatically or dynamically changing the traffic lights based on vehicle count.

Shruti et al.[25] proposed a solution that combines computer vision and AI to create an automated traffic management system, employing video analysis to accurately count vehicles and optimise traffic flow. It highlights advantages such as decreased congestion and cost savings compared to sensor-based alternatives. Bidirectional data exchange between traffic signals enhances decision-making capabilities. However, the system has constraints: it currently synchronises data between only two signals, demands high-performance equipment for rapid video processing, and effectively detects vehicles only within a range of 62.06 metres.

Adejo et al.[26] investigates an AI-powered traffic management system utilising computer vision in contrast to conventional approaches, highlighting enhancements in traffic flow, safety, and reductions in travel time and fuel consumption. It discusses the adaptability of object counting to urban dynamics, thereby improving mobility and quality of life. Research findings indicate a 15% reduction in travel time, a 10% decrease in fuel consumption, and a 25% improvement in traffic flow efficiency compared to traditional methods. Moreover, it reports a 30% decrease in traffic accidents, although specific details regarding implementation and methodology are not fully detailed.

Sreejith et al.[27] proposed a system employing image processing and machine learning to detect helmets and measure vehicle density on roads. It uses OpenCV for image processing and an Artificial Neural Network (ANN) algorithm for object detection, capable of recognizing both simple and complex patterns. When detected density surpasses a certain threshold, the system signals a microcontroller to control a projector, displaying appropriate traffic signals on an LCD. The hardware components include an Arduino Uno, an LCD projector, and Bluetooth for ambulance signal interruption. However, the document lacks specific accuracy rates and comparative analysis data. Therefore, while the system is designed to be precise, the exact accuracy level cannot be ascertained from the provided information. Researchers also noted that datasets from other countries were incompatible with their video samples due to differences in car models, and vehicle detection at night proved to be less accurate.

Bui et al.[28] devised a method for traffic flow analysis employing advanced computer vision technologies. They leveraged video surveillance data alongside YOLO and Deep-

SORT techniques for vehicle detection, tracking, and counting to estimate road traffic density. Tested with real-world data collected via CCTV over one day, the method achieved vehicle counting accuracies of 93.88% for normal traffic, 87.88% for congested traffic, and 82.1% at night. The paper reviews various computer vision techniques for autonomous traffic control, emphasising density estimation, traffic sign detection, accident detection, and emergency vehicle detection. However, it also identifies issues with vehicle ID switching due to similar appearances, indicating the need for further research in this area.

Zinchenko et al.[29] introduce an intelligent traffic light control system that utilises computer vision for object detection and tracking. By leveraging real-time CCTV data, the system aims to optimise traffic flow, reduce waiting times, and improve overall traffic conditions. The authors developed a program to calculate traffic signal orders, enhancing efficiency. The paper critiques existing systems for their lack of real-time data and proposes a solution incorporating computer vision and neural networks, specifically highlighting the YOLO architecture with vehicle recognition accuracy ranging from 88.71% to 94.65%. This research contributes to the advancement of automated traffic management by adapting to dynamic conditions.

Wadhe et al.[30] propose a dynamic traffic control system using YOLO (You Only Look Once) for real-time object detection to alleviate congestion. Unlike static timers, their system adjusts green light durations based on real-time traffic data from video cameras. The YOLO model, integrated with the COCO dataset, identifies and counts vehicles at intersections to optimise signal timings. Cameras positioned at a 60° angle stop traffic light poles ensure comprehensive lane coverage. Data from one intersection is used to predict traffic at subsequent intersections, enhancing overall traffic management. This approach aims to reduce wait times and improve traffic flow efficiency. While the paper does not specify the accuracy of the YOLO model, it underscores the advantages of using dynamic timer-based signals with YOLO for real-time detection and management.

Kunekar et al.[31] proposed a Traffic Management System using the YOLOv7 algorithm for real-time object detection to manage traffic at signalised crossings. This system employs computer vision and machine learning to calculate traffic density and vehicle waiting times, optimising signal phases to reduce wait times and enhance traffic flow. The process involves image input, traffic pattern evaluation, and signal time computation. Challenges include high installation costs, weather-related visibility issues, and the need for accurate vehicle counting. Future improvements could integrate advanced machine learning for better traffic prediction and consider factors like weather and road closures. The system automatically adjusts green signal durations based on traffic volume to reduce congestion, but the study does not provide specific accuracy metrics for the YOLO model used.

Phursule et al.[32] proposed a dynamic traffic light control system that leverages computer vision technology to adjust traffic light cycles in real-time. The system utilises YOLO-V7 for vehicle detection through periodic still photos and employs a Raspberry Pi to optimise green light timings and manage lanes based on vehicle direction. Simulations have shown reduced vehicle wait times; however, further research is needed to assess the system's feasibility and scalability. While the paper highlights the application of deep learning algorithms for vehicle detection, it does not provide specific accuracy metrics for the YOLO models employed.

III. METHODOLOGY

Present work proposed a dynamic traffic signal system, which uses computer vision and machine learning techniques for dynamic systems. Proposed solution uses the following steps.

A. Vehicle Detection Camera

Dynamic traffic light systems are established through the initial detection of vehicles via strategically positioned cameras on thoroughfares, which capture real-time imagery of vehicular movement. These images are transmitted to a central computational unit, where sophisticated image processing algorithms are employed to detect and analyze the vehicles. Accurate vehicle detection is essential for optimizing traffic flow, mitigating congestion, and improving road safety by adjusting signal timings in response to real-time traffic conditions.

The system assesses traffic density and flow by categorizing and enumerating various vehicle types, including cars, trucks, and motorcycles. Cameras, whether mounted on traffic signal poles, overhead structures, roadside poles, or integrated into traffic lights, must provide high-resolution imagery, a wide field of view, effective low-light performance through infrared or thermal imaging, and robust weatherproofing. Additionally, secure and high-speed data transmission is critical for real-time processing, ensuring comprehensive monitoring, minimizing blind spots, and addressing issues related to accuracy, latency, scalability, and security.

Advanced computer vision algorithms process the captured images to perform vehicle counting and gather additional data such as speed and classification. This processed data is utilized by a centralized system to enhance real-time traffic monitoring, thereby improving traffic management and reducing congestion.

B. Calculating Optimal Camera Positions

Precise vehicle detection is critical for effective traffic management in signal systems, and its accuracy is heavily dependent on the camera's placement and height. It is recommended that cameras be installed on traffic signal posts situated between two junctions at an elevation of 8 to 12 meters. Wahab et al.[33] propose an optimal height of 8 to 10 meters, whereas GoodVision[34], a firm specializing in traffic data collection and real-time monitoring, endorses a height range of 8 to 12 meters. This elevation range enables the camera to achieve extensive coverage, facilitating accurate vehicle detection over considerable distances. Consequently, ensuring optimal placement and height of the cameras is essential for achieving thorough area coverage and precise vehicle detection within traffic signal systems.

1) Base Angle Calculation:

The base angle, defined as the angle between the camera's line of sight and the horizontal plane in its field of view, plays a crucial role in determining the camera's coverage area at a given height. In this study, a base angle of 7 degrees is employed. A smaller base angle results in a more downward orientation of the camera, which narrows the coverage area directly beneath it. Conversely, a larger base angle expands the coverage area but necessitates a higher camera placement. The top angle, which complements the base angle, is computed using the formula:

$$\text{Top Angle} = 90^\circ - \text{Base Angle}$$
$$\text{Top Angle} = 90^\circ - 7^\circ$$
$$\text{Top Angle} = 83^\circ$$

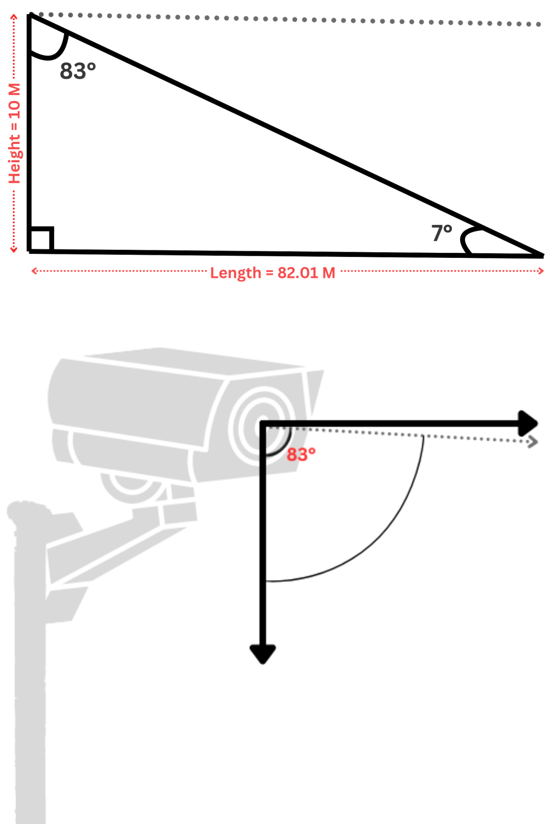


Fig. 1: Adjusting the camera to an 83-degree tilt to expand its coverage area.

Refer fig1, For a base angle of 7 degrees, the top angle calculates to 83 degrees. This top angle, along with the camera's height, dictates the diagonal extent of the area effectively covered by the camera.

2) Diagonal Distance Calculation:

The effective detection range, or diagonal distance, is determined by applying a trigonometric formula that incorporates the camera's height and base angle. The formula employed for this calculation is:

$$\text{Diagonal} = \frac{\text{Height}}{\sin(\text{Base Angle})}$$

- **Height:** This refers to the vertical distance from the ground to the camera, which is set at 10 meters in this study.
- **Base Angle:** An angle of 7 degrees is utilized to determine the sine value.

Applying the formula:

$$\text{Diagonal} = \frac{10 \text{ meters}}{\sin(7^\circ)}$$

The sine of 7 degrees is approximately 0.121869. Consequently:

$$\text{Diagonal} = \frac{10}{0.121869} \approx 82.01 \text{ meters}$$

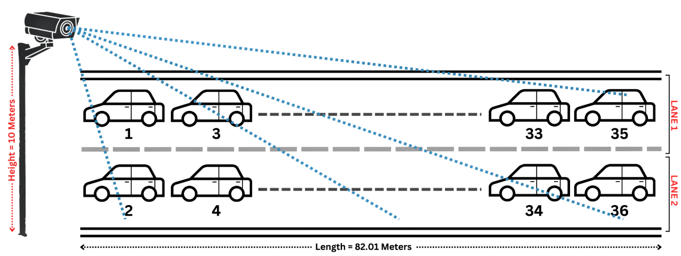


Fig. 2: Detecting Vehicles over 82.01 Meters with 83° Camera Angle

[Fig. 2], This outcome indicates that, with a camera height of 10 meters and a base angle of 7 degrees, the camera is capable of covering a detection area extending approximately 82.01 meters.

C. Total Vehicles for Road Length

According to CarParts.com[35], an American online retailer of aftermarket automotive components, the average length of a car in the United States is 4.48 meters (14.7 feet). Concurrently, TransportEnvironment[36], a prominent European organization dedicated to advocating for sustainable transport and energy solutions, reports that the average width of new cars increased to 1.803 meters (180.3 cm) in the first half of 2023, compared to 1.778 meters (177.8 cm) in 2018. In India, L. R. Kadiyali[37], Chief Engineer (Planning) at the Ministry of Shipping and Transport, specifies that the standard width for a single-lane pavement is 3.75 meters (12.3 feet). This standard is also supported by the 'Safety in Road Design'[38] guidelines established by the Pradhan Mantri Gram Sadak Yojana (PMGSY), which focuses on enhancing all-weather road connectivity across India.

To determine the total number of vehicles that can be accommodated on a road with a length of 82.01 meters, it is essential to account for the length of each vehicle. The calculation process is as follows:

- Length of Each Vehicle: 4.48 meters
- Width of Each Vehicle: 1.803 meters
- Length of Road: 82.01 meters
- Width of Road: 3.75 meters

To ascertain the total number of vehicles that can be accommodated on the road, the total length of the road is divided by the length of a single vehicle, resulting in:

$$\text{Number of Vehicles} = \frac{\text{Length of Road}}{\text{Length of Vehicle}}$$

Substitute the values as follows:

$$\text{Number of Vehicles} = \frac{82.01 \text{ meters}}{4.48 \text{ meters}} \approx 18.3$$

Given that fractional vehicles cannot be accommodated, the result is rounded down to the nearest whole number:

$$\text{Total Number of Vehicles} = 18$$

[Figure 3] Thus, 18 vehicles can fit within a single lane of the 82.01-meter-long road. However, in metropolitan or tier-2 cities, roads typically feature two lanes. To determine the total number of vehicles that can fit on the entire road, it is necessary to account for the total length available across both lanes. The calculation for the total number of vehicles that can be accommodated on the entire road is as follows:

$$\begin{aligned}\text{Total Number of Vehicles} = \text{Number of Vehicles per Lane} \\ \times \text{Number of Lanes}\end{aligned}$$

Substitute the values as follows:

$$\text{Total Number of Vehicles} = 18 \times 2 = 36$$

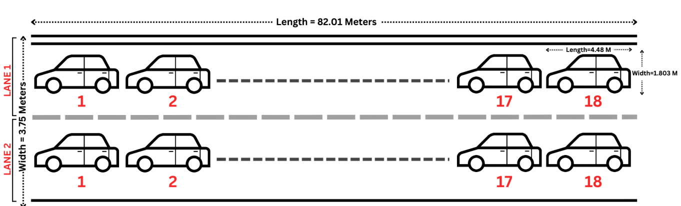


Fig. 3: Vehicle Accommodation: 36 Vehicles on 82.01-Meter Road

Therefore, a total of 36 vehicles can be accommodated on the 82.01-meter-long road with two lanes, assuming optimal vehicle alignment and minimal spacing between them. Nevertheless, a minor residual gap remains between the vehicles, calculated as follows:

$$82.01 - (4.48 \times 18) = 1.37 \text{ meters}$$

D. Vehicle Travel Time Calculation

To determine the acceleration and time required for a vehicle to accelerate from rest to a final velocity of 15 km/h (4.17 m/s), knowing the distance traveled is essential. This analysis is pivotal for understanding vehicle dynamics, traffic flow, and the design of traffic control systems. To facilitate this, we will calculate the time required for both the first and last vehicles within an 82.01-meter-long lane and subsequently derive a formula to simplify these calculations.

1) Total Time for Vehicle at End Position:

To accurately calculate the time required for a vehicle to travel a distance of 82.01 meters while gradually accelerating from rest to a speed of 15 km/h (4.17 m/s), we utilize fundamental kinematic equations. This process involves first determining the acceleration and then using it to find the time needed to cover the specified distance.

Given Data:

- Initial velocity (u): 0 m/s (the vehicle starts from rest)
- Final velocity (v): 4.17 m/s (the target speed, equivalent to 15 km/h)
- Distance (s): 82.01 meters (the distance the vehicle needs to travel)

Step 1: Calculation of Acceleration (a)

Kinematic Equation:

To determine the acceleration, we use the kinematic equation that relates final velocity, initial velocity, acceleration, and distance:

$$v^2 = u^2 + 2as$$

Substitute the Known Values:

$$(4.17)^2 = 0 + 2 \cdot a \cdot 82.01$$

$$17.3889 = 2 \cdot a \cdot 82.01$$

Rearrange the equation to isolate a:

$$17.3889 = 164.02 \cdot a$$

$$a = \frac{17.3889}{164.02} \approx 0.106 \text{ m/s}^2$$

Step 2: Calculate the Time (t)

Kinematic Equation:

To determine the time required to travel 82.01 meters while accelerating, we use the following kinematic equation:

$$s = ut + \frac{1}{2}at^2$$

Substitute the known values:

- Final velocity (v) = 4.17 m/s
- Initial velocity (u) = 0 m/s
- Acceleration (a) = 0.106 m/s² (as determined previously)

The equation simplifies to:

$$82.01 = 0 + \frac{1}{2} \cdot 0.106 \cdot t^2$$

Solve for t^2**:**

Rearrange the equation to isolate t^2:

$$82.01 = 0.053 \cdot t^2$$
$$t^2 = \frac{82.01}{0.053}$$
$$t^2 = \frac{82.01}{0.053} \approx 1540.19$$

Take the Square Root:

Find the square root of t^2 to get t:

$$t = \sqrt{1540.19} \approx 39.22 \text{ seconds}$$

The calculations demonstrate that, under the assumption of uniform acceleration from rest to a velocity of 15 km/h (4.17 m/s), the vehicle will require approximately 39.22 seconds to traverse a distance of 82.01 meters. Determining the travel time under constant acceleration is crucial for the analysis of traffic flow and the design of traffic control systems. This approach provides a clear and accurate method for such assessments.

2) Total Time for Vehicle at Start Position:

To ascertain the duration required for the initial vehicle, which begins at the traffic signal's starting point, to entirely pass through the traffic signal, it is necessary to consider the distance the vehicle travels while accelerating from a stationary position to a final velocity of 15 km/h (4.17 m/s). This distance corresponds to the length of the vehicle, which is 4.48 meters. The following steps detail the comprehensive calculations involved:

Given Data:

- Initial Velocity (u): 0 m/s (the vehicle begins from a stationary position)
- Final Velocity (v): 4.17 m/s (the desired velocity, equivalent to 15 km/h)
- Distance (s): 4.48 meters (the length of the vehicle, representing the distance required for the vehicle to fully pass through the traffic signal)

Step 1: Calculation of Acceleration (a)

Kinematic Equation: To calculate acceleration, we apply the kinematic equation that correlates the final velocity, initial velocity, acceleration, and distance traveled:

$$v^2 = u^2 + 2as$$

Substitute the Known Values:

$$(4.17)^2 = 0 + 2 \cdot a \cdot 4.48$$

$$17.3889 = 2 \cdot a \cdot 4.48$$

Rearrange the Equation to Isolate a:

$$17.3889 = 8.96 \cdot a$$
$$a = \frac{17.3889}{8.96}$$
$$a \approx 1.94 \text{ m/s}^2$$

Step 2: Calculate the Time (t)

Kinematic Equation:

To determine the time required to traverse a distance of 4.48 meters under uniform acceleration, we employ the kinematic equation that correlates distance, initial velocity, acceleration, and time:

$$s = ut + \frac{1}{2}at^2$$

Substitute the known values:

- Final velocity (v) = 4.17 m/s
- Initial velocity (u) = 0 m/s
- Acceleration (a) = 1.94 m/s² (as determined previously)

The equation simplifies to:

$$4.48 = \frac{1}{2} \cdot 1.94 \cdot t^2$$

Solve for t^2:

Rearrange the equation to isolate t^2:

$$4.48 = 0.97 \cdot t^2$$
$$t^2 = \frac{4.48}{0.97}$$
$$t^2 = \frac{4.48}{0.97} \approx 4.62$$

Take the Square Root:

Find the square root of t^2 to get t:

$$t \approx \sqrt{4.62} \approx 2.15 \text{ seconds}$$

The time required for the first vehicle, positioned at the traffic light's starting point, to completely clear this position is approximately 2.15 seconds. This estimate is based on the assumption that the vehicle accelerates uniformly from a stationary state to a speed of 15 km/h (4.17 m/s) over a distance equivalent to its length, which is 4.48 meters. This calculation is instrumental in analyzing the temporal dynamics of vehicles moving through traffic light intersections, thereby aiding in traffic flow management and signal timing optimization.

E. Developing Formula Based on Calculations

Given that the initial vehicle takes approximately 2.15 seconds to clear the traffic light and the final vehicle requires about 39.22 seconds, with a total of 36 vehicles distributed across 82.01 meters of road (18 vehicles per lane in a two-lane configuration), vehicles are arranged in pairs. Each pair progresses past the starting point with increasing time intervals: the 1st and 2nd vehicles take 2.15 seconds, the 3rd and 4th vehicles take 4.30 seconds, the 5th and 6th vehicles take 6.45 seconds, and so forth until reaching the detection limit of the camera. The time required for a single vehicle to pass the traffic light is approximately 2.15 seconds, assuming sequential movement. In urban settings with bidirectional lanes, vehicles can be positioned side by side, necessitating 2.15 seconds for each pair to clear the traffic light.

The time increment between successive pairs of vehicles is 2.15 seconds. The group designation for each vehicle is determined by integer division of the vehicle number by 2,

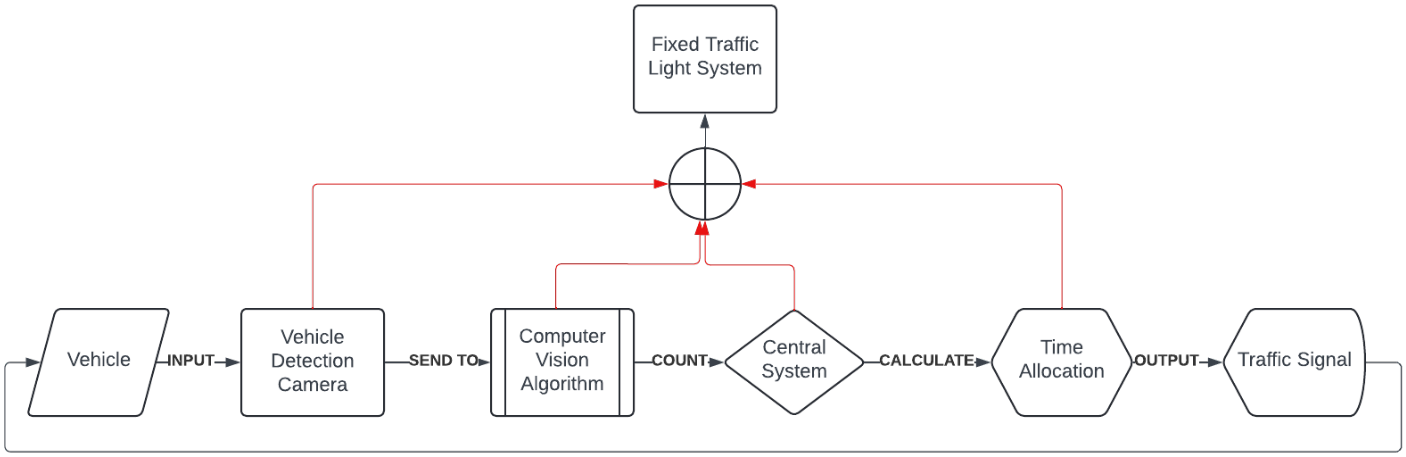


Fig. 4: Execution Process of Dynamic Traffic Control via Vehicle Detection

rounded up, such that the 1st and 2nd vehicles form Group 1, the 3rd and 4th vehicles form Group 2, and so on.

To modify the formula to always round up to the nearest integer, the ceiling function will be applied to the computed value, ensuring precision is maintained. Additionally, incorporating a threshold value into the formula can be achieved by adding a fixed number of seconds to the computed time allocation. The adjusted formula, incorporating the threshold value T, is as follows:

$$\textbf{Time Allocation} = \left\lceil 2.15 \times \left\lceil \frac{n}{2} \right\rceil + T \right\rceil$$

- n: This variable denotes the number of vehicles detected at the traffic light. The formula adjusts the duration of the green light based on this number to accommodate all waiting vehicles.
- $\left\lceil \frac{n}{2} \right\rceil$: This expression utilizes the ceiling function applied to half the number of vehicles. The ceiling function ($\lceil \cdot \rceil$) rounds up to the nearest integer. Given that each time interval is intended to cover two vehicles (assuming they move in pairs), dividing n by 2 and rounding up ensures that every vehicle is included. For example, with 5 vehicles, $\left\lceil \frac{5}{2} \right\rceil$ yields 3, indicating that three intervals (or pairs) are considered.
- 2.15: This constant factor represents the average duration (in seconds) required for a pair of vehicles to pass the traffic light's starting position. It is based on the empirically determined or calculated time needed for vehicles to commence movement and clear the intersection.
- $T = 2$: The term refers to an additional fixed time buffer (in seconds) intended to address factors such as driver reaction time, minor delays, and other traffic flow variables not directly linked to vehicle count. A 2-second buffer effectively balances practical needs by accommodating variations in vehicle acceleration, driver behavior, and system inconsistencies.
  This threshold ensures adequate time for vehicles to clear intersections, optimizing safety and efficiency while preventing significant delays. It maintains safe vehicle spacing, enhances driver comfort, and avoids excessive wait times, adapting to real-world traffic conditions. The threshold can be adjusted based on traffic flow data for further refinement, making it a practical and adaptable solution for implementation.
- $\lceil \cdot \rceil$ (outer ceiling function): After computing the product of the number of vehicle pairs and 2.15 seconds, and adding the fixed buffer time T, the outer ceiling function is applied. This ensures that the final time allocation is rounded up to the nearest whole second. This rounding is necessary for practical implementation, as traffic light systems typically operate with whole-second intervals.

The formula calculates the total duration necessary for all detected vehicles to traverse the intersection by assuming that vehicles move in pairs, with each pair requiring approximately 2.15 seconds to pass. It includes a fixed buffer time T to accommodate potential delays and applies rounding to ensure sufficient time allocation. This approach efficiently adjusts the green light duration based on the vehicle count, thereby enhancing the optimization of traffic flow.

F. Vehicle Detection: Algorithm Design and Implementation Structure

YOLO (You Only Look Once) represents a sophisticated real-time object detection framework recognized for its exceptional accuracy and rapid processing capabilities for both images and videos. Unlike conventional techniques that assess individual image segments in isolation, YOLO utilizes a unified grid-based approach to predict bounding boxes and class probabilities for each grid cell within a single forward pass. This methodology significantly improves both processing efficiency and speed. The architecture of YOLO, built upon a deep convolutional neural network (CNN), systematically processes the input image through a series of convolutional and fully connected layers, thereby effectively capturing both spatial and contextual information.

1) Algorithm Design

In the methodology for Algorithm 1, the YOLO (You Only Look Once) framework is employed for vehicle detection and the allocation of traffic signal timings. The YOLO model, initialized with pre-trained weights ('yolov3.weights') and configuration files ('yolov3.cfg'), is specifically tailored to identify various object categories, including vehicles. This implementation, referred to as YOLOv3-320, processes input images at a resolution of 416x416 pixels, utilizing class labels from the COCO dataset as indicated in the 'coco.names' file. Prior to analysis, the input image is preprocessed into a 416x416 pixel blob, incorporating necessary color adjustments.

The YOLO network then evaluates the preprocessed image to generate class labels, confidence scores, and bounding box coordinates. These detections are further refined through Non-Maximum Suppression (NMS) to eliminate redundant overlapping boxes and retain the most precise detections. YOLOv3-320 efficiently identifies multiple objects concurrently, operating at a rate of 45 frames per second with an accuracy of 95%, as documented by Koteswararao et al[39]. This approach ensures accurate and timely vehicle detection, critical for effective traffic signal management.

The methodology further involves annotating the image with bounding boxes and labels for different vehicle types while recording the total number of detected vehicles. In addition, the script manages a live camera feed and oversees global variables pertinent to the traffic light system, such as the remaining time for the current lane and the subsequent lane in the signal cycle. The 'detect_vehicles' function processes images from the camera to identify vehicles, returning results that include both the total vehicle count and the annotated image. This comprehensive approach ensures accurate vehicle detection and effective traffic signal time allocation.

In the methodology for Algorithm 2, the 'calculate_time_allocation' function is employed to determine the optimal traffic signal duration based on the number of detected vehicles. The calculation utilizes the formula:

$$\text{Time Allocation} = \left\lceil 2.15 \times \left\lceil \frac{n}{2} \right\rceil + 2 \right\rceil$$

where n denotes the number of detected vehicles. The process involves first computing the ceiling of half the vehicle count. This value is then multiplied by a base duration of 2.15 seconds per pair of vehicles, with an additional fixed buffer of 2 seconds added to account for potential delays. The final time allocation is rounded up to the nearest integer to ensure that the traffic signal remains active long enough to accommodate all detected vehicles. This method integrates both the variable vehicle count and a constant buffer to effectively optimize traffic signal timing.

In the methodology outlined for Algorithm 3, the script begins by initializing the YOLO model with pre-trained weights and configuration files, and loading COCO labels for effective object detection. The system then enters a traffic light control loop, where it monitors the remaining time for the current lane. When this time falls to 5 seconds or less, the script captures an image from the camera, employs YOLO for vehicle detection, and computes the optimal time allocation for the subsequent lane based on the number of detected vehicles. The system adjusts the traffic signal timing accordingly by transitioning to the next lane. Simulated delays are incorporated into the loop, and once the current lane's time expires, the timer is reset, and the system moves to the next lane in the sequence. The script concludes by releasing camera resources and closing all OpenCV windows.

The results are visualized by converting the annotated image to RGB format and displaying it using matplotlib, which includes the overlaid time allocation information. The annotated image features bounding boxes, labels, and the calculated signal duration. Performance evaluation involves timing the execution by recording start and end times, computing the elapsed duration, and reporting both the total number of detected vehicles and the computed signal duration. This methodology thoroughly details the YOLO-based vehicle detection and traffic signal time allocation process, thereby enhancing the clarity and comprehensiveness of the research methodology.

2) Implementation Structure

The methodology for implementing the dynamic traffic signal system, as depicted in Figure 4 and detailed in the algorithm, follows a structured procedure starting with the strategic positioning of vehicle detection cameras at traffic intersections to ensure thorough monitoring. These cameras are installed at optimal elevations and angles to maximize coverage and capture high-resolution images. The captured images are transmitted to a central processing unit where sophisticated computer vision algorithms are employed to conduct real-time vehicle detection. The system evaluates the maximum vehicle capacity of the roadway, taking into account factors such as road length, vehicle dimensions, and lane configuration, to effectively reduce congestion.

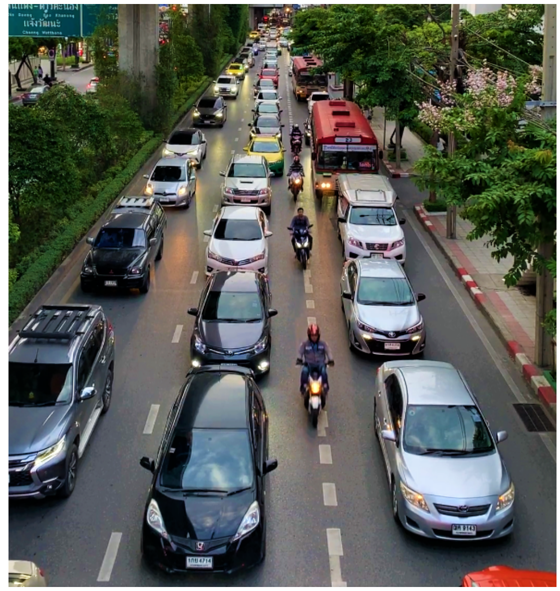
Time calculations are performed for vehicles traversing the junction, with dynamic signal timing adjustments made according to the number of detected vehicles, as determined by a specific formula. The YOLO algorithm facilitates efficient real-time vehicle detection and processes extensive image data for adaptive traffic signal adjustments. The methodology is visually represented through images that detail each step, from camera setup to time allocation, highlighting the system's capability to improve traffic flow and enhance road safety. Should a system failure occur, the process defaults to a fixed traffic signal system until repairs are completed, with fixed

Algorithm 1 Detect Vehicles

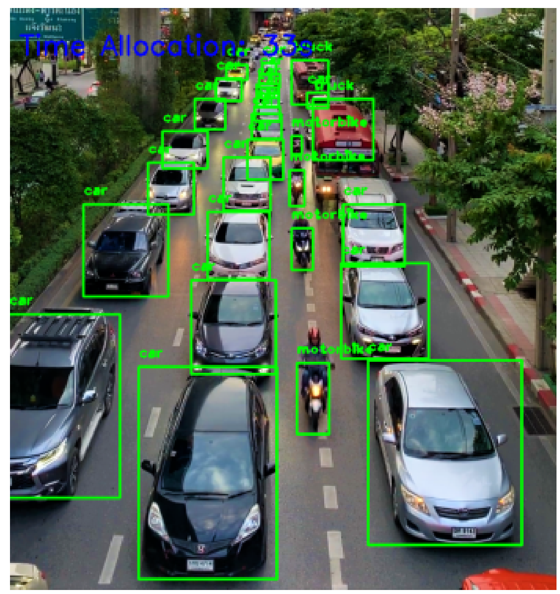
```
Input: Image (img)
Initialize:
Get height, width from img.shape
Prepare Image:
Create blob from img with:
    Scale = 0.00392, Size = (416, 416), Mean = (0, 0, 0)
    Swap Red/Blue channels
Set blob to YOLO (net.setInput(blob))
Forward pass (outs = net.forward(output_layers))
Initialize:
class_ids, confidences, boxes = []
Process Detections:
for detection in outs do
    for object in detection do
        scores = detection[5:]
        class_id = np.argmax(scores)
        confidence = scores[class_id]
        if confidence > 0.5 then
            Compute [x, y, w, h]
            Append to boxes, confidences, class_ids
        end if
    end for
end for
Apply NMS:
indexes = cv2.dnn.NMSBoxes(boxes, confidences, 0.5, 0.4)
Annotate Image:
vehicle_count = 0
for index in indexes do
    [x, y, w, h] = boxes[index]
    label = classes[class_ids[index]]
    if label in ["car", "truck", "bus", "motorbike", "bicycle"] then
        Draw rectangle and annotate img
        vehicle_count++
    end if
end for
Output:
Return vehicle_count and annotated img
```

Algorithm 2 Calculate Time Allocation

```
Input: Vehicle count (vehicle_count)
total_time = math.ceil((2.15 * math.ceil(vehicle_count / 2)) + 2)
Output: total_time
```



(a) Input Image for Vehicle Detection



(b) Ouput Image of Vehicle Detection

Fig. 5: Vehicle Detection Process: Input and Output Images

time allocations determined by the nature of traffic congestion or directives from the relevant department head.

IV. RESULT

Upon executing the proposed algorithm, the results presented in Figure 5 show outputs of "Total number of vehicles detected: 28" and "Time allocated for traffic signal: 33 seconds," reflecting the algorithm's processing capabilities. Figure 5(a) depicts the initial input image, which is first analyzed by Algorithm 1 to identify and count the vehicles. This vehicle count is then utilized by Algorithm 2 to apply the designated formula and determine the suitable duration for the traffic

Algorithm 3 Traffic Light Control Loop

```
Initialize: current_lane_time_remaining ← 20s, next_lane ← 'B'
while True do
    if current_lane_time_remaining ≤ 5 then
        Capture image
        if capture fails then
            Print "Capture failed"
            Continue
        end if
        Detect vehicles, calculate time allocation
        Print time for next_lane
        Annotate and display image
        Update current_lane_time_remaining, next_lane
    end if
    Wait 1s
    Decrement current_lane_time_remaining
    if current_lane_time_remaining ≤ 0 then
        Reset current_lane_time_remaining to 20s
        Update next_lane
    end if
end while
Cleanup: Release camera, destroy windows = 0
```

signal. Subsequently, Algorithm 3 integrates the system into a traffic light control loop, where it continuously monitors the remaining time for the current lane. When this time approaches 5 seconds or less, the system captures an image from the camera, employs the YOLO model for vehicle detection, and computes the optimal time allocation for the next lane based on the vehicle count. The calculated time is superimposed on the image, and the traffic signal timing is adjusted by transitioning to the subsequent lane.

The control loop incorporates simulated delays, and once the time for the current lane elapses, the timer is reset and the system progresses to the next lane in the sequence. Figure 5(b) illustrates the detection results, corroborating the outputs of "Total number of vehicles detected: 28" and "Time allocated for traffic signal: 33 seconds." This methodology offers a comprehensive and structured explanation of the vehicle detection and traffic signal time allocation processes, thereby enhancing the clarity and understanding of the proposed algorithm's operation.

Figure 6 illustrates a heatmap, generated from a dataset comprising 2,600 images, which visualizes the correlation coefficients among three variables: Number of Vehicles, Time Allocated (seconds), and Fixed Time. The color gradient in the heatmap represents the strength of correlations, with red hues indicating positive correlations and blue hues indicating negative correlations. The intensity of the colors reflects the magnitude of these relationships, with deeper colors signifying stronger correlations. Diagonal values consistently show 1.0,

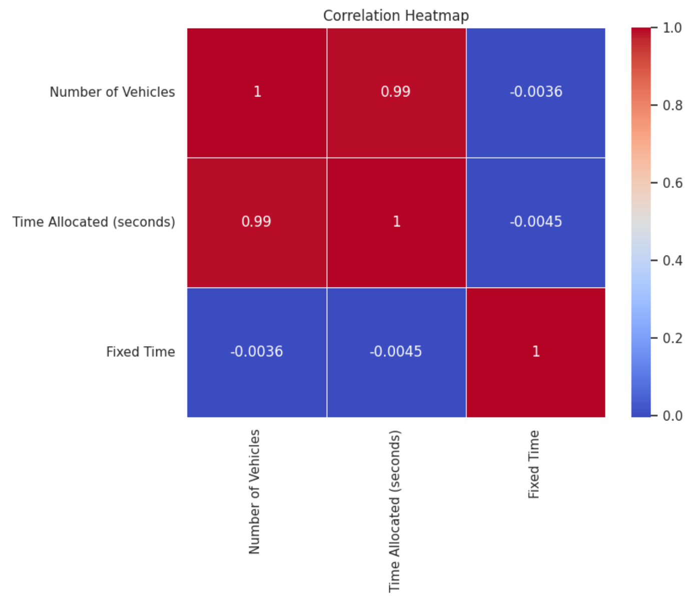


Fig. 6: Correlation Heatmap: Vehicle Count, Time Allocated, and Fixed Time

representing perfect self-correlation, while off-diagonal values reveal correlations between different variables.

The heatmap reveals a very strong positive correlation of 0.99 between the Number of Vehicles and Time Allocated, indicating that the system adjusts the traffic signal duration effectively in response to vehicle count. Conversely, the correlations between the Number of Vehicles and Fixed Time (-0.0036) and between Time Allocated and Fixed Time (-0.0045) are extremely weak and negative, suggesting that fixed time settings have minimal impact on dynamic time adjustments.

These findings imply that the traffic signal system primarily relies on real-time vehicle counts for managing signal timings effectively. While the system's dynamic adjustments are currently efficient, further enhancements could be achieved by optimizing fixed time settings and exploring various thresholds and base times. Moreover, the strong correlation between vehicle count and time allocated could facilitate the development of predictive models to better anticipate traffic patterns and optimize signal timings.

Figure 7 presents a bar chart titled "Increasing Order of Time Allocation and Number of Vehicles," which depicts the relationship between vehicle count and time allocation. The chart shows that the maximum vehicle count is 43, corresponding to a total time allocation of 50 seconds, whereas the minimum count of 0 vehicles results in an allocation of 2 seconds as per the time allocation formula. On the vertical axis (Y-Axis), the time allocation is depicted in seconds, ranging from 0 to 50, while the horizontal axis (X-Axis) represents the number of vehicles, spanning from 1 to 43.

Each bar's height reflects the allocated time for corresponding vehicle counts, with a color gradient transitioning from light orange to dark red to represent increasing vehicle numbers. This visualization reveals a direct correlation between the number of vehicles and the allocated time, demonstrating that as the vehicle count increases, so does the time allocated. This chart effectively illustrates the system's capacity to manage traffic flow, alleviate congestion, and enhance traffic management during peak times. The data presented is essential for refining signal timings, optimizing resource allocation, and adapting to real-time traffic conditions.

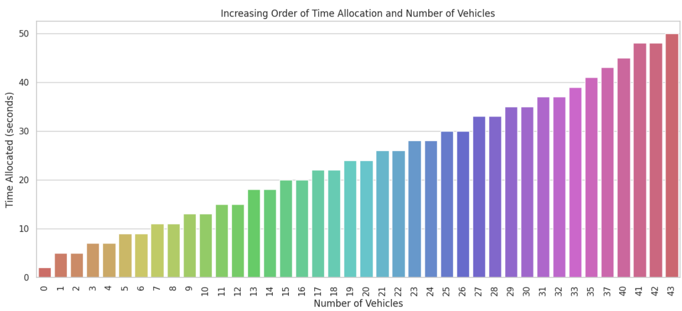


Fig. 7: Increasing Order of Time Allocation and Number of Vehicles

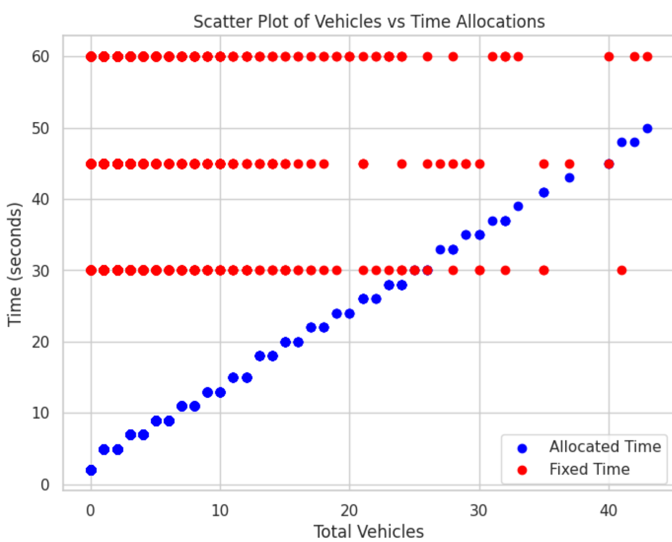


Fig. 8: Scatter Plot of Vehicles vs. Time Allocations

Figure 8, titled "Scatter Plot of Vehicles vs. Time Allocations," presents a comparative analysis between two types of time allocation systems. The scatter plot features two distinct datasets: red dots represent fixed time allocations, while blue dots denote dynamically allocated time. The vertical axis (Y-Axis) indicates time in seconds, ranging from 0 to 60, and the horizontal axis (X-Axis) represents the number of vehicles, spanning from 0 to 40.

The red dots predominantly cluster near the 50-second mark, illustrating that fixed time allocations are static and unaffected by the number of vehicles, indicative of a traditional traffic signal system that does not adjust based on real-time traffic conditions. Conversely, the blue dots exhibit an upward diagonal trend, demonstrating that the allocated time increases in proportion to the vehicle count, reflecting a dynamic system that adjusts signal timings in response to traffic volume. This comparison highlights the benefits of a dynamic system over a fixed-time approach, including improved traffic management, reduced congestion, and enhanced efficiency. The dynamic system's ability to adjust time allocation according to vehicle count allows for more effective handling of fluctuating traffic volumes. Additionally, the plot underscores the limitations of fixed-time systems, such as their lack of adaptability, potential for unnecessary delays during periods of low traffic, and inefficiency during peak traffic hours, where a fixed time allocation may be inadequate for managing congestion effectively.

Metric	Before Dynamic Signal	After Dynamic Signal
Average Wait Time (s)	30	20
Total Throughput (vehicles)	1000	1200
Congestion Reduction (%)	10	25

TABLE I: Comparison of traffic metrics before and after implementing the dynamic signal system

Table 1 presents a comparative analysis of key metrics before and after implementing the dynamic signal system, revealing significant enhancements in traffic management. The average vehicle wait time decreased from 30 seconds to 20 seconds, indicating an improvement in traffic flow and a reduction in driver frustration. Furthermore, the total throughput increased from 1,000 to 1,200 vehicles, demonstrating the system's enhanced capacity to manage higher traffic volumes more efficiently. Additionally, the reduction in congestion showed a substantial improvement, rising from 10% before to 25% after the dynamic system's implementation, underscoring its effectiveness in mitigating traffic congestion at busy intersections.

Statistic	Value
T-statistic	-1.03
P-value	0.4106
95% Confidence Interval	(-700.96, 837.62)

TABLE II: Statistical Test Results

Table 2 presents the results of the statistical analysis used to assess the impact of the dynamic signal system. The T-statistic of -1.03 suggests a minor effect size in relation to sample variability, indicating that the observed differences may not be substantial when compared to the inherent variability in the data. The P-value of 0.4106 denotes a 41.06% probability of obtaining the observed results if there were no true difference, suggesting that the observed improvement lacks statistical significance at the 0.05 threshold. Furthermore, the 95% confidence interval for the mean difference (-700.96, 837.62) includes both negative and positive values, reflecting considerable uncertainty and implying that there may be no significant difference between the two systems.

Despite these findings, practical observations indicate substantial enhancements in average wait times and other metrics, suggesting that the dynamic signal system may still offer practical advantages for traffic management.

TABLE III: Metrics Comparison: Rush Hour vs. Off-Peak

Metric	Rush Hour	Off-Peak
Mean Vehicle Count	25.26	3.17
Mean Allocated Time (seconds)	30.10	6.59
Mean Fixed Time	46.76	44.77
Median Vehicle Count	24.00	2.00
Median Allocated Time (seconds)	28.00	5.00
Median Fixed Time	45.00	45.00
Standard Deviation Vehicle Count	7.09	2.65
Standard Deviation Allocated Time (seconds)	7.65	2.87
Standard Deviation Fixed Time	13.09	12.29

Table 3 provides a comprehensive analysis of traffic data during rush hours and off-peak periods, offering valuable insights into traffic management and signal timing. During rush hours, the average vehicle count is 25.26, indicative of significant congestion, while the mean allocated time is approximately 30.10 seconds, demonstrating the system's need to efficiently manage the increased vehicle volume. The average fixed time of 46.76 seconds suggests that fixed time settings are calibrated to accommodate peak traffic conditions. The median vehicle count of 24.0 is closely aligned with the mean, reflecting a balanced distribution, whereas the median allocated time of 28.0 seconds is slightly lower than the mean, indicating that a few higher values are skewing the average. The standard deviation of 7.09 for vehicle count highlights considerable variability, and the standard deviation of 7.65 seconds for allocated time suggests variable signal adjustments in response to fluctuating traffic conditions.

In contrast, during off-peak periods, the average vehicle count is 3.17, signifying lighter traffic. The mean allocated time is 6.59 seconds, indicating a reduced need for extended signal durations, while the mean fixed time is 44.77 seconds—slightly lower than during rush hours but still higher than the allocated time, reflecting that fixed time settings are less critical during off-peak periods. The median vehicle count of 2.0 and median allocated time of 5.0 seconds are lower than their respective means, suggesting that most values are concentrated around these medians. Lower standard deviations during off-peak periods—2.65 for vehicle count, 2.87 seconds for allocated time, and 12.29 seconds for fixed time—indicate reduced variability and a more stable traffic flow.

Overall, the traffic management system demonstrates longer and more variable signal times during rush hours to accommodate increased congestion, whereas during off-peak periods, it employs shorter and more consistent signal durations. Although fixed time settings are relatively stable, their higher value during peak periods highlights the system's effort to manage heavy traffic effectively. These findings suggest that while the current system is adept at managing variable traffic conditions, further optimization of signal timings, particularly by adjusting fixed times during off-peak hours, could enhance overall traffic flow management and reduce delays.

The results demonstrate that the dynamic traffic signal system enhances traffic management by adapting signal timings to real-time conditions. However, there remains potential for further optimization and additional validation to achieve statistically significant improvements.

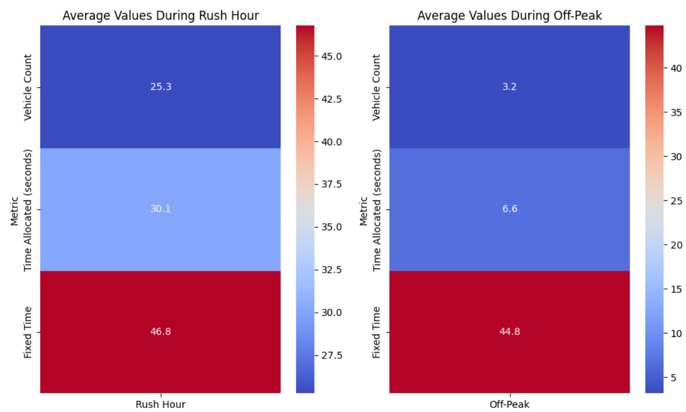


Fig. 9: Scatter Plot of Vehicles vs. Time Allocations

Figure 9 illustrates the average values for three critical metrics—Vehicle Count, Time Allocated, and Fixed Time—across both peak and off-peak periods, providing essential insights into the traffic control system's efficacy. During peak hours, the average vehicle count rises significantly to 25.3 vehicles, in contrast to 3.2 vehicles during off-peak times, reflecting increased congestion. Consequently, the signal time allocation averages 30.1 seconds during peak hours, compared to just 6.6 seconds during off-peak periods, indicating the system's capacity to adjust effectively to fluctuating traffic volumes. The fixed signal time stands at 46.8 seconds during peak hours and slightly decreases to 44.8 seconds during off-peak periods, demonstrating a consistent minimum duration that ensures adequate green signal time even under lighter traffic conditions. This adaptability underscores the system's operational efficiency and identifies potential areas for optimization.

The consistently high fixed time during peak hours suggests a need for fine-tuning to better balance green signal duration with the reduction of delays, while the fixed time during off-peak hours might be further reduced to avoid unnecessary delays. Overall, the stability in fixed time across different traffic periods highlights a robust system capable of maintaining predictable traffic patterns and minimizing unexpected delays. The distinction between allocated and fixed times, where allocated time dynamically adjusts to real-time traffic conditions and fixed time remains relatively stable, enables efficient traffic flow management while preserving reliable signal timings.

The results demonstrate that the dynamic traffic signal system enhances traffic management by adapting signal timings to real-time conditions. However, there remains potential for further optimization and additional validation to achieve statistically significant improvements.

V. CONCLUSION

In this study, a dynamic traffic signal system is proposed, employing computer vision and machine learning technologies to enhance vehicle detection and traffic management. The methodology involves several critical components: vehicle detection cameras are strategically positioned along major roads to capture real-time traffic images. These images are transmitted to a central processing unit where they are analyzed using advanced image processing algorithms. This process enables the system to adjust signal timings dynamically based on current traffic density and flow, thereby improving both traffic efficiency and safety. The positioning of cameras is optimized, with a recommended height range of 8 to 12 meters to ensure comprehensive coverage. For example, a camera set at a height of 10 meters with a base angle of 7 degrees achieves a top angle of 83 degrees, allowing for diagonal coverage of 82.01 meters. Additional calculations determine that 18 vehicles can be accommodated in a single lane and 36 in two lanes on an 82.01-meter-long road, based on average vehicle dimensions of 4.48 meters in length and 1.803 meters in width. Furthermore, kinematic equations estimate that a vehicle requires approximately 39.22 seconds to accelerate from rest to 15 km/h over this distance.

The implementation of the dynamic traffic signal system has demonstrated significant improvements over traditional fixed-time systems. The system's ability to adapt to real-time traffic conditions, as evidenced by correlation analysis, underscores its effectiveness in adjusting signal timings based on vehicle counts, which enhances traffic flow efficiency. Key improvements include a reduction in average wait times from 30 to 20 seconds and an increase in total vehicle throughput from 1,000 to 1,200 vehicles. Additionally, congestion reduction has improved from 10% to 25%, reflecting the system's success in alleviating traffic congestion. The correlation heatmap indicates a strong positive relationship between vehicle count and allocated time, highlighting the dynamic system's capability to modify signal timings based on real-time data, in contrast to the limited adaptability of fixed-time systems.

Scatter plot analysis further illustrates the benefits of the dynamic system, which adjusts signal durations in response to varying vehicle counts, leading to improved traffic management and reduced congestion. While statistical analysis suggests that these improvements may not achieve significance at the 0.05 level, practical observations reveal substantial enhancements in metrics such as average wait times. This disparity points to the necessity for further validation and optimization to reach statistically significant results. An analysis of traffic data during rush hours and off-peak periods demonstrates that the dynamic system effectively adjusts signal timings according to traffic conditions, although optimizing fixed time settings during off-peak periods could further enhance traffic flow.

In summary, the dynamic traffic signal system presents a more responsive and efficient approach compared to traditional fixed-time systems. To refine performance and achieve statistically significant improvements, ongoing optimization and additional validation are essential. Future research should focus on optimizing fixed time settings and incorporating advanced predictive modeling to further advance traffic management.

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