Unlocking Smoother Journeys with Intelligent Traffic Signals

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Abstract. The Urban areas face escalating traffic congestion due to a yearly 35% raise in the no.of vehicles on the roads. Traditional traffic controlling systems, following constant cycles, cannot adapt to changing conditions as human officers can. To address this issue, we propose implementing an Intelligent Traffic Management System. This system utilizes AI and image processing, analyzing live camera feeds at intersections to measure traffic volume accurately. Simulation results suggest a remarkable 32% increase in vehicle flow at intersections compared to the current situation, and further fine-tuning through real CCTV data calibration promises even greater performance improvements.

Keywords: Transportation optimization, Traffic congestion mitigation, Image Processing, Adaptive traffic control, Automated sensing, Object detection.

1 Introduction

Global concerns over rising traffic congestion are fueled by outdated signaling systems and inadequate infrastructure. Traditional systems struggle with dynamic web traffic, performing optimally only under stable conditions. Modern traffic management uses time-sharing and adaptive cycles to respond to real-time conditions. Traffic lights primarily use three methods to regulate vehicle flow.

In our contemporary world marked by rapid population growth and industrialization-driven traffic expansion, managing traffic has become a critical challenge, leading to adverse consequences such as congestion, violations, and delays. An efficient, cost-effective traffic control system is crucial for national development. Implementing mechanization and intelligent control techniques in highway infrastructure and vehicles enhances traffic flow and safety. The growing population strains existing transportation infrastructure, underscoring the importance of intelligent systems like advanced traffic

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control. Mismanaged signals can result in significant waste of time, energy, and resources. Presently, three widely adopted traffic control methods exist.

In their study, In managing traffic, Human Management involves active intervention by traffic police in critical areas. Traditional static traffic signals follow predetermined timer intervals, cycling between red and green lights. Uses Advanced electronic sensors, such as road-based sensors or motion detectors, provide insights into vehicular movements for efficient traffic light management. Real-time surveillance camera footage at intersections monitors and adjusts green light timings based on detected traffic density, offering a promising solution. Precise vehicle categorization enables accurate allocation of green time. Leveraging technologies like YOLO ensures continuous monitoring for adaptive and efficient traffic signal control.

2 Literature Review

In their study [1-3] proposed a two-step approach to optimize traffic signal plans. Using TRANSYT for modeling and VISSIM for micro-simulation, they identified a significant reduction in delay with the adaptive signal control compared to conventional fixed-time strategies.

In their research [4-5] focused on dynamic feedback traffic signal control strategies rooted in a generalized proportional allocation principle. Their work resulted in the development of a differential inclusion, demonstrating successful solutions[6-7]. They emphasized the uniqueness of continuous solutions in cases with orthogonal traffic phases through modifications to the reflection theory. Additionally, by considering controllers as optimizers of an entropy-like function, they explored the stability of these control policies, ultimately demonstrating system stability using this function as the closed-loop system's Lyapunov function[8].

In their work,[9-10] introduced a novel model to address limitations linked to the ideal facility concept. They emphasized the growing importance of intelligent transit in smart cities and proposed an adaptable traffic light system. This system utilizes real-time traffic data to enhance signal efficiency and effectively address current challenges.

Introduced a model for detecting and monitoring traffic accidents[11-12]. Modern advanced traffic management systems capture and interpret real-time video data, often sending it to a traffic management center (TMC) for analysis. This approach can introduce complexities to the network path leading to the TMC[13].

Addressed urban street traffic by employing a memetic algorithm, a hybrid of genetic algorithms and local search methods[14-15].Their approach included improvements like a systematic neighborhood-based simple descent algorithm for efficient search space exploration and an indicator technique to control local search based on the ongoing process[16-17].This demonstrated the effectiveness of their algorithm in streamlining traffic signal configurations.

3 Overview of Existing System

The smart traffic regulating system streamlines urban and suburban traffic, enhancing security and reducing congestion through advanced technology, data analytics, and automation[18-20]. Created a flexible framework by continuously gathering real-time traffic data using sensors like cameras, in-road detectors, and vehicle-to-infrastructure communication devices. While achieving an accuracy rate of 80% to 85%, there is room for improvement, particularly in addressing the challenge of overfitting, requiring focused efforts to enhance analytical skills for more accurate results in the future [21-22].

4 Proposed System

The method utilizes CCTV cameras at intersections for real-time traffic volume statistics (Fig. 1), employing object identification and a YOLO-based vehicle detection algorithm. It counts total vehicles and types, determining traffic density. The algorithm adjusts green traffic light timing considering various inputs, including traffic density, leading to optimized red signal lengths. The following figure 1shows the composition of the traffic lights.

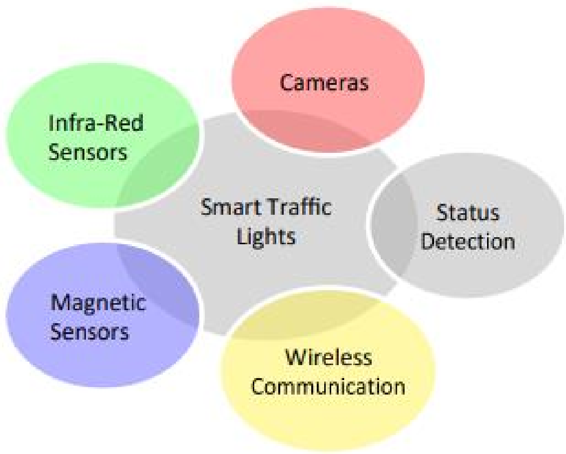

Fig. 1. Composition of Smart Traffic Lights

Simulations will highlight the system's benefits, enabling comparison with static systems. The suggested approach employs the YOLO principle for the Motor Vehicle Detection module, ensuring accurate and efficient identification of passing cars. A specialized YOLO model recognizes diverse vehicles like automobiles, rikshaws, bikes, trucks, and buses, across various sizes and weight classes. YOLO's real-time object detection, utilizing neural net-works, offers speed and precision applicable to diverse fields, including the identification of people, animals, parking meters, and traffic signals.

Real-time object recognition showcases YOLO's excellence in utilizing a sophisticated Convolutional Neural Network (CNN). This approach efficiently processes the entire image using a single neural network. The image is partitioned into smaller sections to predict bounding boxes and related probabilities. YOLO allocates values to these bounding box outlines based on anticipated probabilities, demonstrating its real-time functionality with high precision. Fig. 2 illustrates the method's forward run over the neural network for predictions, emphasizing the use of non-maximal suppression to output detected objects and their corresponding bounding boxes. YOLO's ability to identify each object only once, even with multiple bounding boxes, relies on a single CNN predicting probabilities for various classes.

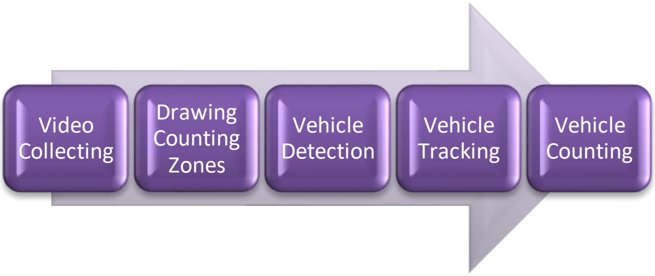

Fig. 2. Work flow of YOLO Algorithm

4.1 YOLO Algorithm working process

In Figure 2, The Darknet open-source software provides a simplified version of the YOLO backbone CNN, aiming to boost processing efficiency. Recognized for its speed, straightforward installation process, and compatibility with both CPUs and GPUs, Darknet notably improves YOLO's accuracy on ImageNet, achieving a remarkable 91.2% accuracy in the top 5 percent. Darknet utilizes 11 filters to reduce output channels, employs a 33-filter technique for feature extraction, and enhances performance with global pooling data for supplementary predictions.

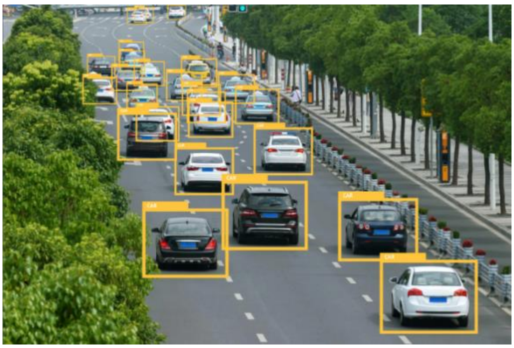

Fig. 3. Vehicle Detection

To find the suitable number of filters, we apply the equation 5*(5 + number of lanes), totaling 45 in our case. In the illustrative example in Figure 3, we witness vehicle object detection, capturing CCTV recording, identifying vehicles within boxed regions. This aligns with the functionality of our traffic monitoring model. The signal switching methodology is crucial, updating red light durations for another signals based on traffic levels from the vehicles detection module. Additionally, it utilizes a timer for regular signal cycling.

We have outlined how the detection module provides information about identified cars to the algorithm. The object label serves as the identifier in the JSON format, including values like self-belief and coordinates. This data allows us to calculate the number of automobiles in each category. Subsequently, we allocate the signal's green time and adjust red light timings for all another signals. This adaptable technique is adaptable to any quantity of traffic lights. Key considerations in developing this algorithm include:

The algorithm begins by setting the default timing for the first signal in the initial cycle. Afterwards, it calculates the timing for each transmission in the first cycle and for every subsequent signal in subsequent cycles. Individual threads are assigned to handle vehicle detection for every direction, while the main thread supervises the overall timing of the signals.

With just 5 seconds remaining, a photo is taken as the next green light approaches. This snapshot enables the system to analyze the image, tally the number of cars in various categories, ascertain the duration of the upcoming green light, and modify both the green and red lights for the subsequent signal. With a quick 10-second turnaround, the process is efficient. By computing the time required for each vehicle type to traverse the intersection, we enhance the green signal duration according to the present traffic conditions at the signal. The algorithm also computes intersection points and predicts the time until the green light activation. In specific locations, we can customize the estimated time for vehicle types to traverse an intersection, crucial for tailoring traffic management to each intersection's unique features, considering the surroundings and adjacent major roadways. This customization can be guided by data from relevant transportation companies.

The direction of the signal is first ignored, and it alternates in a predictable manner. This strategy is consistent with the current setup, in which traffic lights turn green in a sequential and predictable manner. Figure 4 shows the traffic signals. Drivers won't need to change their routes or get lost because to the constancy. The function of yellow lights is also taken into consideration, and the set sequence of traffic signals is maintained. Signal sequence: Red -------- Green -------- Yellow -------- Red

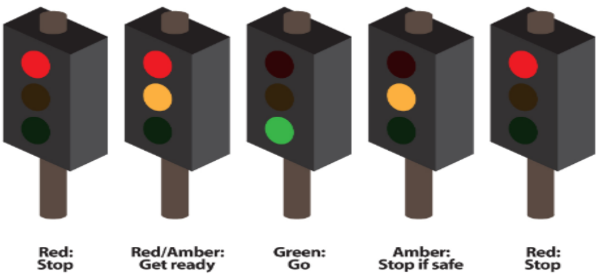

Fig. 4. Traffic Lights

Using the Pygame simulation module, we developed a new traffic simulation featuring timers at each signal indicating the time until the light changes. The simulation tracks the number of cars passing through each intersection, accommodating various vehicles such as automobiles, bicycles, buses, trucks, rickshaws, and others from multiple directions. Realism is enhanced as some vehicles in the far-right lane execute U-turns based on a randomly generated decision at creation. The simulation also establishes a time limit to track elapsed time.

In emergency situations, swift navigation is crucial to minimize potential loss of life and property. Existing studies focus on methods to grant green lights or clear pathways for emergency vehicles, assuming only a single vehicle oncoming from a single direction. Managing this dynamic system involves incident speculation, real-time storage in a traffic maintenance system, data collection on present traffic conditions, urgency assessment for emergency vehicles, and the controller choosing the better route and approving digital traffic lights based on priority levels. Once the incident is resolved, the controller restores normal signal operations.

4.2. Average Wait Time of Vehicles

Calculating the avg wait time of vehicles at traffic signals typically involves a combination of data collection, computer vision, and traffic engineering techniques. Figure 5 shows the steps used to estimate the avg wait time of vehicles at traffic signals:

Fig. 5. Process of calculating Average Waiting Time

To ascertain average waiting times at traffic lights, a comprehensive method involves data gathering through cameras or sensors at the junction, recording incoming cars' quantity, speeds, locations, and signal phase changes. Computer vision techniques like YOLO or Faster R-CNN are then employed for vehicle recognition and tracking based on the video feed. Queue lengths are determined by the number of cars waiting during each signal phase, and individual vehicle waiting times are calculated by tracking entry and exit times. The overall waiting time for a signal phase is obtained by summing individual waiting times. This process is repeated for each step, and results are averaged to determine the total average waiting time. Analysis of gathered data over time reveals patterns and trends, enabling the development of reports and visualizations illustrating typical waiting times during different time periods and signal phases.

$$\text{Waiting times} = \text{Exit time} - \text{Arrival time}$$
$$\text{average waiting time} = \text{sum of waiting times of vehicles} / \text{total number of vehicles}$$

A database serves as a central repository for storing, organizing, and managing data crucial for calculating and analyzing average waiting times at traffic signals. It underpins data-driven decision-making and long-term traffic management improvements.

The accuracy of waiting time estimates depends on quality data collection and effective computer vision and tracking algorithms. Advanced techniques like machine learning and predictive modeling can enhance waiting time predictions.

5 Results and Discussions

The vehicle sensor's accuracy, analyzed across diverse test photos with varying car counts, falls between 75% and 80%, deemed acceptable but with room for improvement. Limited suitable training data is the primary factor hindering optimal performance. To address this, we propose fine-tuning the model using real traffic video evidence for enhanced reliability. Simulations evaluating the adaptive system involved diverse traffic distributions in each quadrant over a five-minute period, generating 15 sets of data for the two approaches the current and the proposed. The performance metric focused on the no.of vehicles crossing the intersection within a specified timeframe.

We focused on a critical parameter, the control time at a traffic light, representing the duration with no vehicles crossing the intersection during a green light signal. In our analysis, we used the existing static system as the baseline for comparison, depicted in Fig 6. Intelligent business lights, often known as smart business lighting systems, serve as outsourced control solutions for companies to manage vehicle and pedestrian flow efficiently. These systems integrate traditional business lighting with a group of sensors and Computer Vision (CV) technology, providing advantages such as responsible public transportation, automated enforcement mechanisms for regulations, and effective systems for marking.

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Hello from the pygame community. https://www.pygame.org/contribute.html
 GREEN TS 1 -> r: 0  y: 5  g: 20
   RED TS 2 -> r: 25  y: 5  g: 20
   RED TS 3 -> r: 150  y: 5  g: 20
   RED TS 4 -> r: 150  y: 5  g: 20

 GREEN TS 1 -> r: 0  y: 5  g: 19
   RED TS 2 -> r: 24  y: 5  g: 20
   RED TS 3 -> r: 149  y: 5  g: 20
   RED TS 4 -> r: 149  y: 5  g: 20

 GREEN TS 1 -> r: 0  y: 5  g: 18
   RED TS 2 -> r: 23  y: 5  g: 20
   RED TS 3 -> r: 148  y: 5  g: 20
   RED TS 4 -> r: 148  y: 5  g: 20

 GREEN TS 1 -> r: 0  y: 5  g: 17
   RED TS 2 -> r: 22  y: 5  g: 20
   RED TS 3 -> r: 147  y: 5  g: 20
   RED TS 4 -> r: 147  y: 5  g: 20

 GREEN TS 1 -> r: 0  y: 5  g: 16
   RED TS 2 -> r: 21  y: 5  g: 20
   RED TS 3 -> r: 146  y: 5  g: 20
   RED TS 4 -> r: 146  y: 5  g: 20
Lane-wise Vehicle Counts   RED TS
 Lane2  1-> r:  :13  47 y:
 Lane5  2 g:  :20
57   RED TS
 Lane3  3-> r:  :73  20 y:
 Lane5  4 g:  :20
34   RED TS
 Total vehicles passed: 4  158-> r:
 Total time passed: 98  300 y:
 No. of vehicles passed per unit time: 5  0.5266666666666666 g:
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Fig. 6. Output Data of Simulation

Our system efficiently handles intersection congestion through automation, offering both automated and manual traffic control options, as depicted in Fig 7. It allows smooth transitions to manual mode when needed, like during rallies. Emergency vehicles are prioritized, underscoring the system's adaptability. The Smart Traffic Light Control System provides a better and straightforward solution to address traffic problems.

Fig. 7. Simulation Output

Our proposed approach consistently surpasses the current static system across diverse traffic distributions, with the level of improvement linked to traffic flow variation between lanes, as shown in Fig 8. The improvement averages around nine percent across all four simulated scenarios. In scenarios with slight traffic skew, our proposal outperforms the existing system by approximately 23%. In cases of highly skewed traffic, the proposed system significantly overcomes the existing system, achieving approximately 36% greater efficiency in simulations 9 and 13.

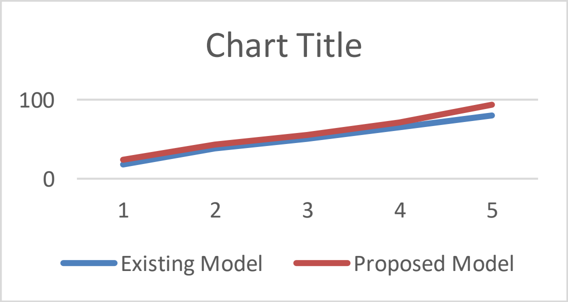

Fig. 8. Accuracy Level

Simulations lasted for 1 hour and 15 minutes (300 seconds), assuming consistent traffic conditions. The proposed solution shows a 24% performance improvement after approximately 5 minutes compared to the current transition stage, benefiting moving vehicles with shorter green light wait times. Our method outperforms previous adaptive systems, achieving an 80% accuracy rate, surpassing the static system by an average of 24%. With 60 randomly chosen cars at the intersection, the average waiting time is an impressive 30 seconds or less. Timings at typical intervals are detailed in the table 1 below.

Table 1. Average Waiting Times at different signal phases.

Signal Phase	Average Waiting Time
1	25.84
2	28.52
3	22.76
4	26.92

6 Conclusion and Future Scope

In conclusion, the suggested approach gives preference to directions with greater utilization rates and vigorously adjusts the time of green lights at crossings based on traffic flow. This modification causes fewer delays, shorter periods of congestion, and shorter wait times, which eventually contribute to less pollution and fuel use. Our simulation results show that the technology successfully boosts throughput of cars crossing the junction by about 24%. The model may be improved and trained using actual CCTV data to increase its efficacy even further. This shows that the suggested framework may be able to improve traffic flow management by integrating with already-installed CCTV systems in major cities. And this can also be improved for prioritizing the vehicles like Ambulances and other necessary vehicles that are needed to be reached their destination on time.

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