Adaptive Traffic Signal Management Using Real-Time Vehicle Detection and Tracking

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***Abstract*—Traffic congestion is one among the major problems in the urban areas causing severe delays, increased fuel consumption, and enhanced harmful gas emissions. The traditional approach or conventional traffic signal systems work at fixed timings without considering dynamic variations within traffic and contribute to it. This paper will be on an adaptive traffic signal control system using the YOLO, or You Only Look Once algorithm, object detection to change the timing of its signals in real-time according to actual traffic flow conditions. This system instals real time vehicle detection and tracking at intersections so that the system can also, based on intelligent management of traffic, extend or reduce green light periods based upon volume and variability of vehicle types. The designed system aims towards a scenario where vehicle recognition and tracking can be done efficiently yet may involve rapid adaptation to continually changing traffic situations. The paper describes the design and implementation of the YOLO algorithm, the mechanism used to track vehicles, and a system-performance evaluation within a simulated environment. The finding points to a superior traffic management approach along with lesser traffic congestion through the system with efficacy in management overall, hence promising to be a solution for smart city traffic control.**

***Index Terms*—traffic signal control, YOLO, object detection, real-time traffic, vehicle tracking, congestion reduction, urban traffic.**

I. Introduction

In India, urbanization has increased rapidly, and the number of vehicles has grown about 8.8% per year in the past decade. This has greatly overloaded roads, worsening already critical traffic congestion and delay problems in cities like Delhi, Mumbai, and Bangalore. The conventional fixed-cycle traffic signal systems cannot respond quickly to traffic demand at any given time and thus worsen traffic flow efficiencies. These delays translate into an estimated 1.5–2% loss in India's GDP every year in the form of fuel wastage and lost productivity besides an alarming increase in vehicular emissions.

Based on the actual real-time detection of vehicles using the YOLO algorithm, this study will dynamically adjust traffic light cycles according to the actual traffic density at intersections with the proposed intelligent traffic management platform to overcome conventional traffic signal control. The system will optimize the flow of traffic with congested traffic and delay in mind by identifying vehicle types and hence their counts and modulating intervals of green lights.

While an intelligent system would, undoubtedly, mitigate traffic bottlenecks, it would also limit fuel consumption—a vital advantage in India, as transport emissions account for 13% of the country's greenhouse gas emission. Such a system could, thus, promote India's vision for smart, sustainable urban transport through effective traffic flow, through accurate vehicle detection and adaptive signal timings, on their way to smarter cities across the country.

The recent advancement in AI, deep learning, and IoT facilitates adaptive efficient control to empower the transformation of traffic management systems. Recently, adaptive frameworks for real-time adaptive traffic management involving AI have been proposed and implemented in Gandhi et al. (2020) [2] and Jonnalagadda et al. (2020) [1], where signal timings are dynamically adapted from vehicle counts to reduce congestion. A closer system comes from Jaiswal et al. (2020) [3] that focuses on emergency vehicles.

Samal et al. (2020) [4] contributed to the analysis of traffic flow by carrying out PCU analyses. This helped in the better quantification and management of traffic density. Further, Ahmed et al. (2019) [5] and Rabby et al. (2019) [6] mentioned how IoT assists in data gathering and makes it responsive to traffic. Javaid et al. (2018) [7] also mentioned how IoT can make vehicle detection more precise.

Papers like Tian et al. (2019) [8] and Kumar et al. (2020) [9] revealed tendencies of studies and models for monitoring the accuracy evaluation and possible use of YOLO and FCOS object detection models in real-time applications where Varma et al. (2019) [11], Ghoreyshi et al. (2020) [12], etc., provided datasets or models customized towards urban environments for better enhancements in the robustness of detection. Dubey et al. (2017) [13], Nodado et al. (2019) [14] studied the implementation of IoT-based adaptive traffic systems and computer vision solutions to be controlled better. Asmara et al. (2020) [15] showed that low-cost devices could be effectively used to predict traffic density, and Nallaperuma et al. (2019) [16] presented an incremental ML platform for big data-driven traffic management.

II. Methodology

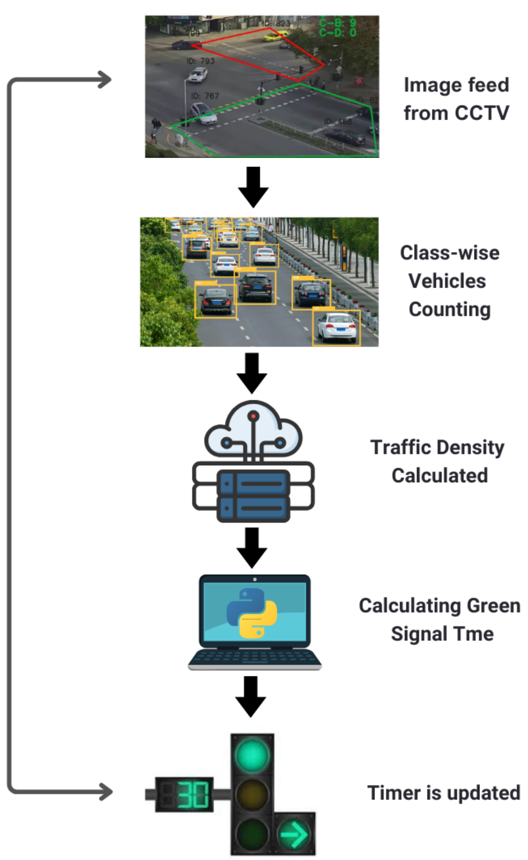


Fig. 1. A flowchart illustrating Adaptive Traffic Signal Management System.

A. Traffic Signal Control Setup

The study utilizes a real-time vehicle detection, tracking, and density-based signal adjustment based on an intelligent modular traffic signal control system to optimize signal timing. Four video feeds representing one specific direction of a traffic junction are captured and processed in real-time to simulate a multi-lane junction, where each feed processes independent vehicle detection, tracking, and classification by type to ensure customized signal timing based on the real-time traffic conditions.

B. Vehicle Type Detection Using the YOLO Algorithm

The YOLO deep learning algorithm is used to perform vehicle detection. It is successful in the one pass of real-time object detection, as it provides both speed and precision, and its task consists of setting up the weights and configuration files of the YOLO model for the types of vehicles, such as cars, motorbikes, and trucks. All vehicle classes are assigned a weight known as the Passenger Car Unit, which is taken as a unit in the calculation of traffic density and to take into account the varying dimensions of vehicles and their influence on the movement of traffic. Cars and autos are treated equally, and buses and trucks are treated equally in detection.

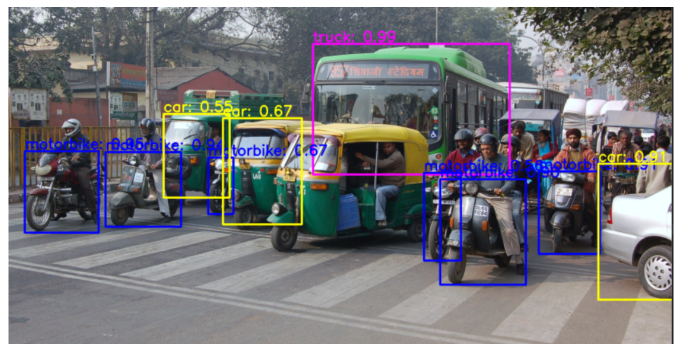


Fig. 2. Type-wise Object Detection of Vehicles.

C. Road Bounding Box and Centroid Tracking

Custom bounding boxes were defined on every video feed to mark areas on the roads where specific vehicles may be detected and counted. This would only count those falling inside the lanes since most times, the periphery or non-relevant features of each frame can likely to contribute to false positives. Thus, centroid tracking is useful to have a consistent tracking of individual items to frames, obtaining a unique ID based on the position of the centroid for avoiding duplicate counts. This means that it is viewed as the same object when the centroid between three frames does not change.

D. Vehicle Counting and PCU-Weighted Density Calculation

After the detection and classification of vehicles, each frame provides a count and estimation of the density of flow with PCU weights. This results in an accurate representation of effective load at every lane. Vehicles that are bigger in size, like trucks, are also considered by obtaining their relevant weight. Such a density data is significant as it is used in determining green signal time, especially in busy intersections where traffic load is dynamically changing.

E. Dynamic Green Signal Timer Calculation

The dynamic modification of the green signal is achieved through real-time changes in the signal timings based on the load detected by the vehicle. The weight used to calculate

TABLE I
PASSENGER CAR UNIT (PCU) FACTORS FOR DIFFERENT VEHICLES

Vehicle Type	PCU
Car / Auto	1
Truck / Bus	3
Bike / Scooter	0.75

traffic density by PCU informs the length of the green signal for each feed. The approach dynamically eliminates normal inefficiencies of fixed-timing signals, adapting to real conditions and facilitating a smoother flow of traffic and less congestion. The time for the green signal is converted into an integer as in the following formula:

$$G = B + (P \cdot E) \tag{1}$$

Where:

G : Green signal time
B : Base time
P : Total PCU (Passenger Car Unit) count
E : Extra time per PCU

To better illustrate how this calculation works in the real world, consider a busy intersection that has four lanes: Northbound, Eastbound, Southbound, and Westbound. In one scenario, the following counts of vehicles were measured (in PCUs) over a stated period:

Northbound Lane : 10 cars and 5 buses (totaling 25 PCUs)
Eastbound Lane : 15 cars and 2 motorcycles (16.5 PCUs)
Southbound Lane : 7 motorcycles and 2 trucks (totaling 11.25 PCUs)
Westbound Lane : 8 cars (totaling 8 PCUs)

Using Eqn.(1) with a base time $B = 5$ seconds and an extra time per PCU $E = 2$ seconds, the green signal times for each lane can be calculated as follows:

Northbound Lane:
Total PCU = $(10 \cdot 1) + (5 \cdot 3) = 25$
Green signal time :

$$G = 5 + (25 \cdot 2) = 55 \text{ seconds}$$

Eastbound Lane:
Total PCU = $(15 \cdot 1) + (2 \cdot 0.75) = 16.5$
Green signal time

$$G = 5 + (16.5 \cdot 2) = 38 \text{ seconds}$$

Southbound Lane:
Total PCU = $(2 \cdot 3) + (7 \cdot 0.75) = 11.25$
Green signal time

$$G = 5 + (11.25 \cdot 2) = 27 \text{ seconds}$$

Westbound Lane:
Total PCU = $(8 \cdot 1) = 8$
Green signal time

$$G = 5 + (8 \cdot 2) = 21 \text{ seconds}$$

F. Signal Interconnection for Coordinated Signal Timing

Along with single-point optimization, interconnection logic is applied to coordinate signals across adjacent lanes. The concept stated in this regard is the computation of green signal timings based on aggregate traffic loads across multiple directions to optimize the balancing of green signal durations and to avoid bottlenecks. The system adjusts the green light duration in a coordinated fashion through analyzing vehicle density in adjoining lanes, allowing interconnected signals to respond jointly to overall conditions. This adaptive interconnect ensures traffic flows more consistently throughout the network, distributing green light durations based on cumulative congestion instead of isolated conditions at each individual signal.

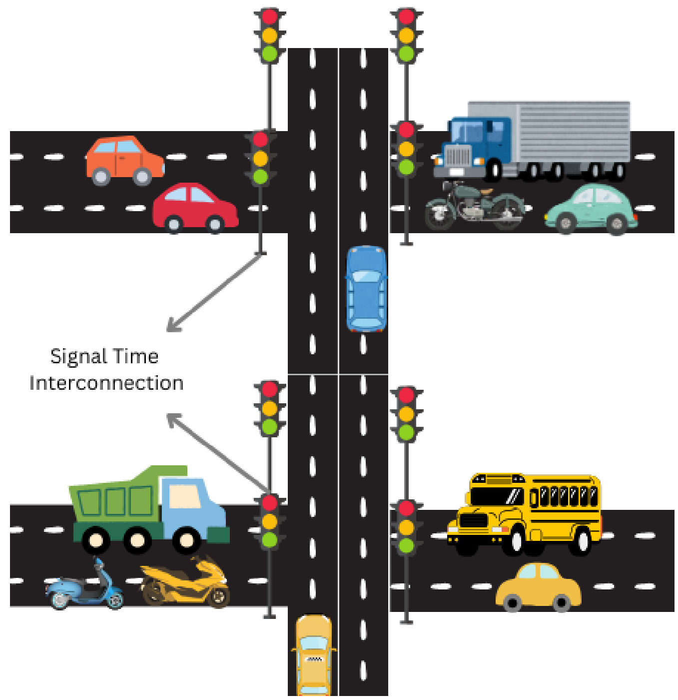


Fig. 3. Interconnection for Coordinated Signal Timing.

G. Final Output and Display Configuration

All of these-processed frames, vehicle counts, and adjusted green signal times-will all display on a 2x2 matrix consolidated screen. Each processed frame will include annotations with a vehicle count and dynamic green time to provide clear and continuous feedback about traffic flow and signal adaptations.

III. CONCLUSION

This adaptive traffic signal system adjusts green times dynamically to optimize efficiency on real-time vehicle counts. This greatly reduces congestion and waiting times at intersections in high-density situations. The solution entails automated adjustment to instances of signal and has the potential for optimizing urban traffic flow and enhancing road safety features and support infrastructures for future smart cities.

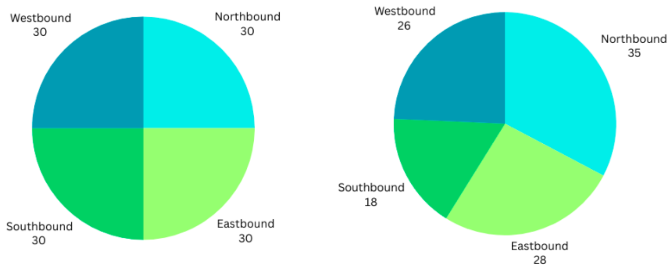
Fig. 4. Final Output with Vehicle count and Green time.

The following example is a demonstration of improvement in traffic flow efficiency based on dynamic adjustment of signal times. The system effectively reduces waiting times by adjusting green signal time based on vehicle count and type.

TABLE II
TABLE OF SIGNAL TIMING EFFICIENCY

Lane Direction	**Static Time (s)**	**Dynamic Signal Time (s)**	**Waiting Time Reduced (%)**
Northbound	30	35	-
Eastbound	30	28	6%
Southbound	30	18	40%
Westbound	30	26	13%
Total Efficiency Improved	**120**	**107**	**10%**

From Table II, it is easily seen how a dynamic signal timing system reduces waiting times of the traffic while improving the flow in the traffic. Due to changes in the green light time based on calculated real-time densities, it reduced the total cycle from 120 seconds to 107 seconds, which accounts for an increase of 10% in general efficiency. The reduction in waiting time was the highest, at 40% in the southbound lane that had the highest density of vehicles. Such an outcome clearly points out the ability of the system to relieve jams in high-density traffic areas. With regard to the northbound lane, while its green signal duration had to be some minutes beyond the pre-set time for the area, this indicates that the system was flexible enough to adapt to the varied nature of the traffic and develop dynamic responses to changing conditions. These results represent the adaptability feature of the system, which will optimize the signal timings in real time to meet the specific needs of every lane while improving multilateral directions' overall traffic management efficiency. Hence, it has vast applicability in urban environments with multiple differing traffic requirements.



(a) (b)

Fig. 5. Pie Chart Comparision of (a) Static and (b) Dynamic Time.

Overall, the results indicate that adaptive traffic management can significantly enhance urban traffic efficiency as a responsive and scalable solution to handle changing conditions in traffic. Wider application may lead to further improvement in mobility in cities and less negative environmental impact.

IV. Future Scope

The proposed system offers approaches for future development. Once developed further, the technology would be deployed with the purpose of identifying emergency vehicles and modifying their movement by changing the duration of time allowed by the signals in real time, at all intersections.

The system can be enhanced to detect accidents or any other occurrence at intersections or roadsides and notify traffic control authorities expeditiously in a real-time manner.

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