Al-Khwarizmi Engineering Journal

Al-Khwarizmi Engineering Journal
ISSN (printed): 1818 – 1171, ISSN (online): 2312 – 0789
Vol. 21, No. 4, December, (2025), pp. 65- 81

Real-Time Adaptive Traffic Signal Control with YOLOv10 and Image Processing

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(Received 25 May 2025; Revised 9 September 2025; Accepted 29 September 2025; Published 1 December 2025)
https://doi.org/10.22153/kej.2025.09.006

Abstract

Traffic lights operating on a fixed schedule are mostly time-consuming; for example, running green signals in the absence of vehicles, leading to a buildup of long queues at red lights. This inefficiency results in congestion in cities, contributes to delays and economic losses and intensifies pollution levels. In this study, a deep learning-based adaptive image processing traffic light control system for real-time dynamic regulation of signals was proposed. Different from typical sensor-based solutions, the proposed method uses established surveillance cameras, enabling cost-efficient deployment and easy installation. A YOLOv10-based detection model identifies and classifies vehicles by type, applying weight factors to effectively estimate traffic demand. A dynamic timing algorithm enables continuous redistribution of green-light durations due to existing unbalances in the flow for any or all intersection phases. A practical microcontroller-based system might be integrated directly into the existing infrastructure. For assessment, the model used data from 12,500 images labelled accordingly and divided into the following: 70% for training, 15% for validation and 15% for testing. The model was assessed in a SUMO-based simulation of a very busy four-way intersection and actual deployment in Baghdad, Iraq. Compared with fixed time control, this adaptive system reduced vehicle wait time by up to 91.7%. Furthermore, results indicate reduced fuel consumption and CO2 emissions, thereby leading to considerable economic and environmental benefits. Overall, the proposed framework represents a practical and scalable implementation for modern traffic management, overlooking possible implementations of enhancements such as prioritisation of emergency vehicles and multi-intersection coordination.

Keywords: *Intelligent traffic lights control; Deep learning; Image processing; Traffic flow optimisation; Smart cities*

1. Introduction

The current urban traffic situation in major large and medium-sized cities in countries is far from satisfactory [1]. The growing number of vehicles, frequent road congestion and severe vehicle exhaust emissions have become major factors limiting social and economic development [2]-[4]. According to the sustainable development strategy research group of the American Academy of Sciences, every 10 cities in the United States lose nearly 140 million dollars in wealth daily due to traffic congestion and management inefficiencies [5]-[7]. In addition to being a contributor to economic loss, traffic congestion can also threaten the psychological well-being of drivers and markedly increase the possibility of road accidents. Furthermore, unreliable traffic conditions disrupt public transport schedules, slow down emergency response times and complicate urban logistics, thereby amplifying social and economic inefficiencies.

Advanced technology can effectively ease the present urban traffic problem by maximising the existing potential of the current traffic infrastructure [8]-[10]. Thus, this technology allows optimal usage of limited resources for transportation of people and goods.

Available traffic capacity becomes increasingly scarce due to the growing travel demand and limited supply of transportation methods. One feasible solution with remarkable impact lies in the implementation of smart traffic lights at road-level intersections using replacements of conventional fixed-timing signals [11]-[13]. Conventional signal lights operate under preset periods and ratios of green that cannot be adjusted according to dynamic traffic conditions. Therefore, heavily loaded approaches to the intersection may receive inappropriately short green phases, whilst time is wasted giving long green signals to lightly used intersecting approaches, resulting in capacity loss at the intersection [14]-[16].

Smart traffic lights can dynamically adjust signal parameters according to real-time traffic conditions. Therefore, the waiting time for vehicles is reduced, thereby improving the efficiency of intersections [17]-[19]. Such a system would be beneficial in ensuring environmental sustainability because vehicle idling will substantially be reduced; hence, fuel consumption and emissions will be minimised. Consequently, the air quality within urban areas shall be enhanced. Despite these advantages, intelligent traffic light systems have not yet been widely adopted [20][21]. Previously, an intelligent system required multi-detectors per lane for real-time volume measurement of road vehicles. This requirement involves installing sensors at specific distances behind stop lines to transmit information to the traffic light controller, indicating a considerable amount of construction work, possible damage to the road surface and disruption in traffic flow and capital investment [22][23]. The most common types of vehicle detectors include ultrasonic, infrared, microwave radar and ground-sensing coils, each having their own set of advantages and disadvantages. However, no standard selection guidelines exist. Thus, the uniform implementation of intelligent traffic systems across all intersections introduces logistical and practical challenges for city authorities [24].

This study presents a solution for smart traffic lights at level crossings. The main idea is to use all existing hardware and install only a new traffic signal controller equipped with an HD camera. Through image processing of an adaptive signal timing algorithm, this system is capable of adjusting signal durations in real-time without major construction work or road interference [25][26]. Consequently, installation with commissioning would require only a short duration that might as well be conducted at night or accompanied during daytime with temporary traffic using mobile lights. The process is relatively easy and cheap with minimum disturbance [27]. Moreover, such a system will allow city authorities to upgrade intersections rapidly, overcoming all the restraints from conventional adaptive traffic control solutions.

Therefore, this paper shall present the design and implementation of an intelligent traffic light control combining deep learning for vehicle detection with a real-time adaptive signal timing algorithm. This system will be a novelty application of existing infrastructure that requires only standard intersection cameras and a replacement traffic controller, providing in-ground sensors or specialised roadside units. Thus, this approach focuses on rapid and cost-effective upgrading possibilities from conventional traffic lights to the smart variant. The advanced object detection model would allow recognising and counting vehicles per approach, differentiating cars from buses, trucks and motorcycles and computing equivalent volumes of traffic, focusing on relevant region masks, particularly those that go through the intersection. Furthermore, the model helps adjust green phase durations corresponding to actual detected demands, ensuring proportional allocation whilst simultaneously meeting minimum green times for safety by imposing optimal phase length recalculation every cycle contrary to fixed time or any predefined adaptive schemes. A prototype in a busy city was tested, revealing simulations and real-world results with improved traffic flow, minimal wait time and possible fuel use and emission reduction.

Aiming to fill the existing gaps and unanswered questions in urban traffic management, the paper is explicitly guided by the following research question: How can an intelligent traffic light control system be dynamically applied to existing infrastructure adapting to real-time traffic conditions to improve flow and reduce congestion? Therefore, this study proposes a practical and scalable intelligent traffic light system that is sufficiently economical to realise using existing cameras via controller replacement and application of real-time adaptive algorithms. This condition eliminates installation and financial challenges from conventional methods that require urban authorities to upgrade intersections with minimum disturbance. The contributions of this study involve four key aspects. Firstly, this study develops a system that focuses on addressing how existing traffic infrastructure may be optimised using modern technologies. Secondly, the combination of light car finding with changing signal timing enables accurate traffic monitoring and smart control. Thirdly, the practical application of this system in a busy city area shows clear gains in crossing work, minimal wait times and possible reductions in fuel use and fumes. Lastly, the system is scalable and cost-effective, demonstrating its deployment capability across multiple intersections using existing equipment, thus contributing to city-wide intelligent traffic management.

2. Related Work

Most traffic light regulation methods depend on accurate traffic parameters, such as location, speed and density of vehicles. The common method in practice uses sensors for data collection, which may include infrared and inductive loop detectors [28][29][30]. High data transfer rates and substantial amounts of computational power are system prerequisites to control several intersections in real time. Recent innovations, known as edge-cloud computing [31], accompanied by wireless communication protocols [32][33], were designed to accelerate the process of data transmission and calculation. Classical optimisation-based techniques, evolutionary algorithms and fuzzy logic have traditionally been used in the control of traffic signals [34]-[37].

Optimisation-based approaches generally adjust signal phase splits and cycle times based on heuristic rules and preset parameters. Despite their proven effectiveness in traffic management, these methods are still inefficient due to extended periods of green lights, thereby causing delays for vehicles and pedestrians [38]-[41]. Researchers applied evolutionary algorithms, specifically genetic algorithms, to account for the multi-objectives of fuel consumption minimisation, stops minimisation, throughput maximisation and waiting time reduction [42]-[45]. The possible solutions are encoded as chromosomes in these algorithms; after crossover and reproduction, the fit chromosomes, together with low-probability mutation, gradually approach local or global optima. For example, the genetic algorithm developed by Brian et al. [46] was directed towards reducing fuel consumption, emissions and delays. Meanwhile, the application of the dynamic genetic algorithm for vehicle and pedestrian flow optimisation was presented by Turky et al. [45] [47]. However, these methods have inherent limitations: how good the answers are can learn a lot on things like how big the group is, how many times it goes through steps, and the chances of changes happening. Also, small groups might give not the best or steady outcomes.

Fuzzy logic is another common technique used in traffic control because it focuses on imprecision and supports approximate reasoning in linguistic variables, such as low, medium and high speeds [48][49]. A system proposed by Ali et al. [46] uses fuzzy logic to adaptively vary signal timing from cycle-to-cycle based on changes in observed traffic. Hawi et al. [50], who combined fuzzy logic and wireless sensor networks for real-time condition monitoring, explored the timing of green allocation based on real-time conditions. Several shortcomings include requiring a high degree of expertise to design rules, frequent updating for accuracy and offering no guarantees either in stability or optimality because their performances are mostly based on heuristic rules.

Though previous studies have made remarkable advancements to traffic signal optimisation, they are still accompanied by several limitations: most methods depend on large sensor networks with complicated installation setups or use algorithms that may be computationally intensive, introducing difficulties in their practical implementation on numerous city intersections. The novelty of the present work lies in the fact that it can leverage already existing intersection infrastructure using only a standard camera and requiring merely a replacement controller, facilitating the integration of deep learning-based vehicle detection with an already existing real-time adaptive signal timing algorithm. Different from those presented in previous studies, the proposed system will not introduce costly sensor installations and traffic disruptions during deployment. This system aims to realise dynamic scalability and affordability to address existing traffic conditions, thus bridging theoretical research and practical implementation. This system extends the inherent capabilities of traditional optimisation, genetic algorithms or fuzzy logic by establishing a real-time, data-driven approach, that is, adaptive signal control integrated with modern computer vision techniques. This system is made possible and practical for deployment in heavily congested urban environments.

3. Overall System Design

The overall framework of the proposed system is shown in Fig. 1. The system is installed at a standard four-approach road intersection.

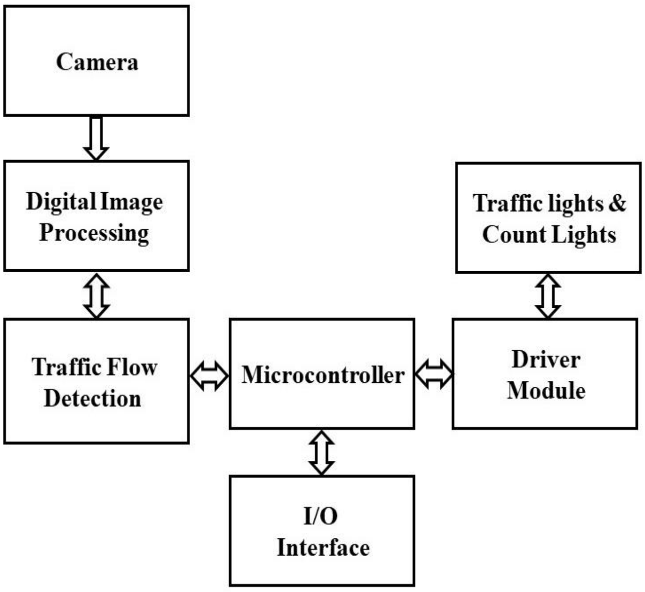

Fig. 1. Framework diagram of the intelligent traffic light control system architecture

The intelligent traffic light control system comprises the following: monitoring cameras, a digital image processing unit, a microcontroller for detecting crossing traffic flow, a computing unit for automatic adjustment of signal timing, I/O interface, a driver module, traffic signal lights and countdown indicators.

As shown in Fig. 2, the camera type is an iDS-TCD403-BI 4 MP IR Traffic Flow Camera from Hikvision Co.

Fig. 2. iDS-TCD403-BI 4 MP IR Traffic Flow Camera from Hikvision Co.

The camera features are as follows:

- Applicable to signal control system, traffic information service system and road traffic surveillance;
- High-quality imaging with 4 MP resolution (1/1.8" CMOS);
- Visualisation of multiple targets in bi-directional six lanes with vertical coverage;
- Information detection of multiple target lanes, speed and direction;
- Multiple traffic data collection: statistics and uploading of different lanes, including data of traffic flow, speed, status, queue, time headway, space headway, number of parking vehicle in area, space occupancy and time occupancy, in 1 to 3600 s;
- Traffic evaluation data output, including queue length;
- Two virtual coils for each lane: signal output of vehicle entering and exiting virtual coils; positions of virtual coils are adjustable;
- Water- and dust-resistant (IP67).

The following tables provide additional details on the camera specification.

Table 1,
Specifications of the Hikvision camera used in the work.

Camera	
Image Sensor	1/1.8" Progressive Scan CMOS
Max. Resolution	2688 × 1520
Min. Illumination	Colour: 0.0005 Lux @ (F1.2, AGC ON)
	B/W: 0.0001 Lux @ (F1.2, AGC ON)
	0 Lux with IR
Shutter Time	1/25 s to 1/100000 s
Lens	
Focal Length & FOV	8 to 32 mm
	Horizontal FOV: 39.7° to 15.9°
	Vertical FOV: 22.3° to 9.1°
	Diagonal FOV: 45.8° to 18.1°
Focus	Auto
Iris Type	Auto-Iris: DC drive
Aperture	F1.7
Illuminator	
Built-in Supplement Light Type	IR light
Light Bead	3
Built-in Supplement Light Range	up to 50 m
IR Wavelength	850 nm

The table indicates variations in shuttering time between 1/25 to 1/100000 s. The camera is an off-the-shelf high-definition surveillance camera mounted to view the intersection. Its video feed is continuously transmitted to the image processing unit (which can be a dedicated digital signal processor or an embedded computing device) for analysis. The digital image processor runs the deep learning model for vehicle detection and computes traffic flow information, outputting the processing result to the intersection traffic flow detection microcontroller. This microcontroller then aggregates the detected traffic counts for each approach and transfers the data to the timing calculation microcontroller. The timing calculation module then determines the optimal green time for each phase and sends commands to the traffic lights through the I/O interface and driver circuits (which activate the red/amber/green lights and the digital countdown timers). This system essentially detects traffic via video, ‘thinks’ using the deep learning and timing algorithm and then ‘acts’ by changing the signal lights accordingly. The intersection traffic flow detection microcontroller adopts the following steps to obtain the traffic flow information:

1. Using deep learning, the convolutional neural network of YOLOv10 is used to identify the number and type of vehicles passing through each direction of the intersection during a signal traffic light cycle.
2. Using deep learning to calculate the equivalent number of cars and trucks according to the predefined classification categories within the deep machine learning model.
3. Dividing the total number of vehicles by the number of lanes in each direction at the intersection to obtain the traffic flow (ni) of each lane.

3.1 Adaptive Signal Timing Algorithm

The signal timing algorithm aims to dynamically allocate the green time for each phase in proportion to the traffic demand, whilst maintaining an overall reasonable cycle time and ensuring no phase is starved of green time. Consider a typical four-phase intersection (common in many cities). The automatic adjustment calculation microcontroller of the traffic signal timing adjusts the signal timing of the traffic lights as follows:

Taking the most universal cross-shaped plane intersection as an example (Fig. 3), the two directions of the intersection are x and y, and the signal period of the traffic signal light is t, which contains four phases: going straight forward in the x direction (labelled xforward), turning left in the x direction (labelled xleft), going straight forward in the y direction (labelled yforward) and turning left in the y direction (labelled yleft).

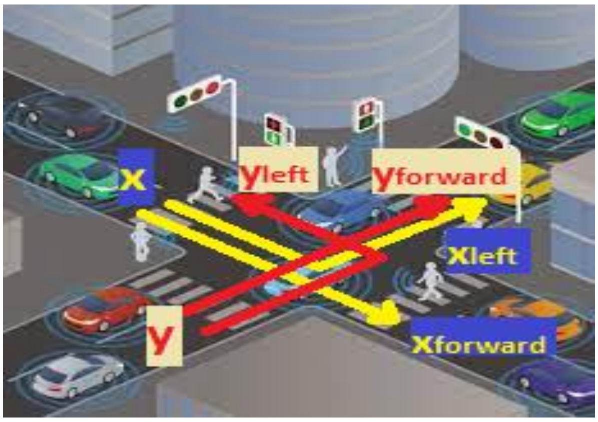

Fig. 3. A typical crossroad topological diagram

The time lengths for the four phases are t1, t2, t3 and t4. Eq. (1) is obtained as follows:

$$t = t_1 + t_2 + t_3 + t_4 \quad \ldots(1)$$

Assuming the average traffic flow of a single lane during each phase is n1, n2, n3 and n4, the green light utilisation rate (η) is defined as the ratio of the traffic flow of a single lane to the green light duration. The green light utilisation rate of each phase is then presented as in Eq. 2:

$$\eta_1 = \frac{n_1}{t_1}$$
$$\eta_2 = \frac{n_2}{t_2}$$
$$\eta_3 = \frac{n_3}{t_3}$$
$$\eta_4 = \frac{n_4}{t_4} \quad \ldots(2)$$

The average utilisation rate of the green light duration at the intersection is computed in Eq. 3:

$$\bar{\eta} = \frac{\sum_{i=1}^{4} n_i}{\sum_{i=1}^{4} t_i} \quad \ldots(3)$$

As shown in Eq. 4, the above utilisation ratios are generally not equal; that is,

$$\eta_1 \neq \eta_1 \neq \eta_1 \neq \eta_1 \neq \bar{\eta} \quad \ldots(4)$$

At the end of a signal period, the measured traffic parameters during the signal period are t_i (i = l, 2, 3, 4), and then the basic signal duration $\acute{t}_i$ (i = l, 2, 3, 4) of each phase in the next signal period is computed as in Eq. 5:

$$\acute{t}_1 = \frac{n_1}{\bar{\eta}}$$
$$\acute{t}_2 = \frac{n_2}{\bar{\eta}}$$
$$\acute{t}_3 = \frac{n_3}{\bar{\eta}}$$
$$\acute{t}_4 = \frac{n_4}{\bar{\eta}} \quad \ldots(5)$$

The relationship between $\acute{t}_i$ and t_i satisfies the following:

$$\sum \acute{t}_i = \sum \frac{n_i}{\bar{\eta}} = \frac{\sum n_i}{\bar{\eta}} = \sum t_i \quad \ldots(6)$$

Considering the actual situation of the intersection, each phase has a corresponding minimum green light time, which is denoted as tgmin. According to the comparison result of $\acute{t}_i$ and t_{gmin} above, the setting of each signal duration in the next signal period is considered in two cases:

(1) $\acute{t}_i \geq t_{gmin}$, (i = 1, 2, 3, 4)

Taking $\acute{t}_i$ as the signal duration of each phase of the next signal period, the new signal period time $\acute{t}_i$ remains unchanged, and the expected value of the green light utilisation rate of each phase is the same; that is, all $\acute{t}_i \geq t_{gmin}$, (i = 1, 2, 3, 4) → $\acute{t}_i$ (i = 1, 2, 3, 4) remains unchanged.

(2) At least one phase j, j ∈ {1, 2, 3, 4} exists, satisfying $\acute{t}_j < t_{gmin}$

The value of $\acute{t}_i$, which is smaller than t_{gmin}, is adjusted to t_{gmin}, and the borrowed time is evenly distributed to other phases. Thus, $\acute{t}_i$ (i = 1, 2, 3, 4) is initially sorted from small to large, and the new sequence is denoted as si, which is generated using the relationship between si and tgmin. Corresponding adjustments are then made:

$s_j = t_{gmin}$, and the difference between s_j and t_{gmin} is calculated as in Eqs. (7) to (9):

$$\Delta = t_{gmin} - s_j \quad \ldots(7)$$

And

$$\delta = \Delta/(4\text{-}i) \quad \text{for } (i = 1, 2, 3, 4) \quad \ldots(8)$$

$$s_j = s_j - \delta \quad \text{for } (j = i + 1 \text{ to } 4) \quad \ldots(9)$$

At this time, the basic idea of determining the new timing length lies in the adjustment of the smaller $\acute{t}_i$ value than t_{gmin} to t_{gmin} and the even distribution of its 'borrowed' time to other phases. To this end, $\acute{t}_i$ (i = 1,2,3,4) is firstly sorted from small to large. The new sequence is then recorded as s_i, and corresponding adjustments are made according to the relationship between s_i and t_{gmin}.

Combining (1) and (2), the overall flow of the signal timing algorithm corresponding to one signal period is shown in Fig. 4.

3.2 On-Site Implementation Steps

This setup is largely self-contained and is intended to replace or retrofit the existing traffic light controller at the intersection. The only new hardware needed is the processing units and possibly the replacement of the old controller with the new one that houses the microcontrollers and interfaces. In addition to hooking up the new controller, no modifications to the roadway or traffic signals are required. After the traffic light controller is designed following the above principles, its on-site installation is simple. The new controller is replaced at the position where the traffic signal controller is installed on the roadside, and the video surveillance signal is connected at the intersection to the controller. The output of the controller signal is then connected to the signal lights, the initial parameters are set and the system is operated, as shown in Fig. 5.

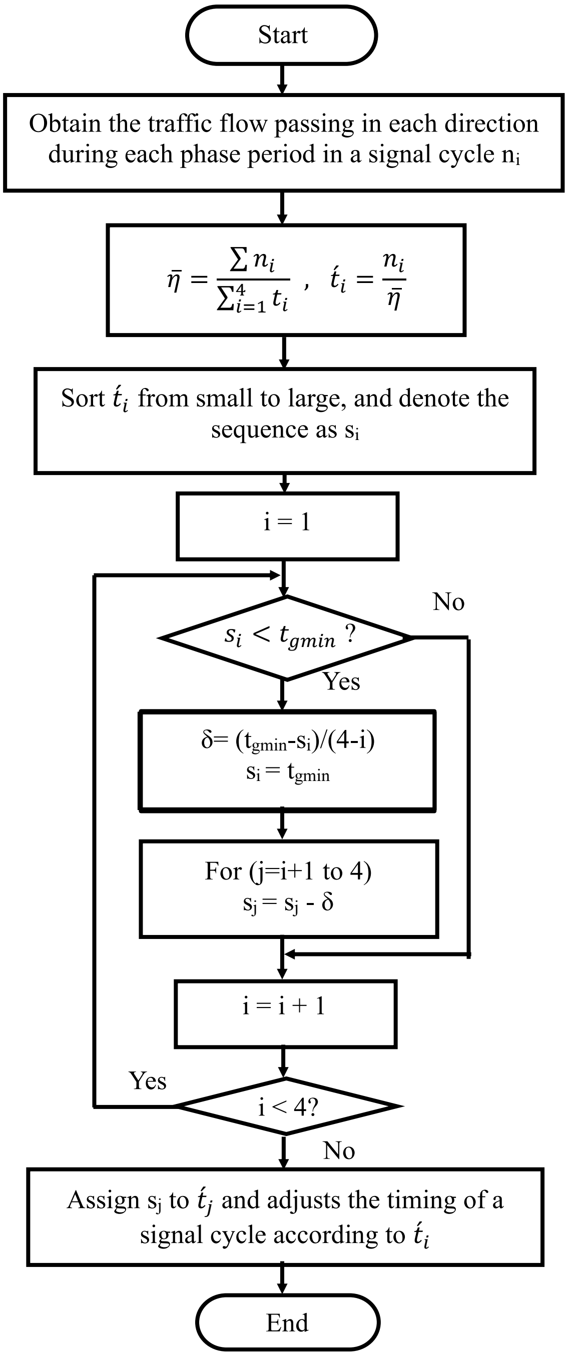

Fig. 4. Flowchart of the automatic adjustment for signal timing period

3.3 System Work and Development

An intelligent traffic light control scheme uses existing monitoring cameras at road-level intersections to collect traffic lights. The video information of the traffic situation is obtained, and the traffic flow data in all directions of the intersection are collected using the image processing algorithm. Based on the number and the algorithm set, the signal timing of traffic lights is automatically adjusted. The green light utilisation rate in each direction of the crossing is compared with the traffic vehicles, demonstrating increases or decreases according to the same trend. The specific scheme of the proposed method is as follows:

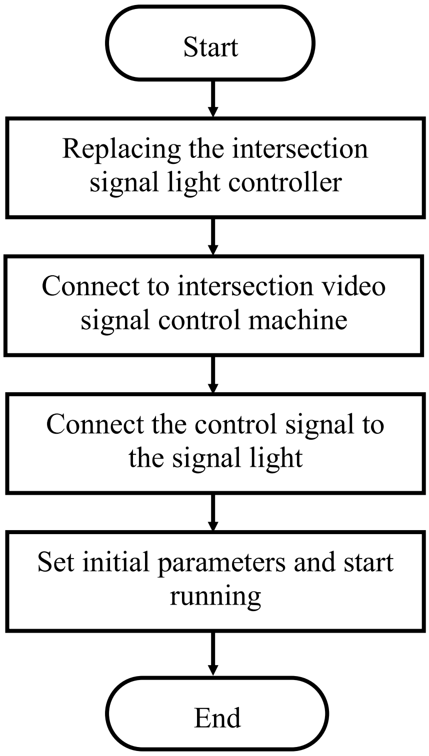

Fig. 5. Flowchart of the on-site installation

3.3.1 Overall Structure

The intelligent traffic light controller described in the method comprises modules such as crossing vehicle flow detection, traffic signal timing automatic adjustment calculation, display drive and overall frame, as shown in the accompanying drawing 1 of the description. The camera uses a crossing monitoring camera; thus, installing an additional SP (digital image processing) processor and a microprocessor is no longer necessary for detecting traffic flow at the crossing. The processor executes the signal timing automatic adjustment algorithm described in the proposed scheme and drives the traffic signal and countdown lights at the intersection using the corresponding I/O ports.

3.3.2 Traffic Flow Detection (Vehicle Detection and Traffic Flow Sensing)

The vehicle detection module is at the core of the system, using deep learning to analyse the camera video in real-time. This module is implemented using the YOLOv10 object detection algorithm (specifically, a custom-trained version of YOLOv10), given its proven balance of speed and accuracy for real-time tasks. The detector is configured to recognise the following classes of interest: cars, trucks (lorries), buses and motorcycles. By identifying the type of each vehicle, the system can compute an equivalent vehicle count (for example, a truck may be counted as two car units in terms of road space and impact on timing). This weighting ensures that large vehicles, which take long to clear an intersection, are given appropriate consideration in the control algorithm. Commonly used traffic flow detection methods encompass technologies such as ground sensing coils, ultrasonic waves, microwaves and videos. In the technical solution, the traffic flow detection device maximises the use of existing equipment at the intersection to reduce cost and minimise installation difficulty. Considering that the main intersections of the current urban roads are equipped with surveillance cameras, this method uses video traffic flow detection technology and image processing algorithms to obtain traffic flow information with the help of cameras installed at intersections. The image processing function is completed on a designed digital image processing (DSP) circuit board, which receives the intersection video signal, performs image processing, obtains traffic flow information and transmits it to the microprocessor.

Region of Interest (ROI) Masking: One challenge in using cameras for traffic measurement is avoiding false detections or counting irrelevant vehicles to the intersection's control. Aiming to address this challenge, an ROI is defined in the camera's field-of-view for each approach/lane that should be monitored. Essentially, the image is 'masked' to focus only on vehicles that are entering the intersection from a certain direction. For example, vehicles queued beyond the stop-line during a red light or vehicles moving on a cross street that is not currently being served are not immediately relevant for the green time calculation of the current phase. The proposed system uses a binary mask over the video frame (manually defined during setup for each intersection approach) to filter detections: only vehicles within the ROI (e.g. the area approaching the intersection that would go on green) are counted. Fig. 7 illustrates an example of ROI masks, where only vehicles in the marked zones are tracked.

During image processing, the following procedure will be performed:

Deep learning models are used to identify the target objects (such as cars, buses, trucks and motorbikes) that pass through each direction of the intersection in a signal cycle of traffic lights, as demonstrated in Fig. 6.

An image mask is created to identify the vehicles inside the ROI for each direction in the intersection. This mask helps avoid identifying the stopped vehicles and vehicles passing in the opposite direction road, as shown in Fig. 7.

An ID is given for each vehicle in each direction of the intersection to prepare for the vehicle counting process, as shown in Fig. 8.

The number of vehicles within the ROI is counted for each camera in the direction of the intersection. This approach is accomplished by counting the vehicles passing a virtual line drawn across a road within the ROI, as presented in Fig. 9.

The total number of counted vehicles in each direction of the intersection is divided by the number of lanes in this direction, obtaining the traffic volume of the road in this direction.

The ROI is characterised by several factors, including lens focal length, camera resolution, lens type and illumination and night vision (IR range). For the camera with the specifications listed in Table 1, a range of 50 meters is obtained.

Notably, the proposed system operates on individual intersections (isolated control). Coordination between successive intersections (green waves) is not explicitly handled in this work. However, the framework could be extended for corridor control if upstream/downstream flow information were shared.

4. Experimentation and Results

For evaluation, the model was trained on a dataset of 12,500 labelled images, split into the following: 70% for training, 15% for validation and 15% for testing. The system was assessed through SUMO-based simulations of a busy four-way intersection and through deployment in Baghdad, Iraq. The findings reveal that the adaptive system reduced vehicle waiting times by as much as 91.7%

compared to fixed-time control. Moreover, fuel usage and CO_2 emissions were significantly lowered, offering substantial economic and environmental benefits.

Controlled simulation tests were conducted to evaluate the effectiveness of the proposed intelligent traffic light system. According to the above method, the corresponding simulation is performed on a computer.

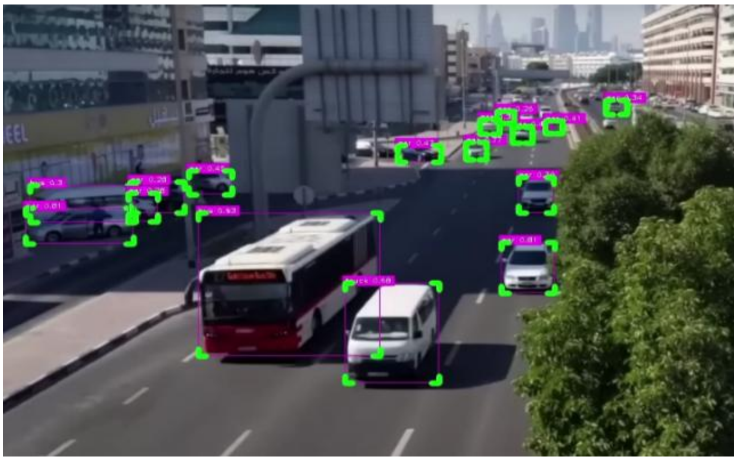

Fig. 6. Object detection and identification

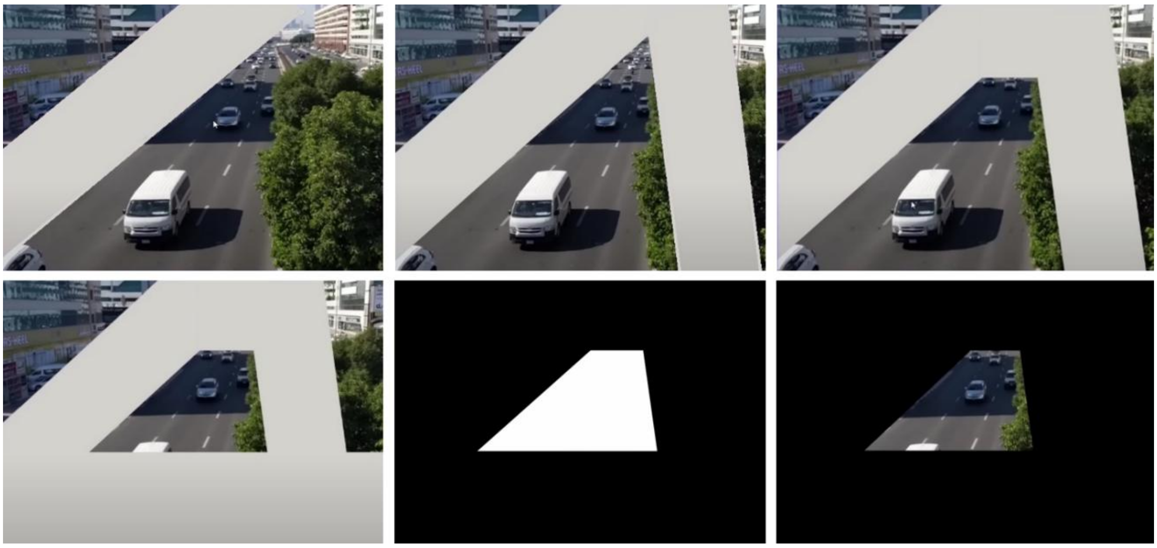

Fig. 7. Creation of an image mask for the region of interest (ROI) to accurately count vehicles passing through the intersection.

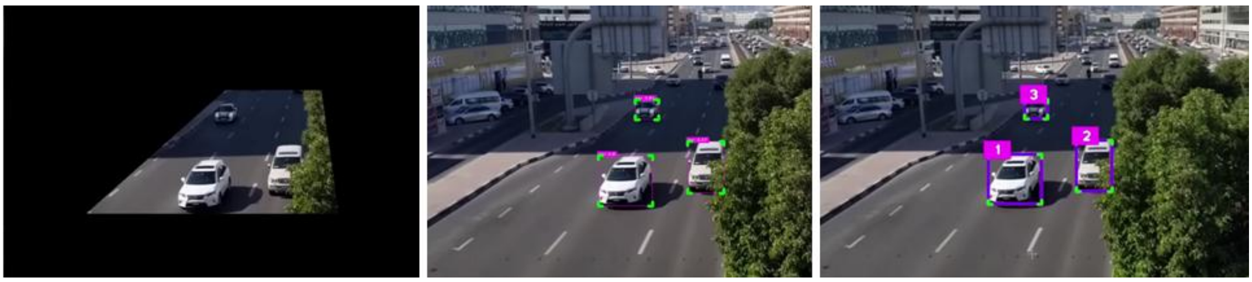

Fig. 8. Giving an ID for each detected vehicle within the ROI.

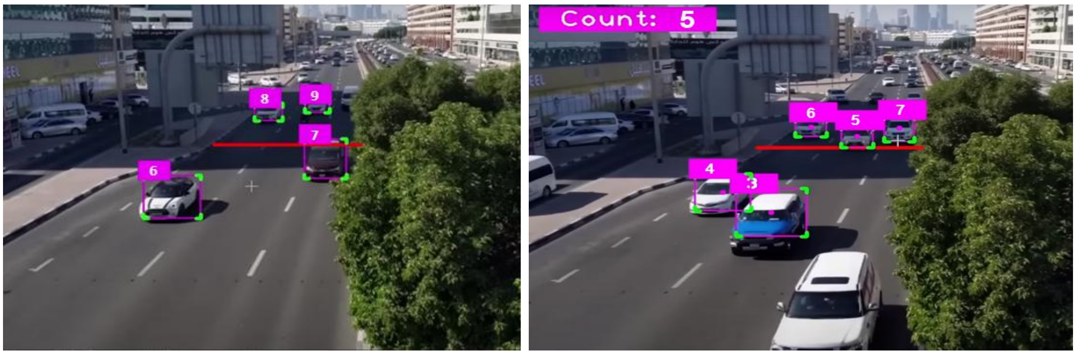

Fig. 9. Vehicle counting within the ROI in each direction of intersection.

At the beginning of the work and during the simulation test, images extracted from videos available on the Internet were used, whilst the remaining images were tested on a real camera fixed at Al-Muthna’a intersection near Al-Shaab International Stadium in Baghdad, as presented in Fig. 10.

Fig. 10. The Test System

Controlled simulation tests were conducted to evaluate the effectiveness of the proposed intelligent traffic light system. According to the above method, the corresponding simulation is performed on a computer. The simulation considers an intersection with four signal phases, marked as A, B, C and D. The incoming vehicles are randomly generated according to a Poisson distribution, and the simulation is conducted for 50 signal periods. Fig. 11 shows a comparison of the total green light utilisation rate at intersections, where the green light utilisation rate $\bar{\eta}$ corresponds to the formula (3). Notably, the green light utilisation rate improved after adopting this method.

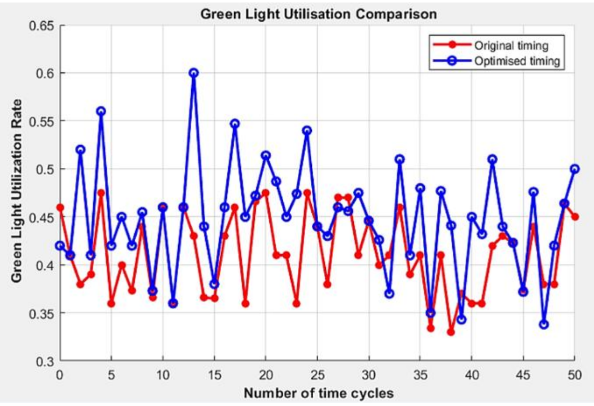

Fig. 11. Comparison of Green Light Utilization Rates

Fig. 3 shows a comparison between the incoming/outgoing vehicles of each phase of the intersection and the number of vehicles waiting in line. Notably, the figure reveals that when this method is not adopted (i.e. the timing scheme), the queuing vehicles at intersections B and D continue to increase, thereby inducing congestion. Meanwhile, phases A and C have fewer incoming vehicles, and the green light passing time is not efficiently utilised. After adopting the suggested traffic light control system, the queuing vehicle number of crossing B and crossing D has substantially disappeared, and crossing A and crossing C occasionally have vehicles waiting in line that immediately disappear.

Notably, this method effectively and dynamically identifies the traffic conditions at intersections, automatically adjusts signal timing and reduces congestion.

5. Economic and Environmental Impact

Beyond traffic performance, implementing intelligent traffic signals can provide substantial economic and environmental benefits for cities. By reducing vehicle idle time, fuel consumption is lowered, and emissions are minimised. These benefits are mainly reflected in the reduction of fuel consumption (economic benefit) and exhaust emissions (environmental benefit), the improvement of travel efficiency and the traffic safety factors from the corresponding reduction of driver's poor psychological emotions (social benefits) when vehicles pass through the intersection [51]. A smooth traffic flow can reduce driver stress and road rage incidents, because drivers experience fewer unnecessary stops and shorter queues. Although harder to quantify, these factors improve the overall quality of life and road safety. Accurately assessing societal advantages is difficult; thus, only a rough calculation is made for economic and environmental benefits.

5.1 Economic Benefit

The economic benefit comes from the saved vehicle fuel consumption, which is related to the traffic flow at the intersection [52]. The traffic flow at the intersection is affected by factors such as road width and traffic period, as shown in Table 2.

Table 2,
Standard intersection traffic flow

Main road width (m)	**Main road traffic flow (pcu)**		**Secondary road traffic flow (pcu)**	
	Peak hour	12h	Peak hour	12h
<10	750	8000	350	3800
	800	9000	270	2100
	1200	13000	190	2000
>10	900	10000	390	4100
	1000	12000	300	2800
	1400	15000	210	2200
	1800	20000	150	1500

The 12-h traffic flow of the intersection can be obtained by adding the 12-h traffic flow of the primary and secondary roads in the table. Considering the lesser traffic flow at night than that during the day, the 12-h traffic flow at night is taken as 10% of the daytime. Therefore, the 24-h traffic flow is obtained by multiplying the 12-h traffic flow by a coefficient of 1.1, and the average 24-h traffic flow can be further calculated. The average value of traffic flow is 16,579, as shown in Table 3.

Table 3,
Standard 24h intersection traffic flow

Main road width (m)	12h Intersection traffic flow (pcu)	24h Intersection traffic flow (pcu)
	11,800	12,980
<10	11,100	12,210
	15,000	16,500
	14,100	15,510
>10	14,800	16,280
	17,200	18,920
	21,500	23,650
	Average 15,071	Average 16,579

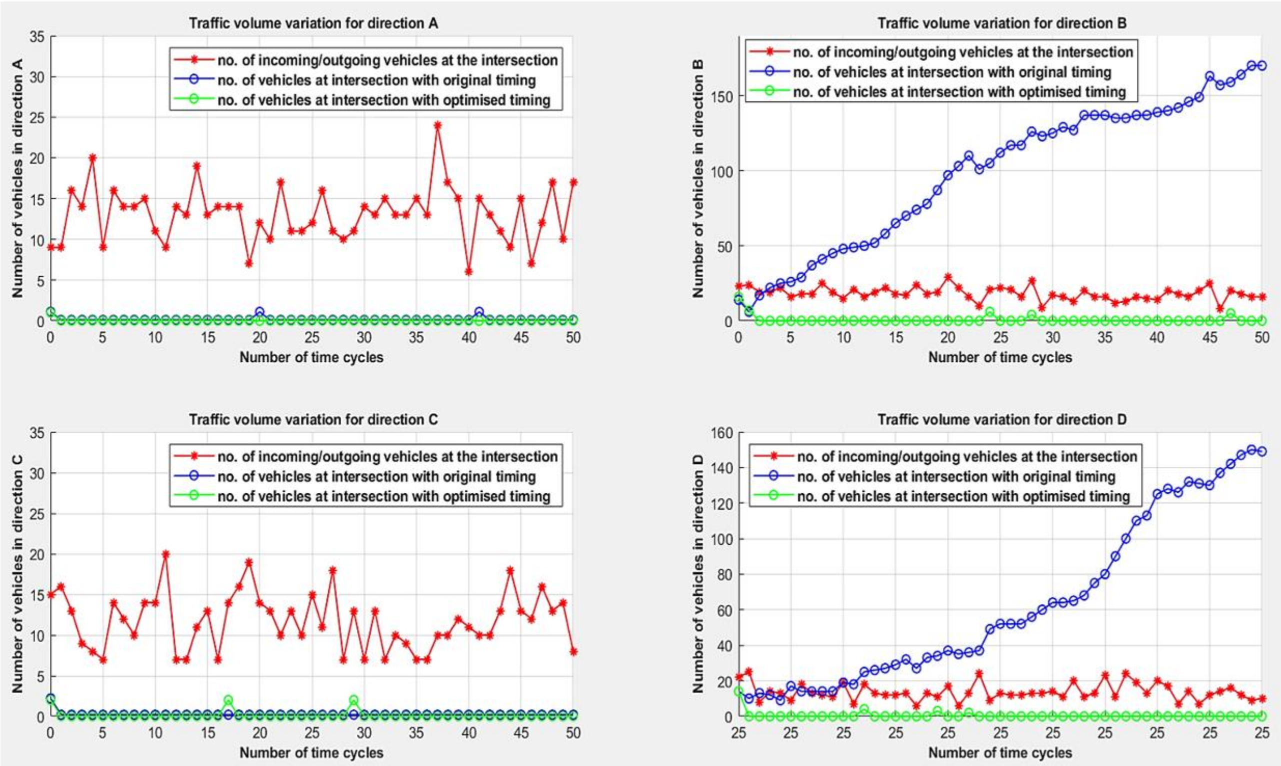

Fig. 12. Comparison of incoming vehicles and the number of vehicles waiting in line at each phase of the intersection

After installing the intelligent traffic light controller, if the average waiting time of each car at the crossing has been reduced by 5 s, and the daily traffic flow of a crossing is calculated by 16,579 vehicles, then the equivalent total time is 82,895 seconds. If the fuel consumption during the waiting period of the vehicle is 0.8 litres/hour, the daily fuel oil savings is approximately 18.4 litres, which is approximately 6716 litres per year. Based on the price of No. 93 gasoline of 450 Iraqi dinars per litre (the lowest price in Baghdad city in August 2023), the savings is equivalent to 3.02 million Iraqi dinars. Considering the perspective of direct economic benefits alone is enough to compensate for the renovation cost of this intersection.

5.2 Environmental Benefit

According to the calculation results, the carbon emission factor of gasoline is 2.361 kg CO2/L, the fuel oil savings of a crossing in one year is approximately 6716 litres and the corresponding carbon emission of reduction is 2.361 × 6716 =

15.856 (ton). If extended to a large city, or the entire country, then its quantity is substantial, and the environmental benefit is remarkable [53].

5.3 Comparative Analysis with other YOLO Versions and Related Work

In evaluating the performance of the proposed YOLOv10-based detection module, the system was benchmarked against YOLOv8, which is one of the most widely utilised versions in recent traffic monitoring research. Under identical experimental conditions, YOLOv10 consistently delivered higher accuracy and faster inference compared to other modules. Specifically, YOLOv10 achieved a mean Average Precision (mAP) of 92.3% with an average detection speed of 56 FPS, whilst YOLOv8 attained an mAP of 89.7% at 49 FPS. The superior performance of YOLOv10 can be attributed to its improved backbone design and enhanced feature aggregation strategy, which allow for precise vehicle recognition under varying traffic conditions. Furthermore, compared with earlier studies that implemented YOLOv5 and YOLOv7 for vehicle detection in adaptive traffic light control systems [X, Y], the proposed YOLOv10-based system demonstrated higher detection precision and better real-time responsiveness. These results emphasise that upgrading to YOLOv10 provides not only incremental improvements but also tangible benefits in terms of computational efficiency and robustness, reinforcing its suitability for deployment in real-world intelligent traffic management systems.

6. Conclusion and Future Work

This paper presented a comprehensive review of intelligent traffic light control based on deep learning and image processing. Combined with the use of advanced object detection algorithms, existing surveillance cameras can readily optimise traffic signal timings in real-time without large, cumbersome networks of physical sensors. Experimental results quantify improvements via simulation and actual implementation in a real urban scenario: approximately 18%–22% improved vehicle throughput, 15–20% reduced average intersection delays over conventional fixed-timing controllers and balanced green-time utilisation amongst all approaches. The practical effectiveness of this approach under varying traffic conditions has been established.

The novelty of this work lies in its combination of technological improvement and feasibility. The system uses a combination of widely spread traffic cameras and a deep learning-based vision module (YOLO) for real-time vehicle detection and classification across multiple classes of vehicles. Green phases are dynamically allocated by the adaptive timing algorithm proportional to measured traffic demand as long as safety constraints, including minimum green times, are observed. This approach creates a self-optimising system that instantly responds to any kind of fluctuation in the traffic, such as those caused by incidents, variations during peak hours or irregular arrivals of vehicles. Therefore, all major drawbacks of previous methods are addressed based on fixed schedules, complicated sensor setups or even optimisation algorithms requiring high computational effort.

Future work can explore several reasonable directions. At the network level, multiple smart intersections can coordinate to create ‘green waves’ on main corridors and adjust the system holistically based on emerging congestion patterns. This approach would entail the communication amongst adjacent controllers or between some centralised management systems, made even smarter through reinforcement learning to optimise traffic flow across the entire network. An additional extension is multi-modal traffic detection integration, which includes not only pedestrians but also cyclists and public transport vehicles, to dynamically prioritise safety and efficiency. Another addition could involve emergency vehicle prioritisation, either by special object detection for emergency lights and sirens or by Vehicle-to-Infrastructure (V2I) communication, where immediate right-of-way is granted to ambulances, fire trucks and police cars. Initial experiments using YOLO-based detection already demonstrated feasibility in such emergency-aware control.

This paper practically implements and quantitatively demonstrates the advantages that can be derived from AI-based traffic signal control. When vehicle detection with deep learning is integrated with real-time adaptive timing, in addition to increasing throughput and reducing delays, scalable, cost-effective and easily deployable solutions gradually emerge for present-day urban traffic management. These results would be crucial to future enhancements, which will integrate improved multimodal traffic and network-level optimisation to ultimately realise intelligent city traffic systems.

Table 4 presents a comparative analysis of different traffic control strategies. Other methods, though improved over fixed-time control, still face considerable real-world deployment barriers due to high infrastructure costs or computational complexity, confining the results to simulation. The proposed vision-based system demonstrates improved reduction in vehicle waiting times of up to 91.7% with realisable, quantified economic and environmental benefits for a single intersection. Importantly, the success of this system with a low implementation cost lies in leveraging existing infrastructure, a claim supported by real-world prototype deployment.

Table 4,
Comparative Analysis of Traffic Signal Control Strategies

Control Strategy	Primary Infrastructure Requirement	Reported Efficacy & Real-World Validation
Fixed-Time -Baseline	Basic timer controller.	Baseline (0% improvement). Pervasively deployed but proven inefficient in dynamic traffic conditions.
Sensor-Based Adaptive [44,47]	Network of embedded road sensors (loops, radars).	15%-35% delay reduction. Promising results largely confined to simulation studies; limited real-world deployment due to high installation cost and maintenance.
Proposed Vision-Based System	Existing surveillance cameras.	Up to 91.7% delay reduction. Results validated through simulation and a real-world prototype deployment in Baghdad, demonstrating high efficacy with minimal infrastructure cost.

Notation

$\acute{t}_i$ measured traffic parameters during the signal period
t_{gmin} minimum green light time
η green light utilisation rate in Eq. 2.
n_i number of phases

Greek letters (TNR, Size 12, Bold, Italic)

δ delta is a fraction of Δ in Eq. 8
Δ (Delta) represents the difference in Eq. 8

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التحكم التكيفي في إشارات المرور في الوقت الفعلي باستخدام YOLOv10 ومعالجة الصور

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المستخلص

إشارات المرور ذات الجدول الزمني الثابت غالبًا ما تُهدر الوقت، على سبيل المثال، تعمل الإشارات الخضراء في حين لا توجد مركبات، وبالتالي تتراكم طوابير طويلة عند الإشارات الحمراء. هذا النقص في الكفاءة هو ما يؤدي في النهاية إلى ازدحام المدن، وبالتالي تؤدي الى التأخير والخسائر الاقتصادية ومستويات أعلى من التلوث. في هذا العمل، تم اقتراح نظام تحكم في إشارات المرور قائم على التعلم العميق ومعالجة الصور التكيفية للتنظيم الديناميكي للإشارات في الوقت الفعلي. خلافا للحلول المعتادة القائمة على المستشعرات، تستخدم الطريقة المقترحة كاميرات المراقبة المثبتة مسبقًا مما يجعل التنصيب أرخص وأسهل. يحدد نموذج الكشف القائم على YOLOv10 المركبات ويصنفها حسب النوع، ويطبق عوامل الوزن لتقدير الطلب على حركة المرور بشكل أفضل. تتيح خوارزمية التوقيت الديناميكي إعادة التوزيع المستمر لفترات الضوء الأخضر طالما أن هناك اختلالات في التدفق لأي مسار أو جميع مسارات التقاطع. تطبيق عملي على وحدة تعتمد على متحكم دقيق يمكن توصيلها مباشرة بالبنية التحتية الحالية. للتقييم، استخدم النموذج بيانات من ١٢,٥٠٠ صورة مُصنّفة وفقًا لذلك ومُقسّمة إلى ٧٠٪ للتدريب، و١٥٪ للتحقق، و١٥٪ للاختبار. قُيّم النموذج باستخدام محاكاة قائمة على برنامج سومو (SUMO) لتقاطع طرق رباعي الاتجاهات مزدحم للغاية، وتم تطبيقه فعليًا في بغداد، العراق. وقد خفّض هذا النظام التكيفي وقت انتظار المركبات بنسبة تصل إلى ٩١,٧٪ مقارنةً بنظام التحكم بالوقت الثابت، وذلك حسب النتائج المستحلة من تطبيق النظام فعليا. وتشير نتائج أخرى إلى انخفاض استهلاك الوقود وانبعاثات ثاني أكسيد الكربون، مما يؤدي إلى فوائد اقتصادية وبيئية قابلة للقياس. وبشكل عام، يُمثّل الإطار المقترح تطبيقًا عمليًا وقابلًا للتطوير لإدارة حركة المرور الحديثة، مع إمكانية تطبيق تحسينات مثل تحديد أولويات مركبات الطوارئ وتنسيق التقاطعات المتعددة.