AI Based System for Emergency Aware Traffic Control

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Abstract : The delays and congestions that are witnessed in the urban intersections are becoming a serious impediment to the prompt movement of emergency vehicles. On the one hand, the traditional traffic lights are founded on the recipes of time tables that also limit their flexibility to dynamism in the traffic or responding to an emergency. The present paper gives a hybrid model that applies artificial intelligence to permit adjustable signal control and priority of emergency vehicles in real-time. The solution proposed will utilize camera monitored solutions which are applied to capture real time traffic around the intersection. The video feed is processed with the help of a vision model that is based on deep learning to determine the degree of traffic density and emergency vehicles. According to the analysis findings, control commands are transmitted wirelessly to an ESP32-based controller, which controls the phases of signals and in the case of emergency vehicles, transmits them instantly by priority. The emergency event does not disrupt the system and the process of adaptive regulation of traffic is reestablished. The system is economical and the fact that it is in a modular form, it can be effectively implemented with time in the smart urban traffic infrastructures.

Keywords: Artificial Intelligence, Deep learning, Emergency Vehicle , ESP32 microcontroller, IoT , Performance metrics, Precision, Recall, traffic control,YOLOv8

1 Introduction

The speedy urbanizing process and the increasing number of cars have left an immensely negative impact on the road systems and traffic congestion has turned out to be the scourge of modern cities. The current traditional traffic lights systems have fixed-time programs, which make unreasonable delays, increase in consumption of fuel and emissions, yet fail to clear emergency vehicles in good time. According to the latest studies, adaptive, information-based signal control can be used to improve the traffic flow by dynamically adjusting signal phases based on current real time conditions [2], [4], [6], [7]. However, the existing emergency vehicle (EV) priority schemes tend to reflect the individual components of the system (detection or signal preemption), and they do not integrate with traffic density estimate and do not assure the adaptive recovery of the EV clearance.
To address these gaps, the paper proposes an AI-created hybrid traffic control scheme, i.e., a combination of real-time density estimation and EV prioritization [1], [3], [5], [8]. It is a single intersection model and there are restrictions in the provision of edge

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processing constraints and communication latency and can be deployed under different lighting and weather conditions.

2 Related work

The past few years were associated with the active efforts of applying the computer vision and the Internet of Things (IoT) technologies to improving the traffic management systems and mechanisms of emergency responses. The article [13] has offered a review of the efficacy of YOLO-based algorithms in identifying objects on traffic to provide a sound basis of the vision-based systems of traffic management.
The big section of the literature is related to the recognition of emergency vehicles and preemption of the traffic lights. In research studies such as [14], it was proposed that balancing emergency vehicles at the traffic lights can serve as one of the measures to make sure that an IoT-based system would prioritize emergency vehicles at the intersection of the road and help reduce the time of emergency response.
In addition, the paper in [18] also sought to research on the emergency signal preemption since spillback effect of the queue is also considered. ESP32-driven prototypes of a low-cost traffic monitoring and signal control system were pro-vided in [16], but YOLO was also applied together with micro-controlled systems to automate the work of traffic signals in [17] as well. Other researchers such as [15] investigated the adaptive signal timing control strategy with respect to real time traffic conditions and they reported positive results in terms of reducing congestions.
As a rule, it can be argued that the existing literature vindicates the utility of AI driven computer vision, IoT driven control and embedded platform in traffic control and emergency vehicle prioritization [9],[10],[11],[12]. The number of such approaches considers the individual components, but, in isolation. Such an absence of such an architecture implies that there is need to have a hybrid AI architecture that integrates the aspects of real-time vehicle detection, adaptive signal control, and emergency vehicle prioritization into a unified scalable and cohesive solution.

3 Methodology

3.1 System overview

The suggested system is comprised of four large units namely video acquisition, AI-based vehicle detection, communication and control, and traffic signal actuation. A high display camera records real time video transmission at the crossing. Every frame is passed through a YOLOv8 object detector model which is trained on a custom dataset. The information received about the detected vehicles is sent to ESP32 microcontroller, which calculates adaptive signal timing decisions. Visual cues are used to identify the emergency vehicles and signal priority is given. The architecture guarantees communication with low-latency and high speed signal response.

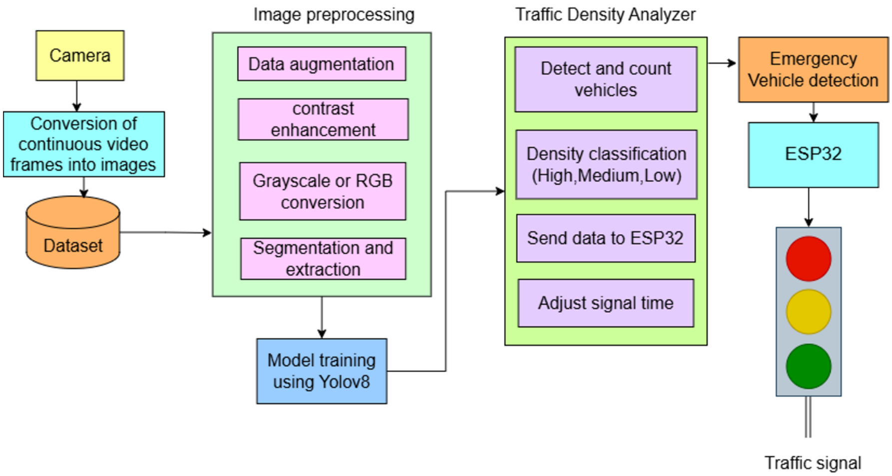

Fig 1. Proposed system

3.2 Hardware specifications

The main hardware components used in this system are ESP32 microcontroller with built-in Bluetooth/Wi-Fi module , USB Camera, RGB LED traffic lights, PCB and current limiting components.

3.3 Dataset description

Custom traffic data is created using real world video frames at the intersection taken under varying conditions of traffic and light. The data set is made of 10,000 annotated images comprising of 5400 car images, 2600 emergency vehicles (with various angles, conditions and augmentation), and 2000 background images divided into training, validation and test sets.

3.4 Data preprocessing

Bounding boxes are manually labeled using programs such as LabelImg. Images and annotations were preprocessed with the YOLOv8 pipeline (annotation validation, scaling to equal 800 x 800 pixels and aspect ratio kept) before being made between [0,1] to train the image. In training, the data augmentation methods included random scaling, horizontal flipping and mosaic augmentation, which are built-in.

3.5 Model training

The YOLOv8s model was trained via transfer learning, and the initial weights were those pretrained with a COCO dataset. The dataset is divided in the ratio of 70 (training):20 (validation):10 (testing) to prevent excessive evaluation due to data leakage. The model was trained to 100 epochs and input resolution of 800 x 800 pixels, a batch of 32 and learning rate of 0.001.

3.6 Traffic Density analysis

The overall number of cars that are observed in the lane i is:

$$N_i = \sum_{k=1}^{Ki} 1 \tag{1}$$

where Ki = number of detected bounding boxes in lane i.

The threshold values are used to classify traffic density:

$$D_i = \begin{cases} Low, \ Ni < T1 \\ Medium, T1 \leq Ni < T2 \\ High, Ni \geq T2 \end{cases} \tag{2}$$

Computation of Gi (green signal) is based on the density and is in form:

$$G_i = G_{min} + \alpha \cdot N_i \tag{3}$$

where G_{min} = minimum green time, α = scaling factor, N_i from equation (1).

3.7 Emergency Vehicle Detection

The model has been conditioned to detect specific features of emergency vehicles. Whenever the system identifies an emergency vehicle, it automatically sets up a priority flag on the right lane. Both of the outputs traffic density and emergency alerts are consolidated into short control messages to facilitate transmission to the microcontroller.

3.8 System Deployment

The camera is installed on a height of about 5 to 7 meters in order to capture all lanes of a single intersection. It continuously captures videos of moving traffic to be handled on an edge device using the trained YOLOv8 model to determine vehicles density and detecting emergencies. The resulting data is sent in the air through Wi-Fi to the ESP32 controller, which is used to control traffic lights. It is a day/night system which operate in basic weather conditions like low light or rain and is designed to work in real world conditions.

3.9 Latency measurement

The sum of the preprocessing, model execution, and post-processing delays is the total inference time whereas the system latency is the system in time which consists of the camera, inference, communication and control delays.

4 Results and discussion

This section compares the experimental results that were achieved using the proposed system and analyzes them against the available methods of traffic control.

4.1 System latency and FPS

It has been shown that there is an average inference latency of around 23 m/s per frame and end-to-end latency of the system is around 40-45 m/s. The system attains a rate of around 40-45 Frames per second (Frames per second = $1000/L_{inf}$) which makes it operate smoothly in real-time.

4.2 Performance evaluation curves

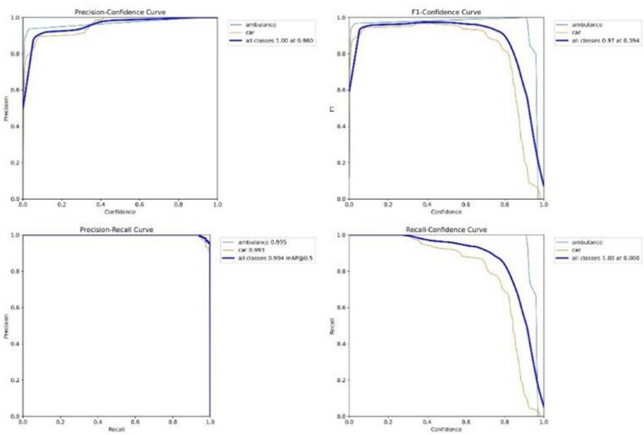

Fig 2. Performance evaluation curves

The results of the comprehensive performance of the classes are shown in the graph below:

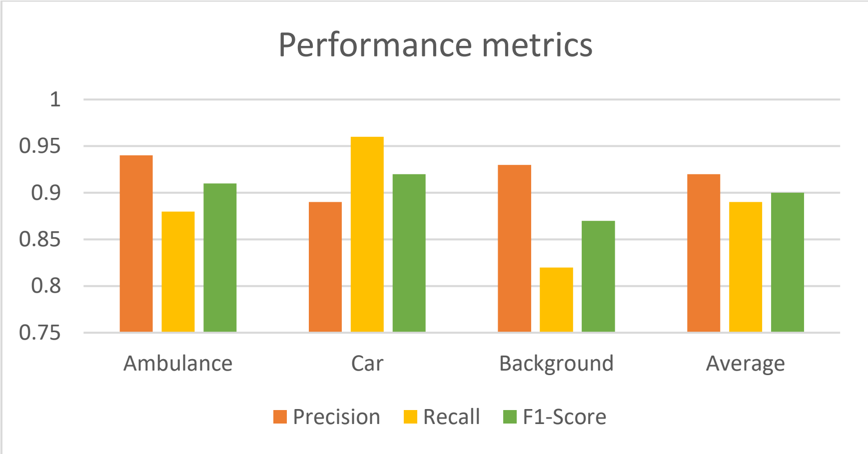

Fig 3. Precision, Recall and F1-score

The model achieves mAP/0.5=0.994 and mAP/0.5:0.95=0.942.

4.3 Confusion matrix

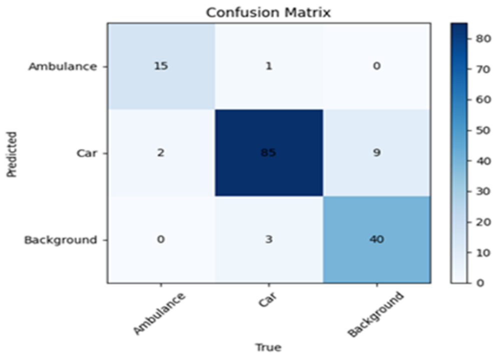

Fig 4. Confusion matrix

In Fig. 4, the performance of the classification is very strong in all the classes with high accuracy in the recognition of ambulances, cars and background objects. According to the confusion matrix, it is possible to state that there is successful separation between vehicle and non-vehicle classes with low misclassification which proves the validity of the proposed model.

Table 1. System level traffic performance metrics

Metrics	Formula	Traditional system (baseline)	Proposed system
Average Vehicle Waiting Time (A)	$A = \frac{1}{N}\sum_{i=0}^{N} W_i$	60-70 s	25-30 s
Traffic Throughput	$T = V_{passed}/time$	150 veh / hr	200 veh/hr
Emergency Vehicle Clearance Time (Time)	$Time = t_{exit} - t_{detect}$	32 s	8-10 s

The waiting time of vehicles will decrease by more than 44 percent and the throughput of traffic will be increased by about 40 percent. The response time of emergency vehicles is shortened nearly by 60 percent, which speaks of the efficiency of the given system in situations of emergency.

Table 2. Comparative analysis of existing traffic control systems and proposed system

Reference	Year	Method	Accuracy
Hazarika et al.[10]	2024	Edge ML	95 %
Arikumar et al.[14]	2023	V2X	94%
Patel & Shah[18]	2022	AI–IoT	92%
Proposed system	-	AI, IoT, CV, Embedded	98%

Conclusion

The proposed traffic control system is superior to the conventional fixed-time and sensor-based approach since it uses real-time computer-vision, deep-learning, and embedded control in a dynamic and adaptive structure. In contrast to the traditional system where manual control and extra roadside infrastructure is necessary in order to prioritize traffic during an emergency, the offered system automatically changes the signal timings depending on the presence of traffic in the area and emergency vehicles. The deep learning model, which is highly accurate, and an ESP32 controller which is based on

edges allow the system to provide low-latency response, it can be scaled easily, it is cost-effective, and fit in the real-life urban environment.
The experimental findings indicate that the overall accuracy is 97-98% with an average precision of 0.94 with high precision, recall and F1-scores in the ambulance, car and background classes. The reliability and usefulness of the system at real time are confirmed by performance analysis on the basis of confusion matrices and confidence-based evaluation curves. Other benefits that the edge-deployable architecture presents include better response, less dependence on infrastructure, enhanced scalability, and resilience to faults. Future developments involve the further development of the framework to handle other types of vehicles, multi-intersection coordination, V2X interoperability and the ability to work under conditions in the night and in bad weather.

References

[1] Mehwish Raza, Majida Kazmi, Hamza Munir Kidwai, Hashim Raza Khan, Saad Ahmed Qazi, Kamran Arshad, " An Edge-Deployed Real-Time Adaptive Traffic Light Control System Using YOLO-Based Vehicle Detection and PCE-Aware Density Estimation", IEEE Access, vol. 13, pp. 153586-153613, 2025, doi: 10.1109/ACCESS.2025.3602844

[2] Sathish Rao, "Traffic Signal Timing and Real Time Optimization", International Research Journal on Advanced Engineering Hub (IRJAEH), vol. 3, issue 5, pp. 2082-2089, 2025

[3] Nithyashree R., Manoj H.K., Huzaif Ahmad, Mohammed Haris, Manohar M., "Smart IoT-Based Traffic Signal Control System with Emergency Vehicle Detection," International Journal of Innovative Research in Technology (IJIRT), vol. 12, issue 2, 2025

[4] Harshavardhan Bhosale Patil, Rajvardhan Desai, Vipul Mengane, Parth Dokare, "Design and Implementation of Smart Traffic Control System Based on Traffic Density", International Scientific Journal of Engineering and Management (ISJEM) , 2025

[5] Ebtihal Rashid Al-Bahri, Bindu Puthentharayil Vikraman, Rana Mohammed Al-Khaife, Al Anood Zahran Al-Rajaib, "A Smart AI-Based System for Emergency Vehicle Prioritization in Urban Traffic", International Journal of Electrical and Electronics, Vol. 13, Issue 3 ,pp. 615-620,2025

[6] M. Sravani, S. Geetha Sri Priyanka, K.N.V.K Sairam, K. Krishna Murthy, "Smart Control of Traffic Light Using Artificial Intelligence", International Journal of Scientific Research in Computer Science, Engineering and Information Technology(IJSRCSEIT),vol. 11,issue 1,2025

[7] Mrs. A. Mohanadevi, M. Poornika, R. Keerthana, “AI - Driven Adaptive Traffic Signal Optimization System With Emergency Vehicle”, International Journal of Engineering Applied Sciences and Technology (IJEAST), vol. 9, issue 09,pp. 38-42,2025

[8] Manar Ashkanani,Alanoud AlAjmi,Aeshah Alhayyan,Zahraa Esmael,Mariam Al-Bedaiwi andMuhammad Nadeem, “A Self-Adaptive Traffic Signal System Integrating Real-Time Vehicle Detection and License Plate Recognition for Enhanced Traffic Management”, Advanced Technologies and Artificial Intelligence for Sustainable and Intelligent Transportation Systems,2025, doi : https://doi.org/10.3390/inventions10010014

[9] Dr G Paavai Anand, M. A. Saianuush, Moomal Arshth, Sanjay. S, “Real-Time Vehicle Detection Using YOLOv8 Model”, International Journal of Advanced Research in Science, Communication and Technology (IJARSCT), vol. 4,issue 3,Nov 2024.

[10] Anakhi Hazarika, Nikumani Choudhury,Moustafa M. Nasralla,Sohaib Bin Altaf Khattak,Ikram Ur Rehman, “Edge ML Technique for Smart Traffic Management in Intelligent Transportation Systems”,IEEE Access,vol.12,pp. 25443-25458, Feb 2024.

[11] Paul Shruti Kanailal, Lavanya E, G. Anbu Selvi, N. Senthamilaras, “Smart Traffic Control System Using Artificial Intelligence” , International Journal for Multidisciplinary Research (IJFMR), Volume 6, Issue 2, March-April 2024, doi : https://doi.org/gtmzs4

[12] Lokesh Pagare, Kaivalya Pagrut, Labhesh Pahade, Suyash Pahare, Prathamesh Paigude, Sanika Pakhare, “AI-Driven Traffic Management System for Emergency Vehicle Prioritization Using YOLO”,International Journal For Research in Applied Science and Engineering Technology https://doi.org/10.22214/ijraset.2024.65461 (IJRASET),2024

[13] M. Flores-Calero, J. Maza and B. S. Lita, “Traffic Sign Detection and Recognition Using YOLO Object Detection Algorithm: A Systematic Review,” International Journal of Computer Applications Technology and Research, Feb. 2024

[14] K. S. Arikumar, S. B. Prathiba, S. Basheer, R. S. Moorthy, A. Dumka, and M. Rashid, “V2X-Based Highly Reliable Warning System for Emergency Vehicles,” Applied Sciences, vol. 13, no. 3, pp. 1950–1962, 2023

[15] K. R. Qasim, M. A. Alwan and A. H. A. Al-Azawi, “An IoT-Enhanced Traffic Light Control System with Arduino and YOLO Object Detection,” Future Internet, vol. 16, no. 10, Oct. 2024, pp. 1–18

[16] S. Roy, P. Banerjee and A. Ghosh, “Real-Time Incident Detection and Adaptive Signal Response Using Computer Vision”, International Journal of Transport Informatics, Sep. 2024.

[17] B. Ahmed, L. Zhou and J. Li, “An ESP32-Based Prototype for Low-Cost Traffic Monitoring and Signal Control”, International Journal of Low-Cost Embedded Systems, 2024.

[18] N. Patel and D. Shah, “Integration of AI and IoT for smart traffic management,” Journal of Emerging Technologies and Innovative Research (JETIR), vol. 9, no. 5, pp. 234 240, May 2022