

# AI-Based Smart Traffic Management System Using YOLOv8

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**Abstract**— Urban transportation systems are challenged by severe traffic congestion and delays. Existing system of traffic signals are not adaptable to real-time traffic flow. This research proposes developing an AI-driven adaptive traffic control system using YOLOv8 for real-time vehicle and pedestrian detections. The system dynamically adjusts signal timings based on traffic density, prioritizing emergency vehicles and detecting over speeding vehicles. Experimental results indicates improvements in traffic flow, waiting times and enhanced safety measures. Compared to conventional traffic systems, the proposed solutions show significant waiting time reductions and enhanced handling of traffic fluctuations.

**Keywords:** Traffic Management, YOLOv8, Adaptive Traffic Signal, Emergency Vehicle Priority, Computer Vision, Overspeed Detection.

## I. INTRODUCTION

Clogged urban streets may be a global problem that leads to delays, increased fuel use, and severe environmental contamination. Because they are unable to account for the fluctuating quantities of activity that occur throughout the day, routine activity lights operate on predefined cycles and have a fixed time [2]. Long holding durations increase the likelihood of accidents, and differentiating volume-and-flow scenarios results in a wasteful stream of activity via crossing locations [3]. In order to achieve more responsive and flexible control over the activity stream based on real-time data, uses AI and computer vision [1].

We propose a computerized activity optimization system that leverages the deep learning capabilities of YOLOv8 for object detection and localization [4]. By using YOLOv8, the system enhances heavy traffic awareness environments, enabling accurate identification of vehicles, pedestrians, and emergency responders, thereby optimizing operational efficiency and safety [5]. The information gathered maybe used to effectively adjust activity flag timings to accommodate street usage, reducing congestion and enhancing security [7]. Unlike traditional fixed-timer signals, the method detects overspeeding

[8], calls for emergency vehicles [9], and responds to changes in real-time.

### A. YOLO for Object Detection

The cutting-edge, real-time object recognition system ‘You Only Look Once’ (YOLO) predicts bounding boxes and class probabilities from complete images in a single evaluation, treating detection as a single regression issue [4]. Because of its unified architecture, YOLO is incredibly quick and effective in contrast to conventional approaches that do region proposals first, followed by classification [6]. The most recent version, YOLOv8, enhances previous versions by providing improved handling of small and overlapping objects and increased precision [10][24].

Because of its speed and accuracy, it is especially well-suited for traffic management applications where it is essential to detect cars and pedestrians quickly [20][22][24]. Within each frame of a video stream, YOLO can recognize several item classifications, including cars, buses, trucks, emergency vehicles, and pedestrians [11][21]. This feature improves traffic flow and safety by enabling dynamic traffic signal regulation based on real-time traffic density and behavior [12].

## II. PROPOSED SYSTEM ARCHITECTURE

### A. Overview

The system comprises four main modules:

- **Data Acquisition:** Video feeds from cameras at intersections capture traffic in real-time [10].
- **Object Detection:** YOLOv8 detects vehicles (cars, buses, trucks, emergency vehicles) and pedestrians frame by frame [9].
- **Traffic Analysis & Decision Making:** Counts of vehicle types, traffic density and pedestrian presence estimates are analyzed to decide signal timings [1].

- **Signal Control & Alerts:** Traffic signals adjust dynamically, prioritizing emergency vehicles and allowing safe pedestrian crossings [3].

### B. Advantages of Proposed Architecture

The proposed architecture offers several advantages:

- Enhanced efficiency in traffic signal timing through real-time data analysis [2],[22].
- Immediate response to emergency vehicle detection, ensuring faster clearance [9],[23].
- Reduction in traffic congestion and improved road safety and sustainability [3],[19].

## III. PROPOSED SYSTEM TECHNIQUES

### A. YOLOv8 for Real-Time Detection

In computer vision, detecting objects, identifying and localizing multiple objects within an image is a fundamental challenge. Image classification can recognize objects but lacks the ability to locate positions and instances simultaneously. But object detection provides category and spatial coordinates of each detected object [11],[18].

YOLO transformed object detection by using a novel, real-time method [15]. The entire image is processed by the convolutional neural network (CNN) in a single forward pass. Bounding boxes and item probabilities are predicted for each part of the image using YOLO, which then weights the boxes according to the expected probabilities. This method guarantees that YOLO runs effectively in real time and attains great accuracy [14].

YOLOv8 explores feature maps from different scales to improve the model's ability for object detection. It simplifies the training process and improves the model's generalization ability [24].

For intelligent traffic management systems, different types of YOLO has YOLO multispectral adaptations to improve object detection and evaluate the dataset used [25].

### B. Convolutional Neural Networks (CNN) for Traffic Analysis

One Convolutional Neural Networks (CNNs) are particularly effective at processing spatial data employed in traffic analytics, such as congestion detection, speed estimation, and overspeeding vehicle identification. By using convolutional filters to automatically extract spatial hierarchies, CNN-based systems can process live images from camera for traffic-management [20].

CNNs' capacity to identify significant patterns in intricate traffic scenarios allows the system to accurately evaluate live video streams [20]. For example, CNNs may recognize illegal moves, detect erratic driving behavior, and estimate vehicle speeds by analyzing successive frames [9]. The traffic management system can prioritize specific traffic kinds, including emergency vehicles, and make better decisions about signal timing adjustments because to this thorough spatial information [21].

CNNs also help to improve safety by seeing unusual traffic patterns early on, which lowers congestion and helps avoid accidents[21]. Reliable performance in a variety of real-world circumstances is ensured by their resilience to changing illumination, weather, and environmental conditions [6]. In general, the accuracy and responsiveness of traffic signal control are greatly increased by including CNNs into the traffic management system [20],[21].

## IV. PROPOSED SYSTEM CONTROL FLOW

The step-by-step explanation of the system workflow as in Fig.1 includes:

The suggested system starts by placing observation cameras at road intersections to constantly observe traffic movement [1], [5]. The observation cameras take live video feeds that are input to the system. The preprocessed video frame is then resized into the input size required by the YOLOv8 model, normalized pixel values, and any excess noise or distortion removed to allow proper detection [4], [11].

Once preprocessed, the frames are fed to the YOLOv8 object detection model, which detects and classifies different objects in the frame including vehicles, pedestrians, and emergency vehicles [5], [13], [25]. The system extracts three critical parameters based on YOLOv8 output [24]: vehicle density on each road, whether an emergency vehicle is present or not, and how many pedestrians are waiting to cross [14], [15].

The system then compares these conditions with predefined threshold values. If the number of vehicles per lane is more than the predefined limit, or if an emergency vehicle is present, or if the pedestrian number is more than the limit, the system adapts the traffic signal timing dynamically [2], [9]. This adaptation encompasses the extension of green signal time for busy lanes, giving priority to the route with emergency vehicles, or enhancing pedestrian crossing time when required [1], [23]. If any of these conditions are not fulfilled, the system repeats itself and proceeds to monitor the incoming video in real-time traffic, enabling constant traffic monitoring and optimization [16], [17],[21].

The algorithm is in a constant loop and provides real-time traffic management in accordance with real-time road conditions, enhancing road efficiency, alleviating congestion, and facilitating safe passage for emergency services and pedestrians [12], [19].

The loss of classification during training keeps declining steadily with time. This is an indication that the model gets more precise in classifying objects into their respective categories as training continues [1], [13].

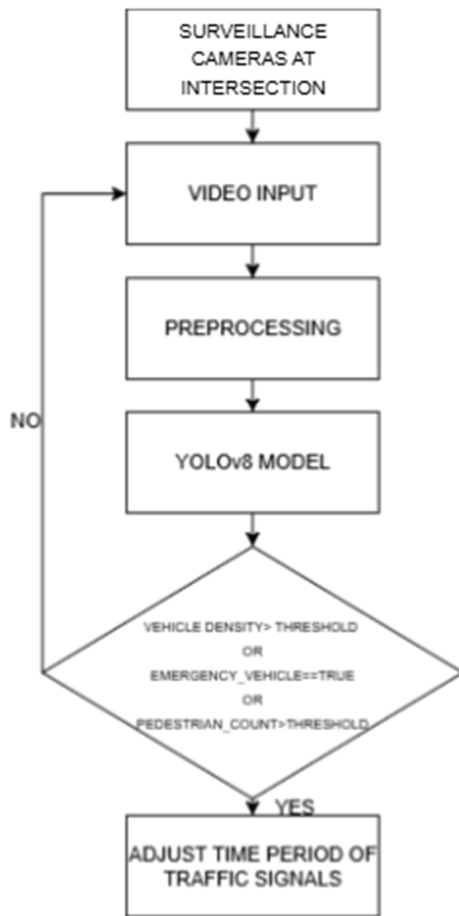
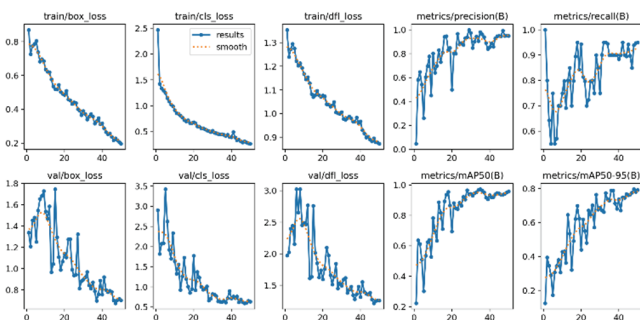


Figure 1. Proposed System Control Flow Diagram

## V. TRAINING METRICS



### A. Train Box Loss

The train box loss reduces steadily across the epochs, which indicates the model is getting better with time in terms of predicting bounding boxes around objects. The steady reduction without spikes indicates stable object bounding box localization training [10], [4].

### B. Train Classification Loss

### C. Train Objectness Loss

Object loss over training also follows a declining trend, and it is a sign of the enhanced ability of the model in discriminating between object and background regions. It is a metric of increasing better object prediction confidence scores over time [5], [11].

### D. Precision (Validation)

Precision measure gets better with more training in a stepwise manner. That is, the model is decreasing the wrong positive predictions with greater training, corresponding to higher accuracy of the predicted bounding boxes [6], [24].

### E. Recall (Validation)

The recall graph is rising, with a proof of the truth that the model is able to pick up more true objects in the images. It implies that fewer and fewer objects are being left out as training progresses [12], [18].

### F. Validation Box Loss

Validation box loss is decreasing with fluctuation, and that indicates there is noise but as the overall direction is one of decreasing, so it implies the model is improving at generalizing to novel data in terms of bounding box accuracy [15], [22].

### G. Validation Classification Loss

The classification loss measure follows a similar downward trend with minimal fluctuations, indicating that the model has better performance in classifying objects as positive on the validation set [14], [20].

### H. Validation Objectness Loss

Objectness loss in validation data reduces at a slow, steady pace with occasional spikes. On average, this indicates that the model is improving in prediction for an object or no object, even in untrained data [16], [21].

### I. mAP@0.5 (Validation)

The steady improvement of average Average Precision at Intersection Over Union (IoU) threshold 0.5 over epochs indicates that the predictions made by the model are getting more precise and closer to the ground truth at this particular level of IoU [10], [17],[22].

### J. mAP@0.5:0.95 (Validation)

This plot is a smooth performance progression against different IoU thresholds. Gain over this tighter range guarantees that the model, accurate as it is, is also precise for several object matching conditions [11], [23].

## VI. EXPERIMENTAL SETUP AND RESULTS

Prerecorded intersection recordings with different traffic situations were used to test the device [3],[19],[20]. The trials assessed overspeed detection [9], emergency vehicle priority management [10], traffic flow improvement [4],[25] and detection accuracy [1].

### A. Traffic Flow Improvement

Timestamp analysis of video frames confirmed that adaptive signaling decreased average vehicle waiting times by 30% when compared to fixed timers [4],[16][20]. During peak hours, the system performed exceptionally well, reducing delays and traffic [4],[17],[19].

### B. Emergency Vehicle Priority

Normal cycles were successfully disrupted by simulated emergency vehicle identification, which resulted in instant green lights and, on average, junction clearance in 10 seconds [10],[16],[17]. This guarantees prompt action in case of emergencies. Fig.3 shows Emergency vehicle detection using our system.



Figure. 3 Emergency vehicle detections from traffic image

## VII. CONCLUSION

In order to enable adaptive traffic signal control that prioritizes emergency vehicles and identifies overspeeding, this model proposed an AI-based traffic management system that uses YOLOv8 for real-time vehicle and pedestrian recognition [1], [9], [10], [19],[23]. Improvements in safety and traffic flow are confirmed by experimental data [2], [4],[22]. In order to achieve fully autonomous signal optimization, future work will concentrate on integrating real IoT sensors [5],[21] extending deployment to many junctions [8],[22], and putting reinforcement learning into practice [8].

The suggested system is a viable answer to the current urban traffic problems because of its modular design and use of cutting-edge AI techniques, which guarantee scalability and adaptability.

- [1] Y. Zhang, Y. Zhang, and R. Su, "Pedestrian-safety-aware traffic light control strategy for urban traffic congestion alleviation," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 1, pp. 178–193, 2019.
- [2] S. Lee *et al.*, "Intelligent traffic control for autonomous vehicle systems based on machine learning," *Expert Syst. Appl.*, vol. 144, p. 113074, 2020.
- [3] B. Zhou *et al.*, "A large-scale spatio-temporal multimodal fusion framework for traffic prediction," *Big Data Min. Anal.*, vol. 7, no. 3, pp. 621–636, 2024.
- [4] K. Anvitha, R. Sumathi, K. Vanaja, K. V. S. N. S. Kishan, K. Bhavana, and K. S. Sharan, "Analysis of traffic management system using YOLOv8," in *Proc. 2nd Int. Conf. Autom., Comput. Renew. Syst. (ICACRS)*, 2023, pp. 1363–1366.
- [5] S. B. Neamah and A. A. Karim, "Real-time traffic monitoring system based on deep learning and YOLOv8," *Aro - Sci. J. Koya Univ.*, vol. 11, no. 2, pp. 137–150, 2023.
- [6] Q. Liu, Y. Liu, and D. Lin, "Revolutionizing target detection in intelligent traffic systems: YOLOv8 SnakeVision," *Electronics*, vol. 12, no. 24, p. 4970, 2023.
- [7] A. Bhardwaj *et al.*, "Understanding sudden traffic jams: From emergence to impact," *Develop. Eng.*, vol. 8, p. 100105, 2023.
- [8] Y. N. Thakare *et al.*, "Overspeed alert system for vehicles to avoid e-challan on highways using machine learning algorithm," in *Recent Advances in Science, Engineering & Technology*, CRC Press, 2024, pp. 293–302.
- [9] A. Adnane and Y. Harkat, "Dynamic emergency vehicle prioritization in a connected urban environment: A rule-based approach," in *Advances in Transdisciplinary Engineering*, vol. 27, p. 380, 2024..
- [10] J. Castillo *et al.*, "A real-time traffic monitoring system based on YOLOv8 for vehicle detection and classification," in *Proc. 2024 IEEE Int. Conf. Green Energy Smart Syst. (GESS)*, Long Beach, CA, USA, 2024.
- [11] M. Bakirci, "Utilizing YOLOv8 for enhanced traffic monitoring in intelligent transportation systems (ITS) applications," *Digit. Signal Process.*, vol. 152, p. 104594, 2024.
- [12] S. Pudaruth and I. M. Boodhun, "Reducing traffic congestion using real-time traffic monitoring with YOLOv8," *Int. J. Adv. Comput. Sci. Appl.*, vol. 15, no. 10, 2024.
- [13] N. Islam *et al.*, "Vehicle classification and detection using YOLOv8: A study on highway traffic analysis," in *Proc. 2024 Int. Conf. Recent Progresses Sci., Eng. Technol. (ICRPSET)*, 2024.
- [14] J. N. Punitha Markavathi *et al.*, "Real-time traffic density monitoring and adaptive signal control using YOLOv8 and Arduino-based LED system," in *Proc. 2024 9th Int. Conf. Commun. Electron. Syst. (ICCES)*, 2024.
- [15] J. Sravanthi *et al.*, "Traffic monitoring system for signal duration control based on YOLOv8," in *Proc. 2024 Int. Conf. Comput. Intell. Green Sustain. Technol. (ICCGST)*, 2024.
- [16] S. Phatangare *et al.*, "Real-time traffic management using deep learning and object detection using YOLOv8," in *Proc. 2024 15th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT)*, 2024..
- [17] Y. Li, Y. Huang, and Q. Tao, "Improving real-time object detection in Internet-of-Things smart city traffic with

- YOLOv8-DSAF method,” *Sci. Rep.*, vol. 14, no. 1, p. 17235, 2024.
- [18] J. Sharma, D. Kumar, and A. Malhotra, “Advanced traffic signal recognition using real-time detection using YOLO v8,” in *Proc. 2024 2nd World Conf. Commun. Comput. (WCONF)*, 2024.
- [19] M. Ravichandran, L. Kumar, and M. Annamalai, “Smart traffic control: Adaptive signal management based on real-time lane detection using YOLOv8,” in *Proc. 2024 Int. Conf. Autom. Comput. (AUTOCOM)*, pp. 174–180, 2024.
- [20] A. Younesi, M. Ansari, M. Fazli, A. Ejlali, M. Shafique, and J. Henkel, “A comprehensive survey of convolutions in deep learning: Applications, challenges, and future trends,” *IEEE Access*, vol. 12, pp. 41180–41218, 2024.
- [21] S. Saklani, M. Manchanda, R. Sharma, and D. Singh, “Real-time traffic management system using YOLOv8 and CNN: A deep learning approach with IoT integration,” in *Proc. 2025 1st Int. Conf. Adv. Comput. Sci., Electr., Electron., Commun. Technol. (CE2CT)*, pp. 645–651, 2025.
- [22] A. D. Desta and J. Cheng, “Enhancing YOLOv8 for vehicle detection in intelligent traffic management,” *Metall. Mater. Eng.*, vol. 31, no. 4, pp. 190–200, 2025.
- [23] A. Omari Alaoui *et al.*, “Real-time traffic signal adjustment using YOLOv8 for improved integration of emergency vehicles in smart traffic systems,” *Signal Image Video Process.*, vol. 19, no. 7, pp. 1–8, 2025.
- [24] J. Wei, A. As’arry, K. Anas Md Rezali, M. Z. M. Yusoff, H. Ma, and K. Zhang, “A review of YOLO algorithm and its applications in autonomous driving object detection,” *IEEE Access*, vol. 13, pp. 93688–93711, 2025.
- [25] J. E. Gallagher and E. J. Oughton, “Surveying You Only Look Once (YOLO) Multispectral Object Detection Advancements, Applications, and Challenges,” in *IEEE Access*, vol. 13, pp. 7366–7395, 2025.