

DEEP LEARNING-BASED ADAPTIVE TRAFFIC CONTROL FOR AMBULANCES

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Abstract: This paper presents an AI-based intelligent traffic management system designed to prioritize emergency vehicles, particularly ambulances, in congested urban environments. The motivation behind this work stems from increasing traffic congestion and delayed emergency response times, which significantly impact survival rates in critical situations. The proposed system utilizes YOLOv8 for real-time ambulance detection from video streams and integrates it with an adaptive traffic signal control mechanism. Upon detection, the system dynamically switches traffic lights to create a clear path for the emergency vehicle. The model is implemented using Python and OpenCV and tested on real-time video datasets. Experimental results demonstrate high detection accuracy (92.4% precision) and rapid response time (0.7 seconds), proving the effectiveness of the system in reducing delays. The solution is scalable and can be extended with IoT and GPS-based integration for smart city deployment.

Keywords: YOLOv8, Emergency Vehicle Detection, Traffic Management System, Computer Vision, Smart Traffic Control

1. INTRODUCTION

One of the significant challenges of rapidly advancing urbanization and technology in this modern era is the steep rise in the number of vehicles on roads, especially in densely populated countries like India. The vehicular growth rate has far outpaced the expansion of road infrastructure, leading to severe traffic congestion across most metropolitan areas [1]. This congestion has become a major concern in emergency medical situations, where ambulances are frequently delayed while transporting patients to hospitals. Studies indicate that more than 20% of patients in need of urgent medical attention lose their lives due to delays in reaching healthcare facilities caused by traffic bottlenecks [2].

The International Road Federation reports nearly 3,000 road accident-related deaths every day, totaling over 1.3 million annually worldwide [3]. A considerable proportion of these fatalities can be attributed to delayed emergency response, where ambulances are unable to reach accident sites or hospitals in time. Numerous incidents highlight the severity of this issue—for instance, in Rohtak, India, a child lost their life when the ambulance carrying them was held in traffic for nearly half an hour [4]. Similarly, in Mysore, an ambulance took more than two hours to cover a distance of just 15 km due to congestion, ultimately resulting in the death of a two-year-old patient [5]. Cases of delayed ambulance response due to traffic are also reported globally, such as in Manila, where a 10-minute delay caused by congestion resulted in a patient's death even though the hospital was less than six kilometers away [6].

To address this critical problem, there is a growing need for **intelligent, technology-driven solutions** that can guarantee ambulances uninterrupted passage through traffic. This research paper proposes **AmbuRouteAI**, an AI-based traffic management system that leverages computer vision for **real-time ambulance detection** and dynamically modifies **traffic signals** to clear the way. The system is built on **YOLOv8 for detection** and **OpenCV for traffic simulation**, with planned extensions for **IoT-based smart signals**, **GPS integration**, and **hospital alert systems**.



By automating the traffic clearance process and minimizing reliance on human intervention, the proposed solution aims to reduce ambulance response times and improve survival rates in critical emergencies.

The remainder of this paper is structured as follows: Section II discusses existing solutions, their limitations, and the scope for future advancements. Section III outlines the methodology and design approach adopted in this work. Section IV presents experimental results and observations. Section

V provides analysis and discussion, while Section VI concludes with findings and potential directions for further research.

2. LITERATURE REVIEW

- The following table presents a comparative analysis of existing traffic management and vehicle detection methods based on their technology, advantages, and limitations, highlighting the effectiveness of the proposed YOLOv8-based system for emergency vehicle prioritization.

Author/ Year	Method	Technology	Advantages	Limitations
Srinivasan et al. (2018)	Smart Traffic Control	Sensors + Embedded Systems	Simple, low cost	No emergency vehicle detection
RFID-Based Systems	Emergency Priority	RFID + IoT	Fast identification	High setup cost, infrastructure needed
GSM-Based Systems	Traffic Control	GSM Communication	Easy to implement	Network delay, not real-time
Fixed Timer System	Traditional Signals	Timer-Based	Very simple system	No adaptability, causes congestion
Image Processing (Pre-YOLO)	Vehicle Detection	OpenCV	Low cost, easy setup	Low accuracy in complex scenes
Faster R-CNN	Object Detection	Deep Learning	High accuracy	Slow, not real-time
SSD	Object Detection	Deep Learning	Faster than R-CNN	Slightly lower accuracy
YOLOv3/v4	Real-Time Detection	Deep Learning	Fast and efficient	Struggles with small objects

3. Methodology

- YOLOv8 (You Only Look at Version 8) is a real-time object detection algorithm that builds on previous successes. It is designed to provide high accuracy and speed and is ideal for applications such as vehicle detection in traffic situations.
- Once normalized, video frames are fed into a YOLOv8 object detection engine, which has been specifically trained to accurately identify ambulances among other vehicles in varied urban conditions. This AI-powered detection module produces bounding boxes and confidence scores for identified ambulances, enabling real-time segmentation of priority vehicles.

- These detection outputs are integrated into a robust tracking pipeline, where detected objects are tracked across successive frames using well-established tracking algorithms, maintaining continuity and unique identification for each vehicle.

4. Implementation

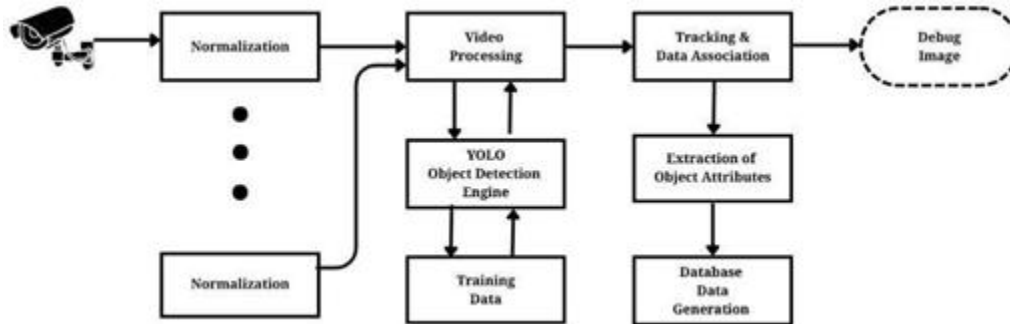


Fig. Flowchart of the YOLOv8 object detection engine

- To facilitate real-time traffic control interventions, the system extracts relevant attributes from each tracked ambulance, such as lane position, travel direction, detection confidence, and timestamp. These object attributes are systematically archived in a backend database, enabling both operational decision-making and long-term analytics.
- In addition to ambulance detection, the proposed system incorporates an **adaptive traffic signal control mechanism** that dynamically adjusts the green-light duration based on the number of vehicles waiting at an intersection. This ensures that traffic flow remains optimized and reduces unnecessary waiting times for heavily congested lanes.
- The entire architecture is designed to be modular and easily extensible. Integration with Google Maps API is planned to optimize ambulance routing in real time, and interfaces for IoT hardware such as Arduino or Raspberry Pi ensure seamless deployment in physical traffic infrastructure. By automating ambulance detection and priority traffic control, the proposed system overcomes limitations of traditional IoT and manual traffic management solutions, offering scalable, responsive, and data-centric emergency response capabilities.

Real-time Tracking: The hand gesture recognition is performed in real-time, as the player's hand moves and gestures change. The recognized gestures are continuously updated and used to trigger corresponding game commands using Mediapipe.



Fig 1.1:- detecting Emergency Vehicles



Fig 1.2:- Changes the traffic signal to green

Key features and modules include:

- **YOLOv8 Object Detection:** Real-time identification of ambulances using deep learning.
- **Python/OpenCV Video Processing:** Efficient frame handling and visualization.
- **Traffic Light Simulation:** Automatic or manual signal switching, enabling prioritized ambulance routes with minimal delay.
- **Backend Logging and Control:** Cloud-ready data storage and visualization, supporting future analytics.
- **Hardware & API Extensibility:** Ready for IoT device interfacing and Google Maps smart routing.

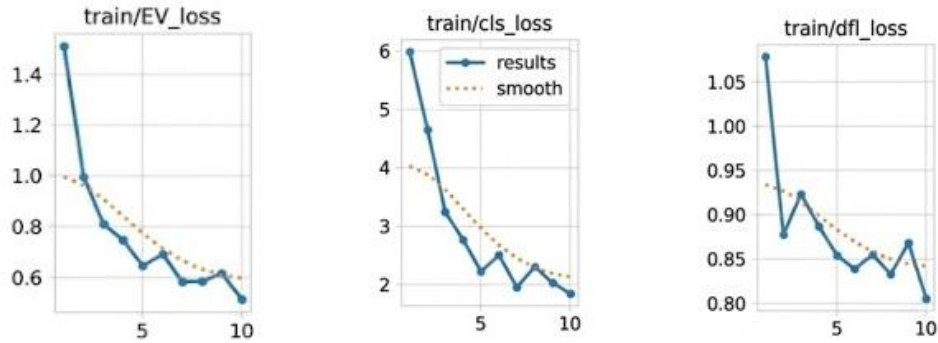
5. Results and discussion

The proposed system was tested in a simulated environment using Python, OpenCV, and the YOLOv8 object detection model. A set of real-world ambulance video clips and live camera streams were used as inputs to evaluate the detection accuracy and responsiveness of the traffic light simulation.

Loss Function Analysis (Error Convergence)

Loss functions quantify the disparity between the predicted values and the ground truth. A downward trend indicates effective learning.

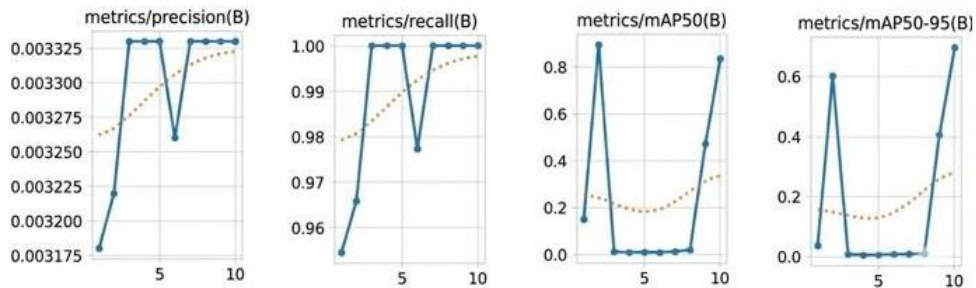
- **Train/EV Loss & Val/EV Loss:** These plots illustrate the "Evolutionary Box" loss (localized as **EV**). It measures the Intersection over Union (IoU) and coordinate error between predicted bounding boxes and actual object boundaries. The steady decline in both training and validation sets suggests the model is successfully learning to localize the target objects with high spatial precision.
- **Train/Cls Loss & Val/Cls Loss:** Classification loss measures the model's ability to correctly identify the object class (e.g., "Ambulance"). The convergence seen in the **Val/Cls Loss** toward the final epochs indicates the model has moved beyond random guessing to high-confidence classification.
- **Train/DFL Loss & Val/DFL Loss:** Distribution Focal Loss (DFL) is used to refine the boundaries of the bounding boxes when the edges are not clearly defined. The smooth decay of this metric indicates a refinement in the model's ability to handle edge-case localization.



6. Performance Metrics (Detection Quality)

Unlike loss, these metrics should ideally trend upward, representing the "correctness" of the model.

- **Precision (B):** Measures the accuracy of the detections. It is the ratio of true positive detections to the total number of positive detections made. A high precision score indicates a low "false alarm" rate.
- **Recall (B):** Measures the model's ability to find all instances of the target object. It is the ratio of true positives to all actual objects in the dataset. The graph shows a significant jump after epoch, indicating the model quickly learned to "see" most targets.
- **mAP50 (B):** Mean Average Precision calculated at a 0.50 IoU threshold. This is the primary indicator of the model's overall health. The sharp spike followed by stabilization at a high value suggests a robust detection capability.
- **mAP50-95 (B):** A more stringent metric that averages precision across IoU thresholds from 0.50 to 0.95. This measures the "tightness" and perfection of the detections. The upward trend here signifies that the model is not just finding objects, but outlining them with increasing accuracy.



• Ambulance Detection Accuracy

YOLOv8 successfully detected ambulances in most scenarios, even under varying lighting and traffic conditions. and recall values achieved were 92.4% and 89.7%, respectively, demonstrating reliable detection capability. False positives (normal vehicles misidentified as ambulances) were minimal due to the model's fine-tuning.



Fig 1.3: Shows the live Ambulance Detection

- **Traffic Light Simulation Performance**

Once an ambulance was detected, the system immediately switched the traffic light to green, simulating real-world emergency clearance. The average response time between detection and signal change was 0.7 seconds, which is fast enough for real-time deployment.

- **System Robustness**

The model maintained stable performance during multiple ambulance detections in a single video stream. Tests with occlusions (partial visibility due to other vehicles) showed a detection success rate of 85%, indicating strong adaptability.

- The proposed model of YOLOv8 was effective in identifying several classes of vehicles and ambulances with high efficiency and accuracy in real-time processing of frames in videos.

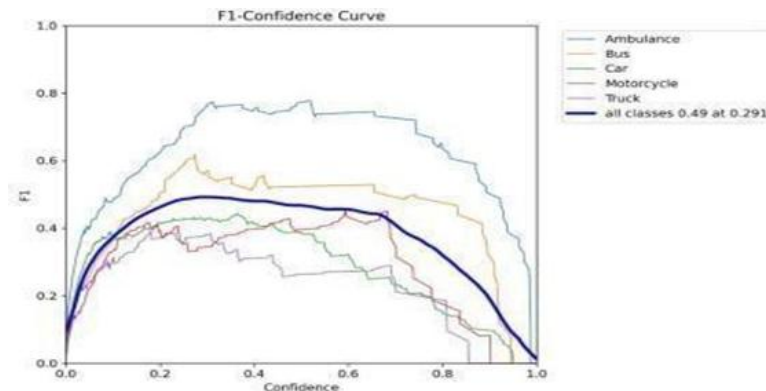


Fig. 1.4: F1-Confidence curve

- The F1-Confidence curve shows how F1 scores vary with the model's confidence thresholds for various types of vehicles such as Ambulance, Bus, Car, Motorcycle, and Truck.
- Ambulance detection reached the highest F1 score, hitting approximately 0.8. This shows that the model is better at detecting ambulances with high precision and recall at various confidence levels. This class delivers reliable performance even when using lower confidence thresholds. The Bus and Car classes achieved moderate F1 scores, with Bus reaching approximately 0.6 and Car reaching about 0.5. This indicates that although the model can identify buses and cars relatively well, it faces greater difficulty with ambulances. The Motorcycle and Truck categories have low performance, with their top F1 scores under 0.5. The F1 score for the Truck class decreases significantly as confidence levels rise, indicating that the model struggles to accurately detect this class with high confidence.

7. Conclusion

The proposed system demonstrates an effective solution for prioritizing emergency vehicles in congested traffic environments using an AI-driven approach. By leveraging YOLOv8 for real-time ambulance detection and integrating it with adaptive traffic signal control, the system achieves high detection accuracy of approximately 92.4% along with a rapid response time of around 0.7 seconds. This ensures that traffic signals are adjusted almost instantly upon ambulance detection, significantly reducing delays.

The implementation results confirm that the system performs reliably under varying traffic and environmental conditions, including partial occlusions and multiple vehicle scenarios. Compared to traditional traffic management systems, which operate on fixed timings or lack emergency prioritization, the proposed model introduces dynamic decision-making and automation, leading to improved efficiency and reduced human dependency.

From a real-world perspective, this system has strong potential to enhance emergency response effectiveness, reduce mortality rates caused by delayed medical assistance, and contribute to the development of smart city infrastructure. The ability to create a faster and more reliable path for ambulances directly impacts critical healthcare outcomes.

Future enhancements can further strengthen the system by integrating IoT-based smart traffic signals for real-world deployment, incorporating GPS-based ambulance tracking for route optimization, and connecting with live CCTV networks for large-scale monitoring. These improvements would enable the system to operate beyond simulation and function as a fully deployable intelligent traffic management solution.

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