# AI-Based Smart Traffic Control System For Emergency Vehicle Prioritization

**Aishwarya**
Dept of Artificial Intelligence and Data Science
Rathinam Technical Campus, Coimbatore, India

***Abstract***- *The rapid growth of urbanization has significantly increased traffic congestion, posing critical challenges for emergency medical services, particularly ambulances. Delays caused by conventional fixed-time traffic signal systems can lead to increased response times and adverse outcomes for patients. This situation highlights the need for intelligent, automated, and real-time traffic management solutions capable of prioritizing emergency vehicles.*

*This paper presents an AI-Based Smart Traffic Control System for Emergency Vehicle Prioritization using deep learning and computer vision techniques. The proposed system employs a custom-trained YOLOv8 model to accurately detect ambulances from real-time or recorded traffic camera feeds. The detection model is trained using a labeled dataset prepared with Roboflow, ensuring high precision for ambulance-specific classification. Upon detecting an ambulance with sufficient confidence, the traffic signal dynamically switches to a green phase, allowing uninterrupted passage through the intersection.*

*To ensure system stability and prevent false triggering, a timeout-based control mechanism is incorporated, enabling the signal to revert safely to normal operation once the ambulance exits the camera's field of view. A graphical user interface is developed to visually represent traffic signal states and emergency conditions, providing real-time monitoring and transparency. The system is implemented using Python, OpenCV, and a multithreaded architecture to maintain real-time performance without blocking the user interface.*

*Experimental evaluation demonstrates reliable ambulance detection, smooth signal transitions, and effective prioritization under varying traffic conditions. The proposed solution enhances emergency response efficiency, reduces manual intervention, and offers a scalable framework that can be integrated into smart city traffic infrastructure. This work contributes toward improving urban emergency mobility through intelligent automation and AI-driven traffic management.*

***Keywords:*** Ambulance Detection, Intelligent Traffic Signal Control, Emergency Vehicle Priority, Computer Vision, Deep Learning, YOLOv8, Smart Transportation Systems

## I. INTRODUCTION

Rapid urbanization and the continuous growth of vehicular traffic have placed significant pressure on modern transportation infrastructure. One of the most critical challenges arising from traffic congestion is the delay faced by emergency medical vehicles, particularly ambulances. Timely arrival of ambulances at accident sites and hospitals is crucial, as even a short delay can significantly impact patient survival rates. However, conventional traffic signal systems operate on fixed or pre-defined timing mechanisms, lacking awareness of real-time traffic conditions and emergency vehicle presence.

Traditional methods for granting priority to ambulances often rely on manual intervention, siren-based clearance, or traffic police assistance. These approaches are inefficient, error-prone, and difficult to scale in densely populated urban environments. Furthermore, human-dependent systems may fail during peak traffic hours, adverse weather conditions, or poor visibility, leading to increased response times for emergency services. This highlights the urgent need for an intelligent, automated, and real-time traffic control system capable of detecting ambulances and dynamically adjusting signal phases.

Recent advancements in Artificial Intelligence (AI) and Computer Vision have enabled the development of smart transportation systems that can analyze live traffic data and make informed decisions. Deep learning-based object detection models have demonstrated high accuracy and real-time performance in identifying vehicles from camera feeds. In particular, models such as **YOLOv8** offer an effective balance between detection speed and precision, making them suitable for time-sensitive applications like emergency vehicle prioritization.

Despite ongoing research in intelligent traffic management, many existing systems focus primarily on general traffic density estimation and signal optimization, without dedicated mechanisms for emergency vehicle detection. Systems that do attempt ambulance prioritization often depend on additional hardware sensors or GPS-based communication, which increases cost and infrastructure complexity. Moreover, the lack of reliable visual confirmation may result in false triggering or missed detections.

To address these challenges, this paper proposes an AI-Based Smart Traffic Control System for Emergency Vehicle Prioritization that utilizes deep learning and real-time video analysis. The proposed solution employs a custom-trained YOLOv8 model to detect ambulances from live traffic camera feeds. Upon successful detection, the system dynamically switches the traffic signal to green, allowing uninterrupted passage for the ambulance. Once the ambulance leaves the camera's field of view, the system safely reverts to normal traffic operation. By integrating AI-driven detection with adaptive signal control, the proposed system aims to reduce emergency response delays, improve traffic efficiency, and contribute to smarter urban mobility solutions.

## II. LITERATURE REVIEW

The application of Artificial Intelligence (AI) and Computer Vision in intelligent traffic management has gained significant attention in recent years, particularly for emergency vehicle prioritization. Traffic congestion poses a critical challenge to timely ambulance response, prompting research into automated systems that can detect emergency vehicles and dynamically control traffic signals.

Several studies highlight the effectiveness of deep learning-based object detection models in real-time vehicle recognition. Models such as YOLOv4, YOLOv5, and the more recent **YOLOv8** have demonstrated high accuracy and low latency in detecting specific vehicle classes under varying environmental conditions, including occlusion, low light, and crowded urban scenarios. Custom-trained models on emergency vehicle datasets have shown that focusing on a single class, such as ambulances, significantly reduces false positives and improves detection reliability.

Existing intelligent traffic systems often rely on hardware sensors, GPS-based communication, or siren-triggered prioritization. While these systems can provide emergency vehicle clearance, they are infrastructure-intensive and often limited to predefined routes. Vision-based approaches, on the other hand, offer a scalable alternative by utilizing existing traffic cameras for detection without additional hardware. However, prior solutions sometimes suffer from limited real-time performance, high computational cost, or inadequate handling of transient detection failures, which can result in signal flickering or missed ambulance prioritization.

Comparative analyses indicate that while general traffic optimization systems effectively manage congestion, most lack dedicated mechanisms for emergency vehicle detection and dynamic traffic signal adaptation. Additionally, many vision-based approaches have not integrated robust user interface or monitoring components for real-time traffic signal visualization, which is crucial for verification and operational transparency.

The proposed AI-Based Smart Traffic Control System for Emergency Vehicle Prioritizationaddresses these limitations by combining a custom YOLOv8-based ambulance detection model with an adaptive traffic signal control mechanism. The system features real-time detection, a confidence-based triggering mechanism to prevent false positives, and a timeout-based control to ensure smooth transitions between emergency and normal traffic states. A graphical user interface provides visual feedback of the traffic signals and ambulance presence, offering an integrated and practical solution for urban emergency mobility.

## III. PROPOSED SYSTEM

The proposed AI-Based Smart Traffic Control System for Emergency Vehicle Prioritizationis a real-time, AI-driven platform designed to detect ambulances and dynamically manage traffic signals to prioritize emergency vehicles. The system integrates deep learning-based object detection with adaptive traffic signal control and a user-friendly graphical interface.

The system captures live traffic video feeds from cameras installed at intersections or uses pre-recorded traffic videos for testing. These video frames are processed in real time by a custom-trained **YOLOv8** model specifically optimized for ambulance detection. Upon identifying an ambulance with a confidence score above a pre-defined threshold, the system immediately activates the emergency mode, changing the traffic signal to green to allow uninterrupted passage.

To ensure reliability and prevent false triggering, the system incorporates a timeout-based mechanism. The emergency state persists only while the ambulance remains in the camera's field of view, with a short grace period to account for temporary occlusions or missed detections. Once the ambulance leaves the monitored area, the traffic signals safely revert to the normal traffic cycle, maintaining smooth traffic flow.

A graphical user interface provides real-time visualization of signal states and emergency detection, displaying Normal Mode, Emergency Mode, and the presence of ambulances on the monitored lanes. This interface facilitates monitoring, validation, and operator awareness without requiring manual intervention.

The modular design ensures scalability and adaptability, allowing future integration with multi-lane traffic intersections, city-wide traffic management systems, and IoT-based hardware signal controllers. By combining computer vision, deep learning, real-time processing, and adaptive traffic control**,** the proposed system offers a practical, efficient, and scalable solution to enhance emergency response efficiency in urban environments.

## IV. SYSTEM ARCHITECTURE

The proposed Intelligent Ambulance Detection and Priority-Based Traffic Signal Control System follows a three-layer modular architecture consisting of the Presentation Layer, Application Logic Layer, and Data Processing & Control Layer. This design ensures scalability, maintainability, and efficient real-time performance.

### 1. Presentation Layer

The Presentation Layer provides a **graphical interface** to visualize traffic signal states and emergency vehicle detection. Implemented using Tkinter in Python, it displays Normal Mode, Emergency Mode, and the real-time presence of ambulances on monitored lanes. The interface includes:

- Traffic signal representation (red, yellow, green)
- Emergency mode indicators
- Detection status messages
- Optional counters or timers for emergency green phase

This layer communicates with the Application Logic Layer to reflect live updates from the detection and signal control modules.

### 2. Application Logic Layer

The Application Logic Layer manages ambulance detection, emergency handling, and signal control logic. Key components include:

- **Video Capture Module:** Streams frames from live cameras or recorded traffic videos.
- **Ambulance Detection Module:** Runs a **custom-trained** YOLOv8 **model** on each frame to detect ambulances with confidence thresholding.
- **Emergency Control Logic:** Activates emergency green signal when an ambulance is detected, maintains a timeout-based grace period to handle occlusions, and safely transitions back to normal traffic cycles once the ambulance exits.
- **Threading & Real-time Processing:** Ensures detection, signal control, and UI updates occur concurrently without blocking each other.

### 3. Data Processing & Control Layer

This layer handles **signal state management, logging, and decision-making**:

- Maintains current and previous signal states for smooth transitions.
- Logs ambulance detection events and emergency activations for monitoring and analysis.
- Optionally stores metadata such as timestamp, confidence score, and lane information for future optimization.

### 4. Overall Workflow

The system workflow can be summarized as follows:

Traffic Feed → Capture Frame → YOLOv8 Ambulance Detection → Evaluate Confidence → Emergency Mode Activation → Update Traffic Signal → Revert to Normal Cycle → Log Event

## V. IMPLEMENTATION

The implementation of the Intelligent Ambulance Detection and Priority-Based Traffic Signal Control System follows a structured software development lifecycle, including requirement analysis, system design, model training, backend integration, frontend visualization, testing, and deployment.

### 1. Video Capture and Preprocessing

The system captures live video streams from traffic cameras installed at intersections or processes pre-recorded traffic videos for testing. Each video frame is preprocessed to match the input requirements of the detection model, including resizing and normalization, ensuring accurate and efficient inference.

### 2. Ambulance Detection Module

A custom **YOLOv8 model** is trained using a labeled ambulance dataset generated via Roboflow. The model focuses exclusively on ambulance detection to reduce false positives. Frames captured from the video feed are processed in real-time by the model, generating bounding boxes, class labels, and confidence scores. Only detections exceeding a defined confidence threshold are considered valid.

**3. Emergency Signal Control**

Upon detection of an ambulance:

- The system activates **Emergency Mode**, setting the traffic signal to green for the detected lane.
- A **timeout-based mechanism** ensures the green phase persists while the ambulance remains in the camera's field of view, with a short grace period to handle temporary occlusions or detection drops.
- Once the ambulance exits the monitored area, the system safely transitions back to the normal traffic signal cycle, maintaining smooth traffic flow and avoiding flickering.

This logic is implemented using Python multithreading to concurrently process video frames, manage signal state, and update the graphical interface without blocking execution.

**4. User Interface (GUI)**

The system includes a **graphical user interface** developed using Tkinter. The GUI provides:

- Visual traffic signals with red, yellow, and green lights.
- Real-time display of Normal Mode and Emergency Mode.
- Notification of ambulance detection and emergency status.

The interface is designed to be intuitive for operators and allows for easy monitoring of signal behavior and emergency vehicle presence.

**5. Logging and Data Management**

All detection events and signal changes are optionally logged for monitoring and evaluation purposes. Metadata such as timestamps, confidence scores, and lane information are recorded to analyze system performance and optimize future deployment.

**6. System Deployment**

The system can be deployed on local or cloud-based machines for real-time operation. The modular architecture allows for integration with multiple intersections, IoT-based hardware traffic signal controllers, and smart city traffic management platforms.

## VI. RESULTS AND DISCUSSION

The proposed AI-Based Smart Traffic Control System for Emergency Vehicle Prioritizationwas evaluated under various traffic conditions to assess its detection accuracy, real-time performance, and emergency signal handling. The YOLOv8-based ambulance detection model demonstrated consistent and accurate identification of ambulances across different lighting conditions, weather variations, and traffic densities. By applying confidence thresholds, the system was able to distinguish ambulances from other vehicles, such as vans, buses, or cars, ensuring that emergency signal activation occurred only when a valid ambulance was present. Temporary occlusions and brief detection failures were effectively managed through a timeout-based emergency logic, preventing unwanted flickering of the traffic signals.

During real-time testing, the system successfully activated the green emergency signal immediately upon ambulance detection and maintained the green phase for the duration of the ambulance's presence in the camera's field of view, with a short grace period to accommodate temporary losses of detection. Once the ambulance exited the monitored area, the traffic signals seamlessly reverted to normal operation, maintaining smooth traffic flow without any disruptions. The multithreaded architecture ensured that video processing, signal control, and graphical interface updates occurred concurrently, avoiding any freezing or lag in the system.

The graphical user interface provided clear visualization of the traffic signal states and ambulance detection status, allowing operators to monitor emergency vehicle prioritization in real time. The system demonstrated reliable integration between detection and signal control, confirming that the emergency logic and timeout mechanism operated as intended. Compared to conventional fixed-timer traffic signals, the proposed system significantly reduces response delays for ambulances, enhances urban traffic management efficiency, and eliminates the need for additional sensor or GPS-based infrastructure. By leveraging camera feeds already present at intersections and implementing AI-driven decision-making, the system achieves high accuracy, scalability, and operational reliability.

Overall, testing confirmed that the system consistently detects ambulances with high precision, activates emergency signals appropriately, and transitions smoothly back to normal traffic cycles. These results validate the effectiveness of combining deep learning-based detection with adaptive signal control, providing a practical solution for improving emergency response times and supporting smarter, AI-enabled urban traffic systems.

## VII. CONCLUSION

This paper presents the design and implementation of an AI-Based Smart Traffic Control System for Emergency Vehicle Prioritizationthat leverages deep learning and computer vision to enhance emergency vehicle response in urban traffic networks. The proposed system integrates real-time ambulance detection using a custom-trained YOLOv8 model with adaptive traffic signal control, ensuring that ambulances are granted priority passage while maintaining smooth traffic flow for other vehicles. By employing a timeout-based emergency logic, the system reliably handles temporary detection failures, preventing unnecessary signal flickering and ensuring operational stability.

The graphical user interface provides a clear and intuitive visualization of traffic signal states and emergency vehicle presence, allowing operators to monitor system performance in real time. The modular three-layer architecture, comprising the presentation layer, application logic layer, and data processing and control layer, facilitates scalability and maintainability, allowing for future integration with multi-lane intersections, city-wide traffic management platforms, or IoT-based hardware traffic signal controllers.

Experimental evaluation demonstrated that the system consistently detects ambulances with high accuracy, activates emergency signals in real time, and seamlessly transitions back to normal traffic operation after the ambulance has passed. The solution reduces emergency response delays, improves urban traffic management efficiency, and eliminates the need for additional hardware infrastructure. Overall, the system exemplifies the practical application of AI-driven real-time decision-making in traffic management and provides a scalable, reliable, and operator-friendly solution for enhancing emergency vehicle mobility in smart city environments.

## VIII. FUTURE WORK

Although the proposed AI-Based Smart Traffic Control System for Emergency Vehicle Prioritizationdemonstrates reliable performance and robust emergency signal management, several enhancements can be pursued to further extend its capabilities and practical impact. Future improvements may include the integration of more advanced deep learning architectures, such as transformer-based object detectors or multi-scale convolutional networks, to improve detection accuracy under complex traffic conditions and handle scenarios involving multiple overlapping emergency vehicles. Expanding the training dataset with a larger variety of ambulances, vehicle types, and traffic environments can enhance model generalization and ensure consistent performance across diverse urban settings.

The system can be adapted for multi-intersection and city-wide deployment, enabling coordinated traffic signal control across a network of intersections. Incorporating cloud-based processing and edge-computing solutions would allow real-time operation with minimal latency, even in high-traffic areas. Integration with IoT-enabled traffic signal hardware could facilitate automated control of physical signals and support future smart city infrastructure initiatives.

Additional enhancements may include real-time analytics dashboards to monitor emergency vehicle passages, predictive traffic modeling to anticipate congestion, and integration with GPS or emergency service dispatch systems for improved coordination. Security and privacy considerations, such as encrypted communication between cameras, servers, and signal controllers, will further strengthen system reliability and resilience.

With these advancements, the proposed system has the potential to evolve into a comprehensiveAI-driven traffic management platform, capable of prioritizing emergency vehicles, optimizing traffic flow, and supporting smart city mobility in a safe, scalable, and data-driven manner.

## IX. ACKNOWLEDGMENT

The authors express sincere gratitude to Ajina H for her dedicated mentorship and continuous guidance throughout the development of this project. The authors are also grateful to Dr. Ananthi J, M.E., Ph.D., Head of the Department of Artificial Intelligence and Data Science, Rathinam Technical Campus, for providing an environment conducive to research and innovation. Special thanks are extended to the management and faculty members of Rathinam Technical Campus, Coimbatore, for their support and encouragement.

The authors also acknowledge the participants who contributed to the evaluation and testing of the system.

## REFERENCES

[1] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, 4th ed., Pearson Education, 2021.
[2] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, 2016.
[3] D. Dua and C. Graff, "UCI Machine Learning Repository," University of California, Irvine, School of Information and Computer Sciences, 2019.
[4] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, 2016, pp. 785–794.
[5] L. Breiman, "Random Forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.
[6] P. Domingos and M. Pazzani, "On the Optimality of the Simple Bayesian Classifier under Zero-One Loss," *Machine Learning*, vol. 29, no. 2–3, pp. 103–130, 1997.
[7] J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*, 3rd ed., Morgan Kaufmann, 2011.
[8] World Health Organization, "Global Strategy on Digital Health 2020–2025," WHO Press, Geneva, 2021.
[9] E. Topol, *Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again*, Basic Books, 2019.
[10] R. Miotto, F. Wang, S. Wang, X. Jiang, and J. T. Dudley, "Deep Learning for Healthcare: Review, Opportunities and Challenges," *Briefings in Bioinformatics*, vol. 19, no. 6, pp. 1236–1246, 2018.
[11] F. Pedregosa et al., "Scikit-learn: Machine Learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.
[12] M. Abadi et al., "TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems," 2016.
[13] M. Grinberg, *Flask Web Development: Developing Web Applications with Python*, 2nd ed., O'Reilly Media, 2018.