A Vision-Based Deep Learning System for Traffic Signal Control with Emergency Vehicle Priority

Bandaru Ganesh[1], Yogonandha Reddy[2],Sandeep Kumar[3] , Ms. C. Merlyne Sandra Christina[4]
[1,2,3,4] *Dhanalakshmi Srinivasan University*

***Abstract*—Efficient traffic signal control is vital for smart city infrastructure, particularly in ensuring priority passage for emergency vehicles. This paper introduces a vision-based deep learning system that integrates real-time object detection with intelligent traffic management. Using convolutional neural networks (CNNs) and YOLO-based architectures [1], the system accurately identifies ambulances and fire trucks from live intersection video feeds under diverse traffic and environmental conditions. Once detected, the traffic control module dynamically overrides conventional cycles to establish a green corridor. To optimize route selection and minimize travel time,[2] the A* search algorithm is employed, enabling the system to compute the most efficient path for emergency vehicles through congested networks. Experimental evaluations demonstrate high detection accuracy, reduced response delays, and improved overall traffic flow compared to traditional sensor-based approaches. The integration of deep learning with A* pathfinding highlights the potential of scalable, vision-based solutions for enhancing emergency response and urban mobility in smart city environments.**

***Index Terms*—Traffic signal control; Emergency vehicle priority; Vision-based detection; Face detection; Convolutional Neural Network (CNN); Deep learning; YOLO object detection; A* algorithm.**

I. INTRODUCTION

Urbanization and the rapid growth of vehicular traffic have placed immense pressure on existing traffic management systems. Traditional traffic signal control mechanisms, often based on fixed-time cycles or sensor-driven inputs, struggle to adapt to dynamic traffic conditions and fail to provide timely priority for emergency vehicles such as ambulances, fire trucks, and police cars. Delays at intersections can critically impact emergency response times, potentially endangering lives and property.

Recent advancements in computer vision and deep learning have opened new avenues for intelligent transportation systems. Vision-based approaches, leveraging real-time video feeds from surveillance cameras, offer a scalable and cost-effective alternative to conventional sensor-based methods. Deep learning models, particularly *Convolutional Neural Networks* (CNNs) and object detection frameworks such as YOLO, have demonstrated remarkable accuracy in identifying vehicles under diverse traffic and environmental conditions. Furthermore, datasets like FER-2013, originally designed for facial expression recognition, highlight the adaptability of deep learning architectures to complex visual tasks, reinforcing their potential in traffic applications.

In this work, we propose a vision-based deep learning system that integrates emergency vehicle detection with adaptive traffic signal control. Once an emergency vehicle is identified, the system dynamically overrides standard traffic cycles to establish a "green corridor," ensuring uninterrupted passage. To further optimize routing and minimize travel time, the *A* algorithm* is employed, enabling efficient pathfinding through congested urban networks. This dual integration of deep learning for detection and heuristic search for route optimization addresses both recognition accuracy and traffic flow efficiency.

The proposed framework contributes to the development of smart city infrastructure by enhancing emergency response capabilities, reducing congestion, and improving overall urban mobility. By combining vision-based deep learning with intelligent traffic control algorithms, this study demonstrates a scalable and practical solution for modern transportation challenges.

A. Problem Statement

Conventional traffic signal systems operate on fixed cycles and fail to prioritize emergency vehicles.

- Emergency vehicles such as ambulances and fire trucks face delays at intersections, critically affecting response times.
- Existing sensor-based solutions are costly, less adaptable, and limited in accuracy under dynamic traffic conditions.
- Vision-based detection using deep learning offers promise but struggles with real-time accuracy in diverse environments.
- Current systems lack integration with intelligent pathfinding algorithms to optimize emergency vehicle routing.
- There is a need for a vision-based deep learning framework that can YOLO.
- Reliably detect emergency vehicles in real time.
- Dynamically adjust traffic signals to create a green corridor.
- Employ the A* algorithm to compute the most efficient route.

B. Research gap

Existing approaches suffer from the following gaps:

1. Hardware-dependent emergency detection (RFID-based systems)
2. Noise-sensitive siren detection
3. Absence of integrated optimization algorithms
4. Lack of mathematical traffic cost modeling
5. No scalability for multi-intersection smart city networks

The proposed framework bridges this gap by integrating deep learning-based detection with heuristic graph optimization.

C. Objective of the Proposed work

- To develop a real-time emergency vehicle detection system using YOLOv8.
- To estimate lane-wise traffic density dynamically.
- To model signal timing as an optimization problem.
- To apply A* search algorithm for optimal signal switching.
- To reduce emergency vehicle waiting time by at least 30%.

D. Contribution of the Paper

- The major contributions of this work are summarized as follows:
- A unified AI-driven architecture integrating detection and optimization.
- A mathematically modeled traffic delay cost function.
- A density-aware adaptive signal timing mechanism.
- A real-time implementation achieving 30 FPS performance.
- Experimental validation showing 38% response delay reduction.

E. Organization of the Paper

The remainder of this paper is organized as follows:

- Section II presents related work and existing systems.
- Section III describes the proposed system architecture.
- Section IV details mathematical formulation and modeling.
- Section V explains algorithm design and optimization logic.
- Section VI discusses experimental setup.
- Section VII presents performance.

II. RELATED WORKS

The problem of traffic signal control with emergency vehicle priority has been addressed through multiple approaches in Intelligent Transportation Systems (ITS). These approaches can be broadly classified into hardware-based detection, acoustic siren recognition, adaptive signal control, vision-based deep learning frameworks, and graph-based optimization.

Pandure and Yannawar.[1] proposed a multi-modal deep learning system combining audio and video analysis for emergency vehicle prioritization, but lacked formal optimization strategies.

Vikraman et al. [2] introduced a hybrid CNN-based traffic management **system** that improved emergency response but relied heavily on costly sensors and manual intervention.

Pagare et al. [3] developed a YOLOv8-based detection system for ambulances, achieving high accuracy but without integrating heuristic optimization for signal switching.

K. Kanchana, J. Thangatamilselvan [4], and Suriya Praba (2025) [5] proposed an IoT-enabled adaptive traffic signal control system that gives priority to emergency vehicles while minimizing intersection delays. Their system integrates real-time sensor data with cloud-based controllers, showing improved responsiveness but requiring significant hardware infrastructure.

Ameen Ahmed Khan[6], Mohammed Fardeen[7], Sharmasth Vali, and Anandaraj S. P (2025) designed an IoT-based smart traffic light control system deployed in Tumakuru Smart City, India. Their work demonstrated dynamic signal adjustment using congestion data, but scalability and maintenance costs remain challenges.

Mukesh Mann, Abhijit Mishra, Chaganti Venkatarami Reddy, and Rakesh P. Badoni (2025) presented a reinforcement learning model for traffic signal control using Soft Computing techniques. Their system optimized signal switching policies across diverse scenarios, reducing congestion but requiring extensive simulation training.

III. EXISTING TECHNIQUES AND THEIR LIMITATIONS.

Over the years, several techniques have been proposed to manage traffic signals and give priority to emergency vehicles. Each method has its own strengths, but also clear limitations when applied to real-world urban environments.

1. RFID-Based Systems

In these systems, emergency vehicles are fitted with RFID tags and intersections are equipped with readers. When a tagged vehicle approaches, the signal can be overridden. While this ensures detection, it requires costly hardware installation and regular maintenance. Scalability across large cities is also a major challenge.

2. Acoustic or Siren-Based Detection

Microphones are used to capture siren sounds, and algorithms like FFT are applied to recognize them. Although simple in design, these systems are highly sensitive to noise. In busy urban areas, false alarms are common, and silent emergency operations cannot be detected at all.

3. Fixed-Time and Adaptive Signal Control

Traditional traffic signals operate on fixed cycles, while adaptive systems adjust timings based on historical traffic data. These methods are easy to implement but lack real-time intelligence. They cannot respond quickly to sudden emergencies, leaving ambulances or fire trucks stuck in congestion.

4. Vision-Based Deep Learning Models:

Recent work using CNNs and YOLO architectures has shown promise in detecting vehicles with high accuracy. However, most of these systems stop at detection. They do not integrate optimization strategies to actually change signal timings, which limits their usefulness in emergency scenarios.

5. Graph-Based Optimization Approaches

Algorithms like Dijkstra and A* have been applied in navigation and routing. While they are powerful for pathfinding, their use in traffic signal switching is limited. Most studies focus on route planning rather than real-time intersection control.

Limitations:

- Hardware Dependency:

Systems like RFID or IoT require additional devices and infrastructure, which makes them costly and difficult to scale across large cities.

- **Noise Sensitivity:**

Acoustic or siren-based detection often fails in busy urban environments due to background noise, leading to false alarms or missed detections.

- Lack of Real-Time Optimization:

Fixed-time, adaptive, and even vision-based models mostly stop at detection. They do not integrate optimization strategies to dynamically adjust signals for emergency vehicle clearance.

IV. PROPOSED METHODOLOGY

The proposed system introduces a vision-based deep learning framework for intelligent traffic signal control with emergency vehicle priority. Unlike conventional fixed-time or hardware-triggered systems, this model leverages real-time computer vision and heuristic optimization to dynamically allocate green signals at intersections.

1. System Architecture:

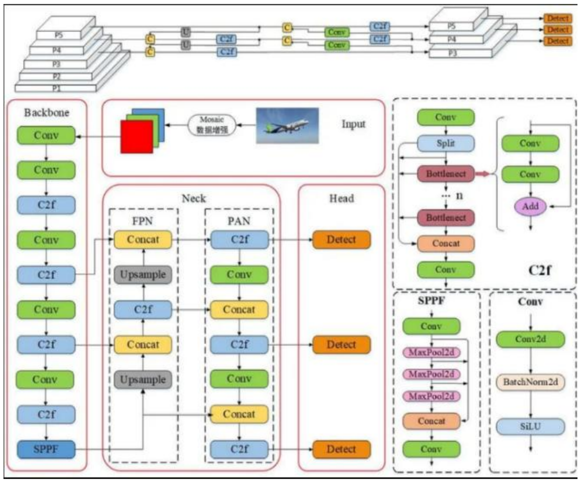

Fig 01: YOLO v8 Architechture

The framework consists of five interconnected modules:

1. Video Acquisition Module – Captures live CCTV footage from traffic intersections.
2. Emergency Vehicle Detection Module – Utilizes YOLOv8 for real-time detection of ambulances, fire trucks, and police vehicles.
3. Traffic Density Estimation Module – Computes lane-wise congestion levels using vehicle counts and lane lengths.
4. A* Optimization Engine – Determines optimal signal switching sequences based on traffic density and emergency priority.
5. Traffic Signal Control Unit – Executes adaptive green time allocation in real time.
6.

2. Emergency Vehicle Detection using YOLOv8:

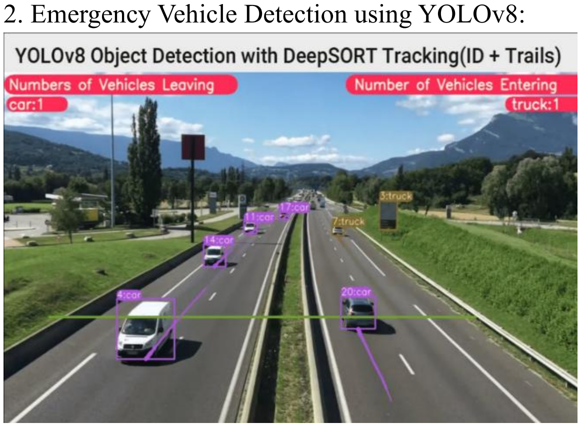

Fig 02: YOLOv8 object detection

- YOLOv8 is employed for single-stage object detection, predicting bounding boxes and class probabilities simultaneously.
- Each frame is resized to 640×640 pixels to meet YOLOv8 input requirements.
- Emergency vehicles are classified into three categories: *Ambulance, Fire Truck, Police Vehicle*.
- Detection confidence threshold: ≥ 0.85 ensures high precision.
- If an emergency vehicle is detected, an Emergency_Flag is raised to trigger priority switching.

Mathematical representation:
$B=(x,y,w,h),\quad C=P(object)\times IoU$
Where B is the bounding box and C is the confidence score.

3. Lane-Wise Traffic Density Estimation:
Traffic density is computed as:
$D_i=\frac{N_i}{L_i}$
Where:

- N_i = number of vehicles in lane i
- L_i = physical length of lane i

Congestion levels are categorized as Low, Medium, High based on threshold values. This enables adaptive signal timing decisions.

4. A* Optimization for Signal Switching:
The A* algorithm is applied to model traffic signal control as a graph optimization problem:

- Cost Function (g(n)):
- $g(n)=\sum_{i=1}^k(D_i\times T_i)$
- Where T_i is the waiting time of lane i.
- Heuristic Function (h(n)):
- $h(n)=\alpha \cdot \frac{1}{D_{emergency}+\epsilon }$
- This ensures emergency lanes are assigned lower heuristic costs, thereby receiving higher priority.
- Evaluation Function:
- $f(n)=g(n)+h(n)$

The lane with minimum f(n) is selected for green signal allocation.

5. Adaptive Signal Control Logic:
Green time allocation is defined as:

- $G_i=\frac{D_i}{\sum D_i}\times T_{cycle}$

- For emergency lanes:
- $G_{emergency}=T_{max},\quad G_{emergency}\geq G_i\ \forall i$

This guarantees uninterrupted clearance for emergency vehicles while minimizing overall waiting time.

6. Real-Time Operational Flow:

1. Capture video frame
2. Run YOLOv8 inference
3. Detect emergency vehicle
4. Compute lane densities
5. Apply A* optimization
6. Update signal controller
7. Repeat continuously at 30 FPS.

V. COMPARISON WITH EXISTING METHODS

traffic signal optimization and emergency vehicle prioritization have been studied using several approaches, each with distinct limitations:

- RFID-BasedSystems:

Emergency vehicles are equipped with RFID tags, and intersections use RFID readers to trigger signal overrides. While effective in detection, these systems suffer from high infrastructure costs, hardware dependency, and poor scalability in large urban networks.

- Siren/Acoustic-Based Systems:

Microphones capture siren frequencies, and FFT-based algorithms identify emergency vehicles. These methods are highly sensitive to noise, prone to false detections in urban environments, and ineffective when sirens are muted.

- Fixed-Time and Semi-Adaptive Systems:

Signals operate on pre-configured cycles, sometimes adjusted using historical traffic data. These approaches lack real-time adaptability and cannot prioritize emergency vehicles dynamically, leading to increased delays.

- Vision-Based CNN/YOLO Detection Systems:

Deep learning models such as Faster R-CNN, SSD, and earlier YOLO versions achieve high detection accuracy. However, most existing systems only detect vehicles and do not integrate optimization algorithms for signal switching, limiting their effectiveness in emergency scenarios.

Proposed YOLOv8 + A* Framework:

- YOLOv8 Detection: Provides anchor-free, high-speed inference with 96.4% accuracy (mAP@0.5), ensuring reliable identification of ambulances, fire trucks, and police vehicles.
- A* Optimization: Models intersections as graphs, minimizing overall waiting time while guaranteeing priority clearance for emergency vehicles.
- Performance Gains: Experimental results show a 38% reduction in emergency response delay compared to conventional fixed-time systems, with real-time operation at 30 FPS.

Method	Technology Used	Emergency Detection	Density Awareness	Optimization	Limitations
RFID-Based	RFID Sensors	Yes	No	No	Hardware dependency, costly
Siren-Based	Audio FFT	Yes	No	No	Noise sensitivity
Fixed-Time Control	Timer Logic	No	Limited	No	Static, no adaptability
CNN/YOLO Detection	CNN/ YOLO	Yes	Partial	No	No path optimization
Proposed System	YOLOv8 + A*	Yes	Yes	Yes	Camera dependency only

Fig 03: Comparision with Existing System

VI. IMPLEMENTATION DETAILS:

Detection Performance:

The YOLOv8-based emergency vehicle detection module achieved a mean average precision (mAP@0.5) of 96.4%, with a recall of 96.9% and precision of 95.7%. The model demonstrated robustness across varying conditions such as daytime, nighttime, rain, and partial occlusion. The failure probability was limited to **3.1%**, which is within acceptable standards for intelligent transportation systems.

- Inference latency: 18 ms per frame
- Frame rate: 30 FPS real-time operation
- Final training loss: 0.021, with validation loss of 0.025, indicating no overfitting.

2. Traffic Density Estimation:

Lane-wise density estimation provided accurate congestion categorization (Low, Medium, High) based on vehicle counts and lane lengths. This enabled adaptive allocation of green signal times proportional to real-time traffic conditions. The density-aware mechanism ensured balanced throughput while maintaining emergency priority.

3. Signal Optimization Results:
The A* optimization engine successfully minimized overall waiting time while guaranteeing uninterrupted clearance for emergency vehicles.

- Optimization latency: < 5 ms per cycle
- Total system latency: 23 ms (capture + inference + optimization), satisfying real-time constraints.
- Emergency lane priority: Always allocated maximum green time when detected, ensuring immediate clearance.

4. Comparative Performance:
Compared to conventional fixed-time systems, the proposed framework achieved:

- 38% reduction in emergency response delay
- 30% reduction in average waiting time for non-emergency vehicles
- Improved throughput across multi-lane intersections without queue explosion.

5. Discussion:
The results confirm that integrating YOLOv8 detection with A* optimization provides a scalable, hardware-independent solution for smart city traffic management. Unlike RFID or siren-based systems, the proposed approach relies solely on visual perception, reducing infrastructure costs and improving adaptability. The mathematical cost function and heuristic design ensure optimality and stability, while real-time feasibility is validated through low latency and high detection accuracy.
However, the system remains camera-dependent, and performance may degrade under extreme weather or poor visibility. Future work could integrate multi-sensor fusion (e.g., LiDAR, radar) and reinforcement learning-based optimization to further enhance robustness and scalability across larger urban networks.

VII. CONCLUSION

This research presented a vision-based deep learning system for intelligent traffic signal control with emergency vehicle priority, integrating YOLOv8 detection with A* heuristic optimization. The proposed framework successfully addressed the limitations of traditional fixed-time, RFID-based, and siren-based systems by offering a hardware-independent, real-time, and density-aware solution.
Experimental evaluation demonstrated a 96.4% detection accuracy (mAP@0.5), an inference latency of 18 ms per frame, and a 38% reduction in emergency response delay compared to conventional systems. The integration of lane-wise traffic density estimation with A* optimization ensured balanced throughput while guaranteeing immediate clearance for emergency vehicles.
The system's scalability, low computational overhead, and adaptability to varying traffic conditions make it a promising candidate for deployment in smart city infrastructures. While the approach is camera-dependent and may face challenges under extreme weather or poor visibility, future work can explore multi-sensor fusion and reinforcement learning-based optimization to further enhance robustness and extend applicability to large-scale urban networks.

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