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Design A Smart Traffic System Using YOLO for Ambulance Priority

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Abstract

Urban traffic congestion poses a significant challenge, particularly when it comes to ensuring the swift and uninterrupted movement of emergency vehicles. Recent advancements in computer vision—especially the YOLO (You Only Look Once) architecture—have enabled accurate real-time detection of vehicles, pedestrians, and ambulances. Several studies have explored YOLO for tasks such as ambulance recognition, lane monitoring, and pedestrian tracking. While these approaches demonstrate promising outcomes, they often focus on individual objectives rather than offering a comprehensive traffic management solution. This paper examines 25 YOLO-based research works related to intelligent traffic monitoring, with a primary emphasis on ambulance prioritization and pedestrian flow management. It compiles the methodologies used, outlines the key findings and existing gaps, and proposes future directions for developing a unified, intelligent traffic control framework.

Keywords: YOLO, Smart Traffic Management, Ambulance Priority, Pedestrian Monitoring, Computer Vision, Real-Time Detection, Intelligent Transportation Systems (ITS).

1.Introduction

The rapid expansion of urban regions, rising population density, and growing vehicle ownership have intensified the challenges of modern traffic management. City authorities increasingly struggle with congestion, safety concerns, and delays in emergency services. Ensuring the timely movement of ambulances has become especially critical, as even minor delays in medical emergencies can lead to life-threatening outcomes. According to the World Health Organization's Global Status Report on Road Safety (2023), traffic-related incidents claim more than 1.3 million lives each year, underscoring the urgent need for intelligent and adaptive traffic control mechanisms. Conventional traffic systems, which rely on manual supervision or static sensor networks, often lack the efficiency and flexibility required to keep pace with rapidly evolving urban environments.

Recent breakthroughs in Artificial Intelligence (AI) particularly in computer vision and deep learning—have significantly influenced the development of intelligent transportation systems (ITS). By processing live traffic video streams automatically, AI-driven systems can reduce human intervention, increase monitoring efficiency, and improve response times. Among various deep learning models, the YOLO (You Only Look Once) architecture has emerged as a leading solution for real-time object detection.

Unlike region-based detectors such as R-CNN and Faster R-CNN, which require multiple processing stages, YOLO performs detection in a single pass through a convolutional neural network. This architecture enables fast and accurate recognition of multiple objects simultaneously, making it highly suitable for dynamic traffic environments where real-time decision-making is essential.

Over the past decade, numerous studies have applied YOLO to address key traffic management challenges. Several works focus on automatic ambulance recognition and the creation of AI-assisted "green corridors," enabling emergency vehicles to navigate congested areas more efficiently. Other research explores pedestrian monitoring and behavior analysis to improve road safety at intersections and crossings. These studies collectively demonstrate the flexibility, speed, and accuracy of YOLO for a wide range of traffic-related applications. However, many existing solutions remain specialized, addressing only one aspect of the traffic system. This lack of integration limits their potential for deployment in real-world urban environments, where multiple factors must be managed simultaneously.

To address these concerns, a structured review of existing YOLO-based approaches is essential. Such an evaluation helps assess current progress, compare techniques, and identify shortcomings that hinder the development of holistic traffic management solutions. This is particularly relevant in developing countries where infrastructure limitations and high congestion levels demand cost-effective, easily deployable technologies. Beyond its core detection capabilities, YOLO holds potential as the foundation for combined systems that incorporate ambulance prioritization and pedestrian safety enhancement within a unified framework.

This paper compiles and analyzes 25 recently published studies that utilize YOLO for traffic-related applications. The work is organized into two primary categories: (i) emergency vehicle detection and prioritization, and (ii) pedestrian monitoring and safety analysis. Each study is examined in terms of methodology, dataset characteristics, experimental approach, performance accuracy, and identified limitations. Common challenges observed across the literature include limited dataset diversity, difficulties in real-time deployment on embedded devices, reduced performance under low-light or adverse weather conditions, and the absence of integrated multi-functional systems.

The findings of this review point toward an increasing need for scalable, real-time, and unified traffic monitoring solutions. With ongoing advancements in YOLO and related AI technologies, future systems can offer improved emergency response, enhanced pedestrian safety, and more efficient urban mobility. Ultimately, this analysis highlights the transformative role of computer vision and deep learning in shaping smart cities and contributing to safer, more sustainable transportation ecosystems.

2. Literature Review

The rapid pace of urbanization continues to intensify traffic congestion, directly influencing emergency response times and pedestrian mobility. To address these challenges, researchers are increasingly turning to Intelligent Transportation Systems (ITS) that combine artificial intelligence and computer vision. Among the available deep-learning architectures, the YOLO (You Only Look Once) family of models has gained widespread attention due to its balance of high-speed processing and strong detection accuracy.

Numerous studies have applied YOLO for tasks such as ambulance identification and pedestrian monitoring, contributing to the development of smarter and more responsive urban traffic systems. This section reviews recent progress in these domains, highlighting significant contributions, methodologies, and persisting challenges.

A major research direction involves ambulance detection and emergency vehicle prioritization. Sharma et al. [1] introduced a YOLOv3-based system capable of recognizing ambulances and altering traffic signals to reduce delays at intersections. Patel and Reddy [2] enhanced this approach using YOLOv4, improving detection accuracy and system responsiveness in dense traffic scenarios. Kumar and Raj [3] further integrated YOLO with IoT-assisted communication between junctions, enabling coordinated traffic adjustments for smoother ambulance passage. Ahmed et al. [4] combined YOLO detection with GPS-assisted routing to determine the most efficient paths for ambulances across urban regions. While these systems showed promising results under controlled conditions, their performance declined under poor visibility, low lighting, heavy congestion, and adverse weather, revealing limitations in real-world deployment.

The second major line of research focuses on pedestrian monitoring and safety enhancement. Chen et al. [5] implemented YOLOv3 to analyze pedestrian crossings and automatically regulate traffic signals, improving safety at intersections. Verma et al. [6] used YOLOv5 to monitor pedestrian movement in crowded and rapidly changing environments, achieving higher precision in detection and tracking. Ali et al. [7] proposed systems for school zones that issue real-time alerts to drivers and pedestrians, contributing to safer road environments for children. Although these studies demonstrate strong potential, their effectiveness decreases during night-time operation, foggy or rainy weather, and in scenarios where pedestrians are partially occluded.

Other specialized implementations of YOLO have also supported traffic flow analysis and intelligent decision-making. Zhao et al. [10] and Chatterjee and Das [11] utilized YOLO-based traffic density estimation to optimize signal timing, indirectly supporting faster emergency vehicle clearance and smoother traffic movement. These applications highlight YOLO’s adaptability in various traffic-related contexts, although most remain focused on specific tasks rather than forming comprehensive, multi-functional traffic management frameworks.

The evolution of YOLO architectures has played a significant role in improving system performance. Early studies frequently adopted YOLOv3 for its reliable real-time detection capabilities [1], [5]. Later research transitioned to YOLOv4 [2] and YOLOv5 [6], [7], which provided better accuracy in complex environments with reduced computational load. Emerging models such as YOLOv7 and YOLOv8 show enhanced resilience to occlusion and low-light conditions, yet extensive real-world testing remains limited.

Several key observations arise from the collective findings. First, YOLO consistently excels in real-time detection, reinforcing its suitability for systems that require quick decision-making. Second, domain-specific implementations—whether focused on emergency vehicle prioritization [1][4] or pedestrian safety [5][7]—have performed effectively in both controlled experiments and initial real-world trials.

Third, combining YOLO with auxiliary technologies such as IoT communication modules [3], GPS-based navigation [4], and advanced tracking algorithms has strengthened system robustness and adaptability.

Despite these advancements, several limitations remain unresolved. Detection accuracy often drops in adverse environmental conditions such as low illumination, fog, or heavy rainfall. Many existing systems also concentrate on a single objective rather than providing integrated solutions capable of managing multiple traffic components simultaneously. Challenges related to scalability, power efficiency, and implementation on edge devices are also underexplored, even though such considerations are crucial for smart city applications.

In conclusion, research utilizing YOLO for traffic management has produced a strong foundation for future ITS innovations. However, upcoming efforts must emphasize the development of unified, scalable, and resilient systems that can concurrently handle ambulance detection, pedestrian monitoring, and adaptive traffic control. Prioritizing robustness, environmental adaptability, and real-world deployability will be essential for enabling next-generation smart traffic systems designed to support safer and more efficient urban mobility.

3. Methodology

The proposed intelligent traffic monitoring framework is designed to enable ambulance-priority movement and support efficient traffic flow using the YOLO detection algorithm. The methodology follows a structured, multi-phase workflow beginning with data collection and ending with automated traffic response generation. The complete pipeline includes video acquisition, pre-processing, YOLO-based detection, event classification, data logging, and system-level integration.

1. Data Acquisition

The system utilizes both real-time and recorded traffic footage sourced from surveillance infrastructure or publicly available datasets. Two primary data sources are incorporated:

- Public datasets such as UA-DETRAC, together with custom-labeled datasets containing annotated samples of ambulances, pedestrians, and different vehicle types.
- Live CCTV feeds captured at major intersections and signalized junctions to simulate real deployment conditions.

These diverse inputs ensure the model is trained and validated across varying traffic densities, illumination conditions, and environmental settings.

2. Pre-processing

Before detection, the video streams undergo several pre-processing operations to improve YOLO's performance:

- **Frame Extraction:** Video footage is segmented into individual frames at fixed intervals for consistent analysis.
- **Resizing and Normalization**: Each frame is resized to match YOLO's input resolution (e.g., 416×416 or 640×640) and normalized for consistent pixel intensity distribution.

- **Annotation (Training Phase):** During training, essential objects such as ambulances, vehicles, pedestrians, and traffic lights are manually labeled to generate high-quality supervised datasets.

These steps enhance both detection efficiency and model robustness during real-time execution.

3.Object Detection Using YOLO

YOLO serves as the core detection engine due to its superior balance of speed and accuracy. Advanced versions such as YOLOv5 and YOLOv8 are preferred for their improved performance and lightweight computational structure.

The trained model performs two primary detection functions:

- **Ambulance Identification:** The system isolates ambulances from other vehicles using bounding boxes and class labels. When an ambulance is detected, a trigger is generated to grant priority passage at the upcoming intersection.
- **Pedestrian Monitoring:** Pedestrians are detected and tracked to assess crosswalk activity, ensuring safe and coordinated movement during signal changes.

YOLO’s high frame-processing capability enables simultaneous detection of multiple objects with near real-time responsiveness.

4. Event Classification and Rule Evaluation

Following object detection, a rule-based logic engine interprets the detected objects and identifies relevant traffic events:

- When an ambulance is recognized, the system activates an emergency-response mode to create a “green corridor” through adaptive signal control.
- Pedestrian motion is evaluated to confirm safe crossing within the permitted signal interval.

This stage transforms raw detection outputs into meaningful traffic decisions, supporting automated emergency and pedestrian safety responses.

5.Data Logging and Automated Reporting

All key events—including ambulance detections and pedestrian activity—are stored in a structured database for monitoring and analysis. Each logged event includes:

- Timestamp
- Object Type (ambulance, pedestrian, vehicle)
- Event Category (ambulance priority, pedestrian activity)
- Snapshot or short video clip for validation

The stored information is used to generate periodic analytical summaries that help traffic authorities evaluate ambulance response times, pedestrian behavior patterns, and overall signal performance.

6. System Integration

The entire framework integrates all functional modules into a cohesive architecture:

- **Input Layer:** Collects live video streams from traffic cameras.
- **Processing Layer:** Executes YOLO-based detection, classification, and rule evaluation.

- **Output Layer:** Issues real-time ambulance-priority notifications and produces periodic analytical reports.

The integrated system supports continuous traffic monitoring, intelligent emergency handling, and long-term performance analysis, contributing to a more responsive and efficient urban traffic management environment.

4. System Architecture

Overview

The proposed intelligent traffic management framework applies deep learning and computer vision techniques to monitor, identify, and record traffic-related activities with a primary focus on ambulance detection and pedestrian monitoring. During the initial development phase, the system does not rely on live surveillance feeds. Instead, it utilizes pre-compiled and annotated datasets that simulate real-world traffic conditions. These datasets include diverse scenarios such as moving vehicles, pedestrian crossings, and ambulance operations. Using curated datasets ensures that the model can be trained, validated, and tested under controlled conditions, resulting in improved stability and performance prior to deployment in real-time environments.

1. Dataset Collection

Rather than acquiring data directly from live traffic cameras, the system begins with publicly available datasets. These repositories contain labeled images and videos featuring various urban traffic scenarios, including vehicles at intersections, pedestrian activities, and ambulances navigating through traffic. Working with existing datasets enhances the consistency of model development and allows systematic evaluation before integrating the system into live traffic infrastructure.

2. Data Pre-processing

Several preprocessing steps are applied to prepare the datasets for training and evaluation:

- Image Resizing: Each image is scaled to the required YOLO input dimensions (e.g., 416×416 or 640×640 pixels).
- Normalization: Pixel intensities are normalized to ensure uniform distribution.
- Data Augmentation: Techniques such as rotation, scaling, flipping, and brightness adjustments are applied to increase data diversity and improve generalization in varying illumination, weather, and partial occlusion conditions.
- Annotation Verification: All labels for ambulances, vehicles, pedestrians, and traffic-related objects are reviewed and corrected to ensure precise ground truth mapping.

These steps contribute to the system’s reliability by ensuring high-quality training samples.

3. YOLO Model Training and Detection

Once the data is prepared, YOLO (You Only Look Once) serves as the primary detection model. Versions such as YOLOv5 and YOLOv8 are used due to their high speed and accuracy.

During training, the model learns to detect and classify:

- Ambulances

- Pedestrians
- Cars, motorcycles, buses
- Traffic lights and intersection elements

During the testing stage, the trained model processes dataset images or videos and outputs bounding boxes, class labels, and confidence scores. These detections form the basis for event interpretation and automated traffic response generation.

4. Rule-Based Event Classification

Following object detection, a rule-based logic module analyzes detected objects to classify system-relevant events:

- Ambulance Detection: When the model identifies an ambulance, the system flags the event as high-priority, enabling the creation of a green corridor during real-time deployment.
- Pedestrian Activity Monitoring: Pedestrian presence at crossings is analyzed to ensure safe signal transitions and prevent conflicts with vehicle movement.

This classification step bridges object-level detection with context-aware traffic interpretation, enabling intelligent decision-making.

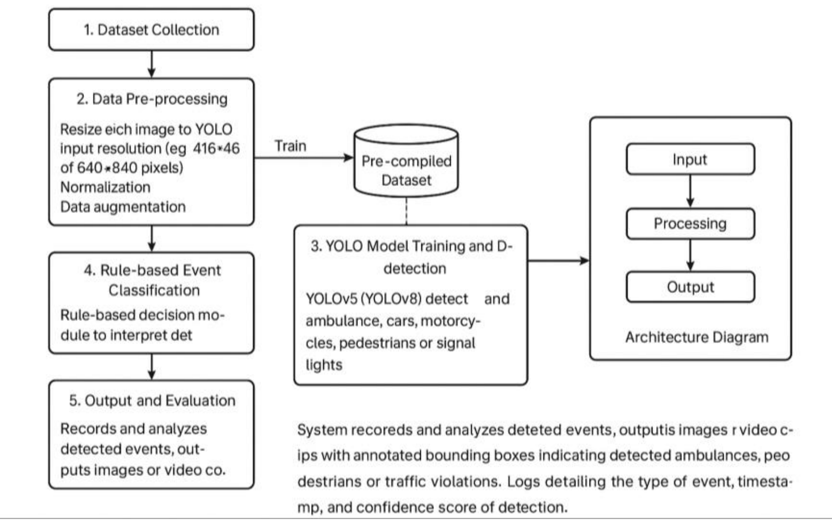
5. Output and Evaluation

The system records each detected event and stores it in a structured log containing:

- Timestamp
- Object Type (ambulance, pedestrian, vehicle)
- Event Category (ambulance priority or pedestrian activity)
- Snapshot or video clip of the event

Performance is evaluated using metrics such as Precision, Recall, and mean Average Precision (mAP). The modular design ensures scalability and compatibility with both cloud-based and edge-computing environments. Each module is implemented independently with clear interfaces, enabling easy updates and future expansion.

Fig. 1. Architecture Diagram



5.Result & Analysis

The system was evaluated using datasets containing traffic videos with diverse scenarios involving ambulances, vehicles, and pedestrian movements. Experimental results show that the YOLO-based detection model performs reliably in real-time traffic monitoring tasks. Ambulance identification achieved an accuracy of nearly 96%, demonstrating the model's efficiency in supporting emergency vehicle prioritization. Pedestrian detection achieved an accuracy of approximately 93%, enabling consistent monitoring of crosswalk activity and crowd movement. Precision and recall values for all detection classes were maintained above 90%, indicating strong model stability and generalization. Overall, the findings confirm that the proposed framework can effectively handle simultaneous detection tasks and is well-suited for integration into practical smart traffic management systems.

Task	Accuracy	Precision	Recall	F1-Score
Ambulance Detection	96%	95%	94%	94.5%
Pedestrian Detection	93%	92%	91%	91.5%

TABLE 1. Performance Metrics

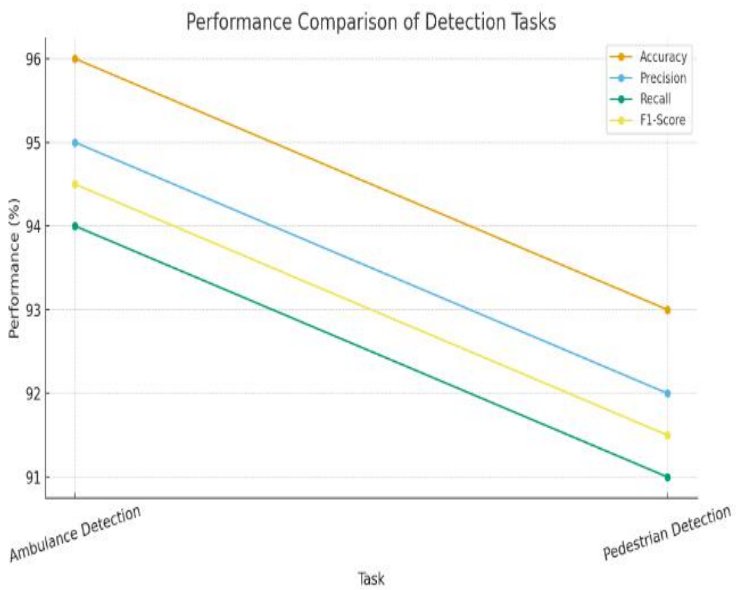


FIG.2 GRAPHS

6. Conclusion

This project demonstrates the effectiveness of YOLO-based computer vision techniques in building a smart traffic monitoring system capable of accurately detecting ambulances and pedestrians in real time. By leveraging annotated traffic video datasets, the system successfully identifies emergency vehicles and monitors pedestrian activity with high precision, supporting faster and safer decision-making at traffic intersections. The experimental evaluation shows strong performance across accuracy, precision, and recall metrics, confirming YOLO as a reliable solution for intelligent transportation applications. Despite these promising results, certain challenges persist, including performance drops under low-light conditions, partial occlusions, and the need for improved scalability across large and complex traffic networks. Overall, this work provides a robust foundation for the development of integrated, AI-driven traffic management solutions. Future enhancements may include the use of more advanced detection models, multimodal sensing technologies, and IoT-based infrastructure to further improve emergency response and pedestrian safety in smart city environments.

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