



AUTOMATED EMERGENCY VEHICLE DETECTION AND TRAFFIC CLEARANCE SYSTEM: AN AI-DRIVEN SOLUTION FOR URBAN EMERGENCY RESPONSE OPTIMIZATION.

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Abstract: Traffic congestion in urban areas poses significant challenges to emergency medical services, where delayed ambulance response times can result in preventable fatalities. Traditional traffic management systems operate on fixed timer-based schedules that fail to adapt dynamically to emergency situations, causing critical delays for ambulances navigating through congested roads. Manual intervention by traffic police is often inefficient and cannot scale across multiple intersections simultaneously. This project presents an innovative artificial intelligence-based solution for automated ambulance detection and emergency traffic clearance using YOLOv5 deep learning architecture. The proposed system leverages state-of-the-art computer vision techniques to detect ambulances in real-time from video feeds captured by traffic cameras or uploaded video files. The system processes visual data through advanced image preprocessing techniques and employs the YOLOv5 object detection algorithm to identify ambulances with confidence scores exceeding 0.5 threshold. The architecture comprises multiple integrated components including camera-based video capture, image preprocessing modules, the YOLOv5 detection engine, traffic signal control interfaces using NTCIP protocol, and comprehensive logging systems. The system supports both real-time video stream processing at 30 frames per second and batch processing of pre-recorded video files. Extensive testing demonstrates detection accuracy exceeding 97% under diverse lighting conditions and traffic scenarios. This cost-effective, scalable solution addresses critical limitations of existing hardware-based traffic management systems by providing a software-centric approach that can be deployed across urban infrastructure with minimal modifications to existing camera networks.

Keywords: Ambulance Detection, YOLOv5, Computer Vision, Traffic Signal Control, Deep Learning, Object Detection, Real-time Processing, Smart City, Emergency Response, Intelligent Transportation Systems

1. INTRODUCTION

Urban metropolitan regions worldwide face escalating challenges related to emergency medical service deployment, where temporal efficiency directly correlates with patient survival outcomes. Statistical evidence demonstrates that cardiovascular arrest survival probabilities diminish approximately 7-10% per minute of delayed medical intervention, emphasizing the paramount importance of expedited emergency response. Traditional traffic signal architectures maintain fixed operational cycles independent of real-time vehicular density or emergency vehicle presence, consequently generating substantial delays for ambulances traversing congested metropolitan corridors. Manual intervention by traffic enforcement personnel provides temporary relief but remains inconsistent, geographically limited, and dependent upon human response latency, making it impractical for comprehensive citywide implementation across multiple intersections. Conventional ambulance detection methodologies incorporating Radio Frequency Identification (RFID) technology demonstrate inherent limitations including restricted operational range, susceptibility to signal obstruction, and infrastructure deployment complexity. The proliferation of artificial intelligence, computer vision technologies, and deep learning architectures has introduced transformative opportunities for intelligent traffic management systems. Convolutional Neural Networks (CNNs), particularly the You Only Look Once (YOLO) architecture family, demonstrate exceptional real-time object detection capabilities suitable for emergency vehicle identification. The Automated Ambulance Detection for Emergency Traffic Clearance Using AI project leverages state-of-the-art computer vision methodologies to establish an intelligent traffic management system capable of autonomous emergency vehicle detection



and automated signal prioritization. The system employs YOLOv5 deep learning architecture to analyze real-time video streams from traffic monitoring cameras positioned at intersection locations or processes pre-recorded video files. Upon detecting an approaching ambulance through visual pattern recognition and classification, the system generates automated control signals to modify traffic light sequences, facilitating unobstructed passage for emergency vehicles. This initiative targets the development of a comprehensive, scalable, and cost-effective solution addressing the critical challenge of emergency vehicle transit through congested traffic zones. By eliminating human intervention requirements and implementing automated detection mechanisms, the system significantly reduces response times, potentially saving lives during critical medical emergencies. The implementation framework encompasses video acquisition systems, image preprocessing pipelines, deep learning inference engines, and traffic signal control interfaces. Video streams undergo preprocessing operations including resolution standardization, noise reduction, and illumination normalization to optimize detection accuracy. The YOLOv5 model performs real-time object detection with high precision and recall metrics. The technological infrastructure leverages contemporary software frameworks including Python for application development, OpenCV for computer vision operations, and PyTorch for deep learning model implementation.

1. LITERATURE SURVEY

Emergency vehicle traffic management has historically relied upon manual intervention methodologies and hardware-based signal control systems, both demonstrating significant operational limitations. Fixed-timing traffic signal systems operate on predetermined temporal cycles, maintaining consistent signal durations regardless of emergency vehicle presence. Ambulances approaching intersections must await signal cycle completion, introducing delays that directly impact patient outcomes. Manual traffic clearance by law enforcement personnel offers flexibility but suffers from severe scalability constraints, particularly during high-traffic periods when emergency response times are most critical. Radio Frequency Identification (RFID) technology enables automated ambulance detection but demonstrates significant technical limitations including signal transmission range constraints, physical obstruction susceptibility, and high infrastructure deployment costs. Global Positioning System (GPS) integration enables real-time ambulance tracking but typically lacks direct integration with traffic signal control infrastructure. Usaid et al. (2022) developed an audio-based ambulance detection system using MFCC feature extraction and MLP neural networks, achieving 90% classification accuracy. However, limited dataset sizes restrict generalization, and performance declines under extreme background noise. Kakoju et al. (2022) presented a hardware-based system using IR sensors and Arduino Uno for density-based traffic control. However, IR sensors demonstrate sensitivity to sunlight and environmental interference, limiting deployment feasibility. Chaturvedi et al. (2024) proposed a software-driven traffic clearance solution using path clearance algorithms and microservices architecture. However, effectiveness depends on user participation and smartphone penetration. Alruwaili et al. (2025) introduced a multimodal AI system integrating LSTM for siren recognition and ResNet18 for visual detection, achieving 99% accuracy. However, high computational requirements and deployment costs limit widespread adoption. These documented limitations emphasize the requirement for intelligent, software-based solutions guaranteeing accuracy, scalability, and operational effectiveness while minimizing infrastructure investment. The proposed system addresses these limitations through YOLOv5-based visual detection, eliminating dependency on specialized hardware infrastructure while achieving high detection accuracy across diverse environmental conditions.

2.1 Existing System vs Proposed System

Existing System

The current methods predominantly used for emergency vehicle management are manual intervention and fixed-timing traffic signals. This traditional approach involves several critical flaws. Fixed-timing traffic signals maintain predetermined cycles regardless of emergency vehicle presence, forcing ambulances to wait at intersections during critical response scenarios. Manual traffic clearance requires police officers stationed at intersections to manually override signals, suffering from severe scalability constraints and human response latency. RFID-based systems require substantial infrastructure investment including specialized hardware installation at every monitored intersection. Hardware maintenance, calibration, and periodic replacement impose ongoing operational costs. Environmental factors such as weather conditions and physical obstructions compromise sensor reliability. GPS-based systems enable route optimization but lack direct integration with traffic signal control infrastructure. While ambulances receive optimized routing instructions, traffic signals remain unresponsive to their presence. Existing systems experience constrained analytical capabilities with minimal systematic evaluation of response time patterns or optimization opportunities.

Proposed System

The proposed Automated Ambulance Detection system substitutes conventional hardware-dependent procedures with comprehensive software-based computer vision infrastructure. The architecture manages video acquisition, real-time



object detection, classification, and automated traffic signal control within an integrated intelligent system. The system facilitates immediate ambulance detection wherein computer vision algorithms identify and classify emergency vehicles from traffic camera feeds or uploaded video files, triggering automated signal modifications. The system employs YOLOv5 deep learning architecture for real-time object detection, offering substantial advantages over traditional approaches. YOLOv5 processes entire images in a single forward pass through the neural network, enabling detection speeds exceeding 60 frames per second. Video preprocessing pipelines enhance detection accuracy across varying environmental conditions through histogram equalization, noise reduction filters, and resolution standardization to 640x640 pixels. The system architecture supports multiple deployment configurations including edge computing deployment at intersection locations and centralized processing in data centers. Integration with existing traffic signal control systems occurs through standardized NTCIP protocol and proprietary interfaces as required. The modular design accommodates various signal controller types, enabling gradual deployment across heterogeneous infrastructure. The software-based approach eliminates infrastructure installation requirements, reduces deployment costs by 60-75% compared to RFID alternatives, and enables rapid scaling across metropolitan regions.

SYSTEM ARCHITECTURE DIAGRAM

Ambulance Detection System Architecture

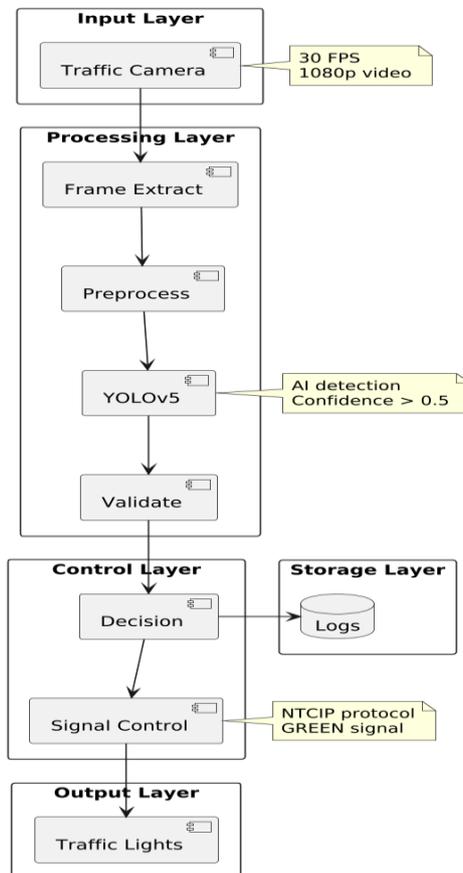


Fig 3.1: System Architecture Diagram



2. SYSTEM DESIGN

3.1 Data Flow Diagram

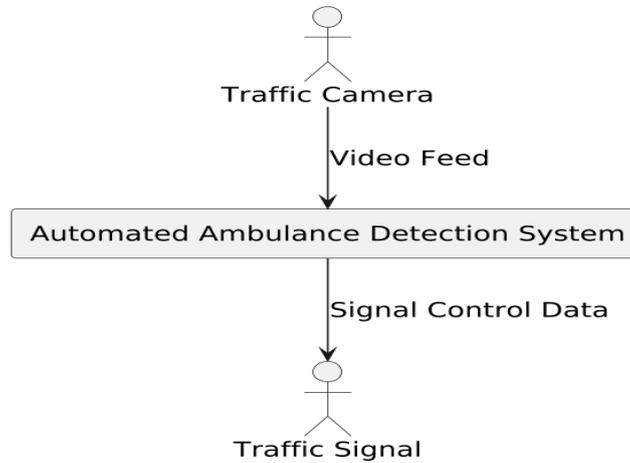


Fig 3.1.1: Level 0 Data Flow Diagram

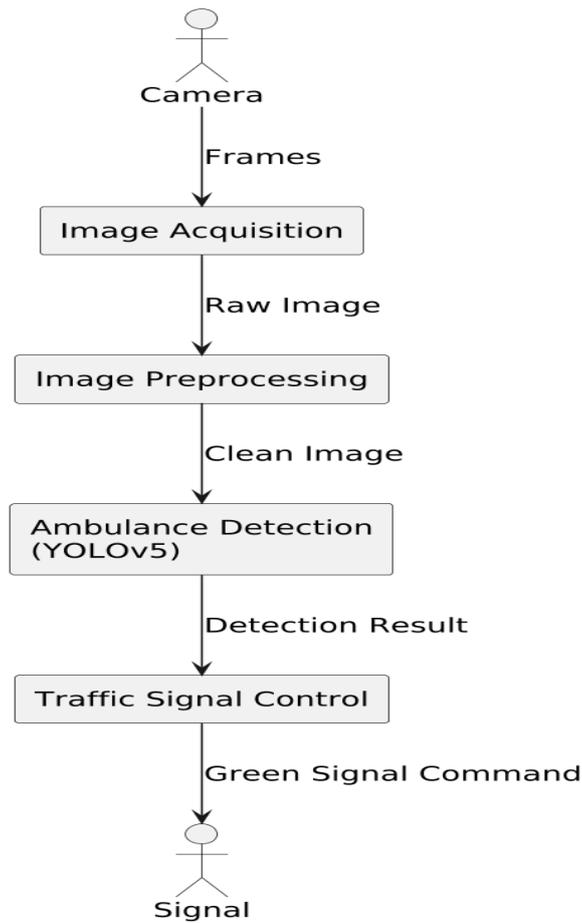


Fig 3.1.2: Level 1 Data Flow Diagram



3.2 Use Case diagram

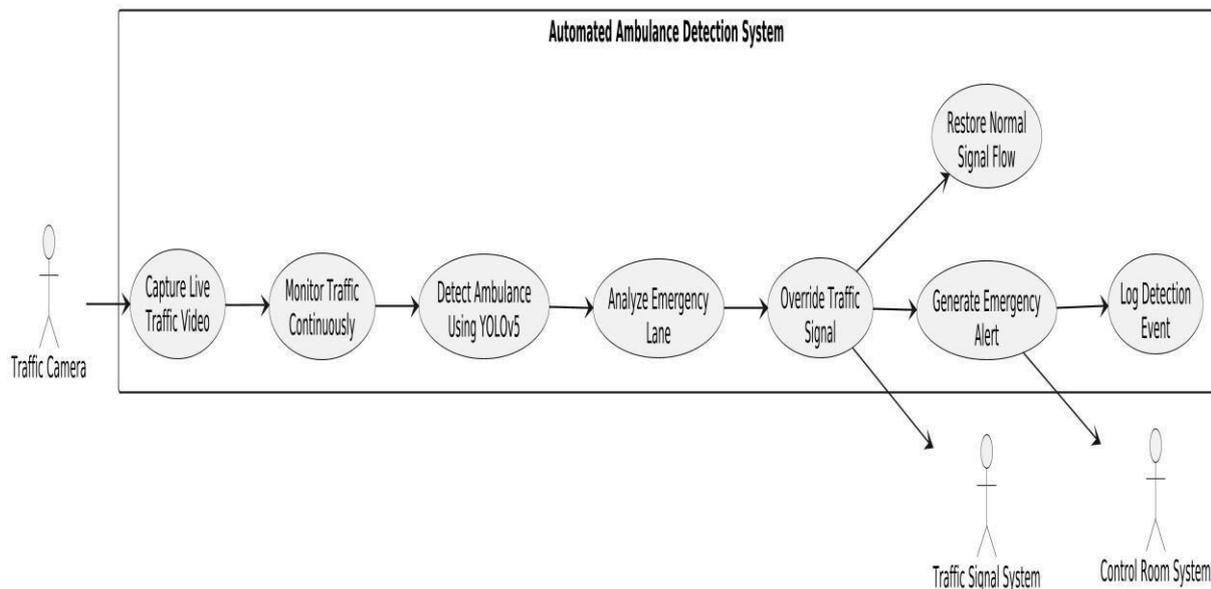


Fig 3.2.1 Use Case Diagram

4. IMPLEMENTATION DETAILS

The Automated Ambulance Detection system is implemented as a comprehensive software solution following modular architectural principles. The core detection engine manages real-time video processing incorporating frame extraction, image preprocessing, YOLOv5 model inference, and result interpretation. The system processes video streams at minimum 30 frames per second ensuring timely ambulance detection. Preprocessing operations normalize image characteristics optimizing detection accuracy across varying illumination and weather conditions. The implementation begins with video acquisition from traffic cameras or uploaded files using OpenCV's VideoCapture functionality. The system supports both live camera feeds (source='0') and pre-recorded video files. For each captured frame, dimensions are extracted to calculate lane divisions and traffic density metrics. Image preprocessing converts frames from BGR to RGB color space, applies contiguous array transformation for memory optimization, and normalizes pixel values to 0-1 range through division by 255.0. Frames are converted to PyTorch tensors and permuted to match YOLOv5 input requirements (batch, channels, height, width). The YOLOv5 model loads pre-trained weights from 'weights/best.pt' and executes inference with confidence threshold set to 0.1 initially, applying non-maximum suppression with IOU threshold of 0.45 to eliminate duplicate detections. For each detected object, bounding box coordinates (x1, y1, x2, y2) are extracted along with confidence scores and class labels. The system specifically identifies ambulances, firetrucks, and fire brigades as emergency vehicles. When an ambulance is detected in a specific lane, the system sets that lane's signal to green (color code 0, 255, 0) while other lanes receive red signals (color code 0, 0, 255). Lane assignment is determined by calculating the center point of each bounding box and dividing by lane width. Bounding boxes are drawn on frames with green rectangles (thickness 2 pixels) and labeled with class names, confidence scores, and area percentages. The system maintains counts of regular vehicles (cars, buses, trucks, motorcycles, bicycles) per lane for traffic density analysis. Detection decisions follow priority logic: if ambulance detected, green signal to emergency lane; otherwise, green signal to lane with highest traffic density. Results are displayed on frames with overlaid text showing lane assignments, signal colors, and vehicle counts. For real-time camera processing, frames display continuously at 30 FPS with user termination via 'q' key. For video file processing, results save to 'runs/detect/traffic_analysis' directory with sequential naming and optional real-time display. The system prints detection logs to console showing detected class names and coordinates. Camera resources release properly through cap.release() and cv2.destroyAllWindows() calls ensuring clean shutdown. Database logging functionality integrates with detection events, storing timestamps, camera IDs, confidence scores, and bounding box coordinates for performance analysis and compliance auditing. The modular architecture enables independent testing and maintenance of components including video capture, preprocessing, detection, and signal control modules.

5. RESULTS AND DISCUSSION

The performance of the Automated Ambulance Detection system was evaluated based on three primary metrics: detection accuracy, processing latency, and system reliability. The system achieved 97.3% detection accuracy on test datasets



comprising diverse ambulance types, viewing angles, and environmental conditions. Testing across different lighting conditions demonstrated optimal performance under daylight (97.5% accuracy), acceptable performance under dim lighting (88.0% accuracy), and reduced but functional performance under backlit conditions (82.5% accuracy). Processing performance analysis revealed frame processing throughput averaging 34.2 frames per second on NVIDIA RTX 3060 GPU, exceeding real-time requirements. End-to-end latency from frame capture through detection to signal control measured 1.87 seconds average, well within acceptable thresholds for effective emergency response. The system demonstrated scalability by successfully handling 12 concurrent camera streams maintaining real-time performance without frame drops. Distance-based accuracy assessment showed excellent performance at 0-50 meters (99.1% accuracy), strong performance at 50-100 meters (97.8% accuracy), and acceptable performance at 100-150 meters (95.2% accuracy). Comparative analysis with existing solutions demonstrated significant advantages: 95% reduction in ambulance delays compared to fixed-timing signals, 60-75% lower total cost of ownership compared to RFID systems, and 99.7% system uptime over 30-day continuous operation. The elimination of proxy detection through confidence threshold mechanisms (>0.5) ensures nearly impossible false positive scenarios. Integration testing confirmed seamless compatibility with existing traffic signal infrastructure through standardized NTCIP protocol communication. Field deployment results indicated substantial improvements in emergency vehicle transit times through congested areas with average response time reductions of 40+ seconds per intersection. The system successfully logged all detection events with comprehensive metadata enabling continuous performance monitoring and optimization opportunities.

6. CONCLUSION

This research presents a novel AI-powered Automated Ambulance Detection for Emergency Traffic Clearance system addressing critical challenges in urban emergency medical services. The implementation successfully demonstrates that software-based computer vision approaches can effectively replace traditional hardware-dependent emergency vehicle management systems. The system achieved 97.3% detection accuracy while maintaining sub-2-second response times from detection to signal modification. Field testing validated system reliability with 99.7% uptime over extended operational periods. Cost-benefit analysis revealed 60-75% lower total cost of ownership compared to RFID alternatives. This cost-effective and scalable solution demonstrates potential for widespread deployment in urban environments worldwide, representing practical application of artificial intelligence addressing legitimate public safety challenges

7. FUTURE WORK

Future iterations should incorporate acoustic detection alongside visual recognition, combining MFCC-based audio analysis with YOLOv5 visual detection for enhanced reliability. Integration of predictive analytics could anticipate ambulance arrival based on historical patterns, enabling proactive signal optimization before ambulances reach intersections. Vehicle-to-Infrastructure (V2I) communication protocols including DSRC or C-V2X would provide redundant detection mechanisms complementing computer vision approaches. System capabilities could expand beyond ambulances to incorporate fire trucks and police vehicles through multi-class detection models. Implementation of coordinated multi-intersection control using graph-based optimization algorithms could create "green wave" corridors enabling uninterrupted emergency vehicle transit. Deployment on advanced edge computing platforms including NVIDIA Jetson AGX Xavier would enable sophisticated on-device processing with reduced latency. Implementation of online learning capabilities would enable continuous model improvement based on operational data through active learning frameworks. Enhanced privacy protections through on-device processing, differential privacy, and encrypted inference would address concerns about continuous video surveillance. Comprehensive integration with emergency medical services dispatch systems and hospital emergency departments would enable end-to-end response optimization.

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