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**Research Article**

# AUTOMATED EMERGENCY VECHICLE RECOGNITIONSYSTEM USING MACHINE LEARNING

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**Abstract**

With the rapid growth of urbanization, modern cities face severe traffic congestion, often delaying emergency response vehicles such as ambulances, fire trucks, and police cars. This paper presents anAI-based real-timeemergencyvehicledetectionsystemusingthe YOLOv8 deep learning model integrated with traffic signal controllers. The proposed system detectsemergencyvehiclesfromlivevideofeeds, tracks them using DeepSORT, and dynamically adjuststrafficsignalstoprovidepriorityclearance. ExperimentalresultsdemonstrateameanAverage Precision (mAP@50) of 92.5% and real-time performance at 38 FPS, proving the system's effectiveness for smart city deployment.

**Keywords:**Emergency Vehicle Detection YOLOv8, DeepSORT, computer vision, traffic management, smart cities, real-time detection.

## Introduction

Urban traffic congestion poses a significant challenge for emergency response systems. Traditional methods such as sirens, manual clearance, and RFID-based systems are often unreliableorcostly. ArtificialIntelligence(AI)and computer vision offer a new paradigm for intelligent traffic management by enabling real- time detection and classification of emergency vehiclesusing surveillance cameras.Thisresearch focusesondevelopingaYOLOv8-baseddetection system integrated with traffic signal control to minimize emergency response delays.

### Literature review

Early approaches relied on siren-based and RFID systems,whichwerelimitedbynoiseinterference and infrastructure costs. Classical image processing methods (edge detection, templatematching)lackedrobustnessundervaryingconditions.Machinelearningmodelsusing HOG+ SVM improved accuracy but required manual feature extraction.The advent of deep learning revolutionized detection accuracy. CNN-based models such as FasterR-CNNachievedhighprecisionbut lacked real-time performance. The YOLO family (You Only Look Once) introduced real-time detection capabilities. Studies using YOLOv3–YOLOv7 achieved accuracies above 90%. YOLOv8, the latest version, offers improved speed, anchor-free detection, and better generalization, making it ideal for this application.

### Methodology

TheproposedsystememploystheYOLOv8model for detection and Deep SORT for tracking. The workflowincludes:DataCollection &Annotation

- ImageslabeledinYOLOformat.Preprocessing
- Resizing to 640×640, normalization, and augmentation.ModelTraining–YOLOv8trained for50epochsusingPyTorch.Real-TimeDetection
- Implemented via OpenCV video stream. Tracking – DeepSORT ensures continuous trackingacrossframes.TrafficSignalIntegration
- Detected emergency vehicles trigger signal priority.The systemarchitecture(Fig.1)includes modules for video input, YOLOv8 detection, DeepSORTtracking,decision-making,andtraffic light control.

### Implementation

The YOLOv8 model was trained using the Ultralights framework. The training achieved:

mAP@50: 92.5%

Precision: 91.3%

Recall:89.7%

A Flask web application was developed to visualize detections in real time. Integration with anArduino-basedtrafficcontrollersimulatedautomatic signal switching when an emergency vehicle was detected.

### Testingandevaluation

PerformanceMetrics:

Precision: 91.3%

Recall:89.7%

F1-Score:90.5%

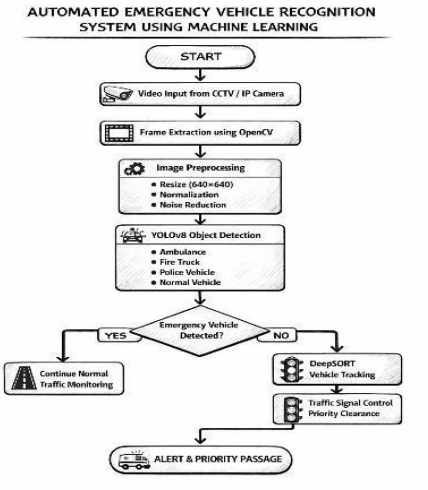
mAP@50-95:87.2%

FPS:38(GPU),12(CPU)

Latency:45ms/frame

Confusion Matrix:

Minor misclassifications occurred between fire trucks and police vehicles due to similar color patterns. Functional tests confirmed accurate detection under various lighting and weather conditions.



**Resultsanddiscussion**

The YOLOv8-system out performed traditional andML-basedmethodSinbothaccuracyandreal- time performance. Compared to RFID and siren- based systems, it requires no additional hardware beyond existing CCTV cameras. The integration withDeepSORTimprovedtrackingstability,even under occlusion.

Advantages:

Real-timedetectionandtracking High accuracy and scalability Cost-effective deployment **Limitations:**

RequiresGPUforoptimalperformance

Reducedaccuracyinheavyrainor fog.

**Conclusionandfuturework**

Thispaperpresents arobust,real-timeemergency vehicle detection system using YOLOv8 and DeepSORT. The system achieved over 92% detectionaccuracyandsuccessfullyintegrate

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