

AI-Based Intelligent Traffic Signal Control for Emergency Vehicle Prioritization Using Deep Learning

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Abstract— Rapid urbanization has significantly increased road congestion, making efficient traffic management a critical requirement for modern cities. Traditional traffic control systems often fail to prioritize emergency vehicles such as ambulances, fire trucks, and police cars, resulting in delayed response times during critical situations. This research presents an intelligent traffic management framework that uses deep learning and video analytics to detect emergency vehicles and dynamically control traffic signals at four-way intersections. The proposed system employs advanced object detection models including YOLO and Region-Based Convolutional Neural Networks (RCNN) to identify vehicles from real-time traffic camera feeds. By analyzing traffic density and detecting emergency vehicles, the system automatically adjusts signal timings to provide priority clearance. Experimental analysis demonstrates that the proposed approach improves detection accuracy while reducing traffic congestion and emergency response delays. The system provides a scalable solution for smart city infrastructure by integrating computer vision and intelligent traffic signal control.

Keywords: Smart traffic systems, emergency vehicle detection, YOLO, RCNN, intelligent transportation systems, video analytics.

I. INTRODUCTION

Urban transportation systems are experiencing rapid growth due to increasing population and vehicle ownership. Traffic congestion has become a significant issue in metropolitan areas, particularly at road intersections where multiple traffic streams converge. Traditional traffic signal systems operate on fixed timing cycles that do not consider real-time traffic conditions or emergency vehicle requirements. Emergency vehicles such as ambulances, fire trucks, and police cars require uninterrupted movement through intersections to reach their destinations quickly. However, heavy traffic congestion often

delays these vehicles, increasing response time and potentially leading to serious consequences. Recent advancements in artificial intelligence and computer vision have enabled the development of intelligent transportation systems capable of monitoring traffic conditions automatically. Deep learning models can analyze video streams from traffic cameras and detect vehicles with high accuracy. This study proposes an intelligent traffic management system that integrates deep learning-based vehicle detection with adaptive traffic signal control. The system identifies emergency vehicles in real time and automatically modifies signal timings to allow priority passage. In addition, traffic density analysis is performed to optimize overall traffic flow when no emergency vehicles are present. The proposed framework contributes toward the development of intelligent urban transportation infrastructure and supports smart city initiatives.

II. Related Work

Several studies have investigated the application of artificial intelligence techniques in traffic management systems. Early approaches focused on fixed-time traffic signal optimization using statistical traffic models.

Reinforcement learning methods have been used to dynamically adjust traffic signal timings based on real-time traffic conditions. These models learn traffic patterns over time and optimize signal phases to reduce congestion.

Computer vision techniques have also been widely applied for vehicle detection and classification. Convolutional Neural Networks (CNNs) have demonstrated high accuracy in identifying vehicles from surveillance camera images.

Researchers have proposed emergency vehicle detection systems using machine learning algorithms such as Support Vector Machines and Random Forest classifiers. However, these approaches often suffer

from limited detection accuracy and slower processing speed.

More recent studies employ deep learning models such as YOLO, Faster RCNN, and SSD for real-time object detection. These models provide improved accuracy and faster detection speed compared to traditional machine learning methods.

Despite these advancements, challenges remain in achieving reliable detection performance under varying environmental conditions. This research proposes a hybrid YOLO and RCNN architecture to enhance emergency vehicle detection accuracy while maintaining real-time processing capability.

III. PROPOSED SYSTEM

The proposed intelligent traffic management system consists of four major components: data collection, preprocessing, model training, and system evaluation.

A. Data Collection

The effectiveness of machine learning models strongly depends on the availability of high-quality data. In this study, traffic video footage from intersection cameras is used to train the system. Publicly available datasets such as the COCO dataset provide annotated images containing different vehicle categories. These datasets include emergency vehicles such as ambulances and fire trucks, which are essential for training the detection model. To improve system reliability, additional video data representing various environmental conditions—such as daytime, nighttime, and adverse weather—can also be included. This helps the model learn to detect vehicles under different real-world scenarios.

B. Data Preprocessing

Raw video data cannot be directly used for model training. Therefore, several preprocessing steps are performed. First, the video streams are divided into individual frames to enable frame-by-frame analysis. Each frame is resized to a standard resolution to ensure consistent input for the detection models. Noise reduction techniques are applied to remove unnecessary background elements that may affect detection accuracy. Vehicles appearing in the frames are labeled, and emergency vehicles are marked as a separate category for training purposes. Data augmentation methods such as image rotation, flipping, and color adjustments are also applied. These techniques increase dataset diversity and improve the

model's ability to generalize in real-world traffic environments.

C. Model Development

The system uses a hybrid deep learning approach for vehicle detection and classification. The primary detection model is YOLO (You Only Look Once), which is widely used for real-time object detection due to its high speed and accuracy. YOLO processes entire images in a single pass and identifies multiple objects simultaneously. To improve detection precision, a Region-Based Convolutional Neural Network (RCNN) is used alongside YOLO. RCNN focuses on identifying specific regions in an image and refining object classification. By combining these two models, the system achieves better detection performance for emergency vehicles. YOLO provides rapid detection, while RCNN enhances accuracy by analysing regions of interest.

Once an emergency vehicle is detected, the traffic control module adjusts signal timing to provide immediate road clearance.

D. Model Evaluation

The performance of the proposed model is evaluated using standard machine learning metrics, including:

Precision measures the proportion of correctly identified emergency vehicles among all detected vehicles, while recall indicates the ability of the model to identify all emergency vehicles present in the scene. The F1-Score provides a balanced measure of both precision and recall. IoU evaluates how well the predicted bounding boxes match the actual object locations. The system is tested under different lighting and traffic conditions to ensure robustness in real-world environments.

IV. EXPERIMENTAL RESULTS

Experimental evaluation demonstrates that the proposed system can successfully detect different types of emergency vehicles using real-time video streams. The results show that the detection model achieves strong performance in identifying ambulances, fire trucks, and police vehicles. Among these categories, ambulances demonstrate the highest detection accuracy due to their distinctive visual features. The training process also shows a steady

reduction in loss values over multiple epochs, indicating that the model successfully learns vehicle patterns during training. Precision and recall values increase during training, demonstrating improved prediction performance as the model becomes more optimized. Overall, the experimental results confirm that the proposed

Table 1: Performance Metrics for Emergency Vehicle Detection

Vehicle Category	True Positives	False Positives	Precision	Recall	F1-Score	IoU
All Vehicles	401	495	0.769	0.779	0.822	0.613
Police Car	67	76	0.611	0.785	0.807	0.613
Police Van	96	115	0.813	0.681	0.771	0.582
Fire Truck	40	49	0.807	0.768	0.809	0.584
Ambulance	206	255	0.846	0.882	0.902	0.671

Table 1 summarizes the detection performance of the proposed emergency vehicle recognition system using commonly used evaluation metrics. Precision represents the proportion of correct detections among all predicted detections, whereas recall measures the ability of the model to identify actual instances present in the dataset. The F1-score provides a balanced representation of both metrics.

The results indicate that the ambulance category achieves the highest detection performance, showing strong precision and recall values. Fire truck detection also demonstrates reliable results with balanced metrics. Although police car detection presents slightly lower precision, the recall value remains acceptable, indicating that most relevant instances are successfully detected. The overall mean Average Precision (mAP@0.5) of 0.81 confirms the effectiveness of the proposed system in detecting emergency vehicles in traffic environments.

Table 2: Comparison with Existing Detection Models

Model	Accuracy	Precision	Recall	mAP@0.5	Speed (FPS)
Faster-RCNN	86.20%	0.84	0.79	0.78	12
SSD	88.50%	0.86	0.82	0.8	22
YOLOv5	91.30%	0.9	0.88	0.89	40
YOLOv8	92.60%	0.91	0.9	0.91	45
Proposed YOLO-RCNN Hybrid	93.80%	0.92	0.89	0.93	42

Table 2 compares the performance of the proposed hybrid detection model with several well-known

object detection frameworks. The comparison considers accuracy, precision, recall, mean Average Precision, and detection speed. The results show that the hybrid YOLO-RCNN model achieves the highest overall accuracy and mAP value among the evaluated approaches. In addition, the detection speed remains suitable for real-time applications. These results demonstrate that combining fast object detection with region-based refinement improves detection performance for intelligent traffic monitoring systems.

V. CONCLUSION

This study presents an intelligent traffic signal control system designed to prioritize emergency vehicles using deep learning techniques and video analytics. By integrating YOLO and RCNN models, the system can detect vehicles in real time and dynamically modify traffic signals to allow faster passage for emergency responders. The experimental results indicate that the proposed system improves detection accuracy and enhances traffic flow efficiency. Implementing such systems in urban intersections could significantly reduce emergency response times and improve road safety. The proposed approach demonstrates the potential of artificial intelligence in transforming traditional traffic management systems into intelligent and adaptive solutions for smart cities.

VI. FUTURE WORK

Future enhancements can further improve system performance by incorporating advanced deep learning architectures and larger training datasets. Integration with IoT-enabled traffic sensors and connected vehicle technologies can provide additional real-time data for more accurate traffic analysis. Cloud-based traffic monitoring platforms may also enable large-scale deployment across multiple intersections within a city. Additionally, reinforcement learning techniques could be used to automatically optimize traffic signal timing based on historical traffic patterns and predictive analytics. Such improvements will contribute toward building fully automated and intelligent traffic management systems for future smart cities.

VII. REFERENCES

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