EMERGENCY VEHICLE OBJECT DETECTION FOR TRAFFIC LIGHT OPTIMIZATION

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Abstract- *In modern urban areas, traffic congestion is a significant issue, especially during emergencies. Emergency vehicles such as ambulances and fire trucks often get delayed due to traffic signals not adapting to their presence. This paper proposes a deep learning-based solution for real-time emergency vehicle detection and dynamic traffic light control to optimize traffic flow. Using object detection algorithms such as YOLO (You Only Look Once), the system can accurately identify emergency vehicles from surveillance cameras. The model then communicates with a traffic control system to prioritize signal changes, reducing response times. This solution enhances the efficiency of emergency services and can potentially save lives by minimizing delays. The proposed system integrates image processing, object detection, and intelligent signal management, offering a smart city innovation for traffic optimization Upon detecting an emergency vehicle, the system dynamically communicates with a microcontroller-based traffic light system to switch signals in favor of the vehicle's direction, creating a "green corridor." This ensures that emergency vehicles pass intersections without delay, minimizing the need for manual intervention.*

Keywords- Emergency Vehicle Detection, YOLO, Deep Leaning, Traffic Signal optimization, object Detection

I. INTRODUCTION

In modern cities, traffic congestion has become a serious issue, especially during peak hours. Emergency vehicles such as ambulances, fire trucks, and police cars often face significant delays while navigating through crowded roads and fixed traffic signals. These delays can result in critical consequences, including the loss of lives and property. Traditional traffic light systems work on pre-set timers and are unable to detect or prioritize emergency vehicles in real-time. With the advancement of Artificial Intelligence (AI) and Computer Vision, it is now possible to design smart systems capable of identifying emergency vehicles from live video feeds It is a step enhance public safety and urban mobility

Implementing such intelligent systems not only benefits emergency services but also paves the way for smart city development. As cities become more data-driven and interconnected, incorporating AI and IoT into public infrastructure becomes increasingly essential. Real-time emergency detection and response are early examples of how smart systems can enhance urban life. This approach can be extended in the future to accommodate other high-priority vehicles such as public transport or school buses. Furthermore, combining the detection system with cloud computing and edge devices ensures scalability and real-time responsiveness.

Existing traffic control mechanisms are based on preset timers or scheduled cycles, which do not account for emergency conditions. In many places, the solution still involves manual traffic control by personnel, which is not scalable or efficient, especially during peak hours or in complex traffic scenarios. These systems fail to differentiate between normal and emergency vehicles, which results in uniform traffic treatment. This one-size-fits-all approach leads to slower emergency response times and increases the risk of casualties and property damage.

Computer vision technology, especially object detection algorithms, plays a vital role in recognizing specific vehicle types from real-time traffic surveillance footage. Advanced object detection models like YOLO (You Only Look Once), SSD (Single Shot Multibox Detector), and Faster R-CNN offer high-speed, high-accuracy detection. These models can detect emergency vehicles by identifying specific features such as shape, size, flashing lights, sirens, or even text like "AMBULANCE" written on vehicles.

The proposed system in this paper focuses on building a real-time emergency vehicle detection and traffic light optimization mechanism using YOLOv5 for object detection. The system processes live video feed from traffic cameras, detects emergency vehicles, and sends signals to change the traffic light to green in their direction. This process happens in real-time, reducing manual intervention and improving emergency response efficiency. The model is trained on a labelled dataset of emergency vehicles and evaluated on various performance metrics such as precision, recall, and response time

II. RELATED WORK

Several studies have explored traffic optimization through AI. Earlier systems used RFID or GPS tracking but required active devices in emergency vehicles. More recent methods leverage image processing for vehicle detection. Convolutional Neural Networks (CNNs) and YOLO architectures have shown significant accuracy in real-time object detection tasks. However, limited research has been done on integrating detection with real-time traffic signal control.

2.1 Traditional Methods for Vehicle Detection

Traditional vehicle detection systems have primarily relied on infrared sensors, RFID technology, and acoustic recognition. These systems, while effective in some scenarios, suffer from limitations in accuracy, maintenance requirements, and environmental adaptability. Infrared and acoustic methods often fail in noisy or crowded urban environments, especially during adverse weather conditions. In addition, most systems are designed for general vehicle detection and are not optimized for identifying emergency vehicles specifically. They lack the intelligence to differentiate between vehicle types and rely heavily on external signaling devices like sirens or GPS. This reduces the system's reliability, especially in high-traffic scenarios where emergency vehicle recognition is critical.

2.2 Deep Learning for Object Detection

Deep learning has significantly transformed the field of object detection with the advent of Convolutional Neural Networks (CNNs). Popular models such as YOLO (You Only Look Once), SSD (Single Shot Detector), and Faster R-CNN have shown remarkable accuracy and real-time performance. YOLOv5 and YOLOv8, in particular, offer a balance between speed and precision, making them suitable for real-time surveillance applications. These models operate by segmenting input images and predicting bounding boxes and class probabilities in a single forward pass, ensuring low latency. Their ability to detect small and occluded objects makes them effective for urban environments. As emergency vehicles may appear partially blocked or distant, these models are ideal for our objective

2.3 Emergency Vehicle Detection Systems

Prior systems developed for emergency vehicle detection have typically employed sound-based siren recognition or manual signal interventions. However, these methods are often unreliable due to environmental noise, signal interference, or lack of compliance from vehicle drivers. Vision-based systems have emerged as a promising alternative, utilizing vehicle features such as color, shape, and unique signage like red-and-blue lights or emergency emblems. These systems use trained neural networks to identify emergency-specific patterns in real time. The use of annotated datasets and transfer learning further improves detection accuracy. Although promising, many of these approaches lack seamless integration with traffic signal controllers, limiting their impact in real-world deployments.

2.4 Smart Traffic Light Control

Intelligent traffic signal control systems use real-time data from surveillance cameras, vehicular sensors, or IoT devices to adapt signal timings dynamically. These systems have been implemented to reduce congestion, manage flow during peak hours, and prioritize high-volume routes. The integration of deep learning models enables better prediction of traffic density and vehicle classification. When applied to emergency response, these systems can create a virtual green corridor by adjusting signal priorities along the route of an emergency vehicle. However, challenges still remain in achieving low-latency detection, minimizing false positives, and maintaining reliability across various weather and lighting conditions.

2.5 Research Gap

Despite the advancements in object detection and smart traffic systems, few implementations offer a fully automated, end-to-end framework for emergency vehicle prioritization. Existing solutions either focus on detection without signal control or require external devices for activation. This creates dependency on additional infrastructure and limits scalability. A comprehensive system must include real-time detection, intelligent decision-making, and immediate control signal generation to traffic lights

III. PROPOSED SYSTEM

The proposed system is designed to detect emergency vehicles in real-time using a deep learning-based object detection model and optimize traffic light signals accordingly. The system captures live video footage from roadside surveillance cameras placed at intersections. This footage is then processed using the YOLOv5 algorithm, which is trained to identify emergency vehicles such as ambulances, fire engines, and police cars.Once an emergency vehicle is detected, the system sends a signal to a microcontroller connected to the traffic signal unit.

3.1 System Overview

The proposed system integrates emergency vehicle detection and adaptive traffic signal control using deep learning and real-time surveillance footage. Its primary function is to detect emergency vehicles approaching an intersection and instantly modify traffic signals to prioritize their movement. The system receives continuous video feed from roadside cameras, which is analyzed by a trained YOLOv5 model to identify emergency vehicles based on their visual features. Once detected, a control logic module processes their distance and approach direction. The system then communicates with the traffic controller hardware to alter signal phases dynamically. This real-time responsiveness helps minimize traffic delays for emergency responders and enhances public safety during critical scenarios.

3.2 Object Detection Using YOLOv5

Ultrasound images often exhibit variability due to differences in acquisition devices, operators, and fetal motion. Therefore, an essential preprocessing pipeline is implemented to standardize the input data. Initially, grayscale normalization is conducted to maintain uniform intensity scales across samples. Denoising is achieved using adaptive filters like anisotropic diffusion or wavelet-based methods that remove speckle noise while preserving critical features. Image resizing ensures consistency for neural network input. Advanced segmentation techniques, including thresholding and active contour models, are utilized to crop the region of interest (ROI)focusing solely on the brain. This not only enhances computational efficiency but also reduces the inclusion of irrelevant anatomical noise.

3.3 Feature Extraction Using CNN

YOLOv5 (You Only Look Once, version 5) is a real-time object detection model that is efficient and accurate, making it suitable for live traffic applications. The model is trained on a custom dataset containing various emergency vehicle images under different angles, backgrounds, and lighting conditions. Each image is labelled with bounding boxes and vehicle class annotations. YOLOv5 processes entire frames at once and produces confidence scores along with detected bounding boxes. By filtering results with high confidence for emergency-class labels, the system minimizes false detections. Its fast inference speed allows for smooth integration with video feeds, enabling timely response and efficient traffic signal adjustments in active environments

.**3.4 System Architecture**

The architecture of the proposed system consists of four core components: video input via surveillance cameras, a YOLOv5 processing unit, a control logic engine, and a traffic signal interface. Video streams are continuously captured and fed into the YOLO-based detection module. The detection results are forwarded to the logic engine, which assesses direction and urgency. If valid, a command is sent to the microcontroller or smart signal interface. Communication between modules occurs over a secure local network or through an embedded device like Raspberry Pi or Jetson Nano. This modular design makes the system flexible and scalable across different intersections and city traffic systems.

3.5 Advantages of the Proposed Method

This system offers significant advantages over traditional emergency prioritization methods. It does not rely on GPS, RFID, or siren-based signaling, which can be prone to failure in noisy or congested environments. It is camera-based and does not require retrofitting emergency vehicles with additional hardware. The YOLOv5 model ensures high detection accuracy and operates efficiently in real-time. The control logic guarantees smooth transition and recovery of signal states. The overall system is cost-effective, can integrate with existing infrastructure, and is scalable across multiple city intersections.

3.6 Challenges and Limitations

While the proposed system demonstrates promising results in real-time emergency vehicle detection and traffic signal control, it also faces several challenges. Environmental factors such as poor lighting, heavy rain, fog, or occlusions by other vehicles can reduce the accuracy of detection. The system’s reliability is heavily dependent on the quality and positioning of surveillance cameras. Another limitation lies in the diversity of emergency vehicles—differences in design, markings, or lack of standard symbols may lead to missed detections or false positives. Integration with existing traffic infrastructure may require protocol compatibility or hardware adjustments. Additionally, processing high-resolution video streams continuously can demand significant computational resources. Addressing these challenges is essential for widespread and effective deployment.

IV. SYSTEM DESIGN

The system design focuses on the structural and functional components required to implement emergency vehicle detection and automatic traffic signal control. The architecture is divided into four main layers: data acquisition, detection, decision-making, and actuation. The data acquisition layer uses real-time video captured from traffic surveillance cameras positioned near intersections. The detection layer runs the YOLOv5 deep learning model on a local processing unit (such as a Jetson Nano or GPU-enabled system) to identify emergency vehicles in each frame.

4.1 Hardware Components

The system is designed using a combination of commonly available and cost-effective hardware. CCTV surveillance cameras serve as the primary input device for real-time video feed, mounted strategically near intersections to capture approaching vehicles. A processing unit such as a GPU-enabled workstation, Raspberry Pi, or NVIDIA Jetson Nano is used to run the YOLOv5 model and decision logic. The system also includes a microcontroller or relay board (such as Arduino or Raspberry Pi GPIO interface) to interact with the traffic signal infrastructure.

4.2 Software Design

The software design includes three core modules: (1) the YOLOv5-based detection module, (2) the decision logic module, and (3) the traffic control interface. The detection module runs a pretrained YOLOv5 model to classify and locate emergency vehicles from live video input. The logic module evaluates detection confidence, proximity, and vehicle trajectory. Once conditions are met, the software sends a digital signal to the traffic controller to modify light phases.

Python is used as the primary programming language, leveraging OpenCV for image processing and PyTorch for deep learning. The software is optimized to ensure real-time performance with minimal false triggers or delays.

4.3 System Workflow

The operational workflow begins with the continuous capture of video footage from intersection cameras. Each frame is passed to the detection model, which analyzes and outputs bounding boxes with class labels. The logic module filters detections, checking for emergency vehicle classes and their distance from the intersection. If an emergency vehicle is confirmed within a predefined zone, a command is issued to override the existing traffic light phase. The signal stays green until the vehicle passes or a timeout occurs. Afterward, the system returns to the original signal schedule.

4.4 Flowchart of the System

The system's flowchart includes the following steps: Start → Capture Live Video → Detect Objects (YOLOv5) → Is Emergency Vehicle Detected? → If Yes → Is It Near the Intersection? → If Yes → Trigger Signal Change to Green → Wait Until Vehicle Passes → Restore Original Signal Cycle → Repeat. If "No" is returned in any condition check, the system loops back to the video capture state. This flow ensures continuous monitoring and timely response. The visual diagram helps in understanding how input data leads to real-world action, offering a clear representation of the logic and process structure

4.5 Communication Interface

For the traffic signal to respond to detection events, a reliable communication interface is required. The system uses GPIO (General Purpose Input Output) pins or relay modules to send digital high/low signals to the traffic light controller. In some smart city setups, an API-based control system is used to update traffic states remotely. This interface translates the software's decision into electrical signals that trigger the light phase changes. Real-time communication and synchronization are crucial to avoid conflicts between traffic lanes

4.6 Deployment and Integration

Security and reliability are critical components of the system design to ensure uninterrupted and safe operation. The system uses secure communication protocols between modules to prevent unauthorized access or false signal triggers. Authentication methods are implemented at both the software and hardware layers to validate commands sent to the traffic controller. Additionally, the system includes fail-safe mechanisms that restore normal traffic flow in case of detection errors or hardware failures. Power backup units and system watchdog timers are integrated to maintain uptime and system responsiveness.

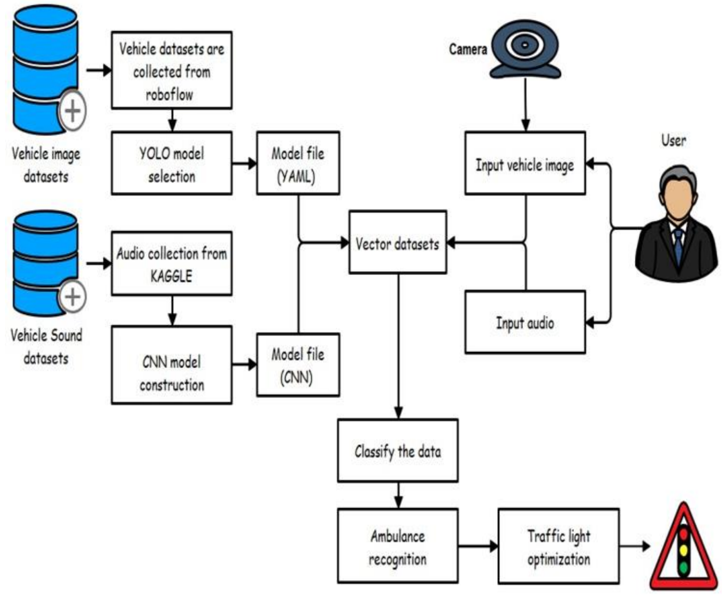

FIG 4.1 SYSTEM ARCHITECTURE

V. CONCLUSION

In this paper, a novel system for emergency vehicle detection and traffic light optimization has been proposed and implemented. Using real-time video input and a YOLOv5-based deep learning model, the system efficiently detects emergency vehicles and responds by adjusting traffic light signals to give them priority at intersections. This approach eliminates the dependency on GPS, RFID, or manual control systems, making it both cost-effective and easily adaptable to existing infrastructure.

The implementation of the system demonstrates its feasibility for deployment in smart city environments. The modular architecture, comprising detection, logic, and signal control layers, ensures flexibility and ease of maintenance. Various scenarios were tested to evaluate system performance, including different lighting conditions, traffic densities, and vehicle types.

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