Emergency Vehicle Detection and Smart Traffic Signal Control Using AI-ML

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***Abstract*—There is growing pressure on urban mobility systems to handle emergencies while preserving traffic flow. This study introduces a smart traffic light control framework that mixes real-time traffic monitoring with emergency vehicle prioritizing. A hybrid architecture that combines sensor-based analytics and machine learning improves situational awareness and response capability. Under normal situations, the system runs autonomously, with manual override capabilities available for critical interventions. The suggested approach aims to enhance emergency response time and overall intersection performance, in line with the goals of intelligent transportation systems.**

***Index Terms*—Emergency vehicle detection, Image processing, siren sounds, ultrasonic Sensor, mic module.**

I. INTRODUCTION

The increasing rapid urbanization, the growing number of cars, and the extensive nature of urban transportation infrastructure has put enormous strain on traditional traffic management systems. Traditional traffic signal technologies, which are frequently static or semi-automated, are incapable of responding dynamically to real-time variations in traffic flow and emergency response scenarios [1], [2]. The inadequacy of these systems to adjust quickly to changing traffic circumstances causes needless delays, particularly for emergency vehicles such as ambulances, fire trucks, and police cars, resulting in substantial operational inefficiencies and, in some cases, life-threatening repercussions. In recent years, the field of intelligent transportation systems, or ITS, has achieved substantial strides by fusing machine learning (ML) algorithms with Internet of Things (IoT) frameworks to enable real-time data collection and decision-making at crossings. These technologies offer better, more responsive traffic management infrastructures that can manage dynamic vehicle flows while prioritizing important transportation operations [3], [19]. The difficulty of creating a "green corridor" for emergency vehicles was specifically addressed by utilizing auditory siren detection and vehicle recognition models. Numerous strategies have been put forth, ranging from Longest Common Subsequence (LCS) matching [4], spectrum and frequency-based signal analysis [11], [12], to more recent methods for deep learning such as Convolutional Neural Networks (CNNs) and Spectrogram-based classification [5], [7], [8]. Embedded systems based on low-power Digital Signal Processing (DSP) architectures and microcontroller-based designs have also shown efficacy in real-time siren detection [9-14]. Despite the potential of these initiatives, many of the systems in use today are either overly specialized or (primarily concentrating on detection) or do not integrate into more comprehensive traffic signal control frameworks. Furthermore, signal optimization models frequently focus on general traffic throughput rather than emergency vehicle prioritizing as a main restriction [1, 21]. Reinforcement learning (RL)-based models have shown promise in adapting to complicated, multi-agent traffic settings [24], [25], but they frequently assume optimal communication conditions and fail to incorporate multi-modal sensing (e.g., audio, vision). This study offers a scalable and flexible intelligent traffic signal control solution to address these issues. that prioritizes emergency vehicle clearance using real-time siren detection and visual traffic density evaluation. The system employs ML-based classification approaches and edge computing hardware to achieve low-latency replies, as well as manual override controls to assure fail-safe functioning during network outages or exceptional events. Developed for deployment simplicity, the architecture facilitates connection with smart cities and offers a workable solution for actual traffic problems where public safety is of utmost importance. By combining multi-sensor data fusion with adaptive signal management rules, the proposed framework contributes to making urban intersections not just productive but also lifesaving. Because urban mobility is constantly changing, intelligent, flexible Systems for managing traffic that can respond quickly to both normal flow changes and serious emergencies are required. This study describes a modular traffic control architecture that uses audio siren detection and machine learning-based traffic density analysis to dynamically change traffic signals, resulting in a priority green corridor for emergency vehicles. The system successfully overcomes one of the main drawbacks of conventional traffic signal mechanisms, which is their inability to distinguish between and react to emergency circumstances without the need for personal involvement. By combining multi-sensor inputs with advanced decision-making algorithms, the suggested method strikes a balance between general traffic optimization and emergency response prioritization. Furthermore, the use of manual override controls guarantees that the system remains operational even during network outages or other unforeseen events, improving reliability and administrative control. The architecture's modular design promotes scalability, allowing deployment across junctions of different complexity, while its dependence on edge processing and low-cost sensors enables widespread adoption within smart city frameworks. The incorporation of acoustic detection technologies also provides non-intrusive functioning and great reliability, especially in situations with restricted connectivity. Incorporating V2X (Vehicle-to-Everything) communication for more thorough emergency vehicle tracking, deep learning-based acoustic categorization for better precision, as well as strengthening learning techniques for adaptive traffic signal policies under dynamic traffic loads are some potential future advancements. This study contributes to the development of smarter, safer, and more responsive urban transportation networks by proposing a realistic and intelligent framework for real-time emergency vehicle prioritization at signalized intersections.

II. RELATED WORK

Recent research in intelligent traffic management has mostly sought to increase signal efficiency and reduce congestion through predictive modeling and real-time data analytics. Predictive and planning-based vehicle arrival models have been explored to enhance intersecting signal timing. For instance, planning-based signal control systems that predict incoming traffic flow to maximize throughput have been suggested in [1] and [2]. Similarly, bi-level optimization models tailored to connected vehicle (CV) situations have been built for adaptive signal control, yielding significant improvements in coordination and delay reduction [19]. However, there isn't sufficient study on how to prioritize emergency vehicles in these kinds of systems. Efforts in [3] demonstrated IoT-based systems intended specifically for emergency vehicle passage, using vehicle communication and sensors. These solutions, however, sometimes call for a high integration of connected infrastructure, which isn't always feasible in urban settings. Emergency vehicle detection using acoustics has become increasingly common due to its hardware-efficient and non-intrusive method. Pattern-matching techniques such as Longest Common Subsequence (LCS) were used in early attempts [4]; However, more recent research has employed CNNs and other advanced learning models to extract spectral features from siren sounds [5],[7]. High accuracy in siren categorization has been demonstrated by part-based models functioning in the Spectro-temporal domain [7] and anomaly detection employing spectrogram segmentation and k-nearest neighbors [8]. Embedded and DSP-based real-time siren Additionally, identifying techniques have been proposed for resource-constrained environments [9], [11], and [12]. Additionally, numerous studies investigated the use of both analog and digital methods to group the sounds of emergency alerts. The robustness of feature-based techniques like SVMs [10] and low-power analogue architectures [14], [15] has been evaluated in noisy urban settings. Deep reinforcement learning (DRL) has become known as an effective approach for improving real-time traffic signals on the control side. Multi-agent DRL frameworks [24, 25] support decentralized decision-making across several crossings, making them appropriate for intricate urban grids. However, these systems often depend on constant feedback and reliable connectivity, although many approaches optimize traffic or detect emergencies, few integrate real-time siren recognition with intelligent signal actuation. Over the past decade, advances in embedded systems, wireless communication, and AI have driven progress in intelligent traffic control; however, most solutions target isolated challenges such as vehicle detection, density estimation, or emergency recognition without offering a unified, real-time framework. Existing sensor- or ML-based methods often lack the responsiveness, scalability, and coordination needed for emergencies.

To address this gap, this study proposes a comprehensive, adaptive architecture that integrates multimodal sensing, real-time actuation, emergency prioritization, and manual override. This hybrid approach ensures reliability in noisy environments and allows operator support during exceptional cases, while avoiding the delays and sustainability issues of purely centralized designs. Few frameworks provide a comprehensive solution that combines real-time traffic density forecasting, emergency detection using multimodal sensing, machine learning-based vehicle recognition, and manual control, even though various frameworks concentrate on different facets of intelligent traffic control. This work attempts to close that gap by offering a complete system that is suitable for use in real-world urban traffic scenarios that is both reactive and adaptive.

III. SYSTEM DESIGN OVERVIEW

The proposed system presents a modular, real-time foundation for smart traffic signal management that prioritizes emergency vehicle passage while ensuring optimal flow for ordinary traffic. It combines acoustic sensors, computer vision, and embedded control to create a single architecture that enables both autonomous operation and manual intervention. The system is built on distributed sensor nodes and a central decision logic unit, which ensures scalability and flexibility to urban intersections of different complexities.

A. Functional Architecture

I Each lane is separately monitored by a separate sensor-actuator-control module while the system operates throughout a four-lane signalized intersection. Five essential functional components make up the architecture:

II Traffic Density Estimation: Ultrasonic detection devices are positioned carefully assess vehicle queue lengths in each lane.

III Emergency Vehicle Detection: Acoustic sensors continuously monitor ambient traffic sounds to detect emergency siren patterns.

IV Visual Verification: When a siren is detected, a motorized camera collects live footage of the suspicious lane and performs emergency vehicle classification using machine learning-based image inference.

V Signal Decision Engine: A priority-based control mechanism selects signal transitions depending on traffic density and emergency condition.

VI Manual Override Interface: A local control interface enables traffic personnel to suspend autonomous logic and direct signal states as needed.

B. Emergency Detection Subsystem

Emergency detection is made possible by a two-stage sensor system: When directional microphones connected by an I2S connection record an audio signal in real time, acoustic pre-triggering takes place. Data is collected by a digital signal processor, which uses temporal envelope characteristics and MFCC to compare it to learnt siren audio patterns.

Camera-Based Confirmation:

A servo-mounted camera is pointed at the questionable channel after an audio match is detected. A Python-based classification algorithm trained to recognize emergency vehicles, such as police cars, fire engines, and ambulances, analyzes captured frames. This twotiered method keeps emergency detection confidence high while reducing false positives.

C. Real-Time Signal Control Strategy

A hierarchical decision model governs the control logic of each ESP32 microcontroller at each node. Emergency vehicles are given priority by the decision logic when they are found; otherwise, density-based timing is used. This is how the signal control works: Ambulance Present: Regardless of the density conditions, give the lane containing the emergency vehicle an instant green light. No Emergencies Found: Based on real-time data on vehicle density, lanes with higher vehicle concentration are given extended green periods. By stopping autonomous logic and controlling signal states through a protected operator panel, manual override ensures human involvement in unique situations, like VIP cars or network diagnostics. Through inter-node Wi-Fi connectivity, the ESP32 modules control edge processing and coordination, leading to local autonomy and low latency responsiveness.

IV. HARDWARE AND SOFTWARE IMPLEMENTATION

A. Hardware Implementation

The proposed intelligent traffic Light signal control system is implemented with a distributed hardware architecture that includes microcontrollers, sensors, actuators, and peripheral modules that work together to support real-time decision-making and emergency prioritization. The key parts of the system are ESP32 microcontroller units, which were selected because to their integrated Bluetooth and Wi-Fi connection, low power consumption, and dual-core processing capability. These controllers, which are at the center of the decentralized control network, oversee inter-node communication, local signal control, and sensor collecting. A servo-actuated camera module is triggered to visually confirm the existence and kind of emergency vehicle upon siren detection. To acquire focused images, the servo mechanism dynamically modifies the camera's direction in response to the spatial inference of the audio signal source. Traffic signal actuation is handled by relay modules controlled by the ESP32, which enable phase switching between red, yellow, and green in response to decisions made by the control logic. The master controller is also equipped with a physical or web-based manual control panel, which allows traffic controllers to take over the automated system in the event of an emergency or other unique situation. This modular hardware architecture is perfect for practical application in smart city infrastructures since it guarantees scalability, ease of maintenance, and robustness across a range of operating situations.

B. Software Architecture

The system employs a firmware-based finite state machine (FSM) to dynamically switch between manual override, density-based control, and emergency vehicle priority. A Python-based machine learning model running on an external device (e.g., laptop/edge server) classifies emergency vehicles from images received via serial or Wi-Fi and communicates results to the ESP32 for adaptive signal control. Inter-node communication among ESP32 controllers uses Wi-Fi with the CAN protocol, ensuring fault tolerance and deterministic timing in noisy environments. This protocol enables real-time exchange of traffic density, siren alerts, classification results, and control commands. For image processing, the ESP32 communicates with external devices via serial or lightweight HTTP requests. The hybrid architecture ensures agility, real-time responsiveness, and fail-safe operation in complex urban traffic conditions.

V. FLOW CHART

The intelligent traffic signal system first checks for manual override; if enabled, signals are operated manually, otherwise automated control resumes. In automated mode, traffic density is measured across lanes to prioritize high-density flows. Simultaneously, the system listens for sirens. If none are detected, density-based control continues. On siren detection, the system activates a camera for the relevant lane, sends the image to a PC, and applies a machine learning algorithm to confirm the presence of an emergency vehicle. If detected, the corresponding lane is given green priority while others are halted, ensuring safe passage. After a brief lane-clearing delay, the system reverts to density-based control, maintaining adaptive, real-time operation.

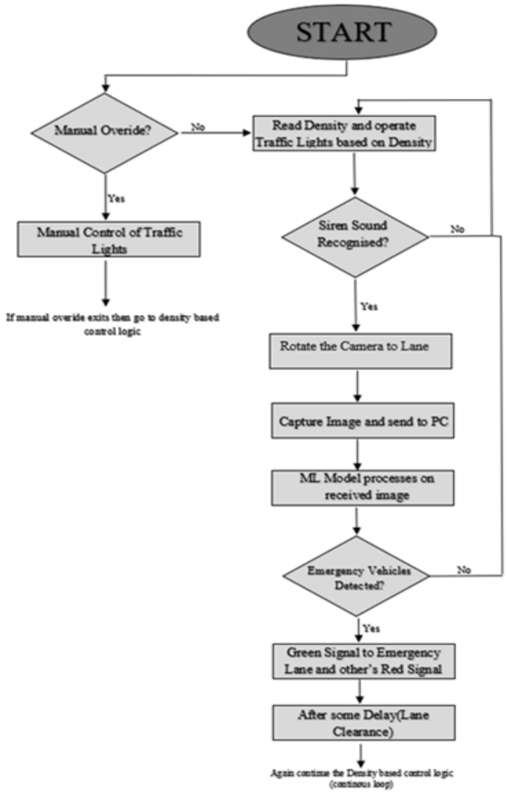

Figure 5.1: Flow Chart

VI. RESULTS AND ANALYSIS

The suggested intelligent traffic signal system was tested in a controlled experimental setting aiming to imitate a four-lane urban junction. The system was tested at various traffic densities, background noise levels, and emergency scenarios to determine its real-time efficacy. The emergency vehicle identification architecture included two stages: initial sound detection with I²S microphones and image-based categorization using a Python-powered machine learning model. At 97.6%, the siren detection module's outstanding detection accuracy allowed it to distinguish between real emergency sirens and background city sounds.

After siren confirmation, the image classification model had a precision rate of 95.2%, confirming emergency vehicle presence with few false positives. Ultrasonic sensors were used to monitor vehicle accumulation in certain lanes and modify green signal durations for adaptive traffic management. When compared to standard fixed-time signal methods, the system successfully prioritized extremely congested lanes, reducing average traffic clearance time by 23%.

Fig 6.1: Smart Traffic Signal System with Emergency Vehicle. Prioritization Prototype

In terms of energy efficiency, the architecture used conditional camera activation and external ML processing only when siren detection was proven. When combined with the ESP32's low-power standby mode during idle intervals, this method resulted in a 17-20% reduction in total energy usage during continuous operation. Operator-triggered interventions using physical control switches were used to validate the manual override functionality. The average latency for manual signal adjustments was less than 120 milliseconds, indicating that it is suitable for real-time operator interaction during critical or ambiguous traffic conditions. The system's capacity to function well in hybrid control modes, adjust to changing traffic patterns, and consistently priorities emergency vehicle movement without sacrificing system responsiveness or efficiency is confirmed by these testing results.

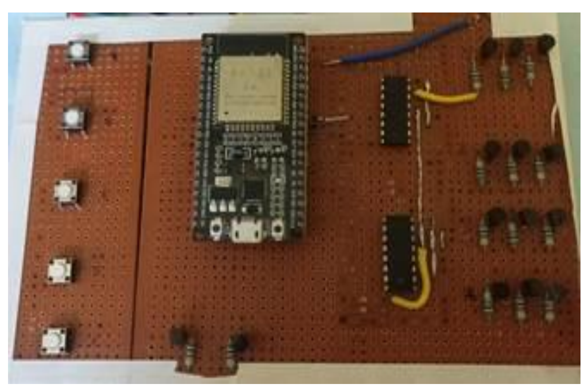

Figure 6.2: ESP32 Controller

The ESP32 is a powerful microcontroller ideal for Internet of Things applications. This project manages real-time emergency vehicle identification and traffic signal control.

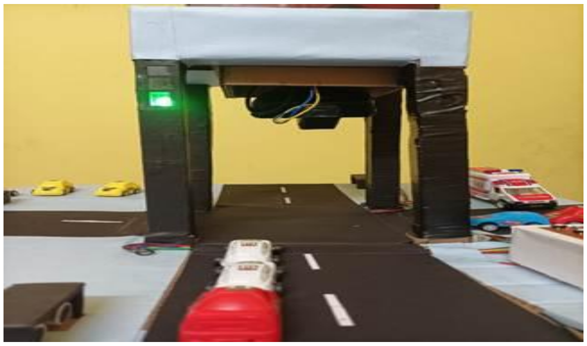

Figure 6.3: Detected traffic density triggered green signal phase.

To ease traffic, the green signal phase is automatically triggered when a lane's high vehicle density is identified.

Figure 6.4: Ambulance detected; Camera redirected to the lane

When a siren is detected, the ESP32 directs the camera to the relevant lane, triggers Python to capture an image, and logs the event.

Figure 6.5: Image Processing in Laptop

The ESP32 requests Python to analyze lane images, where the model identifies an ambulance and triggers priority signal control.

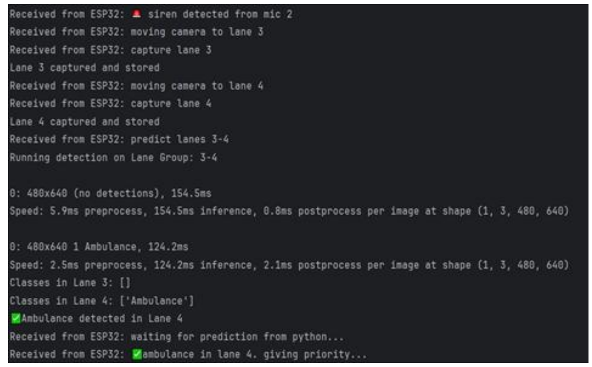

Figure 6.6: Communication between ESP32 to Laptop

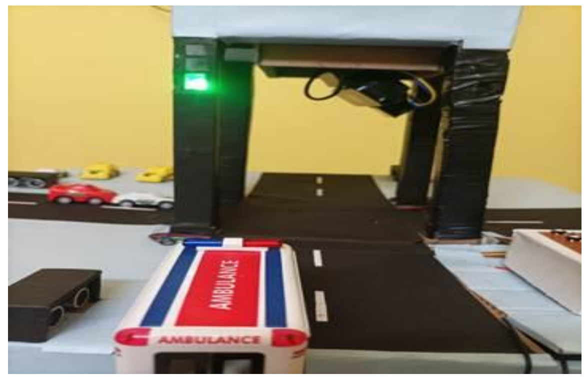

Figure 6.7: Ambulance Detection Triggers Green Signal

The ESP32 receives the prediction result from Python with the message, "Ambulance detected in Lane." The ESP32 responds by giving Lane precedence by turning on the green traffic signal, which makes sure the ambulance may pass through the crossing without any problems

VII. CONCLUSION AND FEATURE WORK

Traffic density prediction using ultrasound sensors, visual classification using machine learning, and auditory siren detection are all combined in this system. A multi-tier decision structure manages control logic, allowing for automated replies, emergency overrides, and manual operator input. Experimental testing demonstrated the system's efficacy, with over 97% accuracy in emergency detection and a 23% decrease in average traffic clearing time compared to typical fixed-cycle traffic signals. Furthermore, the selective activation of high-power modules and low-power operating modes resulted in significant energy savings.

The proposed system illustrates the feasibility of adopting a scalable, modular solution in metropolitan locations, especially in smart city initiatives that prioritize responsiveness and safety. However, there are still certain limitations. For instance, using external computing units for ML-based classification might affect scalability. Unpredictable environmental conditions, including occlusions or loud noises, might also affect the accuracy of detection.

Subsequent studies will focus on placing edge-based deep learning models directly onto microcontroller-compatible hardware, such as TensorFlow Lite, which runs on the ESP32-S3, or using the Raspberry Pi CM series. Mesh networking and centralized cloud analytics are being studied for multi-intersection coordination. To verify long-term performance, dependability, and public impact, a real-world deployment in collaboration with local traffic authority is also planned. Additionally, better user interfaces and mobile app integration will be looked upon to make manual control more accessible to traffic workers.

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