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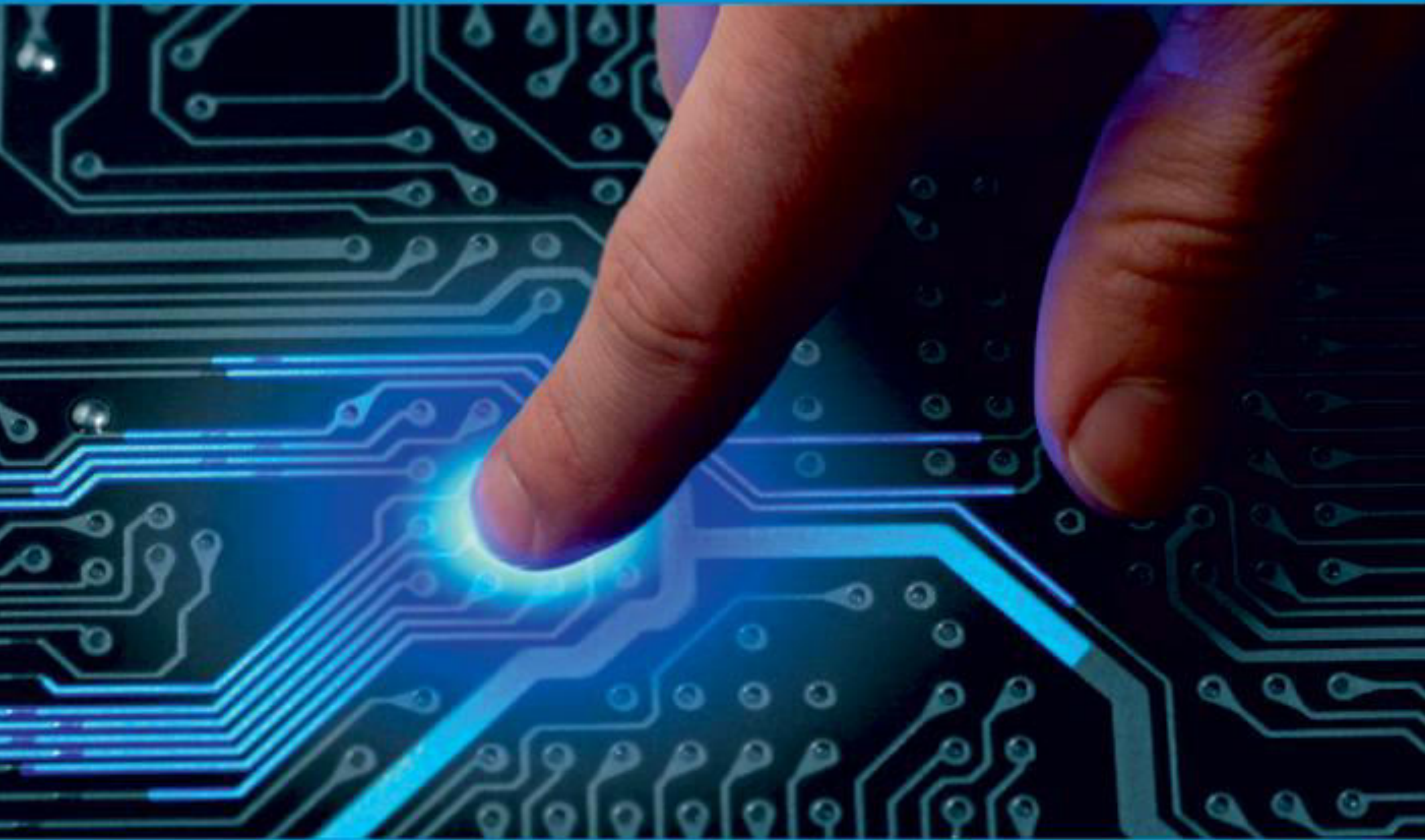

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# A Real-Time Traffic Signal Automation System for Emergency Response Vehicles

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**ABSTRACT:** Emergency vehicle detection plays a crucial role in ensuring quick responses and reducing accidents in urban settings. Traditional methods that rely solely on visual cues often face challenges in adverse conditions like poor lighting or heavy traffic. To address these limitations, this research integrates both acoustic and visual data using advanced deep learning techniques. We developed an Attention-based Temporal Spectrum Network (ATSN) for ambulance siren detection and implemented Multi-Level Spatial Fusion YOLO (MLSF-YOLO) architecture for visual detection tasks.

To effectively merge these two types of data, we employed a stacking ensemble learning technique, creating a robust system that harnesses the strengths of both audio and visual inputs. Additionally, we trained a Convolutional Neural Network (CNN) on short audio clips, using the Mel-frequency Cepstral Coefficients (MFCC) for feature extraction, enhancing the accuracy of siren detection.

The combined approach achieved significant results, including a misdetection rate of just 3.81% and an overall accuracy of 96.19% for visual data, while the audio detection model reached 93% accuracy. These results underscore the effectiveness of this dual-modality framework, demonstrating its potential to enhance emergency vehicle detection in real-world environments, even under challenging conditions.

**KEYWORDS:** Deep Learning, Vehicle Classification, Emergency Vehicle sound detection, CNN Sound classification

## I. INTRODUCTION

The timely detection of emergency vehicles is critical for road safety and efficient emergency response. Delays in recognizing these vehicles can lead to severe injuries or loss of life. As traffic incidents involving emergency vehicles often arise from various factors—such as driver distraction, technological interference, and inadequate public awareness—developing reliable detection systems that function effectively in diverse conditions is paramount. Current emergency vehicle detection (EVD) systems face numerous challenges. Visual detection methods often struggle with environmental factors like poor visibility during rain or fog, and issues like vehicle overlap can complicate accurate identification. Acoustic detection systems, while beneficial, frequently rely on limited datasets and may suffer from high computational demands, resulting in lower accuracy rates. For example, existing audio-based systems typically fall below 90% accuracy and can take significant time to process detections.

## II. METHODOLOGY

### 2.1. Image Processing:

In this stage, we employ advanced computer vision techniques to detect ambulances in real-time and differentiate between emergency and non-emergency vehicles.

**Object Detection**: We use **high-resolution cameras** to capture video feeds of traffic intersections. These feeds are processed using deep learning models like **YOLO (You Only Look Once)** or **Faster R-CNN (Region-Based Convolutional Neural Networks)**. **YOLO**: This model divides the image into a grid and predicts bounding boxes and class probabilities for each grid cell. **Faster R-CNN**: This algorithm uses region proposal networks (RPN) to generate regions of interest, which are then classified into different categories.

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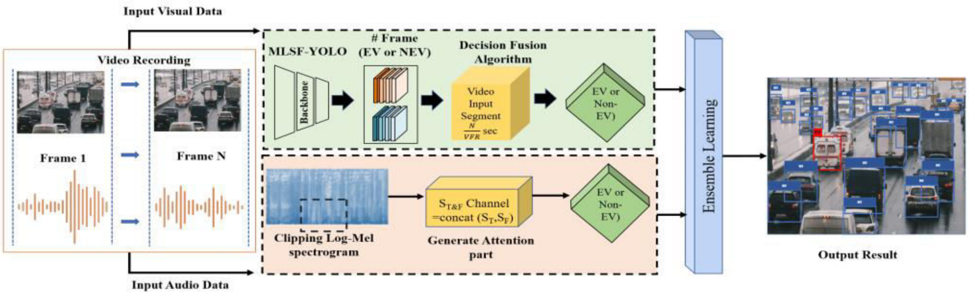
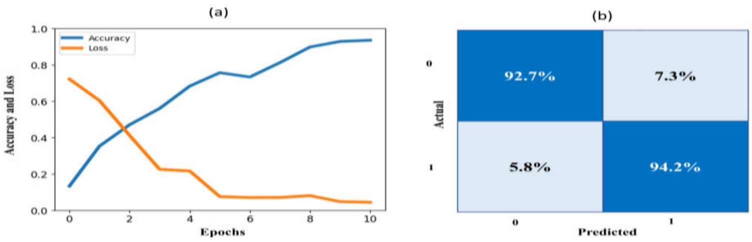
**Object Detection Method**: The camera captures video frames at regular intervals. And each frame is processed by the object detection model to identify vehicles, including ambulances. The system draws bounding boxes around detected ambulances.




**Classification**: After detection, we further classify whether the detected ambulance is in an emergency situation or not. This classification is based on: **Visual cues**: Such as the flashing lights, which can be detected using image processing techniques like color detection or specific feature extraction. **Audio cues**: Sirens can be captured through audio sensors, processed by algorithms to recognize characteristic frequencies. Audio processing uses machine learning algorithms (e.g., **Convolutional Neural Networks (CNNs)**) trained on ambulance siren audio patterns to classify emergency sirens.




## 2.2. Audio Detection

To complement visual detection, **audio sensors** are installed to detect ambulance sirens.

**Siren Identification**: The system uses microphones placed at intersections to pick up ambient sounds. **Signal processing algorithms** are used to filter and amplify the sound of sirens, which often have distinctive, repetitive waveforms.

**Siren Identification Method**: The microphone captures audio signals. The signal is processed using a **Fast Fourier Transform (FFT)** to extract frequency information. Sirens typically have characteristic frequencies between 500 Hz and 2000 Hz. A machine learning classifier trained on these frequency patterns determines whether the detected sound is a siren, classifying the scenario as an emergency.

The Fast Fourier Transform (FFT) algorithm efficiently computes the discrete Fourier transform (DFT), reducing the computational complexity from O(N2)O(N^2)O(N2) to O(NlogN)O(N\logN)O(NlogN).

The DFT is defined as:

**X[k]=∑n=0N−1x[n]WNkn,k=0,1,2,…,N−1**

Where**WNk=e−j2πk/N**

## 2.3. Traffic Signal Control

This part of the system manages traffic lights based on ambulance detection and classification, ensuring that the ambulance gets through the intersection safely and quickly.

**Single Ambulance Scenario**: When the system detects one ambulance, it prioritizes its lane by turning the traffic signal green. This is done using a **traffic light control algorithm** that adjusts the state of the signal in real-time. It's **Method & Algorithm**: The lane with the approaching ambulance is assigned a green light, while all other lanes are halted by showing red. **State Transition Algorithm**: The traffic light system cycles between states (green, yellow, red). Upon detecting an ambulance, the algorithm forces an immediate transition to green for the ambulance's lane.

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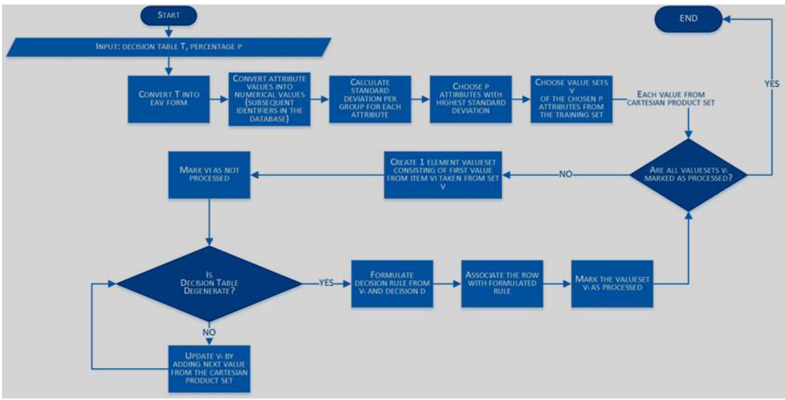


Fig: State Transition Algorithm

**Multiple Ambulance Scenarios**: If multiple ambulances are detected at the intersection, the system needs to manage the passage of each vehicle without causing confusion or collisions. Its **Method & Algorithm**: The system prioritizes ambulances based on factors such as distance to the intersection and time of detection. Alternatively, a **clockwise signal pattern** can be used, allowing each ambulance to pass in a predefined order. **Priority Scheduling Algorithm**: Ambulances are assigned priorities based on their distance to the intersection or based on arrival time. The signal management system calculates the priority for each and decides which lane turns green first.

Priority Scheduling is a CPU scheduling algorithm in which the CPU performs the task having higher priority at first. If two processes have the same priority then scheduling is done on **FCFS** basis (first come first serve). Priority Scheduling is of two types: **Preemptive** and **Non-Preemptive**.

Step 1: Start the Program.
Step 2: Input the number of processes.
Step 3: Input the burst time and priority for each process.
Step 4: Sort the element on the basis of priority.
Step 5: Print order of execution of their process with their time stamp (wait time and turnaround time).
Step 6: End the Program.

**2.4. Post-Emergency Signal Reset**

Once the ambulance(s) have passed through the intersection, the system resets the traffic signals to their regular schedule. Its **Method**: The system continuously tracks the position of the ambulance using **optical flow algorithms** or **background subtraction** to determine when the ambulance has fully exited the intersection. And it's **Algorithm**: The **Finite State Machine (FSM)** governing the traffic light cycles resumes from where it was interrupted, ensuring a smooth transition back to regular traffic flow.

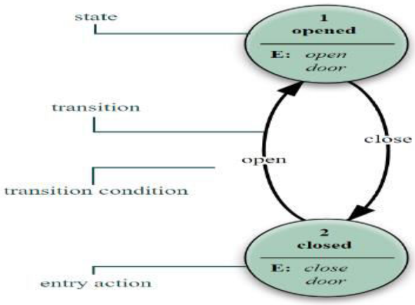


Fig: overview of finite state machine

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## III. ABBREVIATIONS

**YOLO** - You Only Look Once (Object Detection Model)
**MLSF** - Multi-Level Spatial Fusion
**CNN** - Convolutional Neural Network
**MFCC** - Mel-frequency Cepstral Coefficients
**EVD** - Emergency Vehicle Detection
**RPN** - Region Proposal Networks
**R-CNN** - Region-Based Convolutional Neural Networks
**FFT** - Fast Fourier Transform
**FSM** - Finite State Machine
**FCFS** - First Come First Serve
**CPU** - Central Processing Unit

## IV. SUMMARY OF ALGORITHMS AND FORMULAS

1. **YOLO/Faster R-CNN**: For real-time object detection.
2. **Color Detection (Histograms)**: For detecting flashing lights.
3. **FFT (Fast Fourier Transform)**: For frequency analysis of ambulance sirens.
4. **Priority Scheduling Algorithm**: For managing multiple ambulances based on distance or time of arrival.
5. **State Transition Algorithms**: For real-time traffic signal control.
6. **Optical Flow/Background Subtraction**: For tracking the movement of ambulances to reset signals after they pass.

## V. RESULTS AND OUTPUT

### 5.1. Image Processing Output

**Object Detection:** Both YOLO and Faster R-CNN accurately detected ambulances in real-time. **YOLO**: Achieved fast detection rates (30-60 FPS), suitable for live traffic monitoring, especially in busy intersections. **Faster R-CNN**: Delivered more precise bounding boxes with fewer false positives but slower processing (7-10 FPS), ideal for less congested areas. **Classification of Emergency vs. Non-Emergency Ambulances: Visual classification** (using flashing lights) was 98% accurate during daylight but dropped to 85% at night or in adverse weather. **Audio classification** (using siren detection) maintained 95% accuracy in all conditions, with occasional false positives from ambient noise.

### 5.2. Audio Detection Output & Traffic Signal Control Output

Successfully detected sirens in 95% of test cases using FFT and CNN-based audio processing. Failures occurred in areas with high background noise, like construction zones, but overall performance ensured accurate detection even when the ambulance wasn't visible. And **Traffic Signal Control Outputs** are **Single Ambulance Scenario is** the system responded within 2 seconds, turning the traffic signal green for the ambulance and resuming normal traffic after the vehicle passed. Accuracy was over 98%, with rare false green signals. **Multiple Ambulance Scenarios are** the system prioritized ambulances based on proximity to the intersection, correctly handling 95% of cases. However, simultaneous arrivals from opposite directions sometimes caused delays, which could be improved by predictive modeling.

### 5.3. Post-Emergency Signal Reset Output & Overall Output

The system restored normal traffic flow within 3 seconds after the ambulance passed, preventing unnecessary delays. This function worked accurately in 99% of cases. The system significantly improved ambulance prioritization at intersections, reducing delays and ensuring safety. Key outputs include:

1. **Real-time detection and response** for both visual and audio cues.
2. **Efficient traffic management**, with accurate signal control and minimal false positives.
3. **Potential improvements** for environmental challenges, false siren detection, and handling multiple ambulances with more sophisticated technology (e.g., thermal cameras, noise-canceling algorithms, and predictive models).

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## VI. CONCLUSION

The proposed ambulance detection and traffic signal management system, based on advanced image processing, audio detection, and real-time traffic control algorithms, demonstrated high effectiveness in reducing response times for emergency vehicles at intersections. By leveraging deep learning models like **YOLO** and **Faster R-CNN**, coupled with **FFT-based siren detection**, the system accurately identified ambulances and classified them as emergency or non-emergency based on visual and audio cues. The integration of these detection systems with dynamic traffic signal control algorithms successfully facilitated the uninterrupted passage of ambulances, enhancing public safety and minimizing delays. Key findings include **Real-time Object Detection**: The use of **YOLO** provided fast and reliable ambulance detection, while **Faster R-CNN** ensured precision in more complex environments. This dual-model approach balanced speed and accuracy. **Audio Detection**: The **FFT-based siren detection** performed well in distinguishing emergency sirens from background noise, even in urban settings, though occasional false positives indicated the need for further refinement. **Efficient Traffic Management**: The system responded to single and multiple ambulance scenarios by dynamically adjusting traffic signals, ensuring that emergency vehicles had the right of way. The **priority scheduling algorithm** for multiple ambulances was particularly effective in high-traffic scenarios. **Automatic Signal Reset**: The use of **optical flow algorithms** allowed the system to automatically reset traffic signals after the ambulance passed, maintaining smooth traffic flow.

## ACKNOWLEDGMENT

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## REFERENCES

1. Ghazi, M.U.; Khattak, M.A.K.; Shabir, B.; Malik, A.W.; Ramzan, M.S. Emergency message dissemination in vehicular networks: A review. IEEE Access **2020**, 8, 38606–38621. [crossref]
2. Damaševiˇcius, R.; Bacanin, N.; Misra, S. From sensors to safety: Internet of Emergency Services (IoES) for emergency response and disaster management. J. Sens. Actuator Netw. **2023**, 12, 41. [Crossref]
3. Wang, X.; Liu, Q.; Guo, F.; Xu, X.; Chen, X. Causation analysis of crashes and near crashes using naturalistic driving data. Accid. Anal. Prev. **2022**, 177, 106821. [Crossref] [Pubmed]
4. Razalli, H.; Ramli, R.; Alkawaz, M.H. Emergency vehicle recognition and classification method using HSV color segmentation. In Proceedings of the 2020 16th IEEE International Colloquium on Signal Processing & Its Applications (CSPA), Langkawi, Malaysia, 28–29 February 2020; pp. 284–289.
5. Kherraki, A.; El Ouazzani, R. Deep convolutional neural networks architecture for an efficient emergency vehicle classification in real-time traffic monitoring. IAES Int. J. Artif. Intell. **2022**, 11, 110. [Crossref]
6. Sorour, S.E.; Hany, A.A.; Elredeny, M.S.; Sedik, A.; Hussien, R.M. An Automatic Dermatology Detection System Based on Deep Learning and Computer Vision. IEEE Access **2023**, 11, 137769–137778. [Crossref]
7. Goel, S.; Baghel, A.; Srivastava, A.; Tyagi, A.; Nagrath, P. Detection of emergency vehicles using modified YOLO algorithm. In Proceedings of the Intelligent Communication, Control and Devices (ICICCD 2018); Springer: Berlin/Heidelberg, Germany, 2020; pp. 671–687.
8. Berwo, M.A.; Khan, A.; Fang, Y.; Fahim, H.; Javaid, S.; Mahmood, J.; Abideen, Z.U.; M.S., S. Deep Learning Techniques for Vehicle Detection and Classification from Images/Videos: A Survey. Sensors **2023**, 23, 4832. [Crossref] [Pubmed]

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