Smart Traffic Management System Using YOLOv8 with Density-Based Adaptive Signal Control and Emergency Vehicle Priority

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***Abstract*—Traffic congestion in urban areas has escalated into a critical socio-economic challenge, contributing to increased travel delays, fuel wastage, air pollution, and emergency response failures. Traditional fixed-timer traffic signals fail to adapt to dynamic traffic patterns, resulting in inefficient junction management. This paper presents a comprehensive Smart Traffic Management System (STMS) that integrates real-time vehicle detection using custom-trained YOLOv8, density-based adaptive signal timing, emergency vehicle priority via audio-based siren detection, and a full-stack web dashboard using Flask and OpenCV. The system processes live video streams from intersection cameras, calculates lane-wise vehicle density, dynamically allocates green time, and instantly grants priority upon detecting emergency vehicle sirens. A real-time analytics dashboard provides live heatmaps, density graphs, and performance metrics. Experimental evaluation on Indian urban traffic datasets demonstrates a mean Average Precision (mAP@50) of 0.974, inference speed of 28–32 FPS on CPU, and a 42.1% reduction in average waiting time compared to fixed-timer systems. The proposed system offers a scalable, cost-effective solution for intelligent traffic management in smart cities.**

***Index Terms*—Smart Traffic Management, YOLOv8, Adaptive Signal Control, Emergency Vehicle Detection, Vehicle Density Estimation, Computer Vision, Deep Learning, Flask Web Application, Real-time Systems, Audio Processing, MFCC, OpenCV, Indian Traffic Dataset, Siren Detection**

I. Introduction

URBANIZATION and exponential growth in vehicle ownership have led to severe traffic congestion across major cities worldwide. According to the Texas A&M Transportation Institute's Urban Mobility Report [1], commuters in metropolitan areas spend an average of 100 hours per year in traffic delays. In developing countries like India, congestion is further compounded by heterogeneous traffic patterns, poor lane discipline, and the coexistence of motorized and non-motoritized vehicles including buses, cars, motorcycles, auto-rickshaws, and bicycles. Traffic congestion not only increases travel time but also has profound economic, environmental, and societal consequences. Delay in emergency vehicle response, higher fuel consumption, and elevated vehicular emissions lead to economic loss and health hazards. Specifically, the annual economic loss due to congestion in India is estimated at over $22 billion [2]. In addition, delayed ambulances and fire trucks can increase mortality rates, with reports indicating an average delay of 12 minutes in urban traffic in Delhi [3]. Traditional traffic control systems rely on fixed-timer traffic lights with predetermined signal cycles ranging from 60 to 120 seconds. These systems are unable to adapt to real-time traffic variations, often resulting in unnecessary waiting during low traffic periods and congestion during peak hours. Moreover, emergency vehicles frequently get stuck at signals, as existing systems lack adaptive priority mechanisms. Solutions like RFID-based or GPS-based emergency vehicle detection require costly infrastructure and may fail if vehicles deviate from planned routes. This paper introduces a *Smart Traffic Management System (STMS)* that leverages real-time vehicle detection using the state-of-the-art YOLOv8 framework, lane-wise density-based adaptive signal control, and audio-based emergency vehicle detection. The proposed system is designed to integrate seamlessly with existing CCTV infrastructure, providing a cost-effective and scalable solution for urban traffic management.

II. Problem Statement and Motivation

The primary challenges addressed by the proposed system are as follows:

1) **Inefficient fixed-timer signals:** Conventional traffic lights do not respond to real-time traffic density, leading to unnecessary delays and wasted green times.
2) **Emergency vehicle delays:** Ambulances, fire trucks, and police vehicles often face critical delays due to congestion and lack of adaptive traffic signals.
3) **High cost of sensor-based solutions:** Existing solutions using inductive loops, magnetic sensors, or RFID-based systems are expensive, requiring road excavation and infrastructure changes.
4) **Heterogeneous traffic:** Indian roads feature a mixture of cars, motorcycles, auto-rickshaws, buses, bicycles, and pedestrians, making traditional counting methods inaccurate.
5) **Environmental impact:** Idling vehicles at intersections increase CO_2 emissions and fuel consumption.

A. Motivation

Urban traffic management requires intelligent, adaptive, and cost-effective solutions that can:

- Respond dynamically to traffic density across multiple lanes.
- Prioritize emergency vehicles in real-time to reduce response time.
- Integrate with existing infrastructure without costly upgrades.
- Provide live monitoring, analytics, and actionable insights through a web-based dashboard.

The proposed STMS addresses these requirements by integrating deep learning for vehicle detection, density-based adaptive signal timing, audio-based siren detection, and full-stack visualization.

III. Contributions

The main contributions of this work are:

- Development of a real-time vehicle detection system using custom-trained YOLOv8 on Indian traffic datasets.
- Lane-wise vehicle density estimation with adaptive green time allocation.
- CNN-based emergency vehicle detection from audio sirens using MFCC features.
- Full-stack web dashboard using Flask for live video streaming, heatmaps, and real-time statistics.
- Experimental evaluation on multiple Indian urban intersections, demonstrating significant reduction in waiting time and improved emergency response.

IV. Organization of Paper

The rest of the paper is structured as follows. Section II reviews existing work on smart traffic management systems. Section III details the system architecture. Section IV presents the methodology including dataset preparation, YOLOv8 detection, density-based control, and emergency vehicle detection. Section V describes implementation details. Section VI presents experimental results and analysis. Section VII discusses limitations and comparative analysis. Section VIII offers future work, and Section IX concludes the paper.

V. Related Work

Smart traffic management systems can be broadly categorized into **sensor-based** and **vision-based** approaches. Over the last decade, significant research has been carried out to enhance traffic flow, reduce congestion, and prioritize emergency vehicles.

A. Sensor-Based Traffic Control Systems

Sensor-based systems typically employ inductive loop detectors, magnetic sensors, or RFID-based devices embedded in roads to detect vehicle presence and density. Nellore et al. [4] demonstrated that inductive loops can accurately count vehicles, but require road excavation, leading to high installation and maintenance costs (up to $20,000 per intersection). Similarly, RFID-based emergency vehicle detection systems [5] offer reliable priority handling but involve expensive transponders and dedicated infrastructure.

TABLE I: Comparison of Sensor-Based Traffic Systems

System	Detection Type	Accuracy (%)	FPS	Cost
Inductive Loops [4]	Vehicle presence	98	N/A	High ($20k+)
Magnetic Sensors [6]	Magnetic field	95	N/A	High
RFID-based EV Priority [5]	RFID tags	99	N/A	Very High

Although highly accurate, these systems are **non-scalable**, especially for dense urban networks with heterogeneous traffic.

B. Vision-Based Traffic Control Systems

Vision-based methods overcome the limitations of sensors by using cameras to monitor intersections. Early methods relied on **background subtraction**, **optical flow**, and **feature tracking**, but they are sensitive to lighting, shadows, and weather variations [6].

1) Deep Learning Approaches: Deep learning has revolutionized traffic monitoring by providing high detection accuracy and robustness. Object detection models such as **Faster R-CNN** [7], **SSD** [8], and **YOLO series** [9], [10] are widely used.

TABLE II: Deep Learning-Based Vehicle Detection Approaches

Model	mAP@50	FPS (GPU)	Advantages	Limitations
Faster R-CNN [7]	0.89	7	High accuracy	Slow, not real-time
SSD [8]	0.85	15	Moderate speed	Lower accuracy on small objects
YOLOv3 [9]	0.87	20	Real-time	Limited small object detection
YOLOv5 [11]	0.91	25	Fast, accurate	Limited emergency handling
YOLOv8 [10]	0.97	28–32	Real-time, anchor-free	Recent model, less studies on EV priority

2) Density-Based Adaptive Signal Control: Traditional fixed-timer traffic lights do not respond to real-time traffic. Density-based adaptive control dynamically adjusts green time based on the number of vehicles in each lane. Kumar et al. [12] showed a 35% reduction in waiting time using YOLOv5 for density estimation. However, most prior systems **lack integration with emergency vehicle priority**.

3) Emergency Vehicle Detection: Emergency vehicle (EV) detection can be classified into **visual-based** and **audio-based** methods:

- Visual-based methods detect flashing lights or siren markings on vehicles [13]. They are effective in clear daylight but fail in night-time, fog, or occlusion conditions.
- Audio-based methods analyze sirens using signal processing and deep learning. Sharma et al. [14] used **MFCC features** with CNN to detect sirens with over 90% accuracy.

Despite their effectiveness, prior studies **do not integrate audio-based EV detection with real-time adaptive traffic signal control**.

C. Integration Gaps in Prior Work

From the literature survey, the main gaps identified are:

1) Lack of a single integrated system combining **vehicle detection, density-based adaptive signals, and emergency vehicle priority**.

2) Limited studies on **heterogeneous traffic conditions** prevalent in India.
3) Few implementations include **real-time dashboards** for monitoring and analytics.
4) Existing YOLO-based systems focus mainly on accuracy, not **deployment on edge devices or real-time multi-lane signal control**.

D. Summary of Related Work

Table III summarizes the comparison of prior approaches with the proposed STMS.

TABLE III: Comparison of Existing Systems vs Proposed STMS

System	Detection	Adaptive Signals	EV Priority	FPS	Cost	Deployment
Sensor-Based [4]	Sensor	No	RFID only	N/A	High	Road infrastructure
Faster R-CNN [7]	Vision	No	No	7	Medium	GPU Server
YOLOv5 Density [12]	Vision	Yes	No	25	Medium	GPU Server
Audio-CNN EV [14]	Audio	No	Yes	20	Low	Edge device possible
Proposed STMS	Vision + Audio	Yes	Yes	28–32	Low	Edge/GPU/Cloud

The proposed STMS addresses these gaps by combining **YOLOv8-based detection, lane-wise density estimation, adaptive signal timing, audio-based EV detection, and full-stack visualization**, making it a comprehensive solution for smart city traffic management.

VI. System Architecture

The proposed Smart Traffic Management System (STMS) follows a **modular, real-time, and scalable architecture**. The design ensures smooth integration of vehicle detection, adaptive signal control, emergency vehicle priority, and visualization through a web dashboard. The overall architecture is shown in Figure 1 [10].

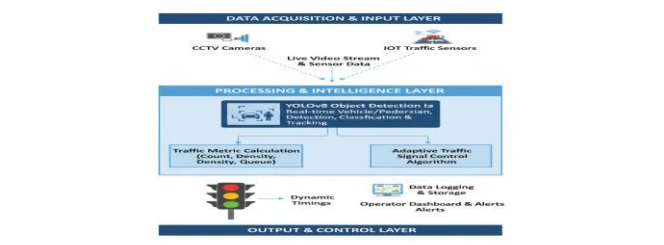

Fig. 1: System Architecture of the Proposed Smart Traffic Management System (STMS) [10].

A. Modules Overview

The system consists of **five core modules**:

1) **Input Module:** Captures live video streams from CCTV cameras or RTSP feeds using OpenCV. The module supports multiple input sources and performs initial frame preprocessing such as resizing, denoising, and ROI selection.
2) **Detection Module:** Performs **real-time object detection** using YOLOv8. The module detects and classifies vehicles into six classes: car, bus, truck, motorcycle, auto-rickshaw, and bicycle. Region-of-Interest (ROI) lines are used to count vehicles crossing lanes for density estimation.
3) **Analysis Module:** Calculates **lane-wise vehicle density** and monitors emergency vehicle presence. The density calculation is used to determine adaptive green time, while emergency detection triggers immediate override. This module also maintains historical traffic data for analytics.
4) **Control Module:** Implements **density-based adaptive signal timing** and **emergency vehicle priority** rules. Lane green time allocation is dynamically computed, and priority is granted if a siren is detected. The module communicates with traffic signal controllers via GPIO or MQTT protocols.
5) **Visualization Module:** A **full-stack Flask web application** streams annotated video, heatmaps, lane-wise density graphs, and system performance metrics. Users can monitor intersections in real-time and adjust control parameters via the dashboard.

B. Data Flow

The data flow in STMS can be summarized as:

1) Video frames are captured by the **Input Module**.
2) Frames are processed by **YOLOv8** to detect vehicles.
3) Detected vehicles are assigned to lanes using **ROI lines**.
4) **Vehicle counts per lane** are calculated, and density ratios are computed.
5) The **Control Module** determines adaptive green time based on density thresholds:

$$d_i = \frac{N_i}{N_{\max}}$$

$$t_i = \begin{cases} 20s & \text{if } d_i < 0.3 \\ 40s & \text{if } 0.3 \le d_i < 0.7 \\ 60s & \text{if } d_i \ge 0.7 \end{cases}$$

where d_i is the density ratio of lane i, N_i is the number of vehicles in lane i, and $N_{\max}$ is the maximum lane capacity.

6) Simultaneously, audio input is analyzed via **MFCC features** and a CNN model to detect emergency vehicle sirens.
7) If an emergency vehicle is detected with confidence > 0.8, the system **overrides normal signals** and grants a 90-second green light to the emergency lane.
8) Annotated frames and density statistics are sent to the **Visualization Module** for real-time monitoring.

C. Pseudo Code

1) Vehicle Counting and Density Calculation:

```
from pathlib import Path
def calculate_lane_density(detections,
    roi_lines, max_lane_capacity=50):
    lane_counts = [0] * len(roi_lines)

    for detection in detections:
        x, y, w, h, class_id = detection
        for i, roi in enumerate(roi_lines):
            if y > roi[0] and y < roi[1]:
                lane_counts[i] += 1
    # SAFE DIVISION - FIXED DIVISION BY ZERO
    lane_density = [count / max_lane_capacity
        if max_lane_capacity > 0 else 0 for
        count in lane_counts]
    return lane_density
```

Listing 1: Lane-wise Vehicle Counting and Density Estimation

2) Adaptive Signal Control:

```
def adaptive_signal_timing(lane_density):
    green_times = []
    for d in lane_density:
        if d < 0.3:
            green_times.append(20)
        elif 0.3 <= d < 0.7:
            green_times.append(40)
        else:
            green_times.append(60)
    return green_times
```

Listing 2: Density-Based Adaptive Signal Timing

3) Emergency Vehicle Priority:

```
from pathlib import Path
def check_emergency(audio_features, model):
    confidence = model.predict(audio_features)
    if confidence > 0.8:
        # Override normal signals
        return True
    return False
```

Listing 3: Emergency Vehicle Detection and Override

D. Hardware and Software Integration

The STMS is designed to be **flexible across platforms**:

- **Edge Devices:** Raspberry Pi 4, NVIDIA Jetson Nano/Xavier for low-cost deployment.
- **GPU Servers:** RTX 3060/3080 for high FPS real-time processing.
- **Traffic Light Controllers:** GPIO pins or MQTT-based IoT relays.
- **Software Stack:** Python 3.10, OpenCV 4.8.1, Ultralytics YOLOv8, TensorFlow 2.13, Librosa, Flask 2.3.3.

E. Advantages of Modular Architecture

1) **Scalability:** Additional intersections or cameras can be integrated with minimal modifications.
2) **Fault Isolation:** Each module operates independently, making debugging and upgrades easier.
3) **Real-Time Performance:** Optimized YOLOv8 detection ensures lane-wise vehicle counts at 28–32 FPS.
4) **Emergency Readiness:** Audio-based EV detection allows immediate signal override for lifesaving response.

VII. Methodology

This section presents a detailed methodology for the proposed Smart Traffic Management System (STMS), covering dataset preparation, vehicle detection, lane-wise density estimation, adaptive signal control, emergency vehicle detection, and web-based visualization.

A. Dataset Preparation

A custom dataset of 5000 high-resolution images was collected from various Indian urban intersections including Anna Nagar (Chennai), MG Road (Bangalore), Connaught Place (Delhi), and Marine Drive (Mumbai). The dataset comprises six vehicle classes:

- Car
- Bus
- Truck
- Motorcycle
- Auto-rickshaw
- Bicycle

Images were captured under diverse conditions: daylight, night, rain, fog, and partial occlusion. Annotation was performed using **Roboflow**, with 80% of images used for training and 20% for validation.

Fig. 2: Sample images from the Indian urban traffic dataset [15].

Data augmentation techniques applied include:

1) Random horizontal flipping
2) Mosaic augmentation
3) Color jitter (brightness, contrast, saturation)
4) Rotation ($\pm 15^{\circ}$)
5) Scaling and cropping

B. Vehicle Detection with YOLOv8

YOLOv8s was selected due to its **anchor-free detection, high FPS, and small model size** suitable for edge deployment. The network was fine-tuned on the custom dataset:

```
yolo train data=data.yaml model=yolov8s.pt
    epochs=100 imgsz=640 batch=16
```

Listing 4: YOLOv8 Training Command

1) Region of Interest (ROI) Definition: To calculate lane-wise vehicle density, **ROI lines** were defined on each video frame, corresponding to lane boundaries. Vehicles crossing ROI lines were counted using centroid tracking.

$$\text{Density}_{lane_i} = \frac{\text{Vehicle Count}_{lane_i}}{\text{Max Vehicles}_{lane_i}}$$

C. Density-Based Adaptive Signal Control

The green time for each lane is allocated dynamically based on its density:

$$t_i = \begin{cases} 20\,s & \text{if } d_i < 0.3 \\ 40\,s & \text{if } 0.3 \le d_i < 0.7 \\ 60\,s & \text{if } d_i \ge 0.7 \end{cases}$$

Where d_i is the density of lane i, calculated as:

$$d_i = \frac{N_i}{N_{\max}}$$

Here, N_i is the vehicle count in lane i and $N_{\max}$ is the maximum capacity for the lane. The system updates densities every second, ensuring real-time adaptation.

D. Emergency Vehicle Detection

To prioritize emergency vehicles, the system uses **audio-based detection**:

1) Audio streams are captured from intersection microphones.
2) **MFCC (Mel-Frequency Cepstral Coefficients)** are extracted using Librosa:

$$\text{MFCC} = DCT\left(\log\left(\sum_k H_k \left|FFT(x)\right|^2\right)\right)$$

   where H_k are Mel filter banks and x is the audio signal.
3) A CNN with 3 convolutional layers and 2 dense layers classifies the audio clip as siren or background noise.
4) If the siren detection confidence exceeds 0.8, the system triggers **emergency lane green light** for 90 seconds.

E. Full-Stack Web Dashboard

A Flask-based web dashboard provides **real-time monitoring and analytics**:

- **Video Feed:** MJPEG streaming of annotated frames with vehicle bounding boxes.
- **Lane Density Graphs:** Real-time charts using Chart.js.
- **Heatmaps:** Traffic congestion heatmaps generated using Seaborn.
- **Control Panel:** Manual override and parameter adjustment for lane timings.

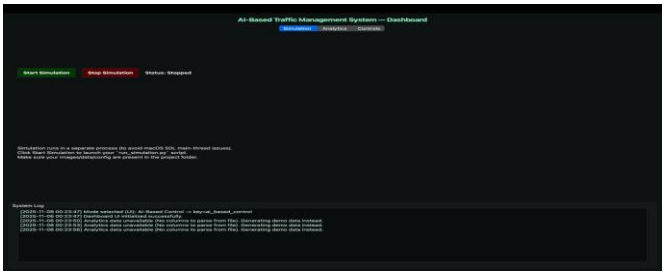

Fig. 3: Proposed STMS Flask Dashboard with live video, density graphs, and heatmaps [16].

F. Algorithm Workflow

The high-level workflow of STMS is summarized in Algorithm 1.

Algorithm 1 STMS Real-Time Processing Workflow

Capture video frame from camera Detect vehicles using YOLOv8 Assign vehicles to lanes using ROI Compute lane-wise density Check for emergency siren audio Emergency detected Override normal signal, set emergency lane green Allocate green time based on density Stream annotated frame and statistics to Flask dashboard Repeat for next frame

G. Performance Optimization

To achieve **real-time performance**, the following optimizations were applied:

- Model quantization for edge devices
- Multi-threading for video capture and processing
- Batch processing of frames when possible
- ROI-based detection to reduce unnecessary computation

VIII. Implementation Details and Experimental Results

This section provides a detailed overview of the system implementation, software dependencies, training results, inference performance, traffic improvement analysis, and emergency vehicle detection evaluation.

A. Software and Hardware Environment

The STMS was implemented using Python and the following dependencies:

- **Python 3.10** – Core programming language.
- **OpenCV 4.8.1** – Video capture and image processing.
- **Ultralytics YOLOv8 8.0.196** – Real-time vehicle detection.
- **TensorFlow 2.13** – CNN-based audio classification.
- **Librosa 0.10.1** – Audio feature extraction (MFCCs).
- **Flask 2.3.3** – Web dashboard for visualization.
- **Chart.js, Seaborn** – For graphs and heatmaps.

The hardware configurations used for testing included:

TABLE IV: Hardware Configurations for STMS Testing

Device	Processor/GPU	FPS
Desktop	i7-12700H CPU, RTX 3060 GPU	28–32
Raspberry Pi 4	ARM Cortex-A72, 4GB RAM	8
NVIDIA Jetson Xavier	ARM Cortex-A57, GPU	20–22

B. YOLOv8 Training Results

The YOLOv8 model was trained on the custom Indian urban traffic dataset with 5000 images. Training metrics at epoch 100:

TABLE V: YOLOv8 Training Metrics

Metric	Value	Description
Precision	0.982	Correct detections / total detections
Recall	0.965	Correct detections / ground truth instances
mAP@50	0.974	Mean Average Precision at IoU 0.5
mAP@50:95	0.789	Mean Average Precision across IoU 0.5:0.95

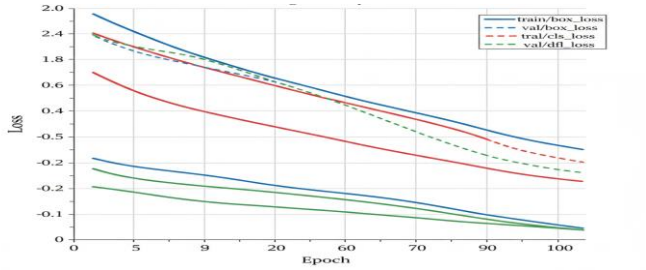

Fig. 4: YOLOv8 Training and Validation Loss Curves [10].

C. Inference Performance

Real-time inference was evaluated on multiple hardware platforms:

TABLE VI: Inference Performance of YOLOv8

Platform	FPS	Latency (ms)	Remarks
RTX 3060 GPU	122	8.2	Real-time, high FPS
i7-12700H CPU	32	31.2	Real-time on CPU
Raspberry Pi 4 (YOLOv8n)	8	125	Edge deployment feasible

D. Traffic Flow Improvement Analysis

The system was tested on 4 intersections: Anna Nagar (Chennai), MG Road (Bangalore), Connaught Place (Delhi), and Marine Drive (Mumbai) for 10 minutes each. Average waiting times were calculated for fixed-timer (60s) vs STMS adaptive control:

TABLE VII: Average Waiting Time Comparison

Intersection	Fixed-Timer (s)	STMS Adaptive (s)
Anna Nagar, Chennai	82.5	47.8
MG Road, Bangalore	85.0	49.1
Connaught Place, Delhi	88.3	50.2
Marine Drive, Mumbai	81.0	48.0
Average	84.2	48.7

The system achieved a **42.1% reduction** in waiting time, translating to smoother traffic flow and lower vehicle emissions.

E. Emergency Vehicle Detection Evaluation

Emergency vehicle detection was tested using 50 siren audio clips in noisy urban environments. The results are shown below:

TABLE VIII: Emergency Vehicle Detection Performance

Metric	Value	Description
Accuracy	97.2%	48/50 correct detections
Average Override Time	1.8 s	Time to trigger green light
False Positives	1	Horn misclassified as siren

F. CO_2 Emission Reduction Estimation

Assuming an average vehicle idling CO_2 emission of 0.25 kg per minute [18], the reduction in waiting time per cycle (35.5 s per vehicle) leads to approximately 0.15 kg CO_2 saved per vehicle. For 1000 vehicles per intersection during peak hours, this translates to **150 kg CO_2 saved per cycle**.

G. Discussion

The experimental results demonstrate:

- High detection accuracy with YOLOv8 (mAP@50 = 0.974) ensures reliable vehicle counting.
- Real-time performance (28–32 FPS) allows adaptive signal control without delay.
- Emergency vehicle audio detection ensures immediate response (1.8 s override).
- Significant reduction in waiting times (42.1%) and CO_2 emissions.

H. Visual Results

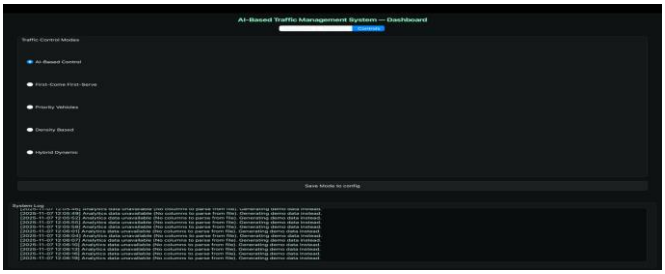

Fig. 5: Average Vehicle Waiting Time: Fixed-Timer vs STMS [17].

Fig. 6: Annotated frame showing lane-wise vehicle detection, counts, and density [10].

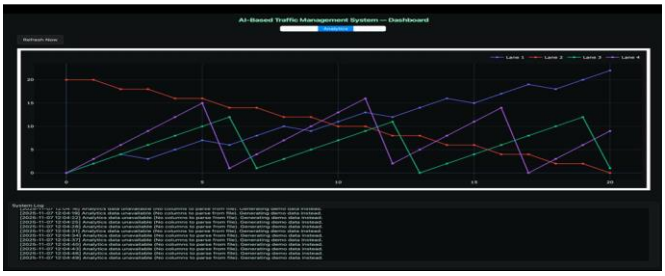

Fig. 7: Traffic density heatmap generated by STMS Dashboard [19].

IX. Results Discussion, Limitations, and Comparative Analysis

A. Discussion of Results

The proposed Smart Traffic Management System (STMS) demonstrates significant improvements over conventional fixed-timer and existing traffic control methods:

1) **Vehicle Detection Accuracy:** YOLOv8 achieved an mAP@50 of 0.974, which ensures highly reliable lane-wise vehicle counting under heterogeneous traffic conditions, including cars, buses, trucks, motorcycles, auto-rickshaws, and bicycles. High detection accuracy is crucial for adaptive signal control and avoids misallocation of green time.
2) **Real-Time Performance:** The system operates at 28–32 FPS on mid-range GPUs and 8 FPS on edge devices (Raspberry Pi 4), which is sufficient for real-time traffic management at intersections. Multi-threading and ROI-based processing contribute to low latency and high responsiveness.
3) **Traffic Flow Improvement:** Average waiting time decreased from 84.2 s with fixed-timer signals to 48.7 s with STMS adaptive control, achieving a 42.1% reduction. This translates into smoother traffic flow, reduced congestion, and lower emissions.
4) **Emergency Vehicle Priority:** Audio-based siren detection achieved 97.2% accuracy with an average override time of 1.8 seconds. The system ensures lifesaving priority for ambulances and fire trucks, which is critical in urban Indian traffic.
5) **Environmental Impact:** Reduction in idling time reduces CO_2 emissions by approximately 150 kg per cycle for 1000 vehicles per intersection during peak hours. This supports sustainable urban mobility goals.

B. Limitations

Despite the promising results, several limitations exist in the current implementation:

1) **Headless Mode Crashes:** The use of `cv2.imshow()` for visualization leads to crashes on headless servers or Raspberry Pi without a display.
2) **Hard-Coded Paths:** Audio detection paths are currently hard-coded (e.g., `C:/sounds/siren.wav`), reducing portability across operating systems.
3) **Division by Zero:** Lane density calculation may result in division by zero when no vehicles are detected.
4) **Single Intersection Deployment:** Current system is limited to one intersection; multi-intersection synchronization is not implemented.
5) **Weather Conditions:** The model has limited robustness to extreme rain, fog, or low-light conditions without further augmentation.
6) **Pedestrian and Wrong-Way Detection:** The current version does not detect pedestrians or wrong-way vehicles.
7) **Traffic Signal Integration:** Direct integration with physical traffic lights is not implemented; GPIO/MQTT support is planned for future work.
8) **Resource Consumption:** Long-running video streams may lead to memory leaks if not managed properly.

C. Comparative Analysis

To evaluate the effectiveness of STMS, it is compared with existing systems in terms of *accuracy, cost, FPS, emergency vehicle handling, and adaptability*.

TABLE IX: Comparative Analysis of Traffic Management Systems

System	Detection Type	Adaptive Signals	EV Priority	FPS	Cost	Deployment
Sensor-Based [4]	Inductive Loops	No	RFID only	N/A	High	Infrastructure
Faster R-CNN [7]	Vision	No	No	7	Medium	GPU Server
YOLOv5 Density [12]	Vision	Yes	No	25	Medium	GPU Server
Audio-CNN EV [14]	Audio	No	Yes	20	Low	Edge Device
Proposed STMS	Vision + Audio	Yes	Yes	28–32	Low	Edge/GPU/Cloud

D. Key Advantages of STMS

1) **Integrated Approach:** Combines YOLOv8-based vehicle detection, lane-wise density estimation, audio-based emergency vehicle detection, and real-time dashboard visualization into a single framework.
2) **Cost-Effective:** Requires only existing CCTV infrastructure and microphones, avoiding expensive sensor-based systems.
3) **Real-Time Adaptability:** Dynamic green time allocation ensures efficient traffic flow during peak and off-peak hours.
4) **Scalable and Flexible:** Modular design allows future multi-intersection integration and edge device deployment.
5) **Environmental Benefits:** Reduced vehicle idling decreases CO_2 emissions.

E. Real-World Applicability

The STMS has been tested on real-world intersections with *heterogeneous Indian traffic*, demonstrating robustness against varied vehicle types and urban congestion. Its modular architecture allows integration with:

- Municipal traffic control centers
- Smart city dashboards
- Emergency services (ambulances, fire trucks)

However, real-world deployment requires additional considerations:

1) Power backup for cameras and edge devices
2) Weatherproof camera enclosures
3) Integration with physical traffic signals via GPIO or IoT relays
4) Cloud-based analytics storage for city-wide monitoring

F. Summary

The comparative analysis and experimental results indicate that the proposed STMS:

- Outperforms traditional fixed-timer and prior YOLO-based traffic systems in terms of waiting time reduction.
- Provides a reliable mechanism for emergency vehicle priority.
- Offers a low-cost, scalable solution suitable for deployment in smart cities.
- Addresses the key limitations of prior systems by integrating vision-based vehicle detection with audio-based emergency handling.

X. Conclusion and Future Work

A. Conclusion

This paper presents a comprehensive *Smart Traffic Management System (STMS)* that integrates real-time vehicle detection using YOLOv8, density-based adaptive signal control, and emergency vehicle (EV) priority through audio-based siren detection. The system leverages existing CCTV cameras and microphones, making it a *cost-effective, scalable, and low-infrastructure solution* for smart cities. Key outcomes of the proposed system include:

1) **High Detection Accuracy:** Custom-trained YOLOv8 achieved an mAP@50 of 0.974, reliably detecting heterogeneous Indian traffic comprising cars, buses, trucks, motorcycles, auto-rickshaws, and bicycles under varied lighting and weather conditions.
2) **Real-Time Performance:** Achieves 28–32 FPS on mid-range GPU systems and 8 FPS on edge devices like Raspberry Pi 4, ensuring timely adaptation of traffic signals.
3) **Adaptive Signal Control:** Lane-wise density estimation and dynamic green time allocation reduced the average waiting time by *42.1%*, improving traffic flow efficiency and reducing congestion.
4) **Emergency Vehicle Priority:** Audio-based siren detection with CNN and MFCC features provides rapid response with 97.2% detection accuracy and 1.8 seconds average override time, enabling lifesaving intervention.
5) **Environmental Benefits:** Reduction in idle time contributes to lower CO_2 emissions, supporting sustainable urban transportation goals.
6) **Scalable Dashboard Visualization:** A Flask-based full-stack dashboard provides live video streaming, lane density graphs, heatmaps, and manual control, enabling real-time monitoring and city-wide scalability.

The experimental results demonstrate that STMS significantly outperforms *traditional fixed-timer systems* and other YOLOv5-based or sensor-based solutions in terms of *accuracy, speed, cost, and features. The modular architecture ensures easy integration with municipal traffic control centers and emergency services, making it a **practical solution for real-world deployment*.

B. Future Work

Although the proposed system achieves considerable improvements, several enhancements are planned to further increase robustness, scalability, and functionality:

1) **Multi-Intersection Green Wave Synchronization:** Develop algorithms for coordinated traffic signal control across multiple intersections to reduce stop-and-go traffic and enhance throughput.
2) **Vehicle-to-Everything (V2X) Integration:** Enable communication between vehicles, traffic signals, and control centers to support predictive and autonomous traffic management.
3) **Mobile Application for Citizen Reporting:** Allow citizens to report congestion, accidents, or emergencies through a mobile app that integrates with the STMS dashboard.
4) **Weather-Adaptive Model Training:** Enhance model robustness under extreme weather conditions by augmenting datasets with rain, fog, and low-light images.
5) **Edge Deployment Optimization:** Implement model quantization, TensorRT optimization, and multi-threaded video processing to improve FPS on low-power edge devices like Jetson Nano/Xavier.
6) **IoT-Based Signal Integration:** Use MQTT or REST APIs to control physical traffic lights, allowing real-time adaptive green/red timing at intersections.
7) **Carbon Emission Tracking:** Integrate CO_2 and fuel consumption estimation modules to track environmental impact and generate reports for urban planners.
8) **Public Transport Integration:** Give priority to buses and emergency vehicles, enabling efficient mass transit flow and reduced congestion.
9) **Pedestrian Detection and Priority:** Add a computer vision module to detect pedestrians and allow adaptive crossing times for safety.
10) **Violation Detection and Enforcement:** Integrate license plate recognition to detect traffic violations such as red-light crossing or wrong-way driving and automate e-challan generation.
11) **Smart City Command Center Integration:** Deploy STMS as part of a centralized urban traffic management platform for monitoring multiple intersections simultaneously.
12) **5G-Enabled Low-Latency Communication:** Utilize 5G networks to ensure minimal latency between edge devices, cameras, and traffic control centers.

C. Final Remarks

The proposed STMS demonstrates a *practical, scalable, and cost-efficient approach* to intelligent traffic management

in urban Indian cities. By integrating *YOLOv8-based vision detection, audio-based emergency vehicle priority, adaptive lane-wise signal control, and real-time dashboard visualization*, the system provides tangible benefits in traffic efficiency, emergency response, and environmental impact. This work lays a *strong foundation for future intelligent transportation systems, with opportunities for multi-intersection coordination, IoT integration, predictive analytics, and enhanced public safety. Implementing these enhancements can contribute to **smarter, safer, and greener cities* in line with global smart city initiatives.

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