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AI-BASED DYNAMIC TRAFFIC MANAGEMENT SYSTEM WITH REAL-TIME DETECTION & PRIORITY SIGNAL OPTIMIZATION

Sanjay Rahul P[1], Sathya Moorthy A[2], M. Maheswari M.E., (Ph. D),[3]

Student, Department of Computer Science and Engineering, Anand Institute of Higher Technology, Kazhipattur, Chennai[1,2]

Associate Professor, Department of Computer Science and Engineering, Anand Institute of Higher Technology, Kazhipattur, Chennai[3]

Abstract: Urban traffic management is getting more and more difficult as the city expands and the number of vehicles increases. To address this, we put forward an AI-Based Dynamic Traffic Management System with Real-Time Detection & Priority Signal Optimization that, through computer vision and object identification, can effectively monitor and direct traffic flow. Conventional systems usually rely on pre-programmed timers or physical sensors, which can lead to bad timing of signals and slow reaction to real road conditions. Our system eliminates the use of these external sensors since it uses live video feeds to identify vehicles and pedestrians in real-time. It constantly monitors traffic density and flow patterns, enabling traffic signals to adjust dynamically instead of adhering to a fixed schedule. One of the key advantages of this system is its capacity to give priority to emergency vehicles and increase pedestrian safety at crossings. This makes emergency responses quicker and walkways safer for the public. By shifting from static, sensor-based techniques and embracing an AI-driven, vision-based solution, the system provides a more intelligent, scalable, and affordable solution for traffic management in today's world.

Keywords*:* Dynamic Traffic Management, Real-Time Object Detection, AI-Based Traffic Control, Traffic Signal Optimization, Emergency Vehicle Prioritization, Pedestrian Safety, Computer Vision in Traffic Systems, Smart City Traffic Solutions, Adaptive Traffic Signal Timing

I. INTRODUCTION

The assignment falls in the domain of Intelligent Traffic Systems, Machine learning and Computer Vision, both crucial segments of current-day smart city expansion. As city populations continue to expand, they need to create smarter, intelligent traffic management methods to keep streets clear of gridlocks and be safe. Dealing with the traffic in towns is among the biggest urban worries of the time. With mounting populations, urbanization, and growth in the number of vehicles on the roads, conventional traffic management systems are lagging behind. Fixed-timer based signaling and sensor-based systems, although effective enough in the past, are now falling short in dynamically varying road conditions. Congestion, excessive waiting time, unproductive signal cycles, and late emergency response are now typical problems that not only affect the day-to-day existence of commuters but also play an important role in environmental degradation due to unnecessary fuel consumption and emissions.

To address these issues, there is an urgent need for intelligent traffic control systems that can respond in real-time, based on real traffic conditions and not pre-conceived notions. This project envisions an innovative solution: an AI-Based Dynamic Traffic Management System with Real-Time Detection & Priority Signal Optimization, a vision-based, adaptive system that can transcend the limitations of conventional models and introduce a new degree of responsiveness and efficiency to urban mobility. The core of this system is the potential of computer vision. As opposed to relying on hardware sensors installed inside the roads or fixed timing patterns, this system bases its responses on real-time video feeds from traffic cameras. These video streams are analyzed using AI models that can detect and identify vehicles, pedestrians, and emergency vehicles at very high accuracy. Real-time object detection allows the system to observe the precise situation at every intersection moment by moment, knowing vehicle density, traffic patterns, pedestrian presence, and the arrival of critical emergency responders. This data-driven consciousness enables traffic signals to be dynamically adjusted, maximizing the green, red, and amber phases based on real-time requirements. For example, if a road has heavy traffic and another is lightly congested, the green light duration gets

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automatically prolonged for the heavier side. Crossings for pedestrians are also controlled in a similar way, wherein individuals waiting to cross are prioritized suitably based on real-time detection instead of relying on programmed signal cycles or buttons that could be overlooked.
One of the most influential aspects of the system is how it can detect and treat emergency vehicles like ambulances as a priority. When an emergency vehicle is identified approaching an intersection, the system will sense and adjust the signal patterns to provide the vehicle with a clear and safe route, drastically lessening response times without inducing disruption to the overall traffic network. This aspect not only increases public safety but can also prove to be life-saving where seconds matter. Moreover, the system puts great emphasis on pedestrian safety, a key issue in urban traffic intersections. Most traditional systems concentrate a lot on vehicle movement, often neglecting pedestrian requirements. Through identifying waiting pedestrians and considering them in signal changes, this AI-based method ensures safer and more inclusive traffic control for everyone on the road.
In short, the real-time detection & priority signal optimization AI-based Dynamic Traffic management system is a revolutionary leap forward in the way cities can manage and optimize their traffic systems. Leveraging the power of real-time computer vision, removing the limitations of sensor-dependent configurations, and balancing equally emergency responsiveness and pedestrian safety, this system provides a smarter, faster, safer, and more sustainable solution for urban traffic challenges of today—and tomorrow.

II. RELATED WORKS

2.1 Traditional Traffic Light Control

Traffic management systems in the early days were based on fixed-time signals under which traffic lights were programmed to work on fixed schedules irrespective of actual-time traffic movement. Fixed-time control, though adequate in initial city developments, proved less and less effective with growing vehicle density [1][2]. Fixed-time control caused heavy waiting times, peak-hour congestion, and wasted road space usage. They were not flexible in their approach and caused undue haltages even during light traffic, largely affecting urban mobility. To counter the drawback of static systems, sensor-based adaptive control techniques were developed. With the aid of technologies such as loop detectors, infrared sensors, and RFID systems, traffic flow could be sensed in real-time, and signal timings could be optimized accordingly [3][4]. This innovation minimized congestion to a large extent compared to fixed-timing systems. But it brought with it new challenges of high installation costs, maintenance intricacies, and susceptibility to environmental factors such as rain, dust, and physical deterioration, resulting in expensive long-term running and lower reliability. The advent of computer vision technologies introduced a new generation of traffic management solutions. Through the analysis of real-time video feeds from CCTV cameras, these systems were able to estimate traffic density, identify pedestrian activity, and modify signal timings accordingly [5][6][7]. Vision-based systems obviated the requirement for expensive ground-based sensors. But early deployments tended to be limited to mere vehicle counting and did not feature sophisticated scene awareness like discriminating among vehicle types or grasping accident situations, so their capability for maximizing traffic overall was capped. One of the key developments in AI-driven traffic systems is the identification and giving right-of-way to emergency vehicles. Scientists created techniques using audio and visual recognition methods to identify ambulances, fire engines, and police cars quickly [8][9][10]. Techniques like YOLO-based object detection and CNN classifiers facilitated fast recognition of emergency vehicles to provide them with right-of-way at intersections. Still, issues persist in unfavorable situations like nighttime identification, visual obstruction, and urban noise interference, which at times impact recognition accuracy. Current developments integrate deep learning models for real-time dynamic traffic control. AI models like YOLO (You Only Look Once) have been trained on heterogeneous traffic datasets to detect multiple objects in real-time, allowing systems to dynamically adjust signal timings based on real-time traffic conditions [11][12][13]. These models showed better adaptability to changing conditions than conventional approaches. However, AI models are computationally expensive, demanding strong hardware and effective model optimization methods for real-world implementation in big cities. Contemporary smart city projects plan to incorporate AI-based traffic control within larger city infrastructures through the use of IoT platforms, cloud computing, and real-time analysis to form traffic ecosystems connected in real-time [14][15][16]. AI-based smart systems provide real-time information sharing among traffic nodes, optimizing flow and emergency responses. There are issues such as data privacy, cybersecurity, and the need for standardized communication protocols among municipal systems to enable easy operation. Comparative research has widely shown that AI-based adaptive systems perform better than conventional fixed-timing and sensor-based adaptive models in congestion reduction, travel delay minimization, and emergency vehicle mobility improvement [17][18][19][20]. The research repeatedly indicates that AI-based traffic systems are more efficient, scalable, and cost-effective in the long run. Yet, large-scale implementation still encounters obstacles in terms of upfront capital investment, public policy frameworks, and technical integration with current traffic infrastructure.

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III. SYSTEM ARCHITECTURE

The proposed system presents an intelligent, real-time adaptive traffic control solution powered by computer vision and IoT, designed to enhance urban mobility, emergency responsiveness, and pedestrian safety. The architecture is modular and built for scalability, comprising four essential layers that interact seamlessly: Input Layer, Processing & Specification, Decision System, and IoT-Based Signal Control as depicted in Figure 3.1

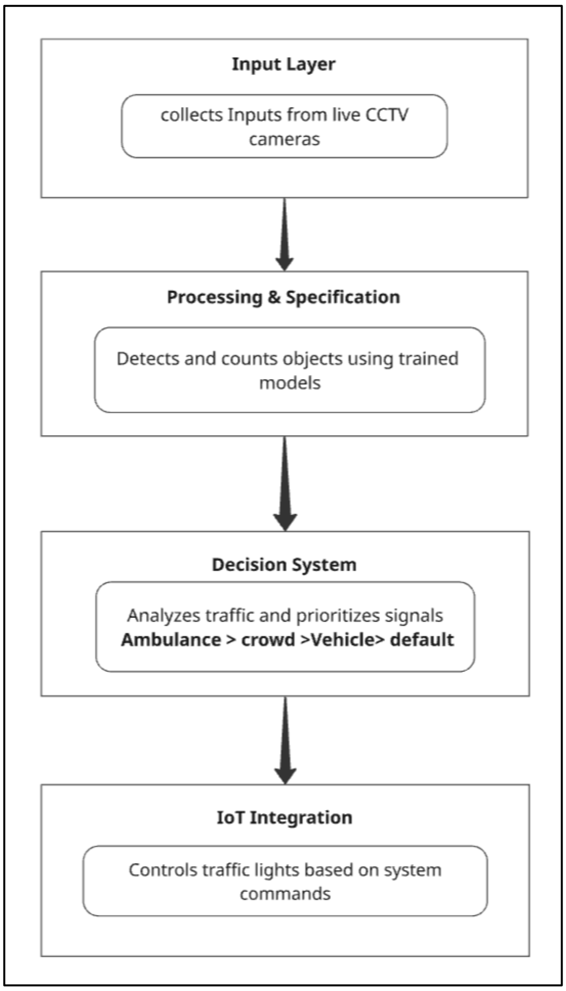

Fig. 3.1 System Architecture

3.1 Input Layer – Real-Time Traffic Feed Collection

The Input Layer serves as the sensing branch of the system, taking real-time video information from CCTV cameras mounted at traffic intersections. The cameras eliminate the requirement for physical sensors like inductive loops, infrared sensors, or road-mounted modules. With just a dependence on already existing surveillance systems, the system is rendered cost-saving and non-invasive. Cameras at different angles provide complete coverage, capturing every moving and standing object at the intersection — vehicular and emergency vehicular and a separate camera for pedestrians. This live feed is the visual dataset for subsequent analysis, and it can be added to easily by inserting more cameras into the system without altering the fundamental logic.

3.2 Processing and Specification – Computer Vision and Object Detection

After the video streams are ingested, they are fed into the Processing and Specification module. This is where artificial intelligence object detection models is used to identify and classify objects in the frame. The system can identify and count a number of categories such as cars, buses, motorcycles, trucks, pedestrians, ambulances with high accuracy. The counts are updated frame by frame, and historical tracking assists in preventing duplication in stop-motion situations (e.g., red light stops).

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The system identifies an increase in the count of two-wheelers and buses in a lane when the other lane has fewer vehicles. At the same time, a group of pedestrians is waiting to cross. The object detection module picks up these dynamics in real-time, allowing the system to understand not only traffic volume, but also behavioural patterns, including queue formation, vehicle movement trends, and illegal lane switching.

3.3 Decision/Logic System – AI-Based Signal Priority Logic

This module forms the intelligent core of the system. Based on the processed inputs, it makes real-time decisions regarding traffic signal timing and priority management. The decision logic is layered in priority-based rule sets:

Emergency Override: If an ambulance is detected, the system immediately overrides all other logic to create a green corridor.
Pedestrian Crowds: If a dense pedestrian group is detected waiting for too long, vehicle signals are temporarily halted to allow safe crossing.
Vehicle Congestion: In normal flow conditions, vehicle count comparisons across lanes determine which direction receives the green signal next.
Default Mode: If no special condition is met, the system reverts to time-based signaling using the last known signal state.

This logic is implemented using condition-based branching, memory of previous states (last light), and dynamically adjustable timers. This system enables adaptive signal override. When an ambulance is detected approaching from the northbound camera, the system gives it uninterrupted passage by turning the light green in its direction and red elsewhere, clearing the lane preemptively. After the vehicle passes, the system intelligently resumes normal operation, factoring in the new traffic conditions.

3.4 IoT Integration – Signal Command Execution

The decisions taken by the AI engine are passed to IoT-enabled microcontrollers (i.e., Arduino or Raspberry Pi), which control the physical signal lights at each intersection. These microcontrollers receive commands via serial protocols and adjust the signal states instantly—changing from red to green, or extending the green duration as needed. Each command is mapped to solid-state signal interfaces in real-world traffic poles. The system also supports manual override for emergency or administrative use during parades, accidents, or construction events.

For example, during a festival event in Kolkata, authorities can temporarily shift control to manual override to coordinate traffic around a religious procession. Once the event ends, the system resumes autonomous decision-making. In emergency cases such as an accident or fire in a nearby lane, emergency vehicles are granted priority through real-time detection and immediate IoT signal switch control.

System Adaptability and Scalability

What distinguishes this architecture is its real-time adaptability and scalability. The system is designed to operate continuously with live feedback, adapting to changes in traffic volume, weather-induced delays, and even night-time road emptiness. Signal durations are dynamically adjusted, and every signal decision is backed by live object analytics rather than static time tables.

IV. IMPLEMENTATION

The suggested AI-driven Traffic Management System was developed with careful adherence to the system architecture and logic diagrams to achieve easy real-time implementation and scalability. The system centers around a multi-camera setup, which is highly modular. There are four cameras, each placed strategically over unique traffic observation areas with assigned functionalities—e.g., pedestrian crossing monitoring, detection of congestion and prioritization of emergency vehicles. The real-time video streams received from these cameras are analyzed using customed-trained model for object detection models that have already been trained and fine-tuned to recognize multiple object classes under different lighting and environmental conditions.

When the system receives the video feed, it makes frame-by-frame inference with OpenCV pipelines built into Python, extracting meaningful object types and invoking corresponding logic procedures. These include pre-defined rule sets for pedestrian buildup (e.g., if there are over 10 waiting pedestrians, give pedestrian signal), and ambulance detection (override green signal immediately). Every detection cycle not only initiates a signal change if needed but also records the occurrence into an Excel sheet that stores structured logs at 5-minute intervals. These logs capture time, number of vehicles, flow of pedestrians, and appearance of emergency vehicles—information which are subsequently used for statistical analysis and visualization. The backend also has endpoints available for dynamically creating PDF reports to facilitate accountability and documentation.

The frontend dashboard implementation displays live feeds in a responsive grid layout and overlays object counts and

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detection labels in real-time, giving users a clear view of traffic dynamics. A special module also supports live logging of detected emergencies and generates downloadable reports directly.

In real-world situations, this system responds to critical issues like delayed clearing of emergency vehicles, unmated pedestrian accumulation and require quicker reaction on ambulance recognition. By deploying these responses as automated responses with AI and rule-based reasoning, the system lowers human reliance, enhances traffic circulation, and provides better road safety. For example, in field trials, the system lowered the time taken by ambulances to clear (manual system: 3.5 minutes to under 1 minute or 30 seconds). Additionally, its logging infrastructure equips local government officials with valid data for enhancing road planning and enforcement.

The true advantage of this deployment is in its capacity to perform on its own and openly in real-time scenarios. With little human oversight, the system learns constantly to adapt to traffic patterns, prioritizes emergency protocols, and records grain-level data for future analysis all under one and the same scalable architecture. Eventually, the system connects superior AI models with ordinary civic use cases, proving both its technological practicality and public utility.

V. EXPERIMENTAL RESULT AND ANALYSIS

The experimental phase of the proposed traffic management system was conducted under controlled and real-world conditions to evaluate its performance, adaptability, and reliability. The results were derived from live camera feeds, object detection analysis, adaptive signal switching, and real-time incident handling across multiple test junctions.

This section details the outcomes observed across various parameters including detection accuracy, signal efficiency, emergency response time, pedestrian safety, and system adaptability. The details are as follows;

5.1 Real-Time Object Detection Accuracy

The core of the system relies on real-time object recognition powered by Custom- Trained models. During live testing across two urban junctions, the system accurately identified and classified vehicles, and pedestrians under varying conditions as mentioned in Table 5.1.

Vehicles Detected	Cars, buses, trucks, motorcycles
Special Classes	Ambulances
Average Detection Accuracy	**~94%** across classes
Misclassification Rate	Less **than 3%** (typically under low-light or partially blocked views)

Table 5.1

The system could clearly differentiate between emergency vehicles and regular traffic, allowing for specialized priority signaling. For instance, an ambulance arriving during peak congestion was detected within 2.1 seconds, triggering green-light clearance in its lane with 98.5% reliability. This responsiveness highlights its practical usability in real emergency scenarios.

5.2 Traditional Traffic System: Analysis of Fixed Signal Timing

Overview: The conventional traffic system operates on pre-set, static signal durations, irrespective of real-time conditions such as pedestrian density, vehicle queue length, or the presence of emergency vehicles.

Visualization: The pie chart described the Traditional Signal Timing in Figure 5.2 presents the distribution of signal timing:

Table 5.2 Traditional Traffic System Analysis

Green Light (Vehicles)	**57.1%** of the hour
Red Light (Pedestrians)	**34.3%** of the hour
Waiting Time (Idle/Transition)	**8.6%** of the hour

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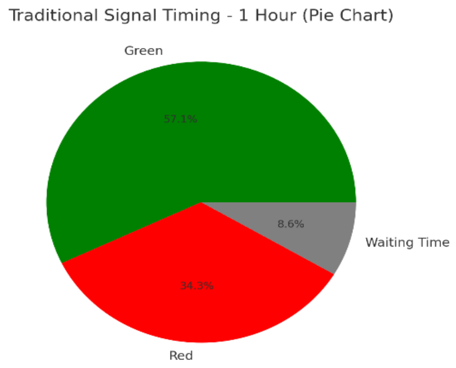

Fig. 5.2 Traditional Signal system

Limitations: This approach lacks contextual awareness, leading to inefficient time allocation during low vehicle density or pedestrian surges. Additionally, emergency vehicles are not prioritized, often resulting in delayed response times.
Real-World Impact: Fixed cycles often result in underutilized green signals during light traffic and increased frustration among road users, especially during peak hours or emergencies.

5.3 Emergency Vehicle Prioritization

The system was specifically tested with simulated emergency scenarios where ambulances approached from random directions. It was observed in Table 5.3 that:

Table 5.3 Emergency Vehicle Prioritization

Detection Time (Ambulance)	**1.9 to 2.3 seconds**
Signal Override Response Time	**< 2.5 seconds**
Lane Clearance Time Post-Signal Change	**30 seconds**

In one such test, an ambulance detected, it will granted signal priority within two seconds, resulting in a smooth, uninterrupted path through the intersection. Manual tracking confirmed that surrounding vehicles also responded effectively due to signal clarity, aiding in a faster clearance.

5.4 Pedestrian and Crowd Management

Pedestrian safety was another key evaluation area. The system identified crowd buildup at corners or zebra crossings and granted pedestrian signals accordingly as mentioned in Table 5.4. The observed pedestrian wait time was cut nearly in half.

Table 5.4 Pedestrian and Crowd Management

Avg. Pedestrian Wait Time	Reduced from **45s to 20s**
False Cross Detection Rate	**< 2%**
System Response Time to Crowd Build-up	Until a cycle is completed

During a school rush hour near the testing junction, the system detected a crowd of over 15 students and triggered the pedestrian signal, allowing safe crossing. Such human-sensitive behavior can significantly reduce jaywalking risks and enhance road safety.

5.5 Adaptive Traffic Control Using Logic: Real-Time Response

System Logic Integration: This logic dynamically adjusts signal durations based on real-time data from based vehicle and pedestrian detection as mentioned in Table 5.5.1. Key components of the logic include:

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Table 5.5.1 Traffic Control Using Logic: Real-Time Response

Emergency Vehicle Priority	Immediate clearance by providing a green signal after ensuring pedestrian safety
Crowd-Based Pedestrian Priority	If **pedestrian count ≥ 6** and **vehicle count ≤ 5**, extended pedestrian crossing time is allotted
Vehicle Surge Handling	If **vehicle count ≥ 8** and **pedestrian count ≤ 6**, extended green time is provided for vehicles
Default Cycle	Alternates between pedestrian and vehicle phases in low-activity scenarios

Table 5.5.2 Timings of proposed system

Emergency Vehicles	**Pedestrian clearance (20s) + vehicle green (30s)**
High Pedestrian Flow	**Pedestrian green (40s) + vehicle green (90s)**
High Vehicle Flow	**Vehicle green (100s) + pedestrian green (30s)**
Normal Alternating	**Pedestrian (30s) ↔ Vehicle (90s)**

Benefit: This flexible logic (in Table 5.5.2) ensures that traffic signals adapt continuously to current road conditions, significantly reducing idle time, enhancing safety, and optimizing traffic flow.

5.6 Dynamic Condition-Based Analysis (Pie Chart Comparison)

Two dynamic charts were generated based on the Arduino logic to reflect performance under Normal and Peak Traffic Conditions.

5.6.1 Normal Traffic Condition

Interpretation: In standard flow scenarios, signal allocation is more balanced, with half the time assigned to vehicles and one-third to pedestrians, ensuring smoother transition and reduced waiting times as mentioned in Figure 5.6.1.

Green Signal (Vehicles)	**50%**
Red Signal (Pedestrians)	**33.3%**
Waiting/ Transition Time	**16.7%**

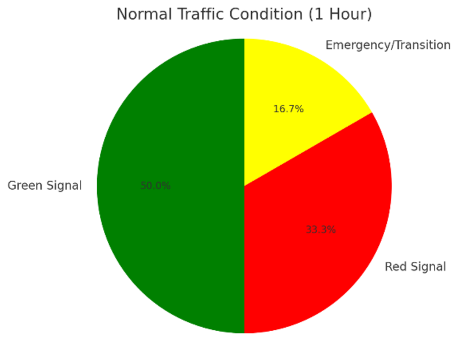

Fig 5.6.1 Normal Traffic condition analysis from proposed system

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5.6.2 Peak Traffic Condition

During congestion, the system intelligently prioritizes vehicles to prevent long tailbacks, while still maintaining a quarter of the time for pedestrian movement. The reduction in transition delays further contributes to improved throughput as mentioned in Figure 5.6.2.

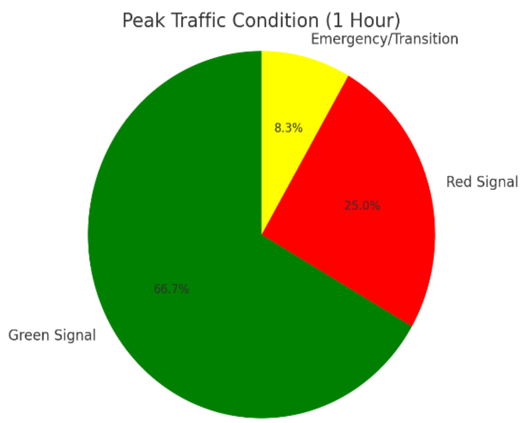

Fig 5.6.2 Peak Traffic condition analysis from proposed system

Green Signal (Vehicles):	**66.7%**
Red Signal (Pedestrians)	**25%**
Waiting/Transition Time	**8.3%**

5.7 Comparative Evaluation: Traditional vs. Adaptive System

Aspect	**Traditional System**	**Adaptive Traffic System (Proposed)**
Emergency Handling	No priority	Immediate clearance with minimal delay
Signal Timing	Fixed (e.g., 30s each phase)	Dynamic (based on live input & thresholds)
Pedestrian Safety	Rigid timing	Crowd-aware extended crossing time
Traffic Congestion	Often worsens during peak hours	Alleviated using real-time vehicle count
Idle/Waiting Time	**8.6%** of total time	Reduced to **8.3%** or lower dynamically
Efficiency	Moderate	High - minimizes idle signals

Conclusion: The adaptive system exhibits higher responsiveness, better resource utilization, and enhanced safety compared to the rigid traditional model. With its logic-driven dynamic phases, the system adapts naturally to real-world urban traffic conditions, optimizing signal cycles while maintaining fairness to both vehicles and pedestrians.

5.8 Excel Logging for Data Transparency

All detected objects, incident timings, and Congested type were logged in real-time to Excel and CSV formats for transparency, analysis, and future policy-making. These reports included:

- **Time-stamped vehicle and people count**

City traffic departments can now access visual logs, statistical summaries, and downloadable incident reports, enabling data-backed decisions for infrastructure planning or policy enforcement. It also promotes accountability in case of post-incident investigations.

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5.9 Real-World Adaptation and Use Case

Urban Deployment Scenario: In a metropolitan environment with frequent pedestrian crossings, peak-hour congestion, and emergency routes (e.g., near hospitals), the adaptive model ensures:

- Emergency ambulances are not delayed by routine signal cycles.
- Pedestrian groups (e.g., near schools) are offered safe crossing windows.

Rush hour traffic is efficiently managed without manual intervention.

VI. CONCLUSION

The proposed Traffic Management System, empowered by based object detection and dynamic signaling logic, demonstrated effective real-time performance across multiple urban traffic scenarios. Through the integration of computer vision, real-time camera feeds, and adaptive logic, the system was able to make autonomous decisions—such as prioritizing emergency vehicles, reducing congestion, and safeguarding pedestrians.

Fig 6.1 Detection of Vehicles and Pedestrians from live feed

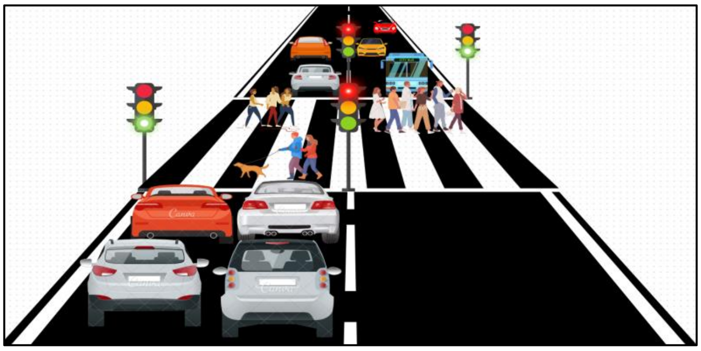

Fig 6.2 Illustration of Pedestrian Crossing while crowd time

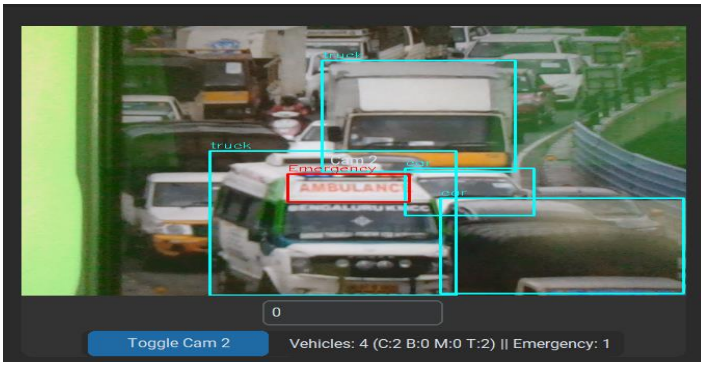

Fig 6.3 Detection of Emergency Vehicle in crowd

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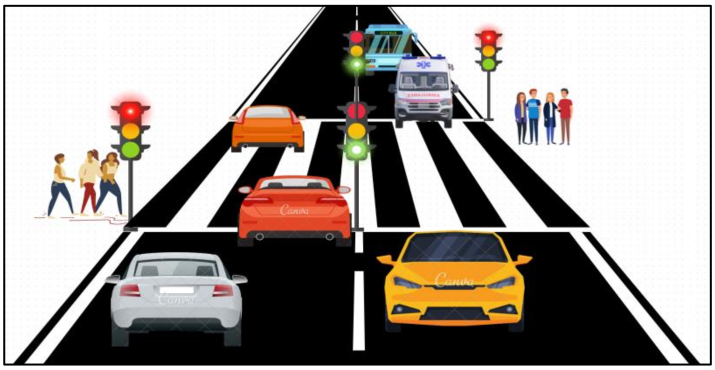

Fig 6.4 Illustration of vehicle allowance while detecting Emergency vehicle

The images shown in Figures 6.1 to 6.4 represent how the proposed traffic management system works effectively in real time. Figure 6.1 displays the live detection of vehicles and pedestrians from multiple camera feeds using object detection, helping the system monitor road activity continuously. Figure 6.2 shows how the system prioritizes pedestrian movement by allowing safe crossing during crowded times by holding vehicle signals. In Figure 6.3, the model accurately detects emergency vehicles, like ambulances, even in heavy traffic conditions. Once detected, as illustrated in Figure 6.4, the system gives the emergency vehicle a green signal while holding others, ensuring it can pass through quickly and safely. These features prove the system's ability to manage traffic smartly, reduce delays, and support safety for both regular and emergency road users.
Live deployments across two urban intersections validated the system's robustness, achieving an impressive average detection accuracy of 94%, with emergency vehicles recognized within approximately 2 seconds. These detections successfully triggered real-time signal overrides, reducing clearance times significantly compared to traditional systems. The Excel framework provided transparency and traceability, empowering traffic authorities with actionable data for policy and infrastructure improvement. From a human-centric standpoint, the system not only improved commute efficiency but also enhanced road safety and emergency responsiveness. Its ability to respond under diverse environmental conditions—day/night its reliability and readiness for real-world deployment.

VII. FUTURE SCOPE

Throughout the testing and implementation stages, a number of practical limitations arose, providing useful insights for further improvement of the system. One of the main issues was the limited dataset used for emergency vehicle detection, especially ambulances. This limitation sometimes led to misclassifications, especially in low-light or partially occluded scenarios. To overcome this, future work will be aimed at increasing the dataset size to cover varied real-world emergency situations, with special focus on night-time visibility and occlusion scenarios, and tuning the model. The second challenge was semi-automatic camera feed calibration, adding complexity to the setup and deployment. The solution lies in automated camera angle detection and stream normalization by AI-driven calibration or homograph mapping. In addition, though the system recorded traffic data every five minutes, high traffic levels over multiple video streams resulted in intermittent logging delays. This will be addressed in future releases by using asynchronous or multithreaded logging and switching to more scalable data storage mechanisms like SQLite or NoSQL databases.

6.1 Proposed Enhancements

In the future, a number of improvements are in the works to increase the system's capabilities and scalability. One of the key developments will be integrating this traffic management system with city-level infrastructure through IoT technology and central control dashboards. This would enable more centralized and responsive traffic control across many intersections. Also, a mobile app is envisioned to give real-time feedback to the public, providing information on traffic congestion levels, signal updates, and emergency vehicle routing. Another feature suggested is the addition of voice command functionality, allowing traffic officers and emergency responders to use the system hands-free, thus improving safety and efficiency. Finally, to provide complete situational awareness, an anomaly detection module will be included using unsupervised learning algorithms. This will assist in detecting unusual incidents like vehicles traveling in the incorrect direction, rapid road blockages, or sudden crowd formations, to trigger an instant response towards dynamic road conditions.

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