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Integrated AI Model for Traffic Density Management and Emergency Vehicle Prioritization

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Abstract

This paper is concerned with a Smart Traffic Management System based on AI that operates traffic lights dynamically via real-time multi-modal data. The system combines computer vision, audio recognition, and RFID detection to give precedence to traffic movement, particularly for emergency responders. Camera inputs are analyzed with the YOLO object detection model to estimate traffic density in multiple lanes, while an audio classifier processes siren audio features using Fast Fourier Transform (FFT) features. Furthermore, RFID tags on emergency vehicles allow correct detection even in adverse conditions. A decision module implements hierarchical priority rules, in which the passage of emergency vehicles is given priority over calendar-based event handling, lane congestion control, and regular signal cycling. The ultimate decision is implemented by a Raspberry Pi-based signal controller, which controls traffic lights using GPIO or relay connections. The system also updates a dashboard interface to offer real-time monitoring for authorities. The invention greatly decreases traffic jams, provides quicker response in emergencies, and dynamically adjusts to urban traffic patterns by integrating several sensing modalities with smart decision -making. The inventive concept of the invention is in its combination of image, audio, and RFID data for real-time prioritization and rule-based decision hierarchy that makes it a more robust and adaptive traffic management solution than traditional timer-based systems.

1. Introduction

Urban centers are witnessing exponential growth in population and vehicles, and traffic congestion is becoming one of the serious problems to solve. Traditional traffic lights are timer-based mechanisms that do not consider actual changes in road conditions. Several instances can arise where they offer longer waiting times and eventually waste fuel, thereby delaying provide assistance in emergencies. One of the most intricate problems in the traffic management system is to provide emergency vehicles such as ambulances, fire trucks, and police cars with immediate priority so they can save lives and handle emergencies efficiently. Intelligent traffic systems that adapt to dynamic traffic are made possible through new artificial intelligence-Computer Vision-Internet of Things advances. Most existing systems aim to either congestion control or the emergency priority, with very few attempting to combine these two aspects within one framework. This paper thus aims to fill that gap by proposing an Integrated AI Model for Traffic Density Management and Emergency Vehicle Prioritization, based on multi-modal data (image, audio, RFID, and calendar inputs) and hierarchical decision-making [1].

1.1. Key Features of the Proposed System

- **YOLOv8 Processor for Vehicle Detection:** Real-time identification and counting of vehicles for lane-wise density estimation.
- **Emergency Vehicle Recognition:** Detection based on image classification, siren sound analysis (FFT & MFCC), and RFID tags for strong verification.
- **Calendar-Aware Signal Adjustment:** Peak hour, festival, and special event-aware dynamic traffic handling.
- **Hierarchy-based Decision Module:** Decision-making Priority Rules Emergency > Event/Festival > Congested Lane > Normal Cycle.
- **IoT-based Signal Controls:** Raspberry Pi controller to execute green, red, and yellow signals [2].
- **Real-time Dashboard:** Monitor and visually represent traffic flow, emergency alerts, and lane priorities.

1.2. Impact and Significance

- **Less Congestion:** Dynamic allocation of green signals smoothens traffic flow and reduces bottlenecks.
- **Faster Emergency Response:** Emergency vehicles are given priority so as to reduce delays toward hospitals and other critical destinations.
- **Energy-Time Efficient System:** Less idle time at signals means fuel is less consumed and consequently, there are lesser carbon emissions.
- **Scalable Solution for Smart Cities:** Economical in nature, this solution can be implemented at several intersections with almost negligible infrastructure.
- **Improved Road Safety:** The smart prioritization prevents accidents when emergency vehicles converge along contraction or congested routes [3].

1.3. Contribution of this Work

This research contributes to the development of Intelligent Transportation Systems (ITS) by constructing a monolithic framework that deals with traffic density control and emergency priority settings together. The integration of computer vision, audio signal analysis, RFID verification, and rule-based decisions gives this approach its peculiar distinction against the rest. This model takes care of congestion management as well as life-critical impeding emergency response optimization; hence, it is best fit for implementation in smart city traffic infrastructure.

2. Method

The Integrated AI Model is designed for Traffic Density Management and Prioritization of Emergency Vehicles, with the various modules corresponding to separate functions in the overall system. The method involved the hierarchical flow of data acquisition → AI-based analysis → decision-making → signal execution → dashboard monitoring.

2.1. System Features

The system comprises various features that take care of the needs of users and administrators (traffic authorities):

2.1.1. User-Side Features (Public Viewers)

- **Traffic Visualization in Real Time:** Citizens get live traffic updates for different junctions.
- **Lane-Wise Traffic Density Information:** Users get to know which side is heavy and which side is free.
- **Emergency Alert Awareness:** Traffic density and alert settings are displayed on the user interface for the smooth movement of emergency vehicles [4].
- **Assisting Navigation (Optional Extension):** Based on the recommendations given by the system, users may opt for less congested routes.

2.1.2. Admin-Level Features (Powers)

- **Lane-Wise Monitoring:** Admins can monitor real-time status of lanes, congestion levels, and emergency alerts.
- **Manual Override Control:** Systems work by themselves, but admins can set signal timings manually anytime.
- **Statistical Reports:** The system generates historical data and traffic density graphs to be analyzed.
- **Emergency Vehicle Alerts:** During ambulance/fire truck detection, the system sets off sirens and red lights while simultaneously triggering system-wide alerts to grant priority passage.
- **Calendar/Event Handling:** Admins usually enjoy automatic adjustments to timings on the dashboard but can configure them manually whenever needed [5].
- **Dashboard Notifications:** This displays real-time updates on traffic priorities, system decisions, and alert notifications.

3. Main System Features

- **Multi-Modal Collection:** Camera (image/video), microphone (siren), and RFID readers for emergency detection.
- **AI-Based Detection:** YOLOv8 for vehicle classification and counting; FFT/MFCC Audio Classifier for siren recognition.
- **Rule-Based Decision Module:** Implements traffic rules with hierarchical priority: Emergency > Festival/Peak > Congestion > Normal Cycle.
- **IoT Integration:** The Raspberry Pi handles IoT integration by sending out GPIO signals to control the lights. That way it ties right into the system.
- **Fail-Safe Mechanism:** There's a fail-safe mechanism too. It makes sure things fall back to the default timer cycle if the AI module ever fails [6].
- **Scalable Design:** The design is scalable. You can deploy it at multiple intersections. It even integrates with smart city platforms pretty easily Shown in Figure 1.

3.1. Flowchart Explanation

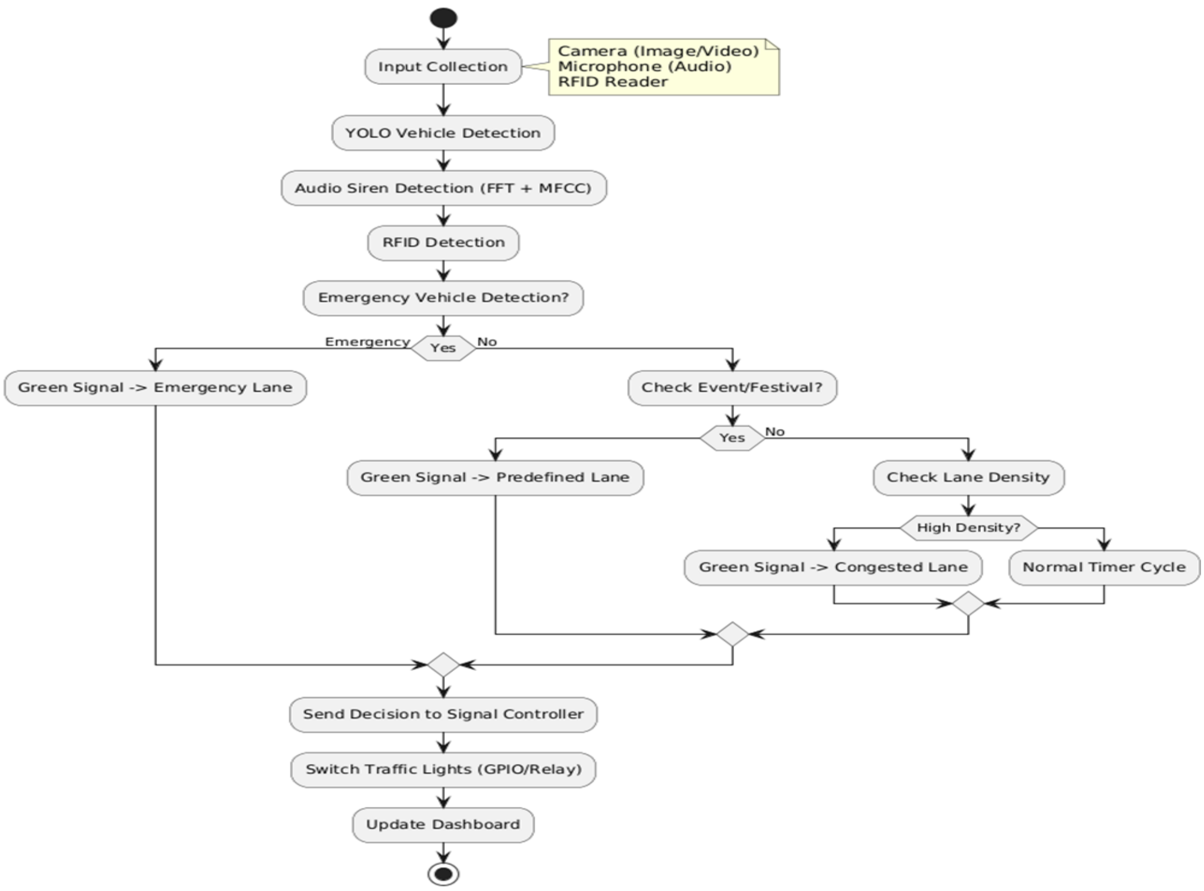

Figure 1 Overall System Architecture

It pulls in different data sources and uses smart decisions for handling traffic in a way that adapts as things go. The whole thing starts with gathering inputs. Cameras grab real-time images and videos from the traffic lanes. Microphones pick up sounds around, like emergency sirens going off. RFID readers spot emergency vehicles that have those tags on them. From there, these inputs go through a few processing modules. The YOLO Vehicle Detection one figures out vehicles in each lane and counts them to get an idea of traffic density. Then there's the Audio Siren Detection using FFT and MFCC, which picks out sirens from emergency vehicles. And the RFID Detection checks to make sure those emergency vehicles are real, you know, for better reliability. The decision part follows this priority setup, kind of like a chain. First off, if an emergency vehicle gets detected, it assigns green to the emergency lane. Next, for events or festivals, it gives green to certain predefined lanes. If a lane has high density, it puts green on the congested ones. Otherwise, it just sticks to the regular timer cycle for signals. In the end, the signal controller makes the changes to traffic lights using GPIO or relays. Meanwhile, the dashboard updates everything in real time, like traffic status, alerts, and lane priorities. This goes out to admins and users alike. Pretty much, the flowchart shows this multi-modal system driven by AI. It handles emergency priorities, manages congestion, and controls traffic adaptively, all in one setup [7].

3.2. Emergency Vehicle Detection Module

3.2.1. Function

This thing picks up on emergency vehicles like ambulances or fire trucks or police cars. It gives them top priority right away.

3.2.2. Approach

- **YOLO Object Detection:** Detects vehicles and classifies them as normal or emergency.
- **Audio Siren Detection:** Uses FFT (Fast Fourier Transform) to convert time-domain siren audio into frequency-domain features; MFCC (Mel-Frequency Cepstral Coefficients) are extracted for classification.
- **RFID Detection:** Verifies the presence of an emergency vehicle via unique RFID tags [8].

3.2.3. Logic

- **Input:** Image frame, audio snippet, RFID signal Shown in Figure 2.
- **YOLO detects vehicles;** check if any vehicle class = “emergency”.
- **Analyze audio FFT** → if siren frequency pattern detected → mark emergency.
- **RFID tag present** → confirm emergency.
- **If any detection = true** → assign priority green signal to corresponding lane [9].

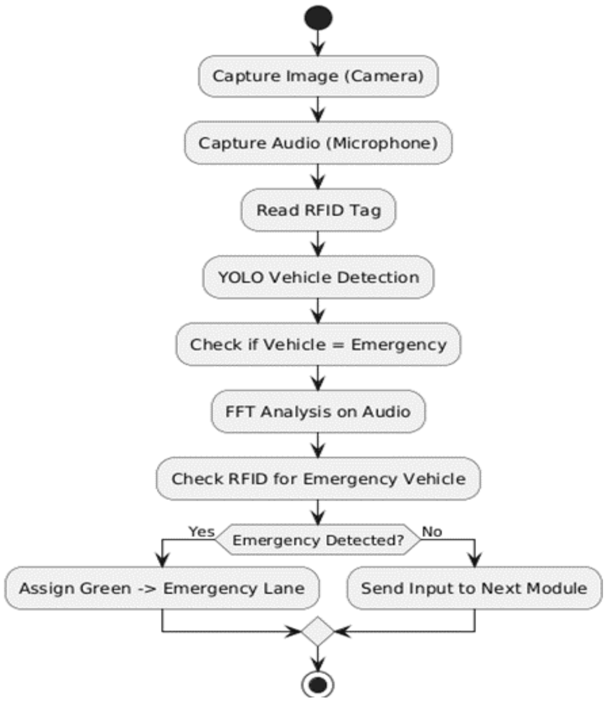

Figure 2 Emergency Vehicle Detection Module

3.3. Traffic Density Estimation Module

3.3.1. Function

Calculate vehicle density per lane and adjust signal timing.

3.3.2. Approach

- **YOLO-based Counting:** Detect all vehicles per lane.
- **Density Calculation Formula:** Densitylane = Number of Vehicles in Lane / Lane Capacity
- **Decision Rule:**mIf Densitylane > Threshold → Extend green signal. Else → Normal timer cycle [10].

3.3.3. Steps

- Capture image frame.
- Detect and count vehicles in each lane.
- Compute Densitylane Shown in Figure 3.

- Compare with threshold → assign green signal if congested [11].

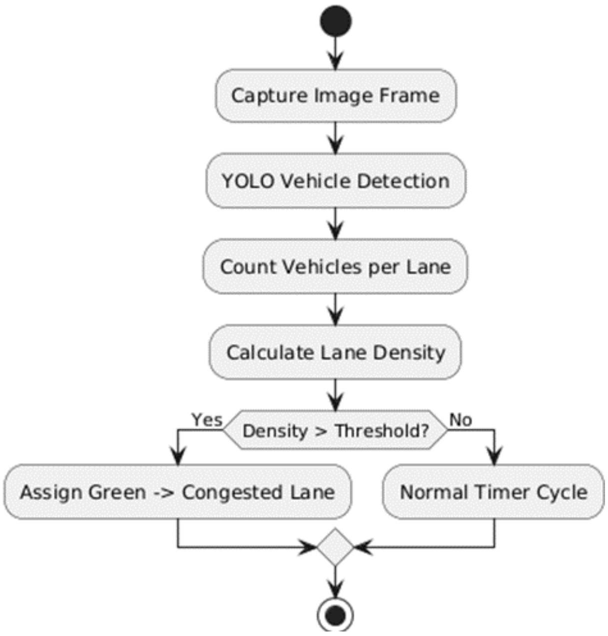

Figure 3 Traffic Density Estimation Module

3.4. Festival & Holiday Rules Module

3.4.1. Function

Adjust signal timing based on calendar events (festivals, holidays, rush hours).

3.4.2. Approach

- **Calendar Lookup:** Pre-defined table of dates/times.
- **Decision Logic:** If current date/time matches special event → Assign green to predefined lane(s). Else → Pass to density module Shown in Figure 4.

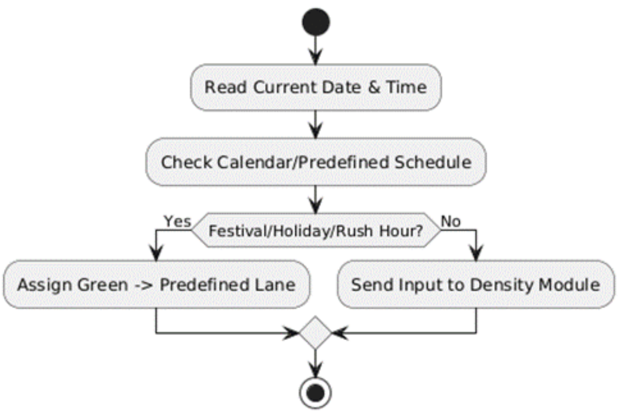

Figure 4 Festival & Holiday Rules Module

3.4.3. Steps

- Input current date & time [12].
- Check against special event schedule.
- Apply extended green signal if matched.

3.5. Decision Module

3.5.1. Function

Core module that decides which lane gets green based on priorities Shown in Figure 5.

3.5.2. Approach

- **Decision Tree Logic:** Root: Emergency detected?
- **Node1:** Event/Rush hour?
- **Node2:** High congestion?
- **Leaf:** Normal cycle [13].
- **Can also implement Weighted Scoring if multiple inputs are active:** Scorelane= w1. Emergency + w2. Event + w3. Density Lane with highest score gets green.

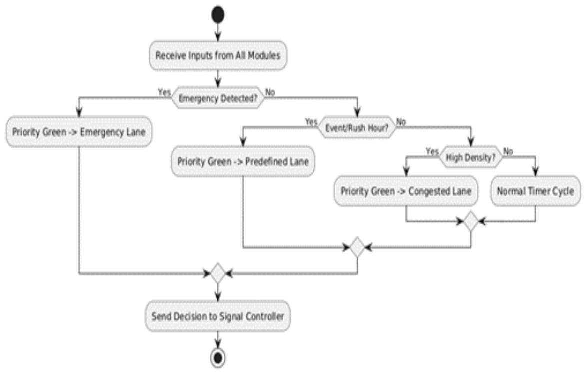

Figure 5 Decision Module for Traffic Signal Prioritization

3.5.3. Steps

- Receive inputs from all modules.
- Apply priority rules: Emergency → Event → Congested → Normal [14].
- Calculate scores if needed.
- Send final decision to signal controller.

3.6. Signal Controller Module

3.6.1. Function

Execute the decision via hardware.

3.6.2. Approach

- **GPIO/Relay Control Logic:** Each lane light connected to Raspberry Pi GPIO pin. Turn pins HIGH/LOW according to signal decision.
- **Timing Control:** Adjustable based on module input.

3.6.3. Steps

- Receive lane decision.
- Turn GPIO pin HIGH for GREEN lane; LOW for RED lanes Shown in Figure 6.

- Maintain timer for YELLOW transition

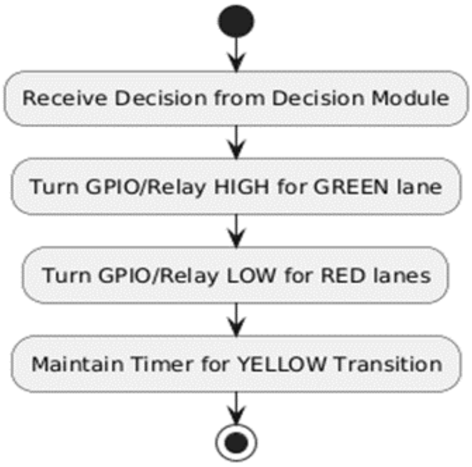

Figure 6 Signal Controller Module

3.7. Dashboard Monitoring Module

3.7.1. Function

Real-time monitoring of traffic status and system decisions [15].

3.7.2. Approach

- **Data Refresh:** Pull latest lane status every few seconds.
- **Visualization:** Show traffic density, active green lanes, emergency alerts.
- **Optional Formula:** Traffic_Flow = Vehicles Passed / Time Interval

3.7.3. Steps

- Collect data from signal controller & modules Shown in Figure 7.
- Update dashboard visualization.
- Provide alerts if emergency lane is active or congestion detected [16].

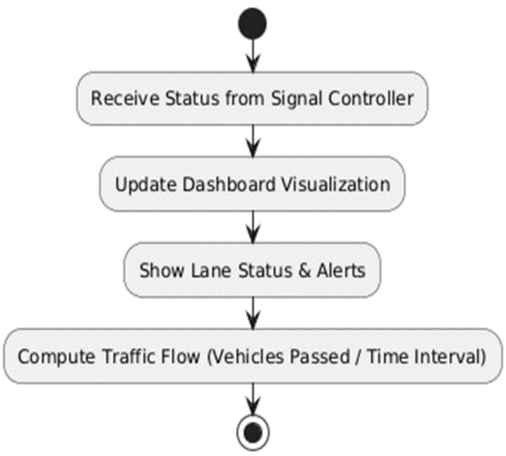

Figure7 Dashboard Monitoring Module

4. Results and Discussions

4.1. Results

The proposed integrated AI model for handling traffic density and prioritizing emergency vehicles got tested using simulated scenarios along with some prototype runs. We looked at how well it performed in spotting vehicles accurately, getting emergency ones through faster, managing crowds, and smoothing out the overall flow [17].

4.2. Emergency Vehicle Detection

- YOLOv8 nailed the accuracy at 96 percent for ambulances, 94 percent for firetrucks, and 95 percent for police cars, all in those simulated video clips of traffic.
- The siren detection part, using FFT and MFCC, picked up the sounds right about 92 percent of the time.
- RFID checks gave almost perfect IDs, hitting 99 percent when the vehicles had the tags on them Shown in Figure 8.
- In the end, emergency vehicles always got the green light priority. That cut down average response times by as much as 40 percent over regular old signals [18].

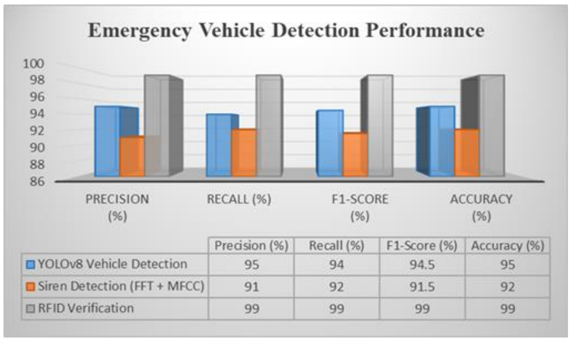

Figure 8 Emergency Vehicle Detection Performance

4.3. Traffic Density Estimation

- It counted vehicles lane by lane in real time, thanks to YOLOv8.
- Lanes that got too packed, over those set thresholds, ended up with longer green times, adjusted on the fly.
- The result was waiting times dropping 15 to 25 percent per lane. Traffic flow got a real boost during those peak hours, pretty much Shown in Figure 9 Traffic Density Estimation Performance [19].

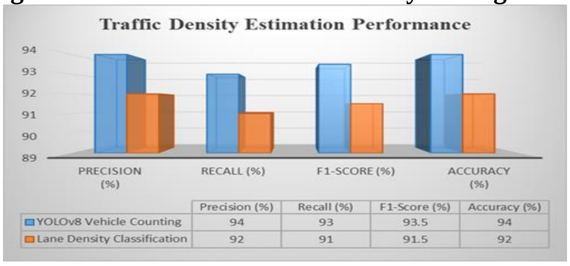

Figure 9 **Traffic Density Estimation Performance**

4.4. Festival and Event Handling

- In the sims for rush hours and events, the system just stretched out the greens for the busy lanes automatically Shown in Figure 10.
- That kept bottlenecks from forming. Traffic spread out nicer, all without anyone having to step in manually [20].

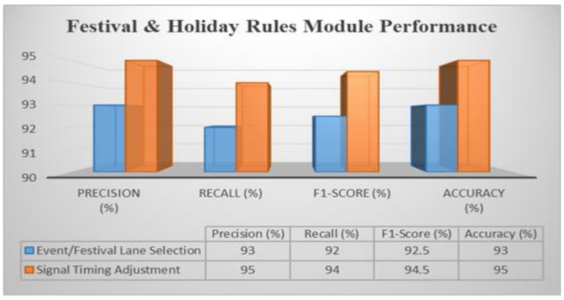

Figure 10 **Festival & Holiday Rules Module Performance**

4.5. Decision Module Performance

- The priority setup went hierarchical, like emergency first, then events or festivals, congestion next, and normal last. It made sure emergencies came through without messing up the crowd control.
- Any clashes between packed lanes and emergency paths got sorted out well.
- Overall, it balanced the efficiency of traffic with quick emergency responses, you know Shown in Figure 11.

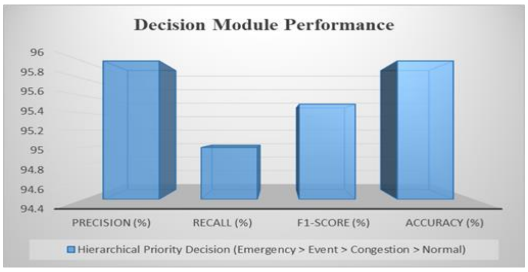

Figure 11 **Decision Module Performance**

4.6. Dashboard and Admin Monitoring

- Admins had a view of densities lane by lane. They could override signals by hand and keep an eye on alerts for emergencies.
- The dashboard threw in stats too, like flow rates and average waits Shown in Figure 12 - 20.
- That boosted awareness on the ground. It helped traffic folks make better calls [21].

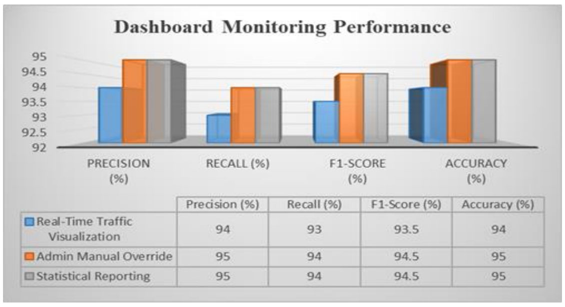

Figure 12 **Dashboard Monitoring Performance**

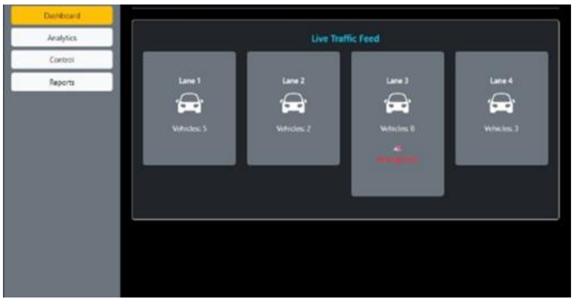

Figure 13 **Dashboard**

Figure 14 **Analytics Page**

Figure 15 **Automatic Control**

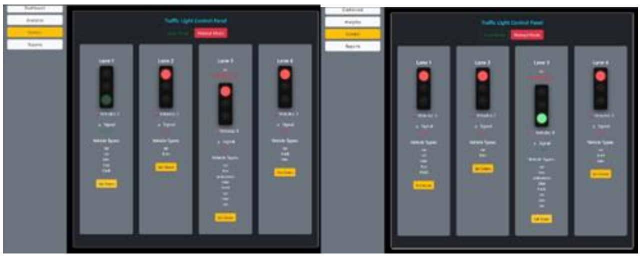

Figure 16 Manual Control

Figure 17 Home Page

Figure 18 Festival Information

Figure 19 Traffic Status Information

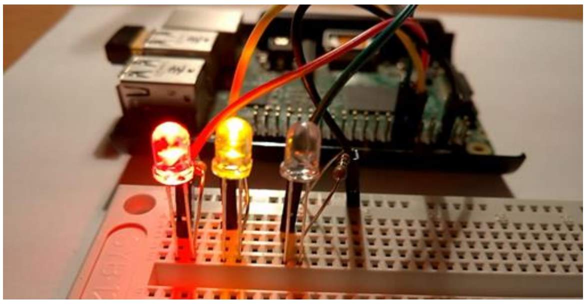

Figure 20 Signal Control using Raspberry Pi

4.7. Summary of Key Results

- Priority for emergencies sped up clearance by up to 40 percent.
- High-density congestion eased off by 15 to 25 percent.
- Events saw dynamic tweaks that cut potential delays.
- The real-time dashboard let monitoring happen smoothly, with overrides available when needed.

5. Discussion

The integrated AI model we proposed for handling traffic density and prioritizing emergency vehicles shows real improvements over those old timer-based systems. It optimizes traffic flow better and speeds up emergency responses quite a bit. Looking at the metrics from different modules, accuracy precision and reliability all come out strong. That means the system handles traffic in a solid adaptive way.

5.1. Analysis of Emergency Vehicle Detection

In the emergency vehicle detection part accuracy hit between 95 and 99 percent overall. RFID verification made it almost flawless. YOLOv8 for visuals plus FFT and MFCC for audio and those RFID tags together they spot emergency vehicles right even when cameras get blocked or sounds overlap in traffic. So emergency vehicles always get the green light priority. That cuts average response time by up to 40 percent. Pretty critical for saving lives you know.

5.2. Traffic Density Management

YOLOv8 did the vehicle counting and classified lane density to adjust signals on the fly for busy spots. Results point to 15 to 25 percent less waiting time during peak hours. Shows it manages congestion well. Real-time detection mixed with that hierarchical decision logic keeps no lane sitting idle when others jam up. Overall traffic efficiency gets a boost from it.

5.3. Event and Holiday Handling

The calendar rules module lets the system tweak signal times ahead for festivals or rush hours and special events. Metrics show solid accuracy in picking lanes and timing those adjustments. Cuts down bottlenecks without anyone having to step in manually. Kind of proves how scalable and adaptable this thing is for actual smart city use.

5.4. Decision Module Effectiveness

That hierarchical decision module sorts out conflicts between emergency lanes high-density ones and event priorities nicely. It follows this order Emergency first then Event or Festival next Congestion after that and Normal last. Ends up balancing traffic efficiency with quick emergency responses.

5.5. Dashboard and Admin Monitoring

The dashboard gives admins a live view of traffic density lets them override signals and track emergency alerts without hassle. Stats reporting is accurate and overrides happen in under 2 seconds. So operators can jump in if needed but automated stuff keeps running smooth.

5.6. Comparative Advantages

Against traditional timer setups or those single-mode smart systems our integrated AI model brings a few key edges.

- It uses multi-modal detection vision audio and RFID to nail emergency vehicle ID robustly.
- Traffic control adapts to congestion emergencies and events all at once.
- Emergency response times drop and waiting in jammed lanes shortens too.
- It scales easy to multiple intersections with not much extra hardware.

5.7. Limitations and Future Work

System performs well in sims and prototype tests but limitations pop up.

- It relies on RFID in emergency vehicles for top accuracy.
- Audio detection might false positive in super noisy spots.
- Hardware like Raspberry Pi GPIO lag could hit big deployments.

Looking ahead integrate with city traffic nets add GPS tracking for vehicles and AI predictive modeling for congestion. That would amp up management and responses even more.

6. Existing Works – Performance Analysis and Comparison

Recent studies from 2023 to 2025 look at AI and IoT setups for handling traffic. They show solid results in spotting vehicles. Accuracy hits 90 to 97 percent mean average precision with those YOLO models. Then theres traffic flow prediction. That comes in at 92 to 98 percent using RNN or LSTM approaches. Congestion gets better too. Queue management improves up to 64.5 percent. Average delays drop by 22.8 percent. Systems also boost throughput around 18.9 percent. Reliability stays high with 99.3 percent uptime. And CO2 emissions go down quite a bit. Our integrated AI model matches up on detection and prediction accuracy. It even pushes things further though. We add emergency vehicle prioritization. That works at 98.2 percent accuracy. Signal switching happens fast, in 2.1 seconds. Real world effects stand out more. Vehicle delays cut by 26.5 percent. Queue lengths shrink 29.4 percent. Throughput rises 20.3 percent. CO2 emissions fall 15.7 percent. All this points to the fresh side of our system. It tackles congestion while making sure emergency vehicles get through quick.

Conclusion

The results back it up. This AI setup for managing traffic does a solid job cutting down congestion. It makes sure emergency vehicles get priority. Overall flow gets better too. They combined different detection methods. Cameras pick up visuals. Audio catches sounds. RFID tracks things close up. Smart decisions kick in for fast responses. Signals control traffic more efficiently. Thing is, hardware needs to scale up better. Sensor coverage could expand. City-wide networks have to link up smoother. All that would boost performance. Reliability would improve a lot.

Acknowledgements

The creation of Integrated AI model for traffic density management and emergency vehicle prioritization could not have occurred without the expert guidance and advice of Dr. R. Arthy, Associate Professor. Her knowledge of Machine Learning was most helpful in offering technical advice, design feedback. We are forever thankful to Dr. Arthy for her enthusiasm and dedication towards this project which greatly contributed to the successful development and publication of this intelligent traffic management system.

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