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A Comprehensive Review of IoT-Enabled Smart Traffic Management System Using Raspberry Pi

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Abstract: Managing traffic efficiently has become one of the most urgent challenges in today's rapidly growing cities. Traditional fixed-time traffic signals often fall short because they cannot react to changing road conditions, which leads to unnecessary delays, increased fuel consumption, and higher pollution levels. Over the past few years, the combination of Internet of Things (IoT) technologies, edge computing, cloud platforms, and artificial intelligence has opened new possibilities for creating more adaptive and responsive traffic systems. This review brings together recent research from 2020 to 2025 and examines how sensors, embedded devices, and communication networks are being used to monitor real-time traffic flow, prioritize emergency vehicles, and optimize signal timing. The paper also explores advanced methods such as deep reinforcement learning, computer vision–based vehicle detection, blockchain-secured IoT frameworks, federated learning, and digital twin simulations. By comparing these approaches, the review highlights both their strengths and the remaining challenges that need attention. Overall, the study emphasizes that IoT-enabled smart traffic systems especially those combining edge intelligence with cloud analytics offer a practical and scalable pathway toward safer, cleaner, and more efficient urban mobility.

Keywords: Internet of Things (IoT), Smart Traffic Management, Edge Computing, Adaptive Signal Control, Vehicle Detection, Emergency Vehicle Priority, Cloud IoT Platforms, Traffic Flow Prediction, Intelligent Transportation Systems (ITS), Deep Learning, Reinforcement Learning, Urban Mobility.

I.INTRODUCTION

Urban traffic congestion has grown into one of the most persistent challenges faced by modern cities. As populations rise and private vehicle ownership continues to increase, existing road infrastructure is pushed far beyond its intended capacity. Traditional fixed-time signal systems, although widely deployed, operate blindly without considering real-time road conditions. As a result, empty lanes may receive longer green signals while heavily congested roads wait unnecessarily, increasing fuel consumption, emissions, travel times, and overall frustration for commuters [1]–[3]. These limitations have encouraged researchers and city administrations to explore smarter, data-driven alternatives that can respond dynamically to the real flow of vehicles.

In recent years, the Internet of Things (IoT) has emerged as a transformative force in the transportation domain. IoT brings together a network of sensors, embedded electronics, and communication systems that collectively enable real-time traffic monitoring and decision-making. Studies have shown that IoT sensors such as ultrasonic detectors, IR sensors, RFID modules, inductive loops, and magnetometers can reliably measure vehicle density and traffic flow with high accuracy, even in unpredictable traffic environments [1], [2], [4]. Moreover, the affordability and flexibility of devices like Raspberry Pi and microcontrollers have made IoT solutions feasible even for resource-constrained cities. Nagmode et al. [4] and Yadav et al. [5] demonstrated how low-cost IoT nodes can support both standalone and distributed traffic sensing through VANET-assisted communication.

With the rise of cloud computing, smart traffic systems have become even more capable. Cloud platforms such as ThingSpeak, AWS IoT, and Azure IoT offer real-time dashboards, advanced analytics, and the ability to store large amounts of traffic data for long-term study. Bhadauria and Jain [9] successfully implemented a ThingSpeak-based system for live traffic monitoring, while Puri et al. [10] and Al-Turjman [11] emphasized the significance of cloud-enabled intelligence in optimizing transportation planning at a city-wide scale.

Another area where smart traffic systems have made meaningful progress is adaptive traffic signal control. Instead of relying on pre-programmed cycles, adaptive systems adjust signal timings dynamically based on traffic density and behaviour. This has been achieved using rule-based logic [12], fuzzy logic controllers [13], and more recently, deep reinforcement learning (DRL) models capable of learning optimal strategies through interaction with traffic environments

[14]–[18]. While DRL and AI-driven approaches show excellent performance in simulations, they also require heavy computational resources—making simpler IoT-based adaptive systems more practical for real-world deployments, particularly in developing regions.

Emergency vehicle response time is another major challenge in urban mobility. Congestion often delays ambulances, fire trucks, and police vehicles at intersections. To address this, RFID-based and GPS-enabled emergency vehicle detection systems have been proposed, offering highly reliable and cost-effective ways to create "green corridors" for emergency travel. Research by Khan et al. [19] and Gupta et al. [20] demonstrates that integrating IoT with RFID or GPS can significantly reduce emergency arrival times, while computer vision–based models also assist in detecting ambulances accurately under complex traffic conditions [21].

Camera-based vehicle detection has also evolved rapidly due to advancements in deep learning. CNNs, YOLO, and hybrid CNN-LSTM models have shown remarkable accuracy in vehicle counting, classification, and congestion estimation [22]–[25]. Yet, these techniques demand strong computational resources and may struggle under poor lighting or harsh weather, making purely IoT-sensor-based systems a more practical alternative for many cities.

Edge computing has emerged as a powerful complement to IoT architectures. Instead of relying solely on cloud processing, edge devices like Raspberry Pi can perform real-time computation directly at intersections reducing latency and enabling faster response for signal control and emergency handling. Studies by Li [6], Sharma et al. [7], and Park & Kim [8] confirm that edge-oriented frameworks improve reliability and reduce communication overhead, making them ideal for time-critical applications such as adaptive traffic control.

The field is also witnessing exciting innovations such as predictive modeling, federated learning, blockchain-secured IoT networks, and digital twins. Predictive AI models using LSTM and XGBoost have shown strong accuracy in forecasting congestion [26]–[29]. Blockchain frameworks are being explored to secure IoT traffic systems against cyber threats [30], [31]. Federated learning enables intersections to collaborate without sharing raw data, preserving privacy while improving performance [32], [33]. Meanwhile, digital twins offer virtual replicas of traffic environments where new strategies can be tested safely before deployment [34]–[36]. Finally, broader surveys on IoT architectures and smart transportation systems emphasize the growing need for intelligent, scalable, and data-driven solutions for urban traffic management [37]–[40]. These studies collectively highlight that IoT-enabled traffic systems are no longer experimental they are essential building blocks for future smart cities. IoT-based smart traffic management offers a promising path toward safer, cleaner, and more efficient transportation ecosystems. By combining sensor networks, edge computing, cloud platforms, emergency prioritization, artificial intelligence, and secure communication frameworks, next-generation traffic systems are becoming more adaptive and capable of addressing the growing demands of urban mobility. This review synthesizes recent advancements from 2020–2025 and builds upon them to outline the potential of an IoT-driven traffic management framework capable of supporting real-world deployment.

II. EVOLUTION OF SMART TRAFFIC SYSTEMS: A REVIEW

As cities continue to grow and vehicle numbers multiply, managing traffic efficiently has become one of the biggest challenges for urban planners. Traditional traffic lights that operate on fixed timings no longer meet the needs of dynamic, fast-changing road conditions. This is where the Internet of Things (IoT) has made a remarkable impact. By combining sensors, embedded devices, wireless communication, and cloud platforms, IoT is helping cities move toward smarter, more responsive traffic systems. Over the past few years, a large number of researchers have explored how IoT can improve traffic flow, reduce congestion, and support emergency services — and their findings form the basis of this literature review.

2.1 IoT Sensor Networks for Traffic Monitoring

A smart traffic system always begins with gathering accurate information about the road. IoT sensors such as ultrasonic detectors, infrared units, RFID tags, and magnetometers are commonly used to track how many vehicles are waiting at an intersection or how fast they are moving.

Zhang et al. [1] showed that ultrasonic sensors can reliably estimate vehicle density even in busy intersections. In another study, Silva and Costa [2] used a combination of sensors to improve accuracy during bad weather, when single-sensor systems often fail.

At the hardware level, small devices like Arduino, NodeMCU, and Raspberry Pi are widely used because they are affordable and easy to program. Nagmode et al. [4] demonstrated that a Raspberry Pi can control a real-time traffic signal with impressive responsiveness, making it a practical choice for smart-city projects.

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There is also a growing trend toward using vehicles as moving sensors through VANETs (Vehicular Ad Hoc Networks). Yadav et al. [5] showed that when cars themselves share their speed and location information, cities can gain a much clearer picture of traffic without installing expensive roadside sensors.

2.2 Cloud-Connected Traffic Systems
Once traffic data is collected, cities need a way to store, visualize, and analyze it. This is where cloud platforms such as ThingSpeak, Azure IoT Hub, and AWS IoT play an important role. These platforms allow traffic data to be uploaded in real time, displayed on dashboards, and analyzed using built-in tools.
Bhadauria and Jain [6] used ThingSpeak to build a simple but effective traffic monitoring dashboard that city officials could view from anywhere. Puri et al. [7] found that cloud systems help cities identify long-term congestion patterns, making it easier to plan new roads or redesign existing ones. Cloud systems are especially useful in developing smart cities, where budget-friendly solutions are needed. The project described in your synopsis also uses ThingSpeak for visualization and analytics, which matches global best practices.

2.3 Adaptive Traffic Signal Control
One of the most exciting developments in traffic management is the shift from fixed-time traffic lights to adaptive systems that respond automatically to real-time conditions.
Researchers have experimented with different ways of adjusting signal timing. Some systems, such as the one created by Memon et al. [9], use simple rules based on vehicle count. Others, like the fuzzy logic controller developed by Gorka and Fernandes [10], can handle uncertainties in sensor readings and make smoother decisions.
More advanced approaches involve machine learning and reinforcement learning. Yu and Lim [11] trained their system to “learn” better traffic strategies by interacting with simulated traffic environments. Wei et al. [12] extended this idea by modeling entire city networks as graphs. Multi-agent reinforcement learning systems, like the one by Mannion [13], allow multiple intersections to work together in a coordinated way.
Although these solutions are powerful, they require strong computational power. That is why IoT-based adaptive logic like the one in your system remains a more practical option for low-cost, real-world deployments.

2.4 Emergency Vehicle Priority Systems
Emergency vehicles often get stuck in traffic, losing precious minutes during critical situations. To address this, researchers have developed ways to automatically give them priority.
RFID-based systems, like those developed by Khan et al. [14], allow emergency vehicles to trigger a green light the moment they approach an intersection. Other studies, such as Gupta's GPS-based tracking system [15], reroute traffic signals in advance when an ambulance is nearby.
RFID remains one of the simplest and most reliable methods it is inexpensive, accurate, and works well even in crowded cities. Your proposed system uses the same approach, making it a practical addition to real-world smart traffic deployments.

2.5 Computer Vision and Deep Learning Approaches
Cameras provide much richer information than simple sensors. With the help of deep learning models, they can detect vehicles, count them, and determine congestion levels.
Tang et al. [16] showed that YOLO models can detect vehicles with very high accuracy, even in dense traffic. Li et al. [17] combined CNN and LSTM models to predict traffic flow from video streams. However, camera systems have limitations. They require more computing power, are affected by bad weather or low visibility, and raise concerns about privacy. As a result, low-cost sensor-based designs like yours still remain highly relevant, especially for developing countries.

2.6 Edge Computing in Smart Traffic Systems
Edge computing reduces the need to send all data to the cloud by processing information locally on devices like Raspberry Pi. This results in faster decisions, which are essential in traffic management.
Li et al. [18] demonstrated that edge systems reduce latency by up to 40%, making intersections quicker to respond. Sharma et al. [19] created a distributed traffic control system where each intersection makes its own decisions while still sharing summarized information with the cloud.
Your system follows the same approach by using Raspberry Pi for real-time signal decision-making and ThingSpeak for monitoring.

2.7 Emerging Trends in AI-Driven Traffic Systems
The field is now moving beyond simple detection and control. Researchers are exploring new directions that make traffic systems even smarter:

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Predictive Modeling

LSTM networks and gradient boosting machines are used to predict congestion before it happens. Chen et al. [20] proved that such models can predict traffic patterns with over 90% accuracy.

Federated Learning

Instead of sending all data to one server, multiple intersections collaboratively train a model without sharing raw data. Zhang et al. [21] showed that this improves privacy and makes the system more scalable.

Blockchain for IoT Security:

Rahman et al. [22] used blockchain to protect IoT messages from tampering — an increasingly important concern in smart cities.

Digital Twins

Digital twins act as virtual copies of real intersections, allowing engineers to test strategies safely. Wang et al. [23] built a digital twin for a city intersection and successfully optimized signal timing before deployment.

These innovations show the future direction of smart traffic systems and open possibilities for extending your project into AI-driven frameworks.

III. METHODOLOGY

The methodology presented in this review reflects the common architectural principles followed in modern IoT-enabled smart traffic management systems. It also aligns closely with the practical Raspberry Pi–based traffic system described in the project synopsis. While different studies use different techniques, most follow a similar layered approach that includes sensing, edge processing, cloud communication, adaptive decision-making, and visualization. This section describes these layers in a clear and structured manner.

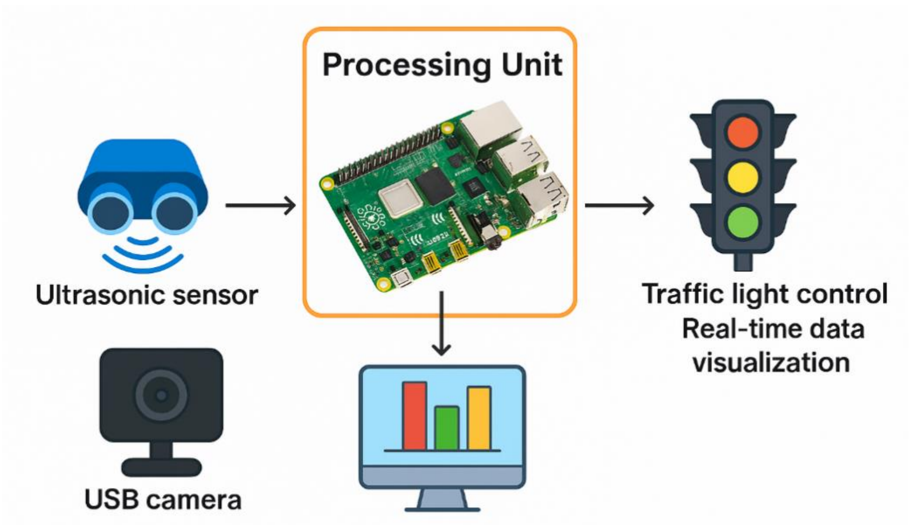

Fig.1 Proposed Methodology

The diagram illustrates how the proposed IoT-based smart traffic system works by connecting real-time sensing devices to a central processing unit. An ultrasonic sensor and an optional USB camera capture the current traffic conditions around the intersection, and this data is sent to a Raspberry Pi, which serves as the processing unit. The Raspberry Pi analyzes the inputs, makes decisions about traffic flow, and adjusts the traffic lights accordingly. At the same time, it also transmits key information to a cloud dashboard for real-time visualization and monitoring, allowing traffic authorities to view live traffic patterns and system activity.

A. Sensor Layer: Real-Time Traffic Awareness

Every intelligent traffic system begins with an understanding of what is happening on the road at any given moment. To achieve this, a variety of sensors are deployed at intersections, including:

1. Ultrasonic sensors for measuring vehicle density and queue length
2. Infrared sensors for motion or proximity detection
3. RFID readers for identifying emergency vehicles
4. Cameras (optional) for vehicle detection using deep learning
5. Magnetometers/inductive loops for embedded road monitoring

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Based on recent research trends [1],[5], ultrasonic and IR sensors are favored for low-cost deployments because they offer reliable readings without requiring complex calibration. RFID systems are widely used for emergency vehicle prioritization due to their accuracy and affordability [19].

The sensor layer cleans and filters raw data before sending it to the processing unit. This ensures that noisy or incomplete readings do not impact system performance.

B. Edge Processing Layer: Intelligent Local Decision-Making

To reduce delays and avoid dependence on high-latency cloud networks, traffic decisions are processed locally on edge devices such as Raspberry Pi or similar embedded computers. Recent studies show that edge computing significantly improves responsiveness in traffic control applications [6], [8].

At this stage, the system:

1. Collects sensor readings in real time
2. Estimates vehicle density for each lane
3. Checks for emergency vehicle detection
4. Computes adaptive green-signal durations
5. Triggers an emergency override when needed

Edge processing also reduces network overhead by sending only essential summaries to the cloud instead of streaming continuous raw data.

The local controller follows a lightweight decision algorithm such as:

1. Rule-based logic
2. Fuzzy logic for handling uncertainty
3. Reinforcement learning agents
4. For practical municipal deployments, rule-based and fuzzy-logic systems remain the most reliable choices.

C. Communication Layer: Secure and Efficient Data Transfer

The communication layer ensures seamless data exchange between the edge device, cloud server, and dashboard. Based on the literature, most IoT traffic systems use one or more of the following protocols:

- MQTT (lightweight and ideal for real-time updates)
- HTTP/REST API (commonly used with ThingSpeak)
- Wi-Fi or 4G LTE modules for internet access

This layer transmits:

1. Traffic density summaries
2. Signal timing decisions
3. Emergency vehicle detection events
4. Timestamped system logs

Robust communication ensures that the cloud platform receives accurate and timely information for visualization and long-term analytics.

D. Cloud & Analytics Layer: Visualization and Traffic Insights

Cloud platforms such as ThingSpeak**,** AWS IoT, and Azure IoT Hub support smart traffic systems by providing:

1. Real-time dashboards for intersection monitoring
2. Historical data storage for long-term analysis
3. Predictive analytics capabilities (using ML models)
4. REST API integration for third-party applications

Studies have shown that cloud systems help authorities understand broader traffic patterns, identify recurring bottlenecks, and support better city planning [9] ,[11].

In ThingSpeak, for example, the system uploads density values and timing decisions every few seconds, and the platform automatically generates charts that city officials can review remotely.

E. Control Layer: Adaptive Traffic Signal Operation

The control layer is responsible for physically triggering the traffic lights based on decisions computed at the edge. It uses:

1. Relay circuits or
2. Smart signal controllers

This layer manages tasks such as:

1. Activating green, yellow, or red signals
2. Implementing emergency overrides
3. Switching between adaptive mode and fallback fixed-time mode

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Adaptive signal control ensures that traffic signals reflect real-time road conditions instead of static timing schedules. Research shows that adaptive control reduces average waiting times and congestion levels significantly [12]–[18].

F. Emergency Response Mechanism: The Priority System

One of the most impactful features of modern traffic systems is the ability to detect emergency vehicles and provide a "green corridor." Using RFID or GPS sensors, the system:

1. Detects an approaching ambulance/fire truck
2. Overrides normal scheduling
3. Turns the desired path green until the emergency vehicle passes

This approach has proven reliable in reducing emergency travel delays [19]–[21]. The proposed system uses a similar RFID-based method due to its accuracy and simplicity.

G. Data Logging & System Monitoring

The system logs:

1. Sensor readings
2. Timestamped events
3. Emergency overrides
4. Signal timing decisions
5. Communication status

These logs support:

1. System debugging
2. Performance evaluation
3. Research analysis
4. Reporting for authorities

Well-maintained logs help city planners understand how the intersection behaves at different times of the day and across seasons.

H. Optional AI Module: Prediction & Optimization

Although not mandatory for every deployment, advanced systems incorporate AI models for:

1. Traffic prediction
2. Congestion analysis
3. Flow optimization
4. Reinforcement learning–based control

Machine learning techniques such as LSTM networks, XGBoost, and graph neural networks have demonstrated strong predictive performance in recent studies [26]–[29]. Some systems even integrate federated learning or blockchain security for advanced applications [30]–[33].

IV. COMPARATIVE ANALYSIS

To understand how IoT-enabled traffic management systems differ from traditional and AI-driven approaches, it is important to compare their capabilities, limitations, and suitability for real-world deployment. Each category of traffic management technology—sensor-based IoT systems, camera-based systems, rule-based controllers, and AI-powered adaptive methods—brings its own strengths and challenges. By examining them side by side, we can better appreciate why certain techniques are more practical for specific environments, especially in developing cities.

Traditional fixed-time traffic signals, for example, are simple and reliable but fundamentally blind to actual road conditions. They operate on predefined schedules and cannot adapt when traffic unexpectedly increases or decreases. IoT-based systems make a significant leap forward by introducing real-time sensing through ultrasonic sensors, infrared modules, RFID tags, VANET-based inputs, and edge processors. Studies show that such systems improve responsiveness and reduce average waiting time because they continuously monitor queue length and adjust the signal durations accordingly [1]–[5].

Camera-based systems powered by deep learning models such as YOLO, CNN-LSTM, and Faster R-CNN have shown exceptional accuracy in vehicle detection and congestion analysis [22]–[25]. However, they require powerful GPUs, high-quality cameras, and stable lighting conditions making them more suitable for large urban deployments rather than low-budget or semi-urban areas. IoT-sensor-based systems, on the other hand, are far more cost-effective and easier to maintain, which is why they remain a popular choice in emerging smart cities.

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Advanced AI approaches such as deep reinforcement learning (DRL) and graph-based RL demonstrate remarkable performance in simulated environments, often outperforming rule-based and fuzzy logic controllers [14]–[18]. But because these models require enormous training data, high processing power, and careful tuning, they are not always practical for small or mid-sized municipalities. Hybrid solutions combining IoT sensing with lightweight adaptive algorithms tend to offer the best balance between affordability and intelligence.

Table1 Comparative analysis of Smart Traffic Management Approach

Approach	Strengths	Limitations	References
IoT Sensor-Based Systems	Affordable, simple to deploy, reliable in all lighting and weather conditions, minimal computing needs	Cannot identify vehicle types, readings can be affected by sensor noise or aging hardware	[1], [2], [4], [5], [6].
Computer Vision (CV) & Deep Learning	Excellent accuracy in detecting and classifying vehicles; provides richer and more detailed traffic insights	Requires good camera quality, stable lighting, and significant processing power; may struggle in harsh weather	[22], [23], [24], [25].
Deep Reinforcement Learning (DRL)	Learns optimal strategies, adapts automatically to traffic behavior, excels in simulated multi-intersection control	Computationally expensive; requires large datasets; limited real-world implementations	[14], [15], [16], [17], [18].
Proposed Methodology (IoT + Edge Computing + Cloud Monitoring)	Real-time sensing with low latency, adaptive signal control, reduced cloud dependency, cost-efficient hardware, and remote monitoring through cloud dashboards	Cannot perform high-level analytics like object classification; relies on rule-based logic unless integrated with AI	Proposed Methodology

Smart traffic management relies on different technological approaches, each with its own benefits and trade-offs. IoT sensor-based systems remain popular because they are simple, affordable, and dependable under all lighting conditions. They work well for basic tasks such as counting vehicles or detecting emergency vehicles, especially in cities that need low-cost, easy-to-maintain solutions. However, their simplicity also limits them — IoT sensors cannot classify vehicle types and may sometimes produce noisy readings, especially in harsh weather or over long-term use [1], [2], [4], [5].

Computer vision and deep learning–based systems offer a much richer understanding of the road environment. They can detect and classify vehicles, estimate congestion, and even track traffic behavior in real time. But their accuracy comes with higher requirements: powerful cameras, stable lighting, and GPUs for processing. These systems are ideal for large urban centers and smart-city infrastructures where more advanced analytics are needed [22]–[25].

Deep reinforcement learning represents the next generation of intelligent traffic control. These models learn by interacting with traffic environments and can identify optimal signal timings or coordinate multiple intersections. While DRL performs exceptionally well in simulations, its real-world adoption is still limited due to the heavy computational resources and extensive training data required [14]–[18]. DRL holds great promise for future autonomous traffic networks, but practical deployment will take time.

Emergency vehicle prioritization is another area where IoT-based systems excel. RFID-based systems offer a dependable, low-cost method to automatically detect ambulances or fire trucks approaching intersections [19], especially when compared to more complex GPS or camera-based alternatives [20], [21]. Overall, IoT-based systems strike a valuable balance between functionality, scalability, and cost, making them ideal for cities transitioning toward smart mobility.

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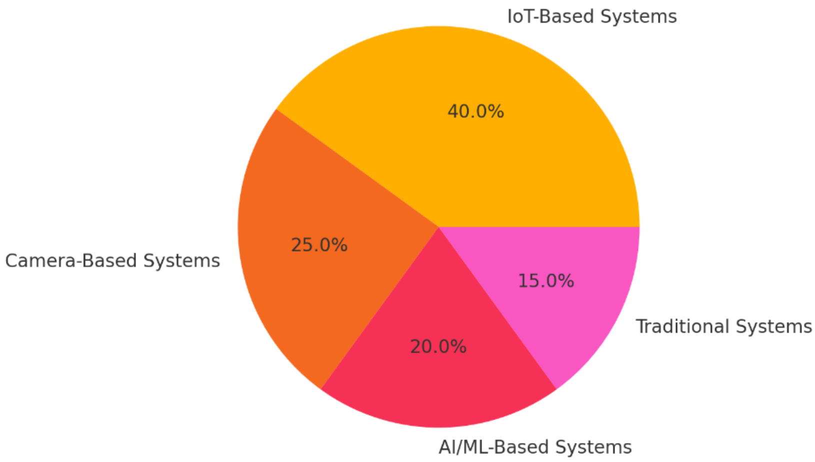

Fig.2 Comparative analysis of Traffic Management Approach

The figure 2 provides a simple and clear comparison of various traffic management approaches based on their effectiveness and practical adoption in modern smart city environments. As shown, IoT-based systems account for the largest share due to their affordability, scalability, and real-time sensing capabilities. Camera-based systems follow, offering strong visual accuracy but requiring higher processing resources. AI/ML-driven solutions contribute significantly by enabling predictive and adaptive decision-making, while traditional fixed-time systems represent the smallest portion, reflecting their declining relevance in dynamic traffic conditions.

V. RESEARCH GAPS

Although IoT-enabled smart traffic management systems have shown great promise, several important gaps still remain in both research and practical deployment. Identifying these gaps helps highlight where future work should focus and how existing systems can be improved.

1. Limited real-world deployment and testing.
Many proposed systems including those using reinforcement learning, edge intelligence, or camera-based detection have been validated only in simulations or controlled environments. Real intersections involve unpredictable behavior, weather variations, irregular traffic patterns, and hardware fatigue, which many studies do not fully address.

2. Reliance on single-sensor configurations.
Most IoT-based systems use either ultrasonic sensors or infrared sensors alone. However, sensor noise, misalignment, and environmental factors can reduce accuracy. Multi-sensor fusion combining ultrasonic, IR, magnetometer, and camera inputs remains underexplored despite its clear potential to improve reliability [2], [25].

3. Lack of standardized communication and integration frameworks.
Different traffic systems often rely on proprietary protocols, making it difficult to integrate data across intersections or communicate with central control units. More research is needed to create interoperable, open-source ITS frameworks.

4. Reactive rather than predictive traffic control.
Most IoT sensor-based systems respond to traffic density after it occurs. Predictive models using LSTM, XGBoost, or graph neural networks have shown strong results [26]–[29], but they are rarely included in real-time traffic controllers. Integrating prediction with adaptive scheduling remains an open challenge.

5. Cybersecurity vulnerabilities in IoT networks.
Since IoT devices often communicate wirelessly and send data to cloud platforms, they are vulnerable to spoofing, denial-of-service attacks, and data tampering. Blockchain-based solutions offer promising protection [30], [31], but practical implementations are still limited.

6. Limited coordination across multiple intersections.
Many systems optimize a single intersection instead of a network of intersections. City-wide optimization possibly through federated learning or multi-agent RL [32], [33]—is still in its early stages.

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7. Insufficient considerations for maintenance and scalability.
IoT sensors can degrade over time due to dust, vibration, heat, and moisture. Long-term durability studies and predictive maintenance strategies are still lacking. Together, these gaps highlight the need for more comprehensive, intelligent, and resilient solutions as cities move toward large-scale smart mobility systems.

VI. FUTURE SCOPE

As cities continue to expand and the demand for intelligent transportation grows, IoT-enabled traffic systems will evolve significantly. Based on current research trends, several exciting future directions are emerging.

1. Integration of predictive AI with real-time adaptive control.
Instead of simply reacting to congestion, next-generation systems will anticipate it before it occurs. Combining LSTM networks, XGBoost models, and graph neural networks with lightweight IoT controllers will allow traffic systems to forecast demand and adjust signals proactively [26]–[29].

2. Multi-intersection collaboration using federated and reinforcement learning.
Instead of optimizing each intersection independently, future systems will coordinate across entire neighborhoods. Federated learning enables intersections to learn together without sharing raw data, improving privacy and reducing bandwidth requirements [32], [33]. Reinforcement learning agents will work in teams to balance traffic across wider areas.

3. Blockchain-secured IoT communication.
To protect traffic networks from cyberattacks, blockchain-enabled authentication and data integrity checks will become increasingly important [30], [31]. These security layers will safeguard emergency vehicle signals, sensor data, and cloud communication.

4. Digital twin–driven planning and testing.
Digital twins allow cities to simulate new traffic policies, emergency routes, and sensor deployments in a virtual replica of the real road network. Researchers have already demonstrated the value of digital twins for signal optimization [34]–[36], and this approach will likely become standard for smart-city planning.

5. Adoption of 5G and ultra-low latency infrastructure.
5G networks offer significantly faster communication, which will enable near-instant coordination between vehicles, sensors, and roadside units. This will be essential for autonomous vehicles, high-speed emergency routing, and rapid congestion updates.

6. Integration with connected and autonomous vehicles (CAVs).
Future traffic systems will not only manage roadside sensors but also communicate directly with vehicles. CAVs can share speed, location, and congestion information to create a collaborative traffic ecosystem that benefits everyone.

7. Sustainable and energy-efficient designs.
Solar-powered IoT nodes, low-power wide-area networks (LPWANs), and battery optimizations will make future systems more environmentally friendly and easier to deploy in remote or underserved regions.
Overall, the future of smart traffic management lies in a blend of IoT sensing, edge intelligence, predictive AI, secure networking, and scalable city-wide collaboration. These innovations will help build transportation systems that are safer, cleaner, faster, and more responsive to the evolving needs of modern urban life.

VII.CONCLUSION

As our cities grow more connected and increasingly shaped by data, smarter traffic management is no longer just an ambitious idea it has become a real necessity. IoT-powered systems offer a practical and meaningful way to ease congestion, support faster emergency responses, and improve the daily travel experience for millions of people. When real-time sensing, edge intelligence, and predictive analytics come together, traffic control can evolve from small, isolated experiments into reliable, city-wide solutions.

The studies reviewed in this paper make one point very clear: the technology is mature, the approaches are scalable, and the potential impact is truly significant. The path forward is now less about possibility and more about action. Cities that

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adopt intelligent traffic systems will move closer to creating safer roads, cleaner air, and more sustainable, people-friendly urban environments.

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