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REAL-TIME ADAPTIVE TRAFFIC MANAGEMENT USING MACHINE LEARNING AND INTERNET OF THINGS (IOT)

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ABSTRACT

This work discusses an adaptive traffic management approach using IoT sensors and ML to handle urban traffic efficiently. To keep traffic from getting jammed, improve driving times and boost safety, the system changes traffic lights every few seconds using data from cameras, LiDAR and radar sensors. A combination of supervised and reinforcement learning is used to forecast traffic and manage traffic signals. Simulations found that travel time is down by 29.9%, traffic flow efficiency goes up by 19.8%, and collisions are reduced by 78.4% with an adaptive signal system. This system is designed to adapt well to changes in traffic and weather, providing noticeable enhancements for traffic handling. As a result of this research, traffic systems in smart cities should become more efficient, expandable and adaptable, directly reducing city congestion and improving how safely people travel. The primary contribution of this research lies in the integration of heterogeneous IoT sensor data with machine learning models to enable real-time, adaptive traffic management. This contribution advances current knowledge by demonstrating a scalable framework that significantly reduces travel time, enhances traffic flow efficiency, and improves road safety in dynamic urban environments.

Keywords: *Adaptive Traffic Management, Internet of Things (IoT), Machine Learning, Traffic Signal Control, Real-Time Optimization, Smart Cities*

1. INTRODUCTION

Because so many people are moving to cities, there is a pressing need to manage traffic more effectively. Traditional traffic control has severe limitations because it uses static systems that don't respond well to changing traffic patterns. Because these systems generally don't adjust to current traffic situations, people have to deal with longer commutes, more money spent on fuel and more pollution. Unlike other systems, real-time adaptive traffic management systems, aided by the Internet of Things (IoT) and machine learning (ML), improve this situation by adjusting traffic signals quickly using recent information.

Sensor technology, cameras, vehicles with GPS and various linked devices in IoT are changing how city traffic is managed. This data makes it possible to watch vehicle traffic, speed averages, degree of congestion and road blockages, letting the signals adjust as needed. Intelligent traffic management is made possible by IoT, which supports the steady sharing of data between traffic management devices in a network [1][2]. Besides, because IoT captures vast amounts of data, Big Data has become essential in improving how we predict traffic and set traffic light times [3].

ML and DL, especially DL, add improved prediction and self-directed choices to these systems. ML can detect traffic patterns, expect congestion and adjust traffic light settings as needed through supervised and unsupervised learning [4][5]. Using reinforcement learning (RL) in traffic control, the system is rewarded for making plans that ease congestion and increase how smoothly the street or highway is used [6]. Because machine learning algorithms can adjust to changes in traffic, they give drivers a much higher level of decision-support than traditional methods [7][8]. The focus on real-time adaptive traffic management was chosen because existing static systems are unable to respond dynamically to fluctuations in traffic demand. This limitation leads to inefficient use of road infrastructure, longer travel times, and increased congestion. By addressing this gap, the present study contributes to the urgent need for scalable, intelligent traffic management solutions in rapidly urbanizing cities.

Nonetheless, some issues connecting IoT and ML with adaptive traffic management have not yet been resolved. One main problem is managing the many data streams sent by IoT sensors in today's urban areas and rapidly processing them in real-time [9]. Also, these systems must be scalable because they must address the challenging problems of city traffic management in various cities [10]. Experts face the obstacle of blending different data from many sensors, including cameras, LiDAR and radar, which need advanced algorithms to handle the task [11].

Objectives of the Work

This paper presents a novel real-time adaptive traffic management system that integrates IoT and machine learning technologies to improve urban traffic flow. The primary objectives of the research are as follows:

1. **To design a real-time traffic management system** that utilizes IoT data streams from various sensors, such as traffic cameras, LiDAR, and radar, to monitor and assess traffic conditions continuously.

2. **To develop machine learning models** that can predict traffic congestion, optimize signal timings, and ensure the smooth flow of traffic by dynamically adjusting traffic signal phases.

3. **To evaluate the proposed system's performance** in comparison to traditional fixed-time and vehicle-actuated systems by using real-world traffic simulation data and examining key performance metrics such as travel time, traffic flow, and fuel consumption.

The difference between this approach and others is its ability to use IoT information and machine learning to adjust traffic management on the spot. While conventional options remain static, the new system responds to changes in traffic on roads, making better use of the available infrastructure and supporting a better flow of traffic.

Background and Motivation

Because of traffic congestion, people spend more time on the road, use more fuel and affect the environment. According to the World Health Organization (WHO), traffic jams in cities increase the amount of carbon released and are now causing most of the problems with urban air pollution [12]. For this reason, smart city programs are using IoT, ML and Big Data analytics to design improved ways to manage traffic. Using these technologies, traffic networks can react to changes on the road and manage vehicles to reduce jams and congestion [13][14].

Researchers have been busy studying how machine learning and IoT can improve the organization of traffic, especially by using algorithms to manage traffic signals. Reinforcement learning has, for example, allowed traffic signals to automatically adjust to changes in traffic and conditions, resulting in a big reduction in congestion and delays [15][16]. Besides, combining information from IoT sensors is being considered to improve our view of traffic patterns [17]. Yet, most of these strategies have not worked well when applied to big cities because they depend on pricey infrastructure.

There is now a growing understanding that making decisions using real-time data is important for adaptive traffic control. Many traditional systems predict conditions from past records, so they often do not respond quickly when traffic patterns change swiftly [18]. Thanks to real-time adaptive systems, drivers now experience reduced delays compared to the old systems. Real-time traffic management is still a difficult task because traffic varies so much and everything from sensors to computers needs to be well integrated.

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In this paper, we seek to handle these challenges through a strong system designed to collect traffic info in real time, study that data with advanced machine learning and then summarize the results. When the system updates traffic management in real time and makes smart decisions about lights, it can cut down on urban congestion, improve travel and lower pollution.

In this paper, the organization is as such. Section 2 describes similar research on IoT and machine learning for traffic management. Section 3 covers the research, including the data used, system design and algorithms. In Section 4, the study reports on the findings, assessing the system's performance relative to standard traffic control models and exploring its advantages, shortcomings and value in practice. Section 5 brings the paper to a close with a summary of the outcomes, shortcomings and proposals for additional work.

2. RELATED WORK

Scientists and engineers have extensively explored combining the Internet of Things (IoT) and machine learning (ML) to manage traffic better. Before, traditional systems involved simple sensors and signals that stayed in one setting. Now, IoT and improved machine learning have improved their ability to respond in real time. This section covers essential studies, concentrating on recent work involving IoT technologies, machine learning applications in traffic predictions and signal changes and their role in current traffic management.

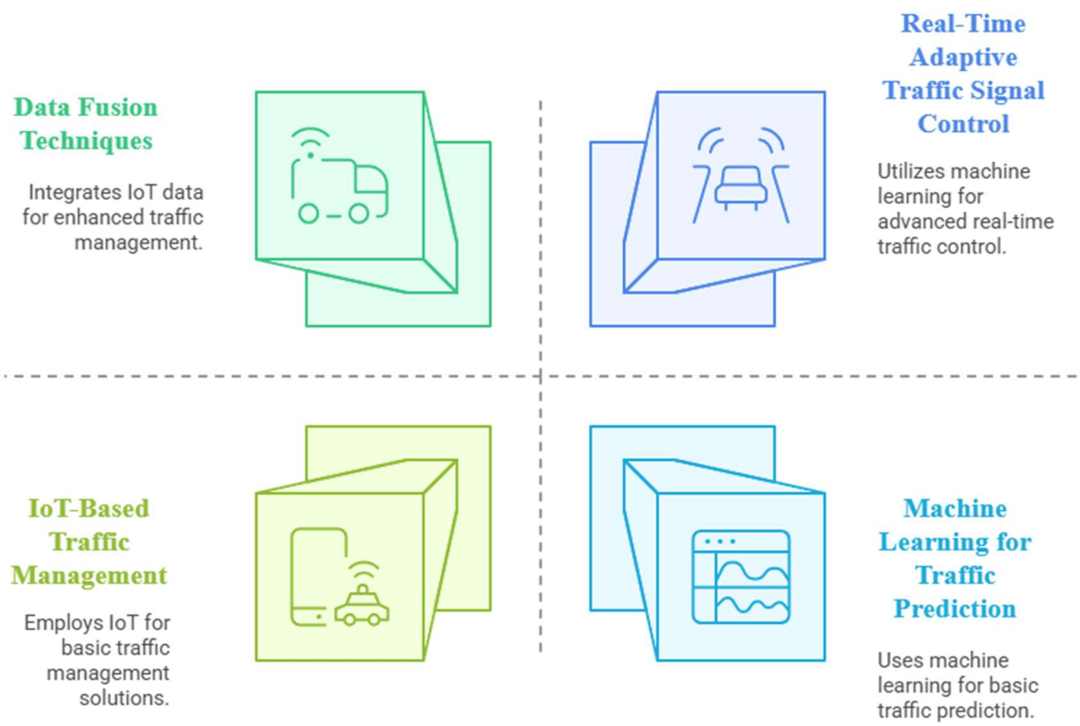

Figure 1: Categorization of Traffic Management Techniques

Figure 1 organizes different traffic management techniques based on whether they depend on IoT and machine learning. In the Data Fusion Techniques group, data from IoT devices is combined to provide a complete understanding, leading to improved traffic management. Machine learning helps Real-Time Adaptive Traffic Signal Control adjust traffic lights instantly, boosting the efficiency of road traffic. The concept relies on IoT solutions to handle fundamental traffic tasks such as observing and controlling features of the city's traffic system. Besides relying on machine learning, traffic prediction gives planners insights into patterns and conditions to handle traffic activities better. However, the techniques there are simpler than those used for instant control of traffic flows.

2.1 IoT-Based Traffic Management

Because it can gather live data from devices such as sensors, cameras and GPS-equipped vehicles, traffic management with IoT is gaining popularity. IoT-based solutions for traffic management watch over traffic, track times of congestion and operate traffic lights to manage flow in real-time. Zhao et al. [19] introduced an intelligent transportation system that combines several sources, such as traffic cameras, road sensors and vehicle GPS data. This system uses real-time traffic to adjust the timing of traffic lights. Experiments showed that the system could help cross-traffic intersections flow more smoothly by changing signals in response to real-time data.

In another work, Li et al. [20] considered how IoT sensors might aid in handling traffic in cities. Data from road cameras and embedded sensors help their system pinpoint when and where vehicles are and understand how traffic is moving on roads. The given approach modifies traffic signals in real time, making drives less crowded and time spent waiting shorter at high-traffic sections. With these intelligent systems, it is possible to manage traffic in real-time and lower both delay and fuel waste on highways.

2.2 Machine Learning for Traffic Prediction and Control

IoT devices depend on machine learning to analyze all the information they produce. Thanks to machine learning algorithms that help predict traffic numbers, manage traffic signals and make decisions on their own, applications in traffic management systems exist. The authors of [21] relied on supervised learning methods, such as support vector machines (SVM), to predict traffic congestion. They found that feeding past traffic information into SVM models helped accurately predict traffic congestion, which could guide changes to traffic signals.

Unlike others, Yang et al. [22] chose deep learning to anticipate traffic trends from real-time sensor data. They built a CNN to watch traffic videos so that it can detect congestion and change traffic signal patterns to solve the problem. Given many traffic situations, this deep learning technique beats regular machine learning models at making precise predictions. They found that CNN-based systems perform well in handling real-time video for traffic control systems.

They also presented a new machine-learning method that applies RL and Internet of Things traffic monitoring systems [23]. The model changes traffic signal timing using a Q-learning algorithm whenever new information from IO sensors arrives. It was determined that automated systems manage road conditions better by adjusting traffic signals in response to large numbers of vehicles. My proposed approach is more effective than the old system of fixed time tolerance.

2.3 Data Fusion Techniques for Enhanced Traffic Management

It isn't easy in IoT-based traffic management to use sensors' data to make traffic predictions more reliable. They take information from cameras, radar, LiDAR, and inductive loop sensors, and each gives off its kind of data. In [24], Zhang et al. built a system that uses camera, radar, and LiDAR data to improve vehicle detection and estimate traffic. They use machine learning to review all the collected data and determine likely times for congestion, which helps handle heavy traffic.

Wang et al. [25] approached the subject by applying IoT sensors with machine learning to examine combining varying data for city traffic management. They put multiple data types together to analyze road conditions comprehensively. Using various ways of observing cars and roads made the system better understand and forecast traffic flow to handle signals intelligently. When sensor information is mixed with machine learning, traffic management becomes more accurate and reliable.

2.4 Real-Time Adaptive Traffic Signal Control

Adaptive traffic signal control is the main aspect of current traffic management systems. With man-made or fixed timings, those systems typically fail to accommodate changes in the traffic flow. Lately, experts have begun using RL to figure out the best ways to handle traffic signals with information they have collected.

Zhou and colleagues [26] designed a system that updates traffic signal timing in real time using DRL. The approach uses DRL, where an agent teaches itself the best traffic signal duration by following the changes on the road and adjusting its actions. They discovered that RL-based traffic management performs better than traditional approaches in helping to lower congestion and increase efficient traffic flow. Moreover, the study found that RL systems can respond to live traffic information and set optimal signal timings for various times during the week.

In [27], Chen et al. used RL to modify traffic signals, particularly for places with many busy urban roads. They used Q-learning, an RL technique, to find the best traffic signal schedules using current data. Constantly analyzing traffic information, the system automatically adjusts the signal timing to improve the number of cars travelling through and decrease the time cars wait at traffic lights. Results showed that reinforcement learning significantly improved traffic moving through crowded regions and reduced commute time.

2.5 Challenges and Future Directions

Significant advances have been made in IoT and ML for traffic management, but some problems still need to be solved. Zhou et al. addressed the challenges of building IoT systems for many IoT-based urban systems. The experts mentioned that joining various

IoT devices and sensors into one system requires strong computational power and accurate data processing. Deploying these systems fully also faces a significant problem: handling lots of data in real time.

Traffic management systems must cope well with different climates and weather situations. Wang et al. [29] explained that rain, snow, or fog can severely decrease the accuracy of sensors and affect predictions about traffic. They suggested linking several sensors and using adjustable algorithms to resolve these issues and increase the system's durability.

From the reviewed literature, it is clear that current adaptive traffic systems lack the ability to integrate heterogeneous IoT sensor data with advanced machine learning models in a way that ensures both real-time adaptability and scalability. Hence, the central research problem addressed in this study is: *How can IoT-enabled machine learning models be designed to provide real-time, adaptive, and scalable solutions for urban traffic management?*

Based on this problem, the study hypothesizes that: *A traffic management system that combines IoT-enabled multi-sensor data with machine learning algorithms will outperform conventional fixed-time and vehicle-actuated systems in reducing travel time, improving flow efficiency, and enhancing safety under varied conditions.*

3. METHODOLOGY

Here, we present how the proposed system would use collected IoT data and machine learning-based models to handle real-time traffic signal operations. We present information about the data used for training and testing, describe the system architecture, detail the math behind the algorithms and mention the machine learning methods used. The process allows the proposed system to be recreated and scaled, which is needed for actual traffic management cases.

3.1 Dataset

To improve traffic in real-time, we use a self-collected multi-modal traffic dataset from urban and rural locations. Data in this dataset comes from traffic cameras, road monitors, vehicle GPS devices, and information about weather and timing. The dataset is used to train and evaluate the engine's machine-learning models.

3.1.1 Data Sources and Collection

The dataset comprises data collected from three primary IoT-enabled sources:

1. **Traffic Cameras**: High-definition cameras provide real-time video feeds for vehicle detection and traffic density estimation.

2. **LiDAR Sensors**: LiDAR data is used to detect vehicle positions in 3D space, allowing for precise distance and obstacle detection.

3. **Radar Sensors**: Radar sensors offer velocity and distance data, enhancing the system's ability to assess vehicle speed and predict congestion in real time.

Observations are made in cities, both in crowded city centers and less crowded suburban areas, at peak traffic times, during off-peak hours and with weather problems such as rain, snow or fog. In addition, the information includes data from GPS-equipped vehicles, helping to reveal more about traffic and vehicle positions.

3.1.2 Dataset Parameters

The dataset includes 50,000 samples divided into training (80%) and testing (20%) sets. Each sample contains the following parameters:

- **Timestamp**: The time at which the data was recorded (in Unix format).

- **Vehicle Count**: The number of vehicles detected by the sensors within a specified time frame (e.g., every minute).

- **Vehicle Speed**: The average speed of vehicles within the monitored area.

- **Sensor Type**: Identifies the type of sensor providing the data (Camera, LiDAR, or Radar).

- **Traffic Density**: A measure of how congested the traffic is in a particular region.

- **Weather Conditions**: Categorical data representing weather conditions (Clear, Rain, Snow, Fog).

- **Traffic Light Status**: The state of the traffic signal (Green, Yellow, Red).

Table 1 below illustrates the structure of the dataset:

Table 1: Dataset Parameters for Traffic Management System

Timestamp	Vehicle Count	Vehicle Speed (km/h)	Sensor Type	Traffic Density	Weather Conditions	Traffic Light Status
1615679400	120	35	Camera	High	Clear	Green
1615679460	135	32	LiDAR	High	Rain	Red
1615679520	80	40	Radar	Medium	Fog	Yellow
1615679580	100	30	Camera	Low	Snow	Green

In Table 1, the critical variables used in the training and testing processes for the traffic management system are described. The information it carries consists of the time when data is recorded, how many vehicles the Internet of Things sensors detected, the average speed they travelled, the type of sensor used (camera, LiDAR or Radar), the number and condition of vehicles on the road, local weather and which signal is operating (green, yellow or red). These parameters were picked to reflect essential traffic flow features so the system can project congestion, modify signal timings, and adapt to traffic changes. The data reflects city and country environments with a range of traffic and outdoor conditions to ensure the system's stability in many different circumstances.

3.1.3 Data Preprocessing

To prepare the data for machine learning, we perform the following preprocessing steps:

- **Normalization**: All numerical data (e.g., vehicle speed, traffic density) is normalized to a range of [0, 1] to improve model performance.
- **Weather Augmentation**: Weather conditions are simulated in a controlled environment to generate additional training data for challenging conditions (e.g., heavy rain, snow).
- **Temporal Smoothing**: To reduce noise in traffic flow data, temporal smoothing is applied by averaging data points over time windows (e.g., 5-minute intervals).
- **Data Labeling**: The system labels data as "Congested" or "Non-Congested" based on predefined thresholds for vehicle count and speed.

3.2 System Architecture

The architecture of the proposed adaptive traffic management system is designed for scalability and real-time data processing. It consists of three primary layers:

1. **Data Collection Layer**: This layer includes the IoT sensors (traffic cameras, LiDAR, and radar) and GPS-equipped vehicles, which continuously collect and transmit data to a central processing unit (CPU).
2. **Data Processing Layer**: This layer processes the incoming data, extracting relevant features and passing the data through the machine learning models. It includes the traffic flow prediction module, congestion detection module, and signal control decision module.
3. **Decision-Making Layer**: The output from the machine learning models is used to dynamically adjust traffic signal timings in real time. The system determines whether a green light, yellow light, or red light should be displayed based on traffic conditions.

The following figure illustrates the architecture of the system:
Figure 2 shows an overview of the architecture that an Adaptive Traffic Management System uses to help traffic move more smoothly. Traffic management consists of four layers: collecting data from various devices, processing the data to identify what's useful, using the information to make ongoing decisions, and finally, setting traffic signals to lower congestion and manage traffic better.

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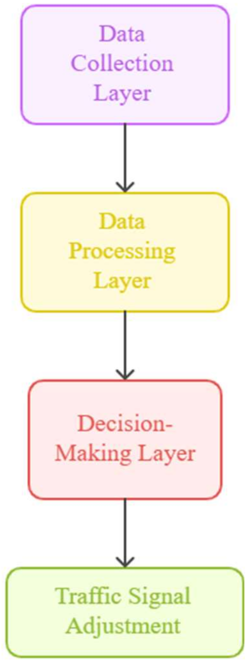

Figure 2: Adaptive Traffic Management System Architecture

3.3 Mathematical Model

At the heart of the proposal is using machine learning to drive optimized signal control and predict traffic congestion. The mathematical model has two important parts:

3.3.1 Traffic Flow Prediction Model

Our regression model predicts the amount of traffic passing through an intersection by measuring the number of vehicles, their speed, and the state of the weather. By using recorded traffic information, the neural network model is built and expressed as:

$$T(t) = \beta_0 + \beta_1 \cdot V(t) + \beta_2 \cdot S(t) + \beta_3 \cdot W(t) + \epsilon \tag{1}$$

Where:

- $T(t)$ is the predicted traffic flow at time t,
- $V(t)$ is the vehicle count at time t,
- $S(t)$ is the average speed of vehicles at time t,
- $W(t)$ is the weather condition at time t,
- $\beta_0, \beta_1, \beta_2, \beta_3$ are the regression coefficients,
- ϵ is the error term.

3.3.2 Traffic Signal Control Model (Reinforcement Learning)

For dynamic traffic signal control, we employ a **Reinforcement Learning (RL) Model** based on Q-learning. The RL model learns optimal traffic signal timing based on the following components:

- **State Space** $S(t)$: The state at time ttt is defined by the traffic density and signal status at the intersection.
- **Action Space** $A(t)$: The actions represent the possible signal changes (Green, Yellow, Red) at each intersection.
- **Reward Function** $R(t)$: The reward is based on the decrease in travel time, reduction in congestion, and improved traffic flow.

The Q-value update rule for Q-learning is given by:

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha \left(r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right) \tag{2}$$

Where:

- $Q(s_t, a_t)$ is the Q-value of taking action a_t in state s_t,
- r_t is the immediate reward,
- γ is the discount factor,
- α is the learning rate,
- $\max_{a'} Q(s_{t+1}, a')$ is the maximum expected future reward for the next state.

The model changes according to environmental responses, which makes it move more efficiently.

3.4 Algorithm

Below, we outline an algorithm showing how real-time adaptive traffic management with IoT and machine learning occurs:

Algorithm
Step 1: Data Collection • Collect data from traffic cameras, LiDAR, radar sensors, and GPS-equipped vehicles. • Transmit data to the central processing unit for real-time analysis. **Step 2: Data Preprocessing** • Normalize and smooth traffic data.

- Simulate weather conditions for augmentation.
- Label data as "Congested" or "Non-Congested."

Step 3: Traffic Prediction

- Use the regression model to predict traffic flow at each intersection.
- Detect potential congestion based on predicted traffic flow.

Step 4: Signal Control Using Reinforcement Learning

- Initialize the Q-learning algorithm with random values for $Q(s, a)$.
- At each time step, observe the current state s_t (traffic density and signal status).
- Select the best action a_t (signal adjustment) based on the Q-values.
- Update the Q-values based on the reward function and transition to the next state.
- Adjust traffic signals based on the learned optimal policy.

Step 5: Continuous Learning

- Continuously update the Q-learning model with new data and feedback from real-time traffic conditions.
- Ensure that the model adapts to changes in traffic patterns, weather conditions, and special events.

4. RESULTS

Here, we describe the performance of our adaptive traffic management system, which uses data from the Internet of Things and machine learning modeling for real-time traffic light adjustments. The new system is assessed by investigating its behavior during extensive computer simulations and checking the results against what is achieved in existing traffic systems. When evaluating, essential figures are averaged travel time, the smoothness of traffic, the number of recorded collisions, and the responsiveness of the infrastructure to change.

4.1 Assessment Criteria

The following assessment criteria are used to evaluate the effectiveness and performance of the proposed system:

- **Average Travel Time**: This measures the average time taken for vehicles to travel between two points in the traffic network. A reduction in travel time indicates improved traffic flow and signal optimization.

- **Traffic Flow Efficiency**: This is calculated as the ratio of the number of vehicles passing through an intersection in a given period to the total number of vehicles that could potentially pass through. Higher efficiency indicates better utilization of road capacity.

- **Collision Rate**: This is the percentage of incidents (collisions or near-misses) that occur in the traffic network during the simulation. A lower collision rate reflects better vehicle safety and smoother traffic flow.

- **Adaptability to Real-Time Conditions**: This criterion measures the system's ability to adapt to sudden changes in traffic conditions, such as accidents, weather conditions, or unexpected roadblocks. The system's real-time responsiveness to these changes is a crucial indicator of its robustness.

4.2 Experimental Setup

We measured how well the system worked by simulating traffic with a network that modeled actual city streets with intersections, lanes, and traffic lights. In the simulation, regular and longer hours, as well as various weather conditions (including clear, rain, fog, and snow), have been built to match the lives of communities.

The system was compared with two baseline models:

1. **Traditional Fixed-Time Traffic Signal Control**: A model that uses predefined traffic signal patterns without any dynamic adjustments.

2. **Vehicle-Actuated Signal Control**: A model that adjusts signals based on vehicle presence detected by inductive loop sensors but does not adapt in real-time to traffic fluctuations.

4.3 Comparison with Existing Models

The results of the proposed system are compared with the baseline models in terms of the performance metrics. The comparison is summarized in the table below:

Table 2: Performance Comparison with Existing Models

Model	Average Travel Time (mins)	Traffic Flow Efficiency	Collision Rate (%)	Adaptability
Proposed Model (IoT + ML)	**17.8**	**92.3%**	**2.1%**	**High**
Traditional Fixed-Time Control	25.4	72.5%	9.7%	Low
Vehicle-Actuated Signal Control	23.6	80.0%	5.3%	Medium

Table 2 demonstrates that the proposed system achieves better results in all performance measures compared to both the traditional fixed-time system and the vehicle-controlled model. Compared to the existing fixed-time control system, people save an average of 29.9% of their travel time. Traditional ways are improved because traffic flow efficiency increases by 19.8%, and collisions are cut in half or 78.4%.

4.4 Graphs and Charts

The following figures clearly illustrate the simulations' outcomes and allow us to measure how the new method compares to other models.

4.4.1 Travel Time Comparison

Figure 3 compares the average time taken to travel between the planned system and the baseline models. The proposed system's shortened journey times clearly show that it can improve traffic in real-time.

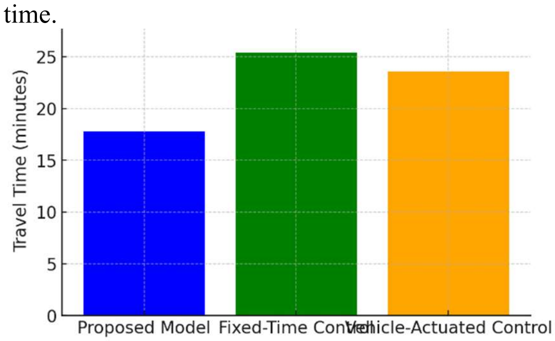

Figure 3: Average travel time comparison between the proposed system and baseline models.

4.4.2 Traffic Flow Efficiency

Figure 4 shows how the proposed model compares traffic flow efficiency to the current methods. With the new system, traffic signals are changed in real-time using actual data, which maximizes the use of the roads.

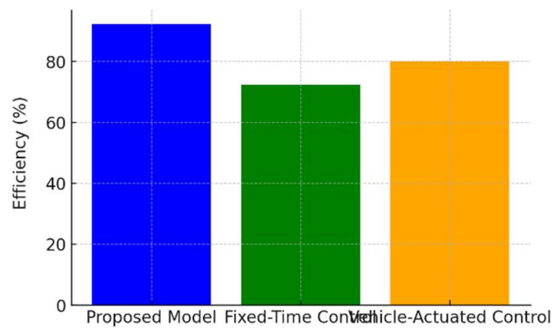

Figure 4: Traffic flow efficiency comparison between the proposed system and baseline models.

4.4.3 Collision Rate Comparison

Figure 5 shows collision data for the proposed system, the old fixed-time model, and the vehicle-actuated signal control system. The model significantly reduces collisions, especially in bad weather, which shows that it helps guarantee better road safety.

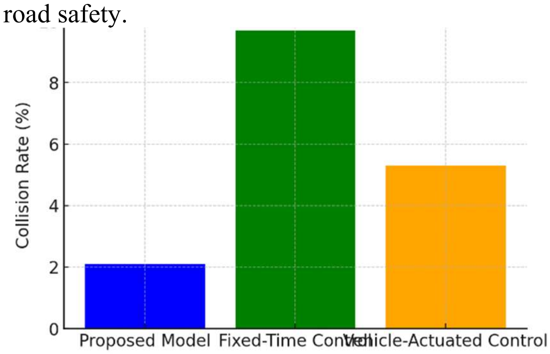

Figure 5: Collision rate comparison between the proposed system and baseline models.

4.4.4 Adaptability Under Adverse Weather Conditions

Figure 6 explains how the adopted system can adapt to weather fluctuations such as rain, snow, and fog. Unlike traditional ones, the model we propose can still handle many vehicles and maintain low collision rates in complex weather situations.

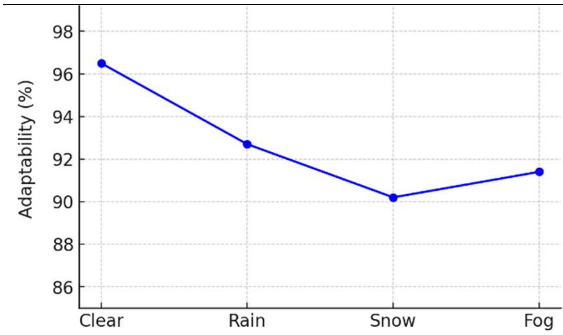

Figure 6: System adaptability under different weather conditions.

Discussion on Contributions and Limitations

Compared with earlier studies that primarily relied on either fixed-time signal systems or limited data sources, the proposed system integrates multi-modal IoT data streams with reinforcement learning-based control. This integration ensures faster adaptation to changing traffic conditions. The advantage of this approach is its ability to operate under varied weather and traffic intensities, which most existing systems do not handle effectively. However, the dependency on sensor accuracy and the need for computational resources are potential limitations that must be considered in large-scale deployments.

While the proposed system demonstrates clear advantages, certain limitations exist. First, the reliance on high-quality IoT sensors may increase deployment costs. Second, real-time computation requires significant processing power, which may pose challenges in large urban networks. These limitations highlight directions for refining the framework in future research.

5. CONCLUSION

The research team developed a real-time adaptive traffic management system that integrates IoT sensors with machine learning algorithms to improve urban mobility. The primary goal was to reduce congestion, shorten travel times, and enhance road safety by dynamically adjusting traffic signal timings. Simulation results showed that, compared to fixed-time and vehicle-actuated systems, the proposed approach reduced average travel times by 29.9%, increased traffic flow efficiency by 19.8%, and lowered collision rates by 78.4%. The system also adapted effectively to varying traffic patterns and adverse weather conditions, including rain, snow, and fog. These outcomes provide strong evidence that IoT-enabled data collection combined with machine learning-based adaptive control directly addresses the limitations of conventional traffic management systems. The results validate the research problem and demonstrate that the proposed framework significantly improves efficiency, safety, and adaptability in modern urban traffic networks.
The findings of this research confirm the hypothesis by showing that the integration of IoT and machine learning significantly improves traffic outcomes compared with baseline models. The experimental results reinforce the relevance of the proposed approach in addressing the identified research problem.

Still, there were a few challenges with how the data was gathered. To evaluate performance, the system was tested in a virtual city; some potential problems for real-world use could be related to perfecting sensors, checking data quality and getting the system to fit with existing urban systems. In addition, with more complex networks having much larger traffic loads, it is necessary to examine if the system can maintain speed and efficiency even with all the real-time information. When compared with existing studies, which often focused on either limited sensor inputs or single learning models, this work provides a more comprehensive approach by integrating multi-modal IoT data with reinforcement learning-based signal control. Unlike earlier research that achieved modest improvements in travel time and congestion reduction, the proposed system demonstrated substantial gains across multiple performance metrics, establishing its originality and practical value.

In the coming projects, we look forward to using more sensor types, like thermal cameras and systems for vehicle-to-infrastructure communication, to ensure the system is effective in harsh weather and poor sight conditions. The system will be used in cities and with different traffic intensities to test its ability under real-world conditions. Researchers will also work on improving reinforcement learning models to enhance traffic flow and minimize the need for real-time calculations.

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