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IoT-Based Traffic Prediction and Management System for Smart Cities Using RASPBERRY Pi

Department of ECE, SVCET, Etcherla, A.P., India

R. Hemalatha [1](hemalatharajana1020@gmail.com), G. Sireesha [1](sireeshag650@gmail.com), N. Sai Chaithanya [1](saichaithanya.nallana@gmail.com), K. Bhanu Prakash [1](bhanuprakash2313@gmail.com), R. S. R. K. Naidu [1](sivarandhi131@gmail.com)

Under the Guidance of Mr. A. Sridhar, M.Tech(Ph.D), Assistant Professor

Abstract

Urbanization and rapid vehicle growth have intensified congestion challenges in modern cities, making traditional fixed-schedule traffic control systems inefficient for dynamic traffic conditions. This project presents an IoT-based traffic prediction and management framework that integrates real- time sensing, cloud analytics, and deep learning for adaptive signal control in smart city environments.The proposed system architecture comprises four layers — Perception, Network, Processing, and Application — enabling seamless data flow from IoT sensors to decision-making systems. IoT devices such as cameras, GPS modules, and RF sensor nodes collect traffic and environmental data, transmitted via MQTT protocols to the cloud for processing. A Long Short- Term Memory (LSTM) deep learning model predicts congestion levels by learning temporal traffic dependencies, achieving a prediction accuracy of 96.4%, RMSE of 0.298, and MAE of 0.213.

Key hardware components include the Raspberry Pi as the central processing unit, USB webcam for real-time video capture and vehicle detection via OpenCV, RF communication modules with HT12E encoder for wireless data transmission, LEDs for status indication, LCD display for local output, and a regulated power supply. The software stack includes Python, OpenCV for image processing, and TensorFlow/Keras for the LSTM model.

Based on LSTM predictions, an adaptive traffic signal algorithm dynamically adjusts signal durations, reducing vehicle waiting time by 32% and fuel consumption by 18%. The system demonstrates scalability, energy efficiency, and real-time adaptability, offering a robust and cost- effective solution for intelligent urban traffic management in smart cities.

Keywords: *Internet of Things (IoT), Traffic Prediction, Smart Cities, LSTM, Deep Learning, Adaptive Signal Control, Raspberry Pi, OpenCV, Python, RF Communication, HT12E Encoder, Machine Learning.*

I. Introduction

The rapid pace of urbanization and the exponential growth in vehicle ownership have placed enormous pressure on existing transportation infrastructures worldwide. Modern cities are struggling to manage the increasing demand for mobility, leading to chronic traffic congestion, excessive travel delays, and environmental degradation. According to the World Bank, transportation-related congestion costs global economies billions of dollars each year in lost productivity and wasted fuel. Additionally, the World Health Organization (WHO) has identified urban vehicular emissions as one of the leading contributors to air pollution, directly impacting public health.Conventional traffic management systems rely heavily on fixed-time signal controllers, pre-defined schedules, or manual interventions by traffic personnel. While these methods may have been sufficient for low-density traffic scenarios, they are no longer effective in the context of today's complex and dynamic traffic patterns. Traditional systems lack the ability to respond to real-time variations such as accidents, road maintenance, weather changes, or sudden surges in vehicle

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volume. Consequently, they often lead to uneven lane utilization, unnecessary idling, and inefficient resource allocation. Moreover, most existing control systems operate independently without communication between adjacent intersections, thereby exacerbating congestion and creating traffic bottlenecks across urban networks.

In recent years, the convergence of Internet of Things (IoT) technologies, cloud computing, and artificial intelligence (AI) has opened new opportunities for developing intelligent transportation systems (ITS). IoT provides the foundational infrastructure to collect real-time data from multiple heterogeneous sources, including sensors, GPS devices, cameras, and connected vehicles. These data streams, when properly analyzed, can offer deep insights into traffic behavior, congestion levels, and travel patterns. Cloud computing platforms provide the computational scalability necessary to process and store massive volumes of IoT data, while AI and machine learning algorithms transform these raw data into predictive and prescriptive knowledge.Among various machine learning models, Long Short-Term Memory (LSTM) networks have gained particular attention due to their ability to model sequential and temporal dependencies effectively. Traffic data are inherently time-dependent, exhibiting daily and weekly patterns influenced by external factors such as weather, time of day, and road conditions. LSTM networks, a specialized form of Recurrent Neural Networks (RNNs), can capture these long-range dependencies without suffering from vanishing gradient problems, making them highly suitable for short-term traffic flow prediction and congestion forecasting.

II. Literature Survey

[1] Doolan and Muntean (2017) explored the use of Vehicular Ad Hoc Networks (VANETs) for improving urban traffic efficiency and reducing emissions. Their study demonstrated that connected vehicle communication reduces idling time and improves fuel efficiency.

[2] Patil et al. (2018) proposed an IoT-enabled real-time congestion detection system using inductive loop sensors and GPS data. The system provided real-time alerts and route suggestions but lacked predictive capabilities.

[3] Lingani et al. (2019) designed a deep learning-based IoT traffic monitoring system using camera feeds for congestion detection. While the model improved detection accuracy, it required high network bandwidth for image transmission.

[4] Yao et al. (2020) introduced an IoT-enabled Capsule Network architecture for urban traffic classification. The model achieved high accuracy using sensor data fusion but suffered from high computational complexity.

[5] Kumar et al. (2022) developed a hybrid IoT-cloud platform for vehicular data collection and centralized congestion monitoring. The system was scalable but relied on reactive responses rather than real-time prediction.

[6] Wu et al. (2023) proposed an IoT-based real-time traffic monitoring and signal optimization system using edge computing. Their approach improved intersection throughput through localized decision-making.

Research Gap

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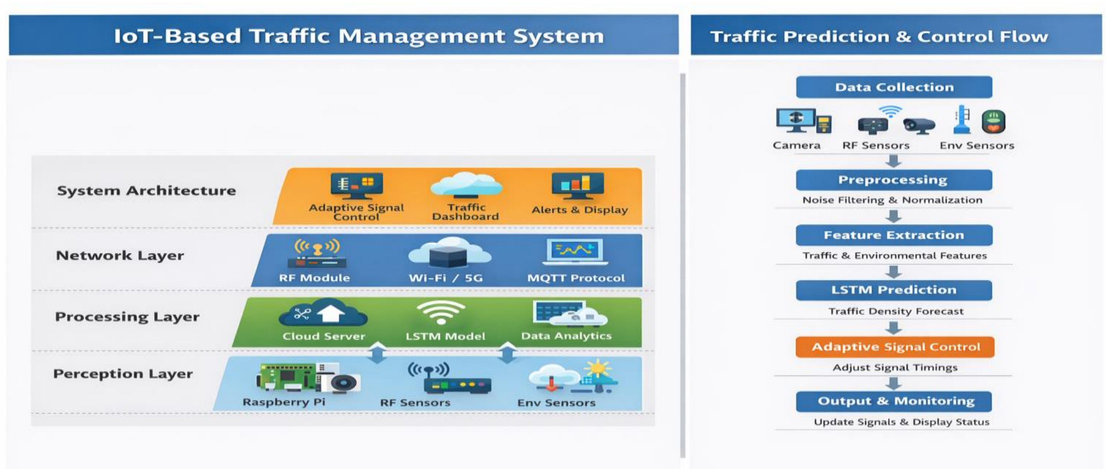
Existing IoT-based traffic management systems primarily focus on real-time monitoring and reactive congestion control. Most approaches lack predictive intelligence, efficient bandwidth utilization, and integration of machine learning models for proactive traffic management. Additionally, there is limited implementation of fully deployable systems that combine IoT sensing, real-time analytics, and adaptive signal optimization in a unified framework.

III. Methodology

III-A. System Architecture

The proposed system follows a **four-layer architecture** consisting of:

- **Perception Layer:** Collects real-time traffic data using Raspberry Pi, webcam (vehicle detection via OpenCV), RF sensor nodes (HT12E encoder), and environmental sensors.
- **Network Layer:** Handles communication using RF modules (433 MHz), MQTT protocol, and Wi-Fi/5G for transmitting data to the cloud.
- **Processing Layer:** Performs data preprocessing, feature extraction, and LSTM-based traffic prediction on cloud infrastructure.
- **Application Layer:** Executes adaptive signal control, displays results via LCD/LEDs, and provides traffic monitoring dashboards and alerts.



III-B. Algorithm

Algorithm: IoT-Based Traffic Prediction and Adaptive Signal Control

Input:
Real-time traffic data (D_t) (vehicle count, speed, density), environmental data, and historical dataset.

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Step 1: Data Collection
Capture traffic data using webcam (OpenCV), RF sensors, and environmental sensors.

Step 2: Preprocessing

- Remove noise using filtering
- Handle missing values (interpolation)
- Normalize data: X_prime = (X - X_min) / (X_max - X_min)

Step 3: Feature Extraction
Extract temporal, traffic, and environmental features (14 features per time step).

Step 4: Sequence Formation
Create time-series input using sliding window (past 60 minutes data).

Step 5: Traffic Prediction (LSTM Model)
Predict future traffic density: V_predicted = LSTM(D_t)

Step 6: Adaptive Signal Control
Compute new signal timing: T_new = T_base + alpha * (V_predicted - V_threshold)

Step 7: Constraint Handling

- Minimum green time = 10 sec
- Maximum green time = 90 sec
- Emergency override via RF signal

Step 8: Output Generation
Send updated signal timing to Raspberry Pi and display results.

Output:
Optimized traffic signal timing with reduced congestion and improved flow.

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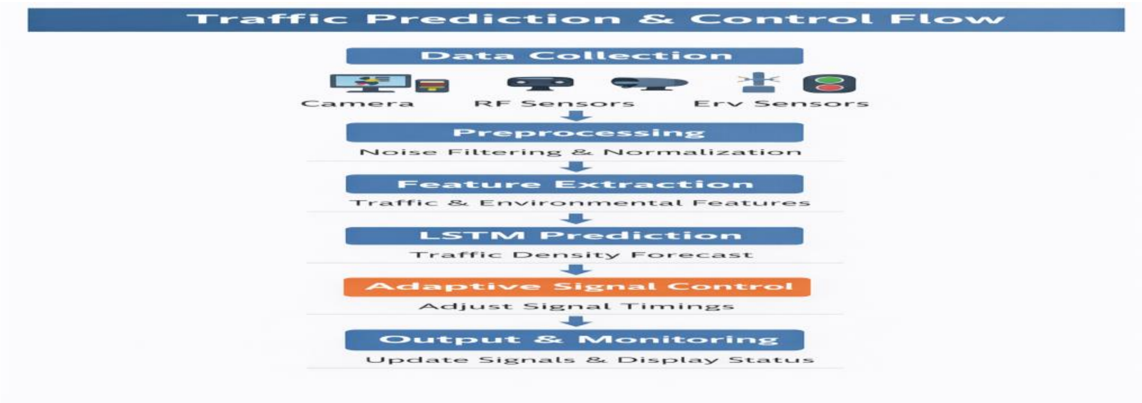

III-C. Modules

The system consists of five major modules:

1. **Data Collection Module**
   - Collects real-time data from webcam, RF sensors, and environmental sensors.
2. **Preprocessing and Feature Extraction Module**
   - Performs normalization, noise removal, and feature extraction.
3. **Traffic Prediction Module (LSTM)**
   - Predicts short-term traffic congestion using temporal data.
4. **Adaptive Signal Control Module**
   - Dynamically adjusts signal timing based on predicted traffic density.
5. **Monitoring and Output Module**
   - Displays traffic status using LCD/LED and sends alerts via dashboard.

IV. Results and Discussion

TABLE I: SYSTEM EVALUATION RESULTS

Metric	Baseline	Proposed
Prediction Accuracy (%)	86.2 (ARIMA)	96.4 (IoT-LSTM)
RMSE	0.523	0.298

Metric	Baseline	Proposed
MAE	0.412	0.213
Delay Reduction (%)	12%	32%
Fuel Efficiency Improvement	—	18%

Mathematical Formulations

Traffic Density:
Density = Number_of_Vehicles / Road_Length

Normalization:
X_prime = (X - X_min) / (X_max - X_min)

LSTM Prediction:
V_predicted = LSTM(D_t)

Adaptive Signal Timing:
T_new = T_base + alpha * (V_predicted - V_threshold)

Error Metrics:
MAE = (1/n) * sum(|Actual - Predicted|)
RMSE = sqrt((1/n) * sum((Actual - Predicted)^2))

Discussion

The proposed IoT-LSTM based traffic management system was evaluated using real-time and simulated datasets. The model achieved a high prediction accuracy of **96.4%**, outperforming traditional models such as ARIMA (86.2%) and Random Forest (90.1%).

The system significantly reduced traffic delay by **32%**, compared to only **12%** in conventional systems. Additionally, fuel consumption was reduced by **18%**, contributing to environmental sustainability.

The integration of IoT sensors and real-time data improved prediction accuracy and system responsiveness. The adaptive signal control mechanism enabled dynamic adjustment of traffic signals, resulting in smoother traffic flow and reduced congestion.

The system demonstrated real-time performance with a prediction-control cycle of approximately **2.5 seconds**, making it suitable for practical deployment in smart city environments.

V. Conclusion and Future Work

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This work presented an **IoT-based traffic prediction and adaptive signal control system** using LSTM deep learning. The system achieved **96.4% prediction accuracy**, **32% reduction in vehicle waiting time**, and **18% improvement in fuel efficiency**, demonstrating its effectiveness over traditional traffic management approaches.

The proposed architecture integrates IoT sensing, cloud computing, and machine learning to enable proactive and intelligent traffic control.

Future Work

- Implement **Edge AI (TensorFlow Lite)** for faster on-device prediction
- Apply **Reinforcement Learning (DQN)** for self-learning signal control
- Use **YOLO-based vehicle detection** for higher accuracy
- Extend system to **multi-intersection coordination using GNNs**
- Add **multi-language and smart city dashboard integration**

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