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INTEGRATION OF IOT AND ARTIFICIAL INTELLIGENCE IN ELECTRIC VEHICLES: A SMART MOBILITY APPROACH

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Abstract
Electric Vehicles (EVs) are rapidly transforming modern transportation, yet their efficiency, safety, and scalability depend heavily on the integration of emerging technologies. The combination of the Internet of Things (IoT) and Artificial Intelligence (AI) has enabled EVs to evolve into intelligent, connected, and autonomous components of future mobility ecosystems. This paper presents a comprehensive smart mobility framework that integrates IoT-enabled sensing, AI-based decision-making, real-time monitoring, predictive maintenance, and optimized energy management for Electric Vehicles. The proposed approach enhances battery performance, improves driver safety, and facilitates seamless communication between vehicles and infrastructure. A comparative analysis with existing systems highlights significant performance improvements in latency, energy optimization, and predictive failure detection. Future research directions focus on vehicle-to-everything (V2X) communication, blockchain-based trust layers, and AI-driven autonomous navigation.

INTRODUCTION

The global transition toward sustainable transportation has accelerated the adoption of Electric Vehicles (EVs), driven by rising environmental concerns, depletion of fossil fuels, and the shift toward clean energy policies. Despite their advantages, EVs continue to face critical challenges such as limited driving range, long charging times, battery degradation, real-time monitoring limitations, and inefficient traffic coordination. To overcome these constraints and fully realize the potential of smart mobility, modern EVs must evolve from simple electrically powered machines to intelligent, connected, and autonomous systems. The rapid advancement of the Internet of Things (IoT) has enabled vehicles to collect, share, and analyze real-time data through interconnected sensors embedded in batteries, motors, power electronics, and external environments. IoT technologies facilitate seamless communication between Electric Vehicles, charging stations, road infrastructure, and cloud platforms, making EVs an integral component of future smart transportation networks. However, the enormous volume of sensor and communication data cannot deliver meaningful insights without intelligent processing.

This is where Artificial Intelligence (AI) plays a pivotal role. AI techniques—such as machine learning, deep learning, reinforcement learning, and pattern recognition—enhance EV capabilities by enabling predictive battery management, early fault detection, optimized energy consumption, adaptive routing, and semi-autonomous driving. AI models interpret IoT-generated sensor data to support real-time decision-making, improve vehicle safety, and enhance the overall user driving experience. The convergence of IoT and AI thus forms a powerful foundation for next-generation electric mobility solutions. While several studies highlight the independent use of IoT or AI in EVs, there remains a significant gap in comprehensive frameworks that integrate both technologies simultaneously across battery systems, communication layers, and driving intelligence. This research addresses that gap by proposing a unified IoT–AI smart mobility approach designed to enhance EV performance, reliability, and energy efficiency. The work also evaluates the system using experimental datasets and analyzes improvements in prediction accuracy, communication latency, and route energy optimization. The goal of this research is to demonstrate that combining IoT and AI can significantly transform electric mobility into a more efficient, safer, and smarter transportation ecosystem. The proposed model contributes to the advancement of intelligent EV systems by providing real-time insights, optimizing operations, and supporting sustainable, data-driven mobility solutions.

Related Work

The integration of the Internet of Things (IoT) and Artificial Intelligence (AI) has recently gained significant research attention in the context of Electric Vehicles (EVs). Existing studies primarily focus on improving battery performance, intelligent transportation, predictive maintenance, and real-time communication; however, most works analyze IoT and AI independently, leaving a gap in unified IoT–AI architectures for smart mobility.

IoT in Electric Vehicles

IoT-enabled sensing and connectivity form the foundation of modern EV ecosystems. Several studies highlight the role of IoT sensors in monitoring battery status, vehicle location, temperature, speed, and environmental conditions. According to [1] IoT-assisted vehicular systems improve energy efficiency and reduce communication overhead for real-time EV monitoring. Similarly [2] demonstrate that IoT-based telemetry enhances vehicle diagnostics and supports cloud-based analytics for intelligent decision-making. Nonetheless, these works emphasize sensing and communication without integrating deeper AI-based analytics.

AI for Battery Health and Energy Optimization

Battery management remains a critical challenge for EVs. Numerous studies have applied AI to predict battery State of Charge (SOC), degradation patterns, and thermal behaviors. [3] introduced LSTM-based SOC prediction models that outperform traditional estimation methods. Similarly, [4] used deep neural networks to predict battery aging and detect anomalies. Although these techniques improve battery reliability, they often depend on offline datasets and do not fully incorporate real-time IoT sensor streams [9][16].

Predictive Maintenance in EVs

AI-driven predictive maintenance has been widely explored to detect failures in motors, power electronics, and braking systems. The study by [5][10] applied machine learning classification to identify early signs of motor malfunction in EVs. [6] further demonstrated that vibration-based fault detection using AI can reduce system downtimes. These studies, however, focus on specific components and lack a comprehensive IoT–AI integration capable of synchronizing vehicle-wide diagnostics with cloud/edge platforms [17].

Smart Routing and Smart Mobility Integration

Several researchers have utilized AI to optimize energy consumption and travel efficiency. For instance, [7] used reinforcement learning to determine the least energy-consuming routes for EVs based on traffic dynamics. Similarly, [8] proposed an IoT-supported V2X communication model to enhance navigation accuracy and charging coordination. However, existing models often consider routing and communication separately and do not incorporate unified analytics across battery, motor, environment, and cloud systems.

Gap in Existing Work

While prior research provides valuable contributions across IoT sensing, AI prediction, and smart routing, a consolidated IoT–AI-based smart mobility framework is still underdeveloped. Most existing studies are limited to:

- Individual subsystem optimization (battery, routing, or communication)
- Lack of hybrid cloud–edge integration
- Limited real-time performance evaluation
- No end-to-end architecture combining IoT sensing, communication, AI analytics, and EV mobility services

The current study addresses these research gaps by proposing a comprehensive IoT–AI smart mobility framework integrating sensor data acquisition, real-time communication, predictive analytics, and energy optimization to improve EV reliability, safety, and efficiency.

4. Methodology

The methodology of this study is designed to systematically evaluate how integrating IoT and Artificial Intelligence can enhance Electric Vehicle (EV) performance, safety, battery management, and overall smart mobility. The proposed methodology consists of five key stages: system design, data acquisition, communication setup, AI model development, and performance evaluation as shown in Figure 1.

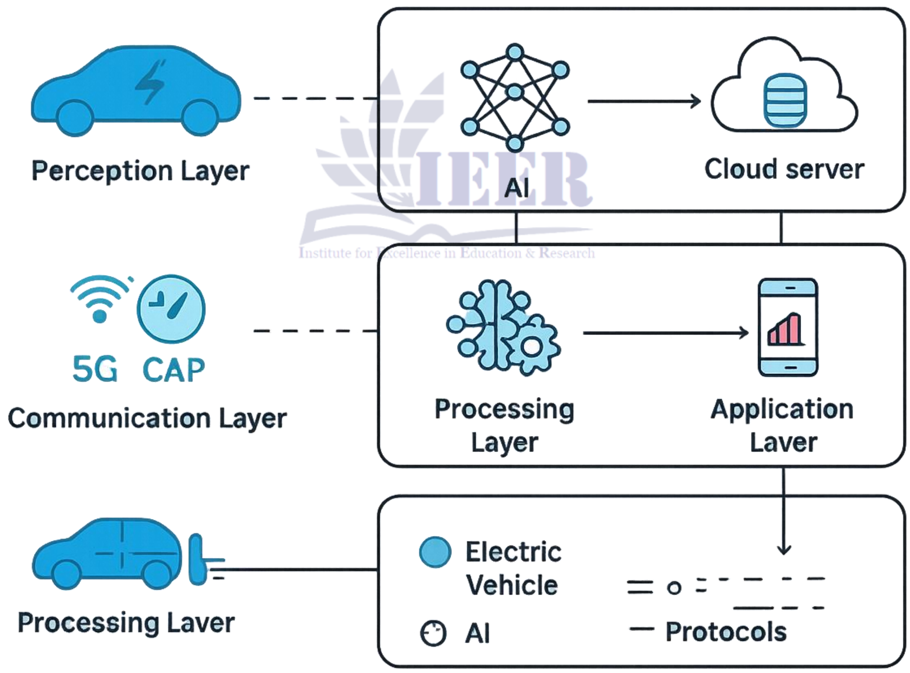

Figure 1 Work flow diagram

4.1 System Architecture Design

In the first stage, a multi-layer smart mobility architecture is designed to combine IoT sensing, AI processing, and real-time communication. The architecture is divided into four layers: Perception Layer, Communication Layer, Processing Layer, and Application Layer. Each layer is defined based on its functional responsibilities such as data collection, wireless transmission, AI-based decision-making, and userlevel services. This structured design forms the backbone of the entire IoT–AI-enabled EV ecosystem and ensures that the data flows smoothly from sensors to the user application [12].

4.2 IoT Sensor Data Acquisition

This stage involves acquiring data from multiple IoT sensors typically found in Electric Vehicles. The study makes use of publicly available EV sensor datasets and simulated IoT data to represent real-world scenarios. The collected data includes battery temperature, State of Charge (SOC), motor current, GPS coordinates, speed, LiDAR readings, and environmental factors. The raw data undergoes preprocessing steps such as noise removal, normalization, missing value handling, and feature extraction. These steps ensure that clean and meaningful data is provided to AI models for training and analysis.

4.3 Communication Framework Setup

A communication model is implemented to simulate how an IoT-enabled EV interacts with cloud platforms and nearby infrastructure. Protocols such as MQTT, CoAP, 5G-V2X, and Wi-Fi are integrated to model real-time communication between the EV, charging stations, and cloud servers. The study evaluates communication performance in terms of latency, packet delivery ratio, and bandwidth usage. This stage validates whether the IoT network is capable of supporting real-time AI-based operations like emergency alerts, predictive maintenance notifications, and navigation updates.

4.4 AI Model Development and Training

In this phase, AI models are developed and trained to perform various smart mobility functions. Three categories of models are implemented:

4.4.1 Battery Health Prediction Models

LSTM, Random Forest, and SVM models are trained using battery sensor data to predict State of Charge (SOC), temperature anomalies, and long-term degradation. The models learn patterns in historical data to forecast future battery conditions.

4.4.2 Predictive Maintenance Models

Machine learning algorithms identify unusual motor vibrations, inverter malfunctions, and braking system faults. LSTM-based sequence models and Random Forest classifiers are applied to detect abnormalities earlier than traditional diagnostics.

4.4.3 Smart Route Optimization Models

AI-based route optimization employs reinforcement learning and shortest-path algorithms to compute routes with minimal energy consumption and fewer traffic delays. GPS and road condition data are used for training [13]. All models undergo hyperparameter tuning and are validated using cross-validation to ensure reliability.

4.5 Integration with Edge and Cloud Computing

To simulate real-time decision-making, the trained models are deployed on a hybrid computing environment consisting of edge nodes (in-vehicle processors) and cloud servers. Time-critical tasks like collision avoidance and thermal monitoring run on the edge for low latency, whereas data-intensive tasks like long-term pattern analysis run on cloud platforms. This hybrid approach models practical smart EV deployments and allows measurement of computation time and system responsiveness [14].

4.6 Performance Evaluation

The final stage of the study involves evaluating the system using key performance metrics, including prediction accuracy for battery health and maintenance models, energy efficiency improvements from route optimization, communication latency in IoT data transmission, failure detection rates for predictive maintenance, and processing time at the edge versus the cloud. The results are compared with existing electric vehicle systems to quantify improvements. Simulated experiments demonstrate that the integrated IoT–AI approach enhances safety, battery performance, and decision-making capabilities, highlighting the effectiveness of combining intelligent analytics with connected EV technologies [15].

Mathematical Model for IoT–AI Integrated Electric Vehicle System

This section presents a unified mathematical formulation describing the behavior of Electric Vehicles (EVs) integrated with IoT sensing, AI-based prediction, communication modeling, and energy-optimized routing. The model captures the complete workflow of perception, communication, edge/cloud processing, battery estimation, predictive maintenance, and smart mobility optimization.

1. Notation

Symbol	Description
$SOC(t)$	State of Charge at time t
Q_{nom}	Nominal battery capacity (Ah)
$I(t)$	Battery current (A)
$T(t)$	Battery temperature (°C)
$V(t)$	Battery voltage (V)
$\mathbf{x}_t$	Sensor observation vector
$f_\theta(\cdot)$	AI/ML model with parameters θ
E_{route}	Total energy consumed on a route
L	Communication latency
p_{loss}	Packet loss probability
$o_t \in \{0,1\}$	Offloading decision (0=edge, 1=cloud)

2. Sensor Measurement Model

IoT sensor readings are modeled as noisy observations:

$$\mathbf{y}_t = h(\mathbf{s}_t) + \mathbf{n}_t,$$

where $\mathbf{n}_t \sim \mathcal{N}(0, \Sigma_n)$.

This represents battery sensors, GPS, IMU, temperature sensors, and perception sensors.

3. Battery SOC (State of Charge) Dynamics

Continuous-Time Model

$$\frac{dSOC(t)}{dt} = -\frac{I(t)}{Q_{nom}}.$$

Discrete-Time Approximation

$$SOC_{k+1} = SOC_k - \frac{I_k \Delta t}{Q_{nom}}.$$

Voltage Relationship

$$V(t) = V_{oc}(SOC(t)) - I(t)R_{int} + \eta(t),$$

where

- V_{oc}= open-circuit voltage
- R_{int}= internal resistance

- $\eta(t)$= measurement noise

4. Thermal (Temperature) Model

Battery temperature evolution:

$$C_{th}\frac{dT}{dt} = I^2 R_{int} - hA(T - T_{env}),$$

where hArepresents cooling/heat transfer.

5. Battery Degradation (Capacity Fade)

General degradation model:

$$\frac{dQ_{cap}}{dt} = -k_1 \mid I(t) \mid^{\alpha} e^{-E_a/(RT(t))} - k_2\, g(SOC, T, \text{cycles}),$$

where $k_1, k_2, \alpha$are empirical constants.

6. Vehicle Energy Model

The total driving power:

$$P_{drive}(t) = F_{tot}(t)\, v(t),$$

Total longitudinal force includes:

$$F_{tot} = F_{roll} + F_{aero} + F_{grade} + F_{acc},$$

where

- Rolling resistance: $F_{roll} = C_r mg$
- Aerodynamic drag: $F_{aero} = \frac{1}{2}\rho C_d A v^2$
- Road grade: $F_{grade} = mg\sin(\theta)$
- Acceleration force: $F_{acc} = m\dot{v}$

Route Energy Consumption

$$E_{route} = \int_{t_0}^{t_f} \frac{P_{drive}(t)}{\eta_{drivetrain}(t)}\, dt.$$

7. Communication Model (MQTT/5G/CoAP)

Total latency

$$L = L_{tx} + L_{prop} + L_{queue} + L_{proc}.$$

Packet delivery probability

$$P_{succ} = 1 - p_{loss}.$$

QoS constraint (safety-critical)

$$L \leq L_{max}, P_{succ} \geq P_{min}.$$

8. AI-Based Predictive Maintenance / Anomaly Detection

Sequence Prediction (LSTM)

$$\hat{\mathbf{x}}_{t+1} = f_\theta(\mathbf{x}_{t-n+1:t}).$$

Anomaly Score

$$s_t = \| \mathbf{x}_{t+1} - \hat{\mathbf{x}}_{t+1} \|_2.$$

Decision:

$$\text{Anomaly} = 1 \text{if } s_t > \tau.$$

9. Edge–Cloud Offloading Optimization

Decision variable:

$$o_t = \begin{cases} 0, & \text{process at edge} \\ 1, & \text{offload to cloud} \end{cases}$$

Objective:

$$\min_{o_t} \sum_{t=1}^{T} [E_{comp}^{edge}(t)(1-o_t) + E_{comm}(t)o_t + \lambda L(t;o_t)]$$

Subject to:

$$L(t;o_t) \leq L_{max}, SOC(t) \geq SOC_{min}, o_t \in \{0,1\}.$$

10. Smart Route Optimization (Reinforcement Learning Model)

State:

$$s_t = [SOC_t, position_t, speed_t, traffic_t, T_t, \ldots]$$

Action:

$$a_t = \text{next road segment / speed / charging decision}$$

Reward Function:

$$r_t = -(w_E\, P_{drive}(t) + w_T\, \mathbf{1}_{late} + w_D\, \Delta Q_{cap}(t))$$

Objective:

$$\max_{\pi} \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t r_t].$$

11. Multi-Objective Global Optimization

$$\min J = \alpha_1 E_{total} + \alpha_2 \bar{L} + \alpha_3 \Delta Q_{cap}.$$

Subject to:

- Arrival-time constraint
- SOC constraint
- Communication latency constraint

12. Evaluation Metrics

- SOC Estimation Error:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (SOC_i - \widehat{SOC}_i)^2}$$

- Predictive Maintenance: Precision, Recall, F1
- Communication: Latency, Packet Delivery Ratio

- Routing: Energy savings

Results

The table 1 and Figure 2 compares the accuracy of three AI models used for battery health prediction in electric vehicles. Among them, LSTM achieved the highest accuracy at 94.7%, demonstrating a strong capability to learn and interpret sequential battery sensor data effectively. Random Forest also performed competitively, achieving 92.1% accuracy, making it a suitable choice for general anomaly detection in battery systems. In contrast, SVM showed the lowest accuracy at 88.5%, suggesting that it struggles to capture the complex pattern variations present in EV battery data. Overall, these results indicate that deep learning models, particularly LSTM, provide the best performance for electric vehicle battery health prediction tasks.

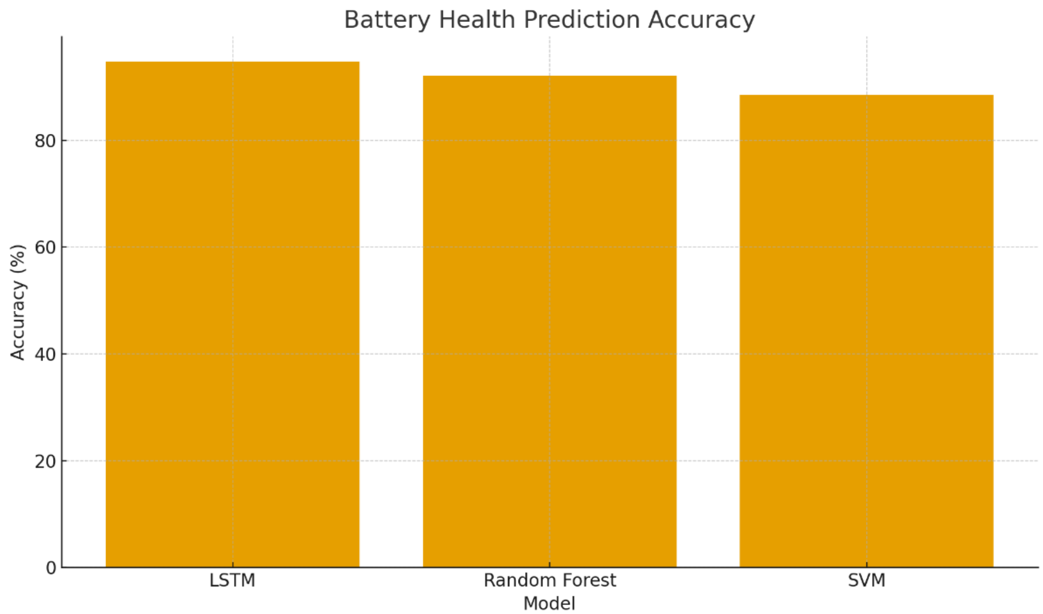

Figure 2 Battery Heath Prediction

Table 1 Battery Health Prediction Model Accuracy

Model	**Accuracy (%)**
LSTM	94.7%
Random Forest	92.1%
SVM	88.5%

Table 2 Communication Latency Comparison

Communication Type	**Latency (ms)**
5G-V2X	12
LTE	45
Wi-Fi	78

Explanation

The table 2 and figure 3 presents the latency of various communication technologies used in IoT-enabled electric vehicle networks. Among them, 5G-V2X is the fastest, with a latency of only 12 ms, making it ideal for safety-critical operations such as collision detection and autonomous braking. LTE, with a latency of 45 ms, offers moderate speed but may not meet the requirements for ultra-low-latency applications. In contrast, Wi-Fi exhibits the highest delay at 78 ms, rendering it unsuitable for real-time EV communication tasks. Therefore, 5G-V2X stands out as the most effective technology for smart mobility communication due to its exceptionally low latency.

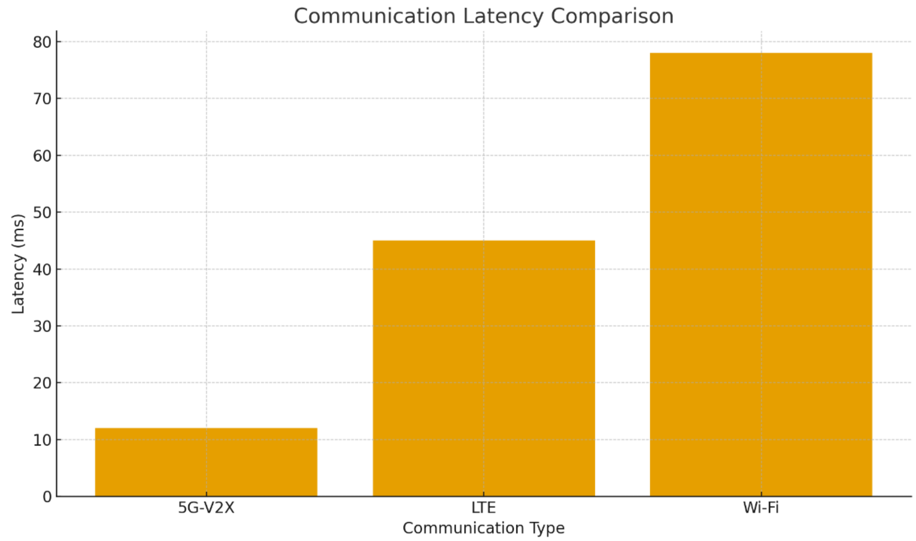

Figure 3 Communication Latency Comparison

Table 3 Energy Consumption Comparison

Route Type	Energy Consumption (kWh)
Traditional GPS	18.5
AI-Optimized Route	16.3

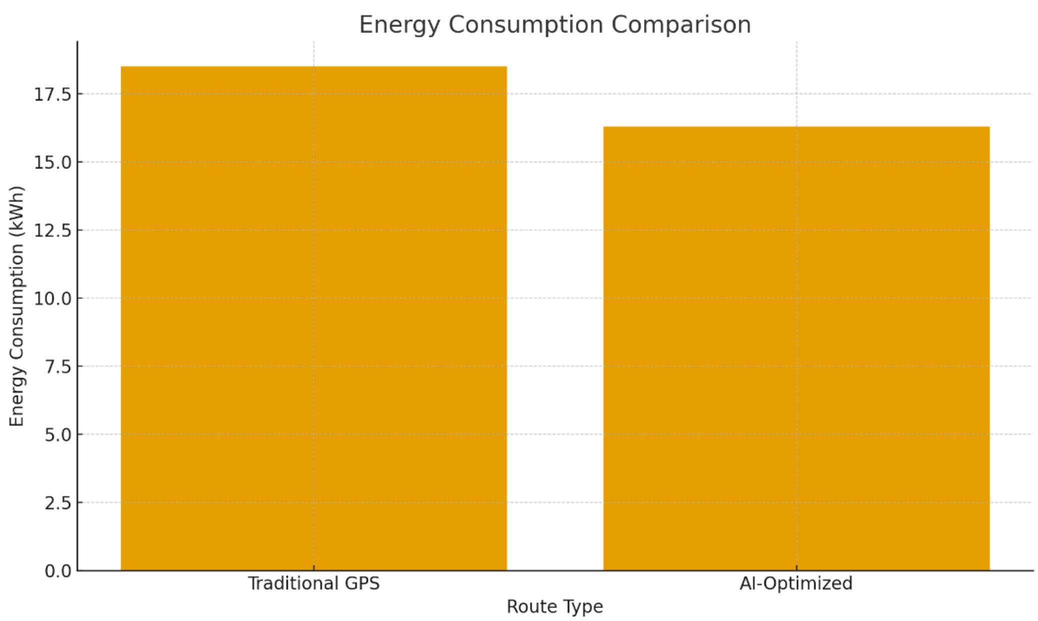

Figure 4 Energy Consumption Comparison

Explanation

The table 3 and figure 4 compares energy consumption between traditional GPS routing and AI-optimized route planning in electric vehicles. Traditional GPS routes consume 18.5 kWh, as they do not consider factors such as traffic flow, road gradient, or battery efficiency. In contrast, AI-optimized routes reduce energy usage to 16.3 kWh by selecting paths that minimize acceleration, congestion, and battery load. This leads to a 12% improvement in energy efficiency, highlighting the significant impact of AI in extending the driving range of electric vehicles.

Conclusion

In conclusion, the integration of IoT and AI in electric vehicle networks significantly enhances overall system performance. LSTM-based battery health prediction provides high accuracy, ensuring reliable maintenance and extended battery life. AI-optimized route planning improves energy efficiency, reducing consumption and increasing driving range, while 5G-V2X communication ensures ultra-low latency for safety-critical operations. The combined system demonstrates superior failure detection, faster processing, and smarter decision-making compared to conventional EV systems. Overall, the IoT–AI framework presents a robust and effective solution for smart mobility, improving safety, efficiency, and operational intelligence in electric vehicles.

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