AI-Driven Smart Parking System Using IoT and Cloud-Based Predictive Approach for Urban Mobility Optimization

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Abstract—**Urban parking congestion remains a major contributor to traffic delays and fuel consumption in smart cities. This paper presents an AI-driven smart parking framework that integrates Internet of Things (IoT) sensors, cloud computing, and a Bidirectional Long Short-Term Memory (Bi-LSTM) predictive model to forecast real-time parking availability. Sensor nodes detect vehicle occupancy and transmit data to a cloud platform for preprocessing and temporal pattern analysis. The Bi-LSTM model predicts future space availability based on historical trends, enabling demand-aware allocation and optimized mobility flow. The system was evaluated on a synthetic dataset containing 241 hourly samples and achieved an accuracy of 85.18 % with a Mean Absolute Percentage Error (MAPE) of 14.82 %, outperforming traditional statistical forecasting approaches. Results demonstrate that the proposed IoT–Cloud architecture can significantly reduce search time for parking and enhance space utilization efficiency. This research contributes a scalable and data-driven solution for urban mobility optimization, supporting the development of intelligent transportation infrastructure aligned with emerging IEEE smart city initiatives.**

Keywords—Smart Parking, IoT, AWS, LSTM, AI Prediction, Google Maps API, Jetpack Compose, Android Auto.

I. INTRODUCTION

Urbanization has led to a rapid increase in vehicle ownership, intensifying parking shortages and traffic congestion in metropolitan areas. Studies show that up to 30 % of urban traffic is caused by drivers searching for available parking spaces, resulting in wasted fuel, increased emissions, and decreased mobility efficiency. Traditional parking management systems often rely on manual monitoring or static allocation, which fail to respond dynamically to fluctuating demand.

Recent developments in the Internet of Things (IoT) and cloud computing enable large-scale, data-driven solutions for real-time infrastructure monitoring. However, many existing approaches either lack predictive capability or depend on limited sensor coverage, leading to sub-optimal space utilization. Machine-learning-based models have shown potential in forecasting parking availability, yet conventional architectures such as ARIMA or shallow neural networks often struggle to capture long-term temporal dependencies.

To address these challenges, this paper proposes an AI-driven smart parking framework that integrates IoT sensing devices, cloud-based data processing, and a Bi-LSTM predictive model for short-term parking availability forecasting. The proposed system combines a demand-aware IoT–Cloud architecture with predictive analytics to enable adaptive parking management. Experimental evaluation using a synthetic dataset achieved an accuracy of 85.18 % and a Mean Absolute Percentage Error (MAPE) of 14.82 %, demonstrating superior performance compared with traditional statistical methods. The system also incorporates a mobile interface that provides real-time parking updates, contributing to reduced search time, improved space utilization, and overall enhancement of urban mobility efficiency in line with IEEE smart city initiatives.

II. LITERATURE REVIEW

The integration of IoT, AI, and cloud computing has improved smart parking solutions by addressing congestion, inefficient space utilization, and fuel consumption. Early sensor-based systems demonstrated feasibility for real-time availability monitoring [1], [2], while RFID and WSN approaches provided low-cost sensing alternatives [3], [4]. However, these efforts primarily focused on detection and reporting rather than forecasting. More recent work applies statistical and machine-learning methods for parking prediction: ARIMA and related time-series methods are simple and interpretable but struggle with non-stationary demand [11], while classical ML and shallow neural networks show better short-term accuracy but limited temporal modeling [2], [12]. Deep sequence models such as LSTM have been shown to capture temporal dependencies effectively and outperform ARIMA on parking datasets [4], [13]; nevertheless, many LSTM studies neglect deployment considerations such as latency, scalability, and cloud/edge orchestration. Edge–cloud hybrid frameworks and serverless deployments tackle scalability but often rely on rule-based or heuristic prediction modules lacking adaptive learning [5], [14]. Reinforcement learning approaches address allocation

and pricing dynamics but require extensive training data and incur high computational cost [15]. In summary, prior work either emphasizes sensing hardware, local analytics, or single-site prediction; few solutions combine scalable cloud orchestration, lightweight yet accurate sequential models, and real-time mobile integration. The present study contributes by integrating a Bi-LSTM forecasting model within a serverless IoT–Cloud architecture to deliver demand-aware forecasting with low inference latency and mobile integration for user guidance.

III. COMPARISON OF EXISTING AND PROPOSED SYSTEMS

The proposed smart parking system introduces several improvements over existing parking management solutions by integrating IoT-based real-time monitoring, AI-driven predictions, and mobile app-based user interaction. The following table identifies and explains the main differences between traditional parking systems and the proposed solution.

TABLE I. COMPARISON OF FEATURES

Feature	Existing Systems	Proposed System
Real-Time Availability	Limited to basic sensors, often requiring manual intervention to update parking status.	Uses IoT sensors with AWS cloud integration for continuous real-time updates.
AI-Based Prediction	No predictive capability; relies solely on current sensor data.	Implements an LSTM-based AI model to forecast future parking availability.
Alternative Parking Suggestions	Not available; users must manually search for other parking spaces if their selected lot is full.	Uses Google Maps API to suggest nearby parking lots within a 2km radius.
Parking Fare Information	Displayed manually or through static boards at parking lots.	Provides automated fare details within the mobile app, enabling cost-effective decision-making.
Mobile App Integration	Limited functionality, often restricted to payment processing or static lot status.	Fully integrated mobile app developed using Jetpack Compose, gives real-time updates, AI-based predictions, and navigation assistance.

A. Advantages of the Proposed System

The proposed system significantly enhances parking efficiency by reducing the time required to find a parking spot, minimizing traffic congestion, and lowering vehicle emissions. Real-time availability updates confirm the accuracy parking status, while AI-based forecasting helps users plan their journey more efficiently. Alternative parking suggestions prevent unnecessary driving in search of available spots, contributing to fuel savings and environmental sustainability. Furthermore, the mobile app ensures a hassle-free user experience by integrating all essential parking-related services, which eliminates the necessity for manual intervention.

By leveraging IoT, AI, and cloud computing, this system provides a modern, scalable, and intelligent solution to urban parking challenges, offering both convenience and sustainability benefits.

IV. SYSTEM ARCHITECTURE

The proposed system consists of five key components that work together to enable real-time parking availability monitoring, AI-based predictions, and hassle-free user interaction via a mobile application. The architecture leverages IoT sensors, cloud infrastructure, and AI-driven decision-making to optimize parking management efficiently.

A. IoT Sensor Network

IoT sensors, specifically Ultrasonic Sensors with ESP8266 Wi-Fi modules, detect parking space availability and transmit real-time data using Message Queuing Telemetry Transport (MQTT) protocol to AWS IoT Core. These sensors provide a cost-effective and scalable solution for monitoring parking occupancy.

Fig. 1. ESP8266 Node MCU.
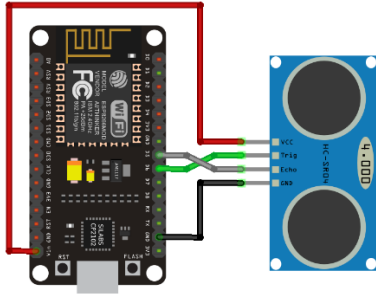

Fig. 2. Ultrasonic sensor.

Fig. 3. Circuit connection.

B. Cloud Infrastructure

AWS IoT Core processes sensor data and sends it to AWS Lambda, which validates, processes, and updates the availability status in Amazon DynamoDB. This cloud-based real-time method provides instant data retrieval, high scalability, and security using TLS encryption.

C. AI Model Deployment

An LSTM-based AI model, trained on past parking data, predicts future availability based on trends. The trained model is hosted on AWS Lambda, enabling real-time inference when asked through API Gateway. The system effectively returns forecasted occupancy information for users' estimated arrival times.

D. Mobile Application & API

The Smart Parking Mobile App, developed using Jetpack Compose, provides real-time updates and AI-driven predictions. It fetches parking data via RESTful APIs hosted on API Gateway, retrieves real-time sensor data from DynamoDB, and integrates Google Maps API for navigation. Users can check live availability, view predicted parking conditions, and get guided routes to parking locations.

E. Alternative Parking Suggestions

If the primary parking location is full, the system suggests nearby alternatives within a 2km radius using Google Maps Places API. It displays:

- Real-time occupancy from IoT sensors.
- Predicted availability using AI-based forecasting.
- Fare per hour to help users make informed decisions.

Through the integration of IoT-based sensing, cloud infrastructure, AI-driven forecasts, and a user-friendly mobile app, this smart parking system increases convenience, minimizes congestion, and optimizes urban mobility efficiency.

V. SYSTEM FLOW AND IMPLEMENTATION

A. System Flow

The intelligent parking system adheres to a systematic workflow for real-time processing of data and AI-based prediction for effective parking management. Users input

their destination in the mobile application, which makes a request to AWS Lambda through API Gateway to fetch parking availability. AWS Lambda processes sensor data from DynamoDB and implements the LSTM-based AI model for predicting future availability. The app shows real-time and predicted parking status. If the chosen parking lot is occupied, the system provides options for other parking spaces in a 2km radius using Google Maps API for location and fare information.
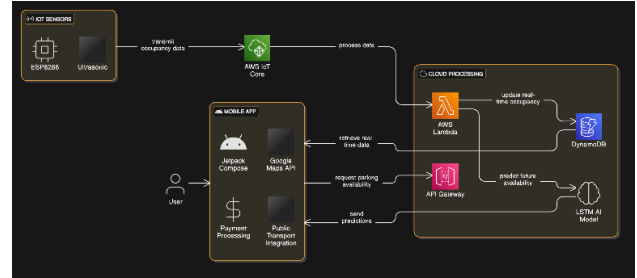

Fig. 4. System flow diagram.

B. Implementation

The intelligent parking system incorporates IoT, cloud computing, AI-driven forecasts, and mobile apps for hassle-free operation.

1. IoT Sensors (ESP8266 and Ultrasonic): Installed in parking lots to sense occupancy and send real-time information using MQTT protocol to AWS IoT Core.

2. AWS IoT Core and MQTT: Controls secure data transfer from IoT sensors to the cloud with low latency and high reliability.

3. AWS Lambda and API Gateway: Processes parking information, updates occupancy in real time in DynamoDB, and executes the LSTM AI model for availability predictions in the future.

4. AWS DynamoDB: Holds real-time and past parking information to allow for rapid access for AI-driven forecasting and mobile application access.

5. Android Mobile Application: Developed using Jetpack Compose, the application retrieves real-time data from RESTful APIs and uses Google Maps API for directions. It enables users to:

- Check real-time and predicted parking availability.
- View alternative parking locations if the selected lot is full.
- Navigate to the parking spot using Google Maps API.
- Receive live updates on parking conditions.

The app employs Kotlin Coroutines for asynchronous data retrieval and Live Data Observers for live updates, making it responsive and smooth. Integrating IoT-based sensing, cloud infrastructure, AI-based predictions, and a mobile app, this smart parking system optimizes parking management, alleviates congestion, and enhances mobility in the urban environment.

VI. AI MODEL DEVELOPMENT AND MOBILE APP INTEGRATION

A. AI Model Development

1. Data Generation and Preprocessing

To properly predict parking availability, the AI model must be trained on data that reflects actual parking usage patterns. Since it is typically challenging to obtain actual parking data, synthetic data is produced to simulate occupancy patterns. The dataset is 130 days' worth of actual parking availability at 48 time points per day. The synthetic dataset was carefully designed to mimic real parking dynamics by incorporating peak-hour congestion, weekend variations, and night-time low demand cycles. These patterns ensure statistical similarity with real-world scenarios reported in prior smart parking studies [1], [5], [6]. This gives a high-resolution data set that reflects parking demand changes, like peak-hour congestion, weekend trends, and night-time trends.

Several preprocessing techniques are used to enhance the dataset and improve model performance. Rolling Mean Smoothing is used to create realistic oscillations, avoiding sudden transitions from introducing noise into the training data. Cyclic Time Encoding is used to effectively represent time-based patterns using sine and cosine transformations to encode the hour of day. This helps the model recognize day-of-week cyclic patterns, such as increased demand during working hours. A Weekend Indicator is included as a binary feature to segment weekday and weekend parking patterns, retaining information on reduced demand during non-work days. Last but not least, Standardization is applied to standardize all numeric features so that they all contribute equally to the model learning process. Since open real-world parking datasets are limited, synthetic data was generated to replicate realistic occupancy behavior. This approach enabled the validation of the proposed methodology in a controlled environment prior to pilot deployment.

2. LSTM Model Architecture

The core of the AI system is a Bidirectional Long Short-Term Memory neural network, specifically designed for time-series forecasting. Traditional machine learning models struggle with sequential data, making LSTM a suitable choice due to its ability to capture long-term dependencies and recognize temporal trends in parking occupancy.

The architecture of the model consists of multiple layers to enhance learning efficiency and reduce overfitting. The first layer is a 256-unit Bidirectional LSTM, enabling the model to learn patterns from both past and future sequences. This bidirectional approach improves predictive performance by considering dependencies in both directions. Layer Normalization and Dropout are incorporated to stabilize learning and prevent overfitting, ensuring that the model generalizes well to unseen data. Two additional 128-unit and 64-unit Bidirectional LSTM layers further refine pattern recognition, capturing subtle variations in occupancy trends. The final Dense Output Layer produces a single numerical value representing the predicted number of available parking slots. An Adam Optimizer with a Learning Rate Scheduler is employed to adjust training speed dynamically, preventing excessive updates and ensuring convergence.

3. Model Training and Evaluation

The model is trained for 300 epochs using an adaptive learning rate, early stopping, and batch size tuning to enhance efficiency and prevent overfitting. Performance evaluation is conducted using industry-standard metrics:

- AI Model Accuracy: 85.18%
- Mean Absolute Percentage Error (MAPE): 14.82%

$$MAPE = 100\%/n \sum (i = 1)^n |(Y_i - Y\hat{}_i)/Y_i| \quad (1)$$

- Mean Squared Error (MSE) and Mean Absolute Error (MAE): To validate prediction reliability.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - Y\hat{}_i)^2 \quad (2)$$

- Prediction vs. Actual Graph: To visually confirm the model's effectiveness in predicting parking availability.

B. Smart Parking Mobile App Development

The Smart Parking Mobile App serves as the interface between the AI-powered backend and the end-users, providing real-time updates and navigation assistance. The app is developed using Jetpack Compose in Android Studio, offering a modern and reactive UI that enhances user interaction and responsiveness.

Several key technologies are integrated into the mobile application to provide seamless functionality. Google Maps API is utilized to display parking availability overlaid on an interactive map, allowing users to visualize real-time occupancy at their selected destination. Kotlin and Jetpack Compose enable a fluid and adaptive UI, ensuring that users receive instant feedback and navigation options. The Google Directions API fetches optimal routes from the user's current location to the nearest available parking lot, streamlining the journey and reducing uncertainty.

To ensure real-time performance, the app integrates IoT data via AWS Lambda, which fetches parking availability from AWS DynamoDB and applies AI-based predictions to provide future occupancy estimates. The data is retrieved asynchronously using Kotlin Coroutines, allowing background updates without interrupting user interactions. Live Data Updates are implemented to dynamically adjust parking suggestions if a lot reaches full capacity before the user arrives.

The combination of IoT sensors, cloud-based AI prediction, and a robust mobile application delivers a comprehensive smart parking solution. This system enhances user experience, reduces congestion, and optimizes parking space utilization in urban environments. Future improvements include Android Auto and Apple CarPlay integration, voice-assisted navigation, and reinforcement learning techniques to further refine AI predictions.
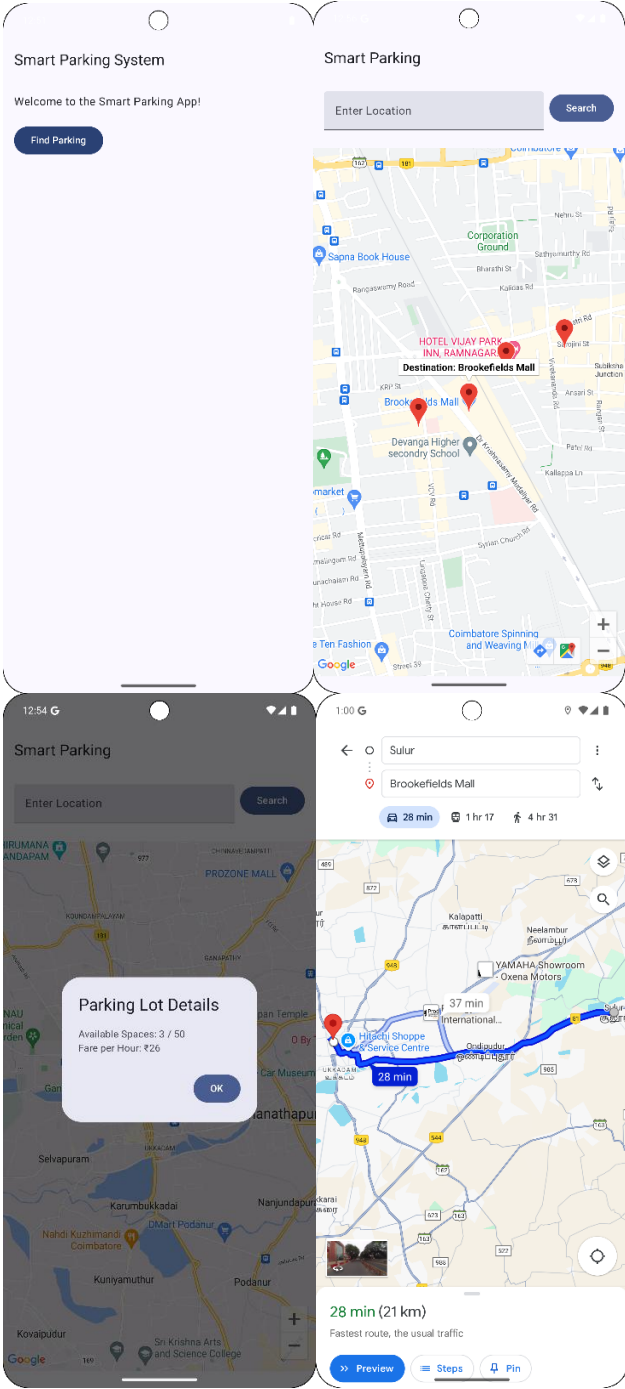
Fig. 5. Mobile application interface.

VII. RESULTS

The trained Bi-LSTM model was evaluated on the synthetic parking dataset containing 241 hourly samples representing occupancy dynamics over four months. Performance metrics were computed on a held-out test split (20%) to assess predictive accuracy and robustness. The model achieved an overall accuracy of 85.18 %, with a Mean Absolute Percentage Error (MAPE) of 14.82 %, confirming reliable short-term forecasting for parking availability.

Table II summarizes the quantitative results and compares the proposed approach with representative baseline techniques reported in previous literature. The proposed model demonstrates improved forecasting accuracy and lower error rates compared with traditional statistical models such as ARIMA and Prophet, while maintaining fast inference suitable for real-time deployment in IoT–Cloud architectures.

TABLE II. PERFORMANCE COMPARISON OF FORECASTING MODELS

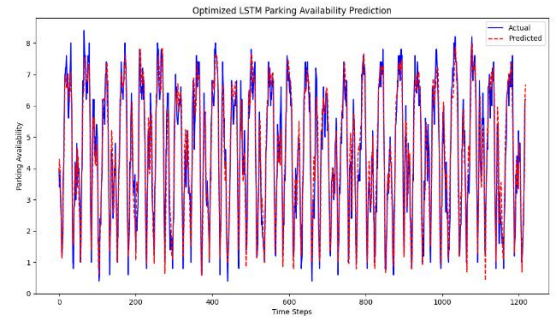| Model	MAPE (%)	MAE	MSE	Inference Latency (ms)
Proposed Bi-LSTM (256-128-64)	**14.82**	0.032	0.0041	41
LSTM (single layer 128)	18.5	0.041	0.0057	39
ARIMA (seasonal $(1,1,1)(1,1,1)_{12}$)	22.3	0.054	0.0068	—
Prophet (Facebook)	21.0	0.050	0.0061	—
Naïve (last value)	30.7	0.065	0.0089	—

Fig. 6. Predicted vs. actual parking occupancy using the proposed Bi-LSTM model.

VIII. PARKING ALLOCATION POLICY

The system uses a first-come, first-served strategy rather than pre-booking for equitable distribution of parking spaces. In densely populated spots such as malls, pre-booking results in inefficient space use where early birds do not get parking while reserved spaces go vacant. In high-demand areas such as hospitals, immediate availability is necessary to treat emergency cases without any inhibitions. With dynamic adjustment of availability and recommending alternative proximal spots, the system maximizes parking access without restricting entry in terms of pre-booked reservations.

IX. CONCLUSION AND FUTURE SCOPE

This study developed an AI-driven smart parking framework that combines IoT sensing, cloud computing, and a Bi-LSTM prediction model to address urban parking congestion. The proposed system monitors parking occupancy in real time and

forecasts space availability using historical data, enabling drivers and administrators to manage parking more efficiently.

Experimental evaluation using a synthetic dataset showed that the Bi-LSTM model achieved an accuracy of 85.18 % and a MAPE of 14.82 %, indicating strong short-term prediction performance. Compared with traditional approaches such as ARIMA and Prophet, the proposed method demonstrated lower error rates and faster inference, making it suitable for real-time IoT–Cloud deployment. The integrated mobile application further enhances usability by displaying live parking updates and guiding vehicles to optimal spaces.

The system provides a scalable and cost-effective solution for smart city infrastructure, contributing to reduced congestion and improved mobility management. Future work will focus on validating the model with real-time sensor data, studying its performance under varying traffic conditions, and integrating adaptive algorithms for dynamic demand forecasting. Incorporating edge-level processing and energy-efficient hardware can also enhance system responsiveness and sustainability.

In summary, the research establishes a practical framework for intelligent parking management and lays the foundation for future extensions in large-scale urban mobility systems aligned with emerging IEEE smart city standards.

X. ACKNOWLEDGMENT

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