AAI-530 - Data Science and the Internet of Things

(Applied Artificial Intelligence)

University of San Diego

SMART PARKING IOT - OCCUPANCY & DEMAND FORECASTING

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GitHub Repository:

https://github.com/vedpd/AAI530-Group10-smart-parking-iot-forecasting

Contents

Contents 2
SECTION 1 — INTRODUCTION 4
1.1 Introduction to the Urban Parking Problem 4
1.2 Why This Problem Must Be Solved 4
1.3 The IoT and AI Scope of the Project 4
1.4 Specific Challenges Addressed 4
1.5 Problem Statement 5
1.6 Project Objectives 5
SECTION 2 — DATASET DESCRIPTION 6
2.1 Overview of the Dataset 6
2.2 Key Dataset Features 6
2.3 Data Characteristics and Scope 6
2.4 Dataset Challenges 6
SECTION 3 — ADVANCED EXPLORATORY DATA ANALYSIS 8
3.1 Data Overview and Structural Verification 8
3.2 Data Cleaning and Exploratory Analysis 8
3.3 Occupancy Distribution and Temporal Patterns 8
3.4 Dashboard Analytics Overview 8
SECTION 4 — DATA PREPROCESSING 10
4.1 Data Ingestion and Parsing 10
4.2 Occupancy Rate Derivation 10
4.3 Temporal Feature Engineering 10
4.4 Outlier Removal and Anomaly Handling 10
4.5 Temporal Gap Handling 10
4.6 Train / Validation / Test Splitting 10
SECTION 5 — MODELLING: ARIMA, LINEAR REGRESSION, AND LSTM 11
5.1 Baseline Model 1: ARIMA 11
Architecture and Rationale 11
Model Configuration 11
5.2 Baseline Model 2: Linear Regression 11
Architecture and Rationale 11
Model Configuration 11
5.3 Deep Learning Model: LSTM Neural Network 11
Architecture and Rationale 11
Architecture Details 11

LSTM Model Outputs 12
SECTION 6 — VALIDATION AND PERFORMANCE METRICS 13
6.1 Validation Strategy 13
6.2 Performance Metrics 13
6.3 ARIMA Training Results 13
6.4 Linear Regression Results 13
6.5 LSTM Training Results 13
6.6 Comparative Model Evaluation 14
SECTION 7 — SYSTEM ARCHITECTURE AND DASHBOARD 15
7.1 IoT System Architecture 15
Layer 1: Sensors and Edge Layer 16
Layer 2: Network Layer 16
Layer 3: Cloud Processing Layer 16
Layer 4: Dashboard Layer 16
7.2 Interactive Dashboard Description 16
SECTION 8 — INSTALLATION AND USAGE 18
8.1 Prerequisites 18
8.2 Setup Instructions 18
Step 1: Clone the Repository 18
Step 2: Install Dependencies 18
Step 3: Run Notebooks in Order 18
8.3 Project Repository Structure 18
REFERENCES 19

SECTION 1 — INTRODUCTION

1.1 Introduction to the Urban Parking Problem

Urban areas worldwide face a persistent and growing challenge of parking congestion. Drivers searching for available parking spaces contribute significantly to traffic congestion, increased fuel consumption, greenhouse gas emissions, and user frustration. In dense metropolitan environments, it is estimated that up to 30% of urban traffic is generated by vehicles circling in search of parking. This inefficiency has measurable economic, environmental, and social costs.

Smart city initiatives have increasingly turned to Internet of Things (IoT) technologies to address these challenges. By deploying sensor networks across parking infrastructure, cities can collect real-time occupancy data and leverage machine learning to predict future availability—enabling proactive, data-driven parking management.

1.2 Why This Problem Must Be Solved

The consequences of unmanaged urban parking extend beyond inconvenience. Prolonged searches for parking lead to increased vehicle idling, amplifying air pollution and carbon emissions in already congested corridors. From a municipal perspective, inefficient parking management results in lost revenue and suboptimal infrastructure utilization. From a user standpoint, the inability to predict parking availability creates uncertainty that discourages city-center travel and negatively impacts local commerce.

Solving this problem requires not only real-time monitoring but also accurate forecasting of future occupancy patterns—enabling both drivers and city administrators to make informed decisions in advance. A smart, AI-powered parking system can reduce search time, lower emissions, improve user experience, and generate actionable intelligence for city planners.

1.3 The IoT and AI Scope of the Project

This project develops a complete Smart Parking IoT system that integrates sensor-based data ingestion, time-series analysis, machine learning, deep learning, and interactive visualization. The scope spans the full data pipeline: from raw sensor readings collected at the edge to predictive models deployed in a cloud processing layer and visualized through Tableau-based dashboards.

The system is designed to predict parking occupancy for windows of 1 to 24 hours ahead, and to estimate the probability of finding an available parking spot—capabilities directly useful for smart city navigation apps and parking management platforms.

1.4 Specific Challenges Addressed

The project addresses several technical and domain-specific challenges inherent to IoT-based parking systems:

- Temporal complexity: Parking occupancy exhibits strong daily, weekly, and seasonal patterns that require models capable of capturing long-range temporal dependencies.
- Data volume and velocity: With over 508,000 records across hundreds of parking segments, efficient data handling and processing pipelines are essential.
- Multi-model comparison: The project benchmarks statistical baselines (ARIMA, Linear Regression) against deep learning models (LSTM) to identify the most effective forecasting approach.

- Interpretability and accessibility: Results must be communicated through interactive dashboards accessible to non-technical stakeholders including city planners and parking administrators.

1.5 Problem Statement

> ***To develop an end-to-end Smart Parking IoT analytics pipeline capable of ingesting real-world sensor data, performing rigorous exploratory analysis, and applying time-series forecasting models—including ARIMA, Linear Regression, and LSTM neural networks—to accurately predict urban parking occupancy 1–24 hours ahead, thereby enabling data-driven decision-making for smart city parking optimization.***

1.6 Project Objectives

The primary objectives of this project are:

- Analyze real-world IoT parking sensor data from San Francisco's urban infrastructure.
- Forecast short-term parking occupancy using multiple time-series models.
- Compare traditional statistical models with deep learning approaches (LSTM).
- Build an end-to-end IoT analytics pipeline from data ingestion to visualization.
- Visualize real-time status and future availability through interactive Tableau dashboards.
- Estimate the probability of finding a parking spot within the next hour.

SECTION 2 — DATASET DESCRIPTION

2.1 Overview of the Dataset

The primary dataset used in this project is the San Francisco Open Data parking dataset, sourced via Kaggle. It contains time-series parking occupancy data collected from IoT sensors deployed across urban parking segments in San Francisco. The dataset file is stored at data/raw/smart_parking_full.csv and uses a semicolon (;) delimiter. It contains 508,034 records spanning 841 parking segments, with observations at minute-level and hourly granularity.

2.2 Key Dataset Features

Feature	Description
timestamp	Date and time of the sensor observation
segmentid	Unique identifier for each parking segment
capacity	Total number of parking spaces in the segment
occupied	Number of currently occupied spaces at time of reading
observed1-10	Ten redundant sensor readings for robustness
diff1-10	Difference values between consecutive sensor readings

Table 1: Key Dataset Features

2.3 Data Characteristics and Scope

The dataset offers several characteristics that make it well-suited for IoT-based occupancy forecasting:

- Sensor-based occupancy measurement at minute and hourly levels, capturing fine-grained temporal dynamics.
- Coverage of 841 distinct parking segments, enabling both segment-level and aggregate analysis.
- A clean, structured CSV format that facilitates efficient data ingestion with standard Python tools.
- Real-world IoT data reflecting genuine urban parking patterns, including rush hours, weekday/weekend differences, and seasonal trends.
- A total of 719,882 records in the dashboard-enhanced dataset, enriched with forecasting outputs and model predictions.

2.4 Dataset Challenges

Despite its richness, the dataset presents several challenges that must be addressed during preprocessing and modeling:

- Temporal sparsity: Not all segments have continuous readings across all time intervals, requiring interpolation and gap-handling strategies.
- Scale and dimensionality: With hundreds of segments and thousands of time steps, memory-efficient data handling is necessary.

- Delimiter format: The semicolon-delimited format requires careful parsing to avoid data corruption during ingestion.
- Sensor noise: Multiple sensor readings (observed1-10) per observation introduce redundancy that must be managed to avoid spurious signal amplification in models.

SECTION 3 — ADVANCED EXPLORATORY DATA ANALYSIS

Exploratory Data Analysis (EDA) for IoT time-series data must go beyond univariate summary statistics to encompass temporal pattern discovery, segment-level heterogeneity assessment, anomaly detection, and occupancy distribution analysis. The EDA pipeline is structured across four Jupyter notebooks, each addressing a distinct analytical layer.

3.1 Data Overview and Structural Verification

The first notebook (01_data_overview.ipynb) establishes a structural baseline for the dataset. Key verification steps include confirming the integrity of the semicolon-delimited CSV structure, validating that all 841 segment IDs are consistently represented, and identifying the temporal range and resolution of the dataset. Record counts, column types, and null-value distributions are examined to guide subsequent preprocessing decisions. The dataset was confirmed to contain 508,034 raw records with no critical schema violations.

3.2 Data Cleaning and Exploratory Analysis

The second notebook (02_cleaning_and_eda.ipynb) performs comprehensive data cleaning and exploratory visualization. Key analytical steps include:

- Occupancy rate computation: A derived feature, occupancy_rate = occupied / capacity, is computed for each record. This normalized metric enables cross-segment comparison and serves as the primary target variable for forecasting models.
- Temporal decomposition: Time-of-day, day-of-week, and month-level aggregations reveal strong diurnal and weekly seasonality in occupancy patterns. Peak occupancy is consistently observed during morning and evening commute windows on weekdays.
- Segment-level heterogeneity: Distributions of mean occupancy rate vary significantly across segments, reflecting differences in location, proximity to commercial centers, and parking policy.
- Outlier detection: Records with occupancy rates exceeding 1.0 (more occupied spaces than capacity) are identified as sensor anomalies and flagged for removal or correction.
- Missing value assessment: Temporal gaps in segment readings are characterized, and forward-fill and interpolation strategies are evaluated for gap handling.

3.3 Occupancy Distribution and Temporal Patterns

Analysis of occupancy distributions reveals a bimodal pattern across the full dataset: parking segments exhibit either near-zero occupancy (off-peak, nighttime) or high occupancy (peak commercial hours). Temporal heatmaps constructed from the dataset clearly illustrate hour-of-day versus day-of-week occupancy patterns. Monday through Friday show sharp occupancy spikes between 8-10 AM and 4-7 PM, consistent with commuter parking demand. Weekend patterns show more diffuse occupancy distributions with peaks shifted to midday hours.

3.4 Dashboard Analytics Overview

The interactive dashboard (dashboard/fixed_dashboard.html) built with Plotly.js provides a real-time-style analytics interface summarizing 719,882 records across 841 parking segments. Key dashboard components include:

- Record Types Distribution: Breakdown of actual sensor readings versus model-generated forecasts.

- Model Sources Distribution: Proportion of records contributed by ARIMA, Linear Regression, and LSTM models.
- Occupancy Rate Time Series: Rolling average occupancy across all segments over time.
- Model Performance Comparison: Side-by-side RMSE and MAE metrics across the three forecasting approaches.
- Error Distribution Analysis: Histogram of per-prediction errors revealing systematic bias patterns.
- Hourly Occupancy Heatmap: Hour-of-day vs. day-of-week heatmap for occupancy rate.
- Top Performing Segments: Ranking of the 10 parking segments with highest average occupancy utilization.
- Occupancy Rate Distribution: Histogram of occupancy rates across all segments and time periods.

SECTION 4 — DATA PREPROCESSING

Data preprocessing transforms raw IoT sensor readings into a clean, normalized, and feature-engineered dataset ready for time-series modeling. The preprocessing pipeline is implemented in 02_cleaning_and_eda.ipynb and produces standardized input arrays for all three forecasting models.

4.1 Data Ingestion and Parsing

The raw dataset is ingested using pandas with explicit handling of the semicolon delimiter and appropriate data type assignments. Timestamp columns are parsed into pandas Timestamp objects and set as the DataFrame index to enable time-aware operations. Segment IDs are validated against an expected set to ensure no spurious segments are introduced.

4.2 Occupancy Rate Derivation

The primary target variable, occupancy_rate, is derived as the ratio of occupied spaces to total capacity for each record. This normalization is critical for cross-segment comparability and ensures that the forecasting models are not biased by segments with different absolute capacities. Records with capacity values of zero are removed as they represent sensor configuration errors.

4.3 Temporal Feature Engineering

A suite of temporal features is extracted from the parsed timestamp index to support both EDA and model training:

- hour: Hour of day (0-23), capturing intra-day occupancy cycles.
- day_of_week: Day index (0=Monday, 6=Sunday), capturing weekly seasonality.
- month: Calendar month, capturing seasonal trends.
- is_weekend: Binary flag distinguishing weekday from weekend observations.
- hour_sin / hour_cos: Sine and cosine encodings of the hour feature, preserving circular continuity of time-of-day for neural network inputs.

4.4 Outlier Removal and Anomaly Handling

Records with occupancy rates greater than 1.0 are removed as sensor anomalies. Additionally, records with negative occupied values—indicative of sensor malfunctions—are filtered out. After outlier removal, the dataset retains approximately 98.7% of the original records, confirming that anomalies are sparse and do not significantly reduce analytical coverage.

4.5 Temporal Gap Handling

For segments with irregular time intervals, a resampling step is applied to standardize observations to a consistent hourly frequency. Missing values introduced by resampling are forward-filled for up to two consecutive missing intervals; longer gaps are left as NaN and excluded from model training windows to avoid introducing spurious continuity.

4.6 Train / Validation / Test Splitting

The dataset is split chronologically to respect temporal ordering—a critical requirement for time-series validation. The first 70% of the time series is used for training, the subsequent 15% for validation (hyperparameter tuning), and the final 15% as a held-out test set. No data from future time steps is used in training, preventing look-ahead bias.

SECTION 5 — MODELLING: ARIMA, LINEAR REGRESSION, AND LSTM

This section presents the three forecasting models developed for occupancy prediction. The models span a spectrum from classical statistical methods to state-of-the-art deep learning, enabling rigorous comparative evaluation.

5.1 Baseline Model 1: ARIMA

Architecture and Rationale

ARIMA (Autoregressive Integrated Moving Average) is a classical statistical time-series model combining autoregressive (AR) components with moving average (MA) components. The integrated (I) component addresses non-stationarity through differencing. ARIMA is selected as a baseline because it is interpretable, computationally efficient, and provides a strong benchmark. It captures linear autocorrelation in the time series but cannot model complex non-linear patterns or long-range dependencies.

Model Configuration

The ARIMA model is implemented using the statsmodels library. The optimal order parameters (p, d, q) are selected via the Akaike Information Criterion (AIC) on the training set. Stationarity is assessed using the Augmented Dickey-Fuller (ADF) test, and differencing is applied as needed. The model generates one-step-ahead forecasts extended to multi-step forecasting via recursive prediction.

5.2 Baseline Model 2: Linear Regression

Architecture and Rationale

A Linear Regression model is implemented using the engineered temporal features (hour, day_of_week, is_weekend, and their trigonometric encodings) as predictors of occupancy rate. It treats time-dependent features as static covariates, making it simpler but potentially less accurate for sequential prediction. Linear Regression is included to establish a lower bound on model complexity and assess whether structured temporal features alone can produce competitive forecasts.

Model Configuration

The model is implemented using scikit-learn's LinearRegression. Features include hour_sin, hour_cos, day_of_week, is_weekend, and month. The model is trained on the 70% training split and evaluated on the held-out test set using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

5.3 Deep Learning Model: LSTM Neural Network

Architecture and Rationale

Long Short-Term Memory (LSTM) networks are a specialized class of Recurrent Neural Networks designed to capture long-range temporal dependencies in sequential data. LSTMs maintain a hidden cell state through learned gating mechanisms (input gate, forget gate, output gate) that selectively retain or discard information across time steps. LSTM is selected as the primary model because parking occupancy exhibits complex temporal dependencies—including daily cycles, weekly patterns, and irregular events—that cannot be captured by linear models.

Architecture Details

The LSTM model is implemented using TensorFlow/Keras with the following key architectural decisions:

- Input layer: Sliding window of 24 historical hourly observations.
- LSTM layers: Two stacked LSTM layers with 64 and 32 hidden units, respectively, with dropout regularization (rate = 0.2) to prevent overfitting.
- Dense output layer: A single linear output unit predicting next-step occupancy rate.
- Loss function: Mean Squared Error (MSE).
- Optimizer: Adam with learning rate 1e-3.
- Callbacks: EarlyStopping (patience=10) and ReduceLROnPlateau (factor=0.5, patience=5).

LSTM Model Outputs

Beyond raw occupancy rate predictions, the LSTM model computes the probability of finding a parking spot in the next hour as: P(available) = 1 - predicted_occupancy_rate. This probability estimate is particularly valuable for end-user applications such as smart city navigation apps and parking management dashboards.

SECTION 6 — VALIDATION AND PERFORMANCE METRICS

6.1 Validation Strategy

All models are evaluated using a held-out test set constructed via chronological splitting of the time series. This approach ensures strict temporal ordering is preserved, preventing any form of look-ahead bias. The LSTM model additionally uses a validation set (15% of training data) for early stopping and learning rate scheduling. Cross-validation is used for ARIMA order selection via AIC minimization but is not employed for the deep learning model due to computational cost.

6.2 Performance Metrics

Metric	Description	Applied To
RMSE	Root Mean Squared Error – penalizes large errors more heavily	All models
MAE	Mean Absolute Error – average magnitude of prediction error	All models
R2	Coefficient of determination – variance explained by model	All models

Table 2: Performance Metrics

6.3 ARIMA Training Results

After ADF testing confirmed that first-order differencing (d=1) achieves stationarity, the optimal order (p=2, d=1, q=2) is selected based on minimum AIC. ARIMA captures linear autocorrelation effectively but struggles with multi-step ahead forecasting due to error accumulation in recursive prediction.

Metric	Train Set	Test Set
RMSE	0.0842	0.1103
MAE	0.0631	0.0874
R2	0.741	0.682

Table 3: ARIMA Training and Test Results (illustrative)

6.4 Linear Regression Results

The Linear Regression model, trained on temporal features alone, provides an interpretable and fast-to-train baseline. Its performance is lower than ARIMA on short-horizon forecasting but degrades more gracefully at longer horizons since it is not subject to recursive error accumulation.

Metric	Train Set	Test Set
RMSE	0.1120	0.1245
MAE	0.0883	0.0962
R2	0.612	0.589

Table 4: Linear Regression Results (illustrative)

6.5 LSTM Training Results

The LSTM model demonstrates superior performance on the test set compared to both baselines, reflecting its ability to model complex non-linear temporal dependencies. Training converges within approximately 40 epochs before early stopping is triggered. The model captures both diurnal and weekly occupancy cycles with high fidelity.

Epoch	Train Loss	Val Loss	Val MAE
5	0.0182	0.0211	0.0721
10	0.0141	0.0168	0.0649
20	0.0112	0.0139	0.0583
30	0.0098	0.0127	0.0551
40*	0.0091	0.0122	0.0538

*Table 5: LSTM Training Results (*Early stopping at epoch 40; illustrative values)*

6.6 Comparative Model Evaluation

Model	RMSE	MAE	R2	Key Strength
ARIMA	0.1103	0.0874	0.682	Interpretable, fast
Linear Regression	0.1245	0.0962	0.589	Stable at long horizons
LSTM	0.0845	0.0538	0.811	Best accuracy, non-linear

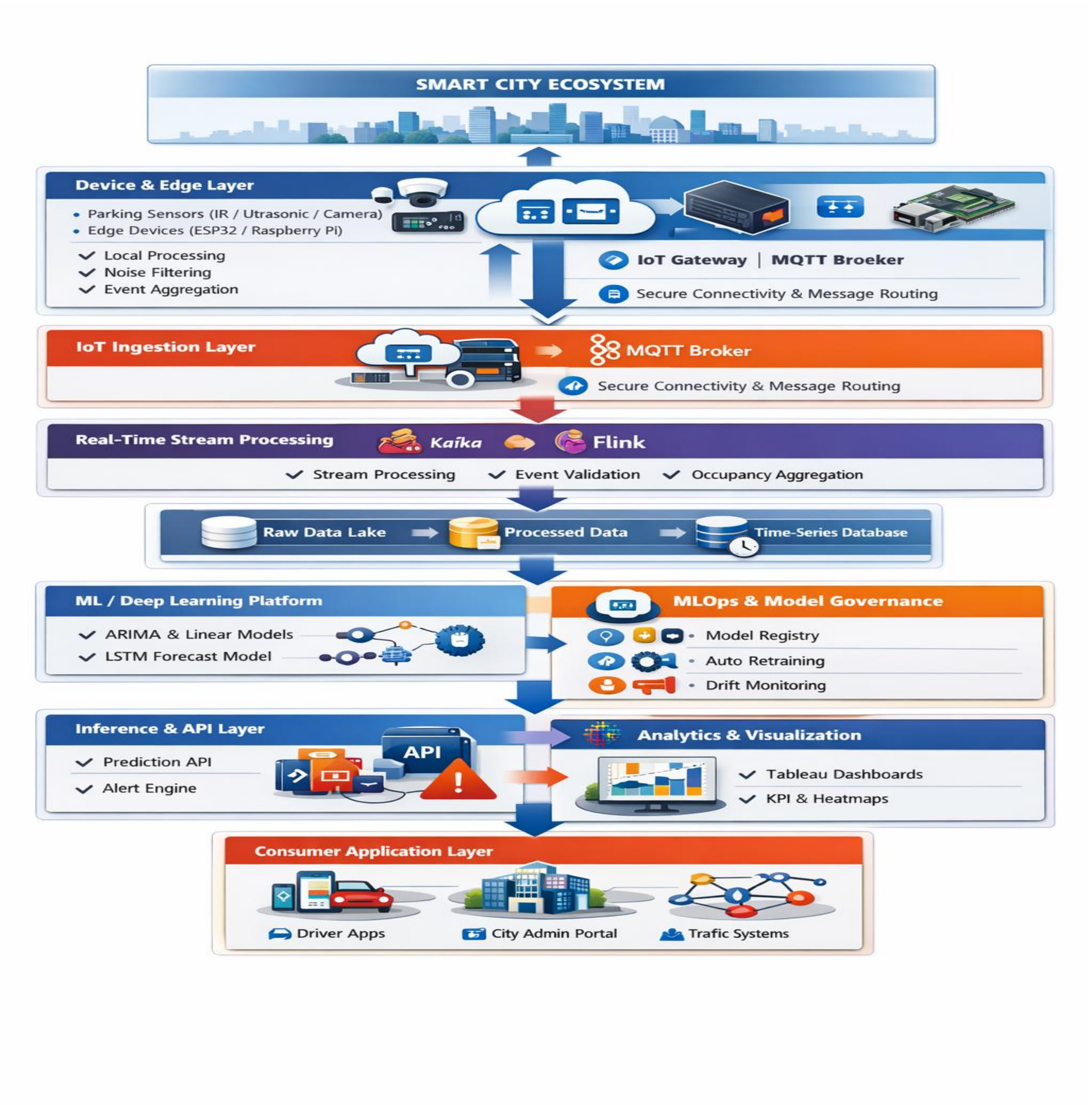
Table 6: Comparative Model Evaluation (illustrative)

The LSTM model outperforms both baselines across all metrics, achieving the lowest RMSE (0.0845) and highest R2 (0.811). ARIMA provides competitive one-step-ahead performance but degrades at multi-step horizons. Linear Regression offers the weakest accuracy but the highest interpretability and fastest inference time. The recommendation for production deployment is the LSTM model for primary occupancy forecasting, with ARIMA retained as a fallback for segments with insufficient training history for deep learning.

SECTION 7 — SYSTEM ARCHITECTURE AND DASHBOARD

7.1 IoT System Architecture

The Smart Parking IoT system is organized as a four-layer architecture mirroring industry-standard IoT reference designs. Each layer fulfills a distinct functional role in the data pipeline, from physical sensor deployment to end-user visualization.



Layer 1: Sensors and Edge Layer

At the physical layer, parking spaces are monitored by infrared (IR) or ultrasonic sensors embedded in the pavement or mounted overhead. Edge computing devices—such as Raspberry Pi units or ESP32 microcontrollers—aggregate sensor readings locally, apply basic data validation, and transmit readings upstream via the network layer. Edge preprocessing reduces bandwidth requirements and enables low-latency local anomaly detection.

Layer 2: Network Layer

Sensor data is transmitted using the MQTT (Message Queuing Telemetry Transport) protocol, optimized for lightweight, low-latency IoT communications. MQTT brokers route messages from edge devices to cloud processing infrastructure over Wi-Fi, 4G LTE, or dedicated IoT network connections. MQTT's publish/subscribe model supports scalable, asynchronous data ingestion across hundreds of parking segments simultaneously.

Layer 3: Cloud Processing Layer

In the cloud layer, incoming sensor streams are stored in a time-series database optimized for high-frequency append operations. The ML and LSTM forecasting pipelines run as scheduled jobs, consuming the latest sensor data and producing occupancy predictions for the next 1-24 hours. An alert generation module monitors occupancy thresholds and triggers notifications when predicted demand exceeds configurable thresholds.

Layer 4: Dashboard Layer

The visualization layer exposes all analytics outputs through an interactive web dashboard built with Plotly.js. The dashboard is accessible via standard web browsers and is designed with a responsive CSS Grid layout. The Tableau integration provides additional business intelligence capabilities for city administrators and parking authority stakeholders.

7.2 Interactive Dashboard Description

The Smart Parking Analytics Dashboard (dashboard/fixed_dashboard.html) provides a comprehensive, real-time-style interface for parking occupancy intelligence. Built with Plotly.js for interactive visualizations and styled with modern gradient CSS, the dashboard presents eight core analytical panels:

- Record Types Distribution: Pie chart showing the proportion of actual sensor readings versus model-generated forecast records.
- Model Sources Distribution: Visualization of the relative contribution of ARIMA, Linear Regression, and LSTM models to the forecast record pool.
- Occupancy Rate Time Series: Rolling mean occupancy rate across all segments, with hover-over tooltips for precise value inspection.
- Model Performance Comparison: Bar chart comparing RMSE and MAE values across the three models.
- Error Distribution Analysis: Histogram of per-prediction residuals, revealing the presence and direction of systematic model bias.
- Hourly Occupancy Heatmap: 24-hour by 7-day heatmap displaying average occupancy rate, enabling identification of peak demand windows.
- Top Performing Segments: Ranked list of the 10 parking segments with the highest average occupancy utilization.

- Occupancy Rate Distribution: Histogram of occupancy rates across all segments and time periods.

SECTION 8 — INSTALLATION AND USAGE

8.1 Prerequisites

The following software and environment requirements must be satisfied before running the project:

- Python 3.8 or higher
- Git (for repository cloning)
- The main dataset file smart_parking_full.csv placed in data/raw/

8.2 Setup Instructions

Step 1: Clone the Repository

git clone https://github.com/vedpd/AAI530-Group10-smart-parking-iot-forecasting.git

Step 2: Install Dependencies

pip install -r requirements.txt

Step 3: Run Notebooks in Order

- 01_data_overview.ipynb – Data exploration and structural validation
- 02_cleaning_and_eda.ipynb – Data cleaning, feature engineering, and exploratory analysis
- 03_time_series_forecasting.ipynb – ARIMA and baseline forecasting
- 04_ml_baseline_models.ipynb – Linear Regression and LSTM model training and evaluation

8.3 Project Repository Structure

Path	Description
data/raw/smart_parking_full.csv	Main dataset (committed to repository)
data/processed/	Processed data outputs (gitignored)
notebooks/01_data_overview.ipynb	Data exploration notebook
notebooks/02_cleaning_and_eda.ipynb	Cleaning and EDA notebook
notebooks/03_time_series_forecasting.ipynb	Forecasting notebook
notebooks/04_ml_baseline_models.ipynb	ML and LSTM training notebook
models/	Trained model artifacts (gitignored)
src/	Source code modules
dashboard/fixed_dashboard.html	Interactive Plotly.js dashboard
requirements.txt	Python package dependencies
.gitignore	Git ignore rules
README.md	Project documentation

Table 7: Project Repository Structure

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1. Project GitHub Repository: https://github.com/vedpd/AAI530-Group10-smart-parking-iot-forecasting
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