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Availability Status Prediction of EV Charging Stations via Deep Learning and Decision Tree Explainability

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Abstract
The increasing adoption of electric vehicles (EVs) has intensified the need for efficient management of charging infrastructure. This project addresses the challenge of predicting the availability status of EV charging stations — classifying whether a slot is available or not available — using a deep learning model and enhancing its interpretability through a decision-tree- based Explainability approach. A sequential LSTM-GRU model was developed to predict the availability status of charging slots at multiple stations in Paris, incorporating temporal, spatial, and contextual features such as time of day, day of the week, location coordinates, and trend indicators. To ensure the transparency and reliability of the deep learning model's predictions, a Decision Tree classifier was employed as an interpretable surrogate model. By analyzing the feature importance's derived from the Decision Tree, the study identified 'Longitude' and 'Latitude' as the most significant factors influencing charger availability, highlighting a strong spatial dependency in EV infrastructure usage patterns. The integration of interpretable models alongside deep learning models enhances decision-making confidence and provides actionable insights for urban mobility planners and infrastructure managers.

Keywords: *Electric Vehicles (EVs), Charging Slot Availability, LSTM-GRU Model, Decision Tree Explainability, Spatial-Temporal Prediction, Smart Mobility Infrastructure.*

1. Introduction

The twenty-first century has witnessed a transformative shift in how the world envisions mobility. With rising environmental concerns, stringent emission regulations, and the global push toward decarbonization, electric vehicles (EVs) have emerged not just as an alternative to traditional automobiles, but as a cornerstone of sustainable urban transport [1]. At the heart of this revolution lies an often-overlooked yet indispensable component: the EV charging infrastructure. Without an accessible, intelligent, and reliable network of charging stations, the momentum behind EV adoption can falter [2]. Cities like Paris, which have embraced the green mobility movement, offer a living laboratory for understanding the challenges and possibilities of modern electric infrastructure. One such opportunity presents itself in the form of rich, high-resolution data gathered from 91 EV charging stations scattered across the Paris metropolitan area. From July 2020 to March 2021, these stations recorded their operational status every 15 minutes, creating a dataset that offers both temporal depth and spatial breadth. Each station, equipped with three plugs, logs the number of plugs that are actively charging, available, idle, or in an undefined state. This granularity not only captures the dynamic rhythm of EV usage across time but also reveals the behavioral patterns of users and the operational challenges faced by the charging network. Included in this dataset are features such as timestamps, station IDs, geolocation coordinates, regional classifications, and time- based attributes like time of day and day of week—creating a goldmine for predictive modeling. Yet, data by itself is inert. Its true potential lies in how it can be transformed into foresight—into intelligent predictions that can improve real-world outcomes. The urgency of this transformation is clear. EV users often face the frustrating experience of arriving at a charging station only to find all plugs occupied.

Infrastructure operators, on the other hand, wrestle with questions of load balancing, maintenance scheduling, and strategic expansion. In both cases, the inability to anticipate future station availability creates inefficiencies, missed opportunities, and diminished user satisfaction. As cities prepare for a future defined by electrified transport, the capability to predict EV charging station occupancy is not just a convenience—it is a necessity [3]. This is where predictive modeling steps in, offering a solution grounded in data science and powered by machine learning. The challenge, however, is far from trivial. Real- world data is messy, riddled with anomalies, missing entries, and non-linear patterns that defy simple statistical modeling. Moreover, the behavior of EV users is influenced by a complex web of temporal cycles, spatial distributions, social trends, and external disruptions. Understanding and accurately forecasting this behavior requires more than just data—it demands a thoughtful integration of preprocessing, feature engineering, anomaly detection, and model training, all aligned toward a singular goal: reliable, real-time prediction of plug availability. The objective of this research is to build such a system. Through meticulous analysis of the Paris EV dataset, this project seeks to develop a predictive framework that can fore- cast the state of charging station plugs—available, charging, idle, or otherwise—using a blend of historical usage data, tem- poral features, and spatial attributes. By employing techniques such as Isolation Forest [4] for identifying anomalous patterns and Principal Component Analysis (PCA) for dimensionality reduction, the project ensures that the modeling pipeline is both robust and efficient. These techniques are then integrated into supervised learning models that learn from past behaviors to predict future availability. But this project is not merely a technical exercise—it is a step toward smarter cities and more seamless electric mobility experiences. By turning passive historical data into proactive decision-making tools, the research envisions a future where users no longer guess, but know in advance where to find a charging spot. Infrastructure planners can rely on data- driven insights rather than assumptions. Energy providers can optimize grid loads and maintenance without disruption (Figure 1). The result is a win-win ecosystem where technology enhances sustainability, convenience, and reliability.

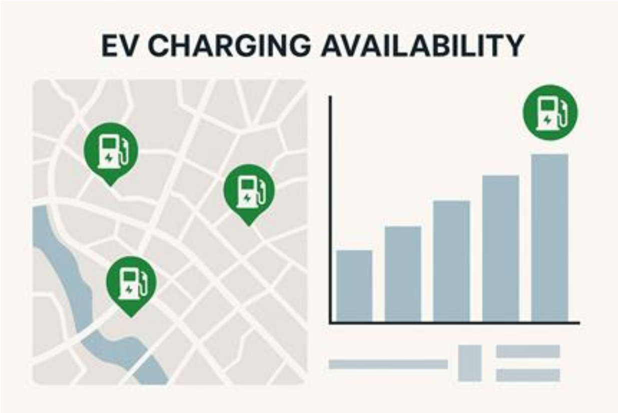

Figure 1 **EV Charging Availability**

In essence, this study does not just aim to build a prediction model—it aims to bridge the gap between data and foresight, between infrastructure and intelligence. It demonstrates how a well-designed machine learning pipeline can convert com- plexity into clarity, enabling cities like Paris—and the world at large—to better navigate the electric future that is already unfolding.

2. Related Work

The increasing adoption of electric vehicles (EVs) has driven significant interest in optimizing charging station infrastructure using predictive analytics. Prior studies have explored diverse machine learning techniques to forecast plug availability and improve infrastructure planning.mLiu et al. [5] utilized long short-term memory (LSTM) networks to capture complex, non-linear trends in EV charging demand, outperforming traditional statistical models. Zhao et al. [6] enhanced forecasting accuracy by combining seasonal decomposition with neural networks, although such methods often demand high computational resources and auxiliary data. Spatial-temporal clustering approaches, such as that pro- posed by Yuan et al. [7], helped identify high-demand areas for station deployment, demonstrating the value of geographic context. Meanwhile, Knapen et al. [8] applied decision trees and support vector machines to predict plug availability using external data sources like traffic and weather—highlighting the need for

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more self-sufficient models. From a data quality standpoint, Isolation Forests introduced by Liu et al. [4] have become a robust method for detect- ing anomalies in high-dimensional time-series data. Dimen- sionality reduction techniques, such as Principal Component Analysis (PCA), have also been validated for improving model efficiency without sacrificing predictive performance [9]. Unlike prior research that depends heavily on external datasets or computationally intensive architectures, our study focuses on building a scalable, lightweight pipeline that lever- ages only intrinsic time-series and spatial features. This en- sures practical deployment in real-world urban EV networks.

3. Dataset and Preprocessing

3.1. Dataset Description

The foundation of any meaningful data-driven research lies in the quality, richness, and relevance of the dataset being analyzed. For this project, the data originates from the Smarter Mobility Data Challenge [10], an initiative aimed at empowering data scientists to explore real-world mobility issues using open datasets. Hosted on GitLab, this platform provides curated datasets designed to simulate challenges faced in modern transportation systems, particularly in the context of electric vehicle (EV) infrastructure. The dataset used in this study, focusing on EV charging stations in Paris, offers a rare and valuable opportunity to examine real-time plug usage across an operational city-wide network.

Data was collected from 91 EV charging stations across the city, each equipped with three plugs. The plug status was recorded at 15-minute intervals, documenting how many plugs were available, actively charging, idle (passive), or in an undefined state. Alongside plug activity, the dataset includes metadata such as station ID, geographic coordinates (latitude, longitude), postal code, region label (e.g., North, South), and time-related features like day of week, hour of day, and a “trend” variable that represents time progression numerically. Overall, the dataset provides a rich, multidimensional view of EV charging behavior in an urban environment. Its combi- nation of high-frequency sampling, detailed plug-level status, and contextual metadata makes it ideally suited for time-series forecasting, anomaly detection, and behavioral modeling. This depth allows for the development of robust machine learning models capable of anticipating plug availability, optimizing station deployment, and enhancing user satisfaction in the
evolving EV ecosystem.

3.2. Data Preprocessing

Before predictive modeling, the dataset underwent essential preprocessing to ensure consistency, reliability, and readiness for time-series analysis. Like most real-world sensor data, the EV charging station dataset contained missing values, formatting inconsistencies, and required transformation. The data consisted of plug-level time-series logs with fields such as timestamps, plug status, station IDs, and geographic labels. Timestamps were converted to date time objects, allowing the extraction of temporal features like hour of day and day of week—crucial for capturing recurring usage patterns. Missing values, especially in plug status, stemmed from communication gaps or station maintenance. Short gaps were filled using forward-fill methods to maintain sequence continuity, while longer gaps were excluded to avoid bias. Redundant or static features—such as station names or constant codes—were removed, and only influential fields like plug status, plug ID, and derived time features were retained. Data types were standardized: timestamps and categorical fields were converted appropriately. Plug status and other categorical variables were encoded numerically to fit machine learning requirements. Boolean and constant fields were either removed or transformed based on relevance. To align feature scales, numerical attributes such as plug counts were normalized using min-max scaling, improving model convergence and performance. Simultaneously, eploratory data analysis (EDA) revealed key usage patterns, such as weekday peaks and regional demand variation. These insights guided the creation of additional features like rolling averages and usage ratios to enhance predictive power. In preparation for model training, a target variable named ’is available’ was engineered to represent the plug’s binary avail- ability status. This field was derived by mapping plug status values (e.g., “AVAILABLE” as 1 and all other states—such as

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"CHARGING", "OUT OF SERVICE", etc.—as 0). This binary target enabled the formulation of the forecasting task as a classification problem, allowing the model to predict whether a plug would be available in future time steps. Overall, these preprocessing steps transformed raw charging station logs into a refined dataset structured for robust plug availability forecasting, with high data integrity and minimal noise.

4. Model Implementation

4.1. LSTM-GRU Hybrid Model for Prediction

The hybrid architecture begins with an LSTM layer, which retains long-term dependencies through its gated memory cells. The LSTM update equations for the forget, input, and output gates are given as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

where h_t is the hidden state and c_t is the cell state that is updated based on the temporal dynamics of the input sequence. The GRU layer follows, updating its hidden state using the reset and update gates:

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r)$$

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z)$$

To forecast EV plug availability with temporal precision and adaptability, a hybrid deep learning architecture combining Long Short-Term Memory (LSTM) [11]and Gated Recurrent Unit (GRU) [12] networks was implemented. Figure 2 The architecture of the proposed LSTM-GRU model that combines both LSTM and GRU layers in a bidirectional RNN framework optimized for binary classification. The model utilizes dropout regularization and dense layers for effective feature transformation and prediction. The sequential nature of plug usage data—reflecting daily patterns, weekly cycles, and operational dynamics—necessitated a model capa- ble of learning both long-range and short-term dependencies effectively. By integrating both layers into a hybrid structure, the model leverages the long-term retention of LSTMs with the efficiency and adaptability of GRUs [13].

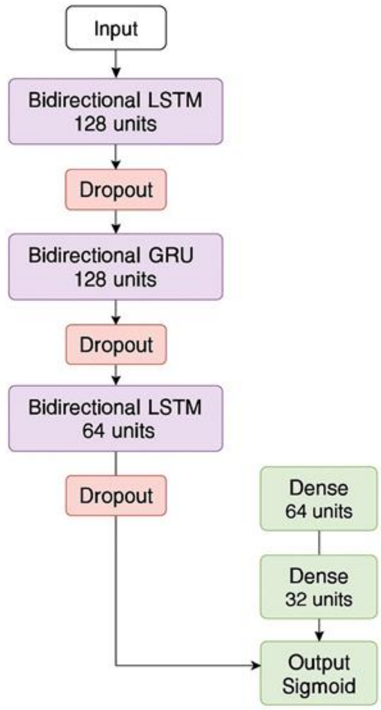

Figure 2 Architecture of the Proposed LSTM-GRU Model

The architecture begins with an input sequence composed of preprocessed features, including plug status encodings, temporal indicators (hour of day, day of week, weekend flag), and other engineered time-based attributes. This input is first passed through an LSTM layer to capture broad temporal trends, followed by a GRU layer that refines these representations by focusing on immediate temporal transitions. Dropout layers are placed strategically between the recurrent layers to prevent overfitting by randomly disabling neuron connections during training. Batch normalization is applied where necessary to ensure training stability and accelerate convergence. The final dense layer outputs a forecasted plug availability value for each time step in the input sequence. A key aspect of the modeling process was the creation of a binary target variable, 'is available', derived from the original plug status logs. This target indicates whether a plug was available (1) or not (0) at a given timestamp, simplifying the prediction task while preserving its practical relevance. This target framing supports various downstream use cases, including probabilistic forecasting or binary classification.

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The training pipeline used sequences of time-ordered data as input, with each window spanning a fixed temporal length to allow the model to learn transitions and cycles. Training was conducted using the Adam optimizer, minimizing mean squared error as the loss function. To prevent overfitting and optimize training time, early stopping was applied based on validation set behavior. A sliding window prediction strategy was adopted during inference. This approach enables the model to forecast plug status at each future time step by consuming a rolling window of the most recent observations, making it well-suited for real-time applications in intelligent transportation and charging infrastructure management. This hybrid LSTM-GRU model forms the core of the forecasting system, offering a balanced combination of interpretability, efficiency, and predictive capacity tailored to the complex rhythms of EV plug utilization.

4.2. Decision Tree for Explainability

The Decision Tree model is interpretable because it builds a series of decisions based on the features of the data. For classification tasks, the algorithm uses criteria like Gini Impurity or Entropy to select the best features for splitting. The Gini Impurity for a node t is calculated as:

$$Gini(t) = 1 - \sum_{i=1}^{C} p_I{}^2$$

where pi is the proportion of class i at node t. At each node, the decision tree algorithm aims to minimize the Gini Impurity (or Entropy) by choosing the feature that best separates the data [14]. For regression tasks, the **variance reduction** criterion is applied:

$$Var(t) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2$$

where yi represents the target values at node t, and $\bar{y}$ is the mean value at that node [14]. The final prediction at each leaf node is based on the majority class (for classification) or the average target value (for regression). In the realm of machine learning, model interpretability is often the critical bridge between high predictive performance and practical, real-world adoption. Among the many algorithms available, the Decision Tree stands out as a uniquely interpretable model due to its inherently transparent structure [15]. Unlike black-box models such as deep neural networks or ensemble techniques like Random Forests and Gradient Boosting, Decision Trees offer a step-by-step, rule-based decision path that mirrors human reasoning [16]. Each internal node in a Decision Tree represents a decision rule based on a specific feature, while each leaf node corresponds to a final prediction outcome. This hierarchical structure allows stakeholders—ranging from data scientists to domain experts and policy makers—to visually trace and audit the reasoning process behind a prediction. For instance, in applications involving medical diagnostics, loan approval systems, or vehicle fault detection (as explored in this study), understanding why a decision was made is often just as important as the decision itself. Moreover, the simplicity of Decision Trees facilitates feature importance analysis [17], enabling researchers to pinpoint which variables most influence outcomes. This can guide future data collection, model refinement, and even policy decisions. In our work, the Decision Tree not only served as a baseline classifier but also as a valuable interpretability benchmark, helping to validate and contextualize predictions made by more complex models. By leveraging the clarity and traceability offered by Decision Trees, we empower users to trust and adopt machine learning solutions in critical and high-stakes environments.

5. Evaluation and Result

5.1. LSTM-GRU Model Evaluation and Result

The LSTM-GRU model, designed to capture the temporal dynamics of the EV charging station dataset, demonstrated strong performance in predicting station availability based on features like time of day, day of the week, and usage trends. Trained with the Adam optimizer (learning rate 1e-4) and binary cross-entropy loss, the model achieved an accuracy of 87.58 %, precision of 86.79%, recall of 90.27%, F1-score of 88.49%, and ROC-AUC of 93.85%. These metrics highlight the model's effectiveness in learning temporal patterns and its reliability in classifying station availability. The combination of LSTM and GRU layers enabled the

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model to capture both long-term trends and short-term variations, making it well-suited for the dynamic nature of EV charging station usage. The high recall and AUC indicate strong predictive power, suggesting the model could be effectively deployed in real-time systems for improving user experience and station management.

5.2. Decision Tree Classifier Evaluation and Result

The Decision Tree Classifier was implemented as a baseline model to compare against the deep learning approach. The input features were reshaped into a two-dimensional format, and the tree was constrained to a maximum depth of 5 to prevent overfitting. On evaluation, the Decision Tree achieved an accuracy of 80.59% on the test data. The Decision Tree model identified 'longitude' and 'latitude' as the most influential features for predicting charger availability as observed in Figure 3, revealing a strong spatial dependency embedded within the dataset. This finding under- scores the importance of geographic context in determining EV charging behavior—some locations are consistently more active than others due to surrounding infrastructure, traffic flow, or urban density. Such insights are particularly valuable in guiding decisions about infrastructure investment and resource allocation.

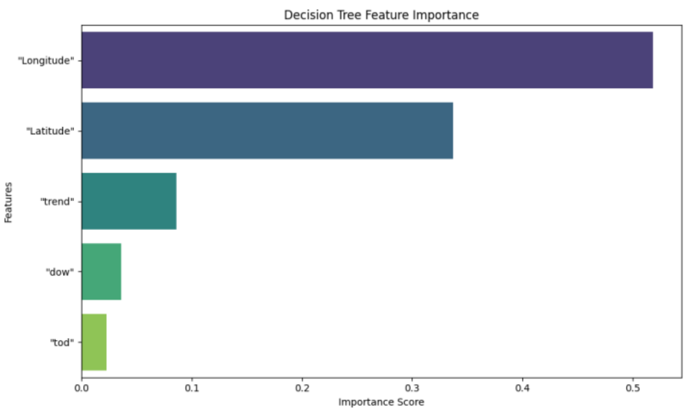

Figure 3 Decision Tree Feature Importance

Dependency embedded within the dataset. This finding under- scores the importance of geographic context in determining EV charging behavior—some locations are consistently more active than others due to surrounding infrastructure, traffic flow, or urban density. Such insights are particularly valuable in guiding decisions about infrastructure investment and re- source allocation. In our sequential deep learning model, these spatial features were not just retained—they were strategically embedded as static contextual inputs within each time window. This design allowed the LSTM-GRU architecture to learn temporal availability patterns that are not only time-dependent but also geographically conditioned. In other words, the model could differentiate how availability trends vary between stations in the city center versus those in suburban areas, even if their temporal patterns look similar at first glance. What makes this alignment especially compelling is the agreement between two very different types of models. The Decision Tree, known for its transparency, and the LSTM- GRU, recognized for its complexity and temporal learning capacity, both converge on the same key features. This overlap enhances the trustworthiness of the deep learning model by confirming that its internal logic resonates with interpretable, rule-based reasoning. It bridges the gap between explainability and performance, making the deep learning model's predictions not only accurate but also more understandable and justifiable to stakeholders.

Conclusion

A. Insights and Findings

At the heart of this project was a simple but vital question: Is an electric vehicle charging slot available at a specific location and time? Through the analysis of high-frequency data from 91 charging stations in Paris—collected every 15 minutes over nine months—we explored patterns in availability and usage. The workflow involved cleaning and preparing the data, reducing complexity using PCA, and detecting anomalies to highlight stations behaving unexpectedly [18]. The result was a comprehensive view into when and where charging slots are likely to be free or occupied [19], [20]. Through this analysis, we discovered that the availability of EV charging slots is far from random; it follows strong temporal and spatial trends. Charging slot availability tends to decrease during typical working hours when demand peaks, especially in commercial and high-traffic areas. Conversely, late-night and early morning hours often show higher avail- ability. Location plays a critical role—stations in central zones or near transit hubs are more likely to be occupied, while peripheral stations tend to maintain better availability. Time of day, day of the week, and station location together emerged as key predictors of whether a charging slot is likely to be free. Additionally, certain stations consistently deviated from expected patterns, indicating underlying issues such as maintenance problems or localized demand surges. These patterns lay the groundwork for building targeted prediction models that can inform users where to find an available slot before they even begin driving.

B. Limitations

Despite the depth of the dataset, several blind spots remain. It did not include external factors such as weather, traffic conditions, or local events—elements that often affect when and where people choose to charge. Also, while the analysis provided valuable insights and clustering of behaviors, it did not fully implement predictive models to forecast availability in real time. As such, it serves more as a foundation for future decision-making than a plug-and-play solution.

C. Future Work

The next step is to build on this foundation with predictive modeling. Incorporating additional data sources like weather forecasts, traffic patterns, and public events could significantly improve accuracy. Developing real-time models that forecast availability at the station level would make this project directly actionable for EV users and infrastructure planners. Further- more, scaling the approach to other cities would help compare network performance and drive more equitable and efficient deployment of charging stations. Ultimately, the goal is to ensure that whenever and wherever an EV driver needs to charge, availability is never in question.

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