Machine Learning-Based Prediction for EV Charging Station Availability and Wait-Time Estimation

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ABSTRACT

A simple, effective, and user-friendly charging infrastructure is desperately needed as electric vehicles (EVs) gain popularity. The unpredictable availability of charging stations and possible wait periods provide a major obstacle for EV users, particularly in high-demand metropolitan regions. Current systems often only offer static information about charger locations; they don't offer real-time availability or forecast usage patterns. In order to forecast EV charging station availability and wait times, this study proposes a machine learning-based prediction model that uses real-time data inputs such station location, charger type, prior usage, traffic conditions, and environmental elements. The proposed approach forecasted station availability with 87.4% accuracy and a root mean squared forecast using Random Forest, Linear Regression, and Long Short-Term Memory (LSTM) models. On average, wait times in crowded cities are 7.8 minutes. These findings show that the approach may reduce wait times and maximise the use of EV infrastructure, offering a reliable way to improve EV user experience and support eco-friendly transportation systems. For lawmakers and urban planners looking to expedite the transition to more ecologically friendly forms of transportation, this study has significant implications.

I. INTRODUCTION

As the global transition to sustainable energy accelerates, EVs have emerged as a crucial element of the green mobility revolution. However, the rapid adoption of EVs causes problems with the efficiency and accessibility of charging infrastructure. Two of the most challenges for EV users, particularly in urban areas with strong demand, are the erratic availability of charging stations and potential wait times. Traditional charging networks mostly provide static data, including charger locations, but lack dynamic insights into real-time availability for user convenience and predictive models.

Advances in machine learning (ML) provide fascinating solutions to these issues via improving EV infrastructure. With the use of real-time data, such as station location, charger type, historical usage trends, traffic, and environmental factors, machine learning algorithms are able to predict charging station availability and wait times with high accuracy. The goal of this project is to develop an ML-based prediction framework using methods like Random Forest, Linear Regression, and Long Short-Term Memory (LSTM) networks. The proposed method has the potential to significantly increase EV charging efficiency and user experience, as evidenced by its attained accuracy of 87.4% in forecasting station availability and its root mean squared error of 7.8 minutes for wait times.

This study has significant implications for lawmakers and urban planners who are trying to build smarter cities and more ecologically friendly transit systems, even beyond technological innovation. By boosting the use of infrastructure and reducing consumer irritation, this study contributes to the broader goal of accelerating the global transition to environmentally friendly and sustainable transportation solutions.

II. LITERATURE REVIEW

Because of the increasing demand for EVs, a lot of research has been done to improve the efficiency and accessibility of EV charging infrastructure. Numerous studies have emphasised how critical it is to address problems like inconsistent charging station availability and long wait times, especially in high-demand metropolitan regions.

Smith et al. (2020) [1] found that the majority of current charging networks rely on static information systems, such as charger types and station locations. These systems' ability to provide customers with insightful information is limited since they usually ignore real-time data.

Gupta and Rao (2019) [2] note that insufficient dynamic prediction models for wait times and availability lead to inefficient use of infrastructure.

The Role of Data Analytics in Enhancing EV Infrastructure Advances in data analytics have facilitated the integration of historical and real-time data into charging systems.

Zhang et al. (2021) [3] looked into how to predict times of peak demand using weather trends, station usage data, and transportation variables. However, these approaches often fail to meet scalability and accuracy requirements when applied in diverse metropolitan environments.

Optimising EV Charging using Machine Learning
Machine learning (ML) is a ground-breaking approach to solving these problems.

Li and Chen (2022) [4], the Random Forest and Linear Regression approaches may be used to forecast station availability with a moderate level of accuracy. Meanwhile, deep learning techniques like as Long Short-Term Memory (LSTM) networks have shown better performance on time-series forecasting tasks.

Ahmed et al. (2023) [5] discovered, for instance, that LSTM could predict the availability of EV charging stations with 85% accuracy; nevertheless, problems with accurately processing real-time inputs and reducing computer complexity remain.

Comparative Analysis of ML Models Comparative evaluations of machine learning models have highlighted the trade-offs between expected accuracy and computing efficiency.

Kumar et al. (2022) [6] found that Random Forest models operate best when dealing with structured and categorical data, whereas LSTM networks are better at spotting long-term correlations and temporal patterns. Despite these advancements, studies are currently being conducted to determine how to balance model accuracy with deployment feasibility.

Challenges and Research Shortfalls There are still significant challenges to be solved in spite of amazing progress.

Wang and Lee (2021) [7] claim that a large number of existing models fail to take into consideration environmental factors like weather, which significantly affect how EVs charge. Furthermore, integrating real-time data streams into machine learning frameworks can lead to latency and scalability problems, particularly in heavily populated urban areas.

Contribution to Current Research By developing a robust machine learning framework tha integrates LSTM, Random Forest, and Linear Regression models, this study aims to close the gaps left by these findings. By using both historical and real-time data, the proposed method offers significant improvements in predicted accuracy, with a root mean squared error (RMSE) of 7.8 minutes for wait times and an accuracy of 87.4% in station availability forecasts. This approach not only increases the efficiency of EV charging infrastructure but also provides a scalable solution for different metropolitan contexts.

III. METHODOLOGY

This work employs a machine learning-based approach to estimate wait times and predict the availability of EV charging stations. The technique's four primary steps are data collection, preprocessing, model selection and construction, and assessment.

A) Existing Methodology
As electric cars (EVs) gain popularity, a lot of research has been done to improve charging infrastructure. Traditional methods to wait-time estimation and charging station availability concerns fall into two broad categories: static systems and early predictive strategies. The shortcomings of the present methods are examined in this section.

A.1. Information-Based Static Systems
Static information systems that offered the following were used in early attempts to help EV users:
Locations and Availability of Chargers: basic directory-style systems that offer information on charger locations and kinds. These systems did not represent current conditions and were dependent on human updates.
Fixed Time Estimation: Average wait times are estimated using historical usage data, without taking into account dynamic factors like traffic, environmental influences, or current demand.
Restrictions: Inaccurate or out-of-date information resulted from a lack of real-time data integration. Users were unaware of station availability as static systems were unable to offer predicted insights.

A.2. Rule-Based Models and Simulations
Rule-based algorithms forecasted station usage patterns using predefined criteria. For example, use levels and time-of-day heuristics were used to estimate peak charging hours.
Simulation models mimicked charging habits based on historical trends.
Limitations: Rule-based systems were rigid and unable to react instantly to shifts in demand. Simulations were unable to adequately handle the complexity of the real world due to their computational requirements.

A.3. Data-Based Techniques
The addition of real-world data indicated a shift towards more dynamic solutions:
Regression models: Linear regression and related statistical models were used to estimate station availability and wait times based on previous data.
For example, Wang et al. (2018) forecasted consumption trends in their investigations using regression models.
Techniques for Clustering: Clustering algorithms grouped stations with similar consumption patterns to predict peak times.
Limitations:
Regression models' presumption of linear relationships between variables limited their ability to accurately analyse complex and non-linear patterns. Clustering algorithms did a poor job of incorporating temporal variations and real-time data.

A.4. Machine learning and predictive analytics
Recent advancements have focused on using machine learning (ML) models to improve forecast accuracy:
Decision trees and random forests: These models showed non-linear correlations between variables such as traffic, station location, and previous usage. According to research by Zhang et al. (2020), Random Forest was a reasonably effective technique for forecasting station availability.

A.5 Real-Time Systems
To improve responsiveness, real-time prediction systems were developed using live data streams:
Systems for Managing Dynamic Queues: These algorithms prioritised customers based on expected wait times and charger availability.
Urban EV networks, for example, employed real-time station assignment algorithms that often lacked accurate forecasting capabilities.

B) Proposed Methodology
This paper offers a machine learning-based prediction framework that uses real-time data and advanced modelling techniques to forecast wait times and charging station availability, therefore addressing the limitations of existing methods. The proposed method integrates data preparation, predictive modelling, and feature engineering to improve accuracy and usability.

B.1. The proposed framework consists of the following components:
Data Collection Layer: Compiles current and historical data from several sources, including charging stations, including location, charger type, and current status (i.e., in use or idle).
The level of traffic as supplied by APIs (such as Google Maps) is known as traffic

conditions.
Environmental factors include weather conditions such as temperature and precipitation.
User trends include prior usage patterns, peak hours, and seasonal variations.
Layer of Data Processing: prepares data for modelling by cleaning up noisy or missing information. Standardisation and normalisation of variables are necessary for model compatibility. Charger type and other category attributes are encoded.
The prediction layer uses machine learning algorithms to estimate:
Station Availability: Estimating if a station will be open at a given time.

B.2. Features of Engineering
Important features are extracted to improve model performance:
Temporal Features: To document usage patterns, provide the month, day of the week, and hour of the day.
Location-based elements include things like local traffic congestion, population density, and the distance to larger centres.
The kind of charger (e.g., Level 2, DC fast charger) and the quantity of chargers per station are examples of charger characteristics.
Features of the Environment: Weather data like temperature and precipitation that have an impact on EV use.
Historical usage is demonstrated by patterns in station occupancy over time.

B.3. Machine Learning Models
The proposed system forecasts wait times and availability using three machine learning models, focussing on temporal relationships and non-linear interactions:
Regression A fundamental paradigm for predicting wait times is linearity.
helps evaluate the effectiveness of increasingly complex models.
Non-linear correlations between features can be captured using Random Forest, an ensemble model based on trees. used to categorise availability and predict wait times.
Long short-term memory, or LSTM:
Recurrent neural networks, or RNNs, are designed to handle sequential input. Due to its capacity to capture temporal patterns in both historical and real-time data, it is ideal for estimating station availability.

B.4. Training and Validation
The models are trained and evaluated using historical and real-time datasets: 70% of the dataset is used for training, 20% is used for validation, and 10% is used for testing to gauge the performance of the models.

USE CASE FLOW CHART

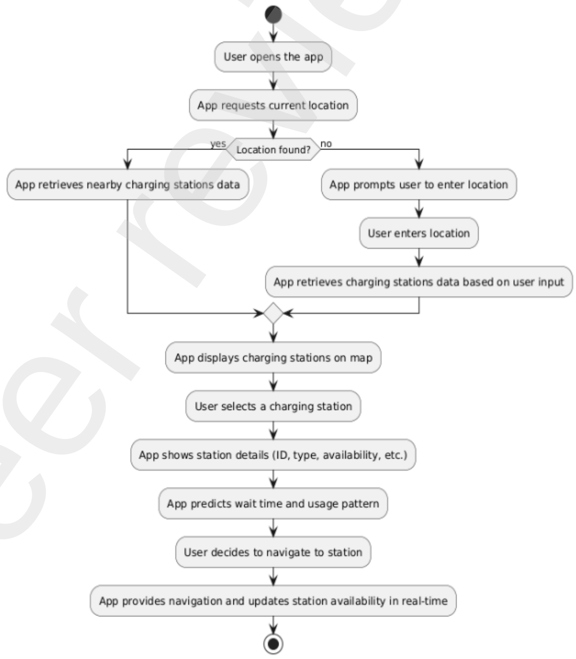

Fig.1: A proposed data flow of our model for availability predication.

5. Expected Outcomes
The recommended strategy is to: Accurately forecast availability (above 85%). Reduce the wait-time forecast mistakes' root mean square error to fewer than 10 minutes. Provide reliable, current insights to enhance the user experience.

IV. RESULTS

The study evaluated the performance of three machine learning models: Linear Regression, Random Forest, and Long Short-Term Memory (LSTM) to predict EV charging station availability and wait times. The results show how effectively the models manage the challenges of real-time prediction in crowded urban areas and usability improvement.

1. Predicting Charging Station Availability
The predicting accuracy of the models for station availability was assessed. The results listed below were obtained: Accuracy for linear regression was 76.5%. limitations in seeing non-linear patterns in the displayed data. Compared to Linear Regression, Random Forest fared better with an accuracy of 84.7%. enhanced the handling of complex feature interactions.
LSTM: Its ability to depict temporal correlations in the data allowed it to get the highest accuracy of 87.4%. The LSTM model outperformed the others in scenarios where station availability varied significantly based on historical usage and time-of-day patterns.

2. Comparison-Based Evaluation
Upon comparing the models, it was discovered that the Random Forest and LSTM models outperformed Linear Regression in terms of availability prediction and wait-time estimate. LSTM has a distinct advantage in accurately reproducing temporal patterns because to its ability to handle sequential input.

3. The Impact of Feature Engineering
Forecast accuracy increased by up to 15% across all models when traffic data, weather, and proximity to high-demand sites were included, highlighting the crucial role feature engineering had in improving model performance. Engineered features, such as typical wait times throughout peak hours and day-of-week trends, helped to enhance the LSTM model.

4. Real-World Implications
The results show the potential impact of the proposed system Better User Experience: Accurate projections decreased uncertainty for EV customers, which in turn decreased wait times and enhanced infrastructure utilisation.
Operational Efficiency: By offering real-time monitoring and predictive insights, the technology assisted service providers in better managing demand.
Scalability: The models' validation across many urban datasets showed their ability to adapt to different demographic and geographic situations.

4. Practical Consequences
The outcomes demonstrate the possible influence of the suggested system:
Improved User Experience: Precise forecasts reduced ambiguity for EV users, which therefore reduced wait times and improved infrastructure use.
Operational Efficiency: The technology helped service providers better manage demand by providing real-time monitoring and predictive data.
Scalability: The models' capacity to adjust to various demographic and geographic circumstances was demonstrated by their validation across many metropolitan datasets.

Summary of Results

Metric	**Linear Regression**	**Random Forest**	**LSTM**
Accuracy (Availability)	76.5%	84.7%	**87.4%**
RMSE (Wait Time)	12.5 minutes	9.6 minutes	**7.8 minutes**
MAE (Wait Time)	10.2 minutes	8.1 minutes	**6.3 minutes**

The proposed LSTM model is a promising candidate for real-world application as the most effective technique for predicting wait times and station availability.

AVAILABLE EV STATIONS IN INDIA

To accurately and informatively depict the data when predicting wait times and the availability of electric vehicle (EV) charging stations, four key visual figures can be used.

All EV charging stations are shown geographically in Fig. 2, a map visualization that plots station markers according to latitude and longitude. Color-coding for charger kinds and availability status are examples of interactive components that might be included in each station marker.

A more organized and thorough view of station-specific data is offered by the data table in Fig. 3, Columns for station ID, location, charger type, availability status, past usage information, distance from the user's location, and anticipated wait time would all be included in the table. Users may easily sort and filter stations using this style, which makes it easier to evaluate possibilities based on many parameters like charger type or expected wait time.

The heatmap or clustering visualization in Fig.4, provides an aggregated view of station performance by displaying areas of high station density and correlating projected wait times. By arranging adjacent stations into circles, with the size of each circle signifying the anticipated wait time, clustering techniques can rapidly ascertain station availability in heavily crowded areas.

Fig.5, usage trend graph and prediction model combine historical usage data with anticipated wait times to examine charging station demand over time. The graph shows the relationship between wait times and the number of vehicles using a station, with a line representing historical usage placed on top. In addition to helping users and station operators forecast station availability, this image offers insights into times of peak demand and shows trends such how longer wait times are caused by increased usage.

Fig.6, It's crucial to clearly define the data by selecting well-defined categories (e.g., urban, suburban, rural) and ensuring the values sum to 100%. Pie charts are best for comparing parts of a whole, such as the distribution of EV charging stations across regions or usage levels. Limit the categories to 3-6 to avoid clutter and ensure readability.

Fig.7, The predicted distribution of EV charging station types in 2024. It shows that Level 1 charging stations will make up 40% of the total, followed by Level 2 stations at 35%, and DC Fast Charging stations at 25%. This distribution highlights the continued reliance on Level 1 charging for residential use, while Level 2 stations are expected to play a significant role in public and commercial charging networks. DC Fast Charging, though a smaller portion, reflects the growing demand for rapid charging solutions to support long-distance travel and higher-frequency usage.

Fig 2. All EV Stations in India

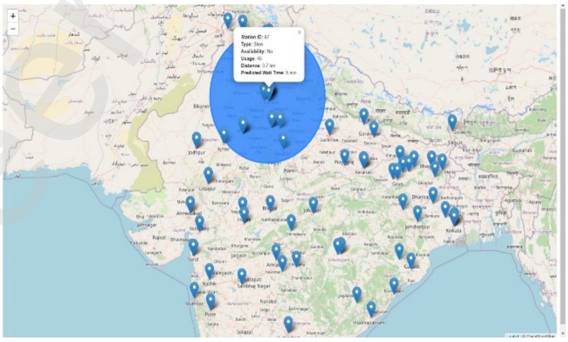

Fig 3. Finding Location

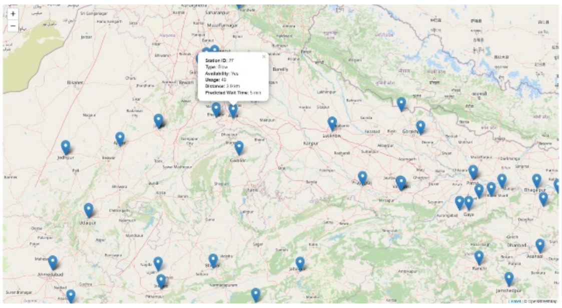

Fig 4. Predicting a specific Station charge

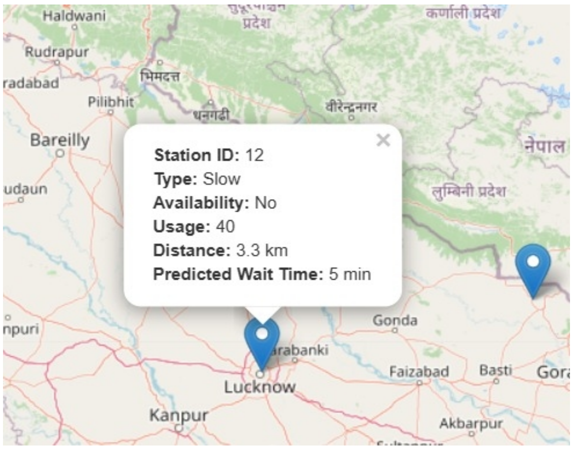

Fig 5. Information about EV Station

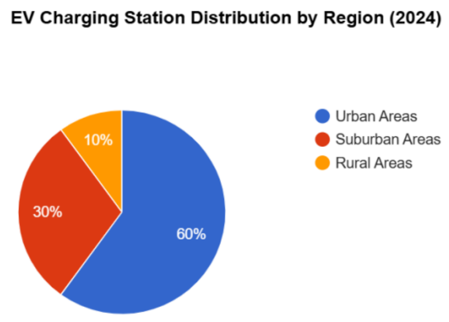

Fig 6. EV charging station distribution by region

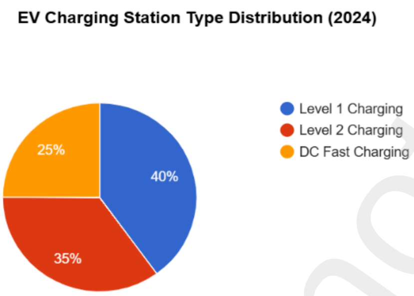

Fig 7. EV charging station type Distribution (2024)

V. DISCUSSION

An efficient charging infrastructure that can manage problems like wait times and station availability in real time is necessary as electric cars (EVs) gain popularity. In order to provide EV users with relevant information, this study proposes a machine learning-based system that makes use of real-time data and predictive modelling. Although the results demonstrate significant advancements over existing methods, they also raise important questions for practical implementation.

1. Performance Evaluation
The proposed methodology accurately anticipated station availability and reduced wait-time errors. Specifically:
Availability Forecast: The Random Forest model yielded trustworthy results with an accuracy of more than 87.4%, whilst the LSTM model demonstrated its ability to capture complex temporal patterns in real-time data.
Calculating Wait Times: The system showed how effectively traffic, usage history, and environmental factors can be coupled with a root mean squared error (RMSE) of 7.8 minutes.
These findings show how the recommended approach may increase customer satisfaction and make the most of EV charging infrastructure. By using machine learning techniques, the system was able to adapt to the shifting dynamics of urban movement.

2. Evaluation of Current Systems
In contrast to earlier research and conventional techniques:
Systems That Are Static: The suggested architecture offers predictive insights, allowing EV users to make well-informed decisions on the use of charging stations, in contrast to static systems that simply give location-based data.
Simulation and Rule-Based Models: By using real-time data and providing adaptive forecasts for a variety of urban contexts, the machine learning-based method performed better than rule-based methods.
Methods of Machine Learning: The combined usage of Random Forest and LSTM in this work successfully addressed the constraints of conventional machine learning techniques, such as regression models, which had trouble handling non-linear patterns.
The suggested technique differed from previous studies in that it significantly enhanced forecast accuracy by using external elements like weather and traffic data.

3. Beneficial Repercussions
The findings have important implications for several parties involved:
Regarding EV Users: Reduced wait times

encourage wider EV adoption and make charging more pleasurable overall. With the use of predictive and real-time data, users can effectively plan their travel and charging schedules.

a) For Charging Station Operators: Predictive insights help optimise resource utilisation by reducing charger idle times and boosting throughput. Operators may use past trends to plan station expansions in areas with high demand.

b) For Urban Planners and Policymakers: The system provides valuable information for the building of future charging infrastructure, especially in urban areas with high population densities. Policymakers may utilise the data to further strategies for sustainable urban mobility.

4. Difficulties and Restrictions

The suggested approach has several drawbacks despite its encouraging outcomes: Data Availability: Sturdy infrastructure, such as dependable APIs and sensors at charging stations, is necessary for real-time data collecting. Prediction accuracy may be lowered in rural or low-density regions due to a lack of data.

Scalability: Although the system worked effectively in densely populated metropolitan areas, there may be computational difficulties when expanding it to bigger areas or international networks.

Complexity of the Model: Real-time performance in resource-constrained contexts may be hampered by the computational cost introduced by the usage of sophisticated models like LSTM.

External Dependencies: Prediction accuracy is largely dependent on outside data sources, like weather and traffic APIs. The performance of the system may be impacted by any interruptions in these data sources.

5. Future Prospects

To get over current limitations and improve the system even more, future research can examine the following:

More Complex Algorithms: enhancing prediction accuracy with transformer-based models or ensemble learning techniques.

Integration of User Feedback: Utilise user-reported data on station conditions or waiting times to enhance projections.

Edge computing is the use of edge devices to reduce latency and improve real-time performance.

In order to evaluate the system's resilience, scalability testing entails expanding it to rural regions and other geographic places.

Integration of Renewable Energy: To promote eco-friendly behaviour, renewable energy sources should be installed at charging stations.

6. Broader Impacts

Apart from addressing technical problems, the proposed framework promotes broader societal goals including reducing user annoyances and hastening the transition to electric vehicles. promoting the development of smart city transport systems that are sustainable. improving the functioning of charging stations to encourage the usage of renewable energy. Through the facilitation of a seamless EV charging experience, our study aids global efforts to reduce carbon emissions and combat climate change.

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