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Efficient Reservation System For Electric Vehicles Using Machine Learning

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Abstract: In the face of depleting fossil fuel resources, global attention has shifted towards sustainable and efficient green energy solutions. The rapid advancement of Electric Vehicle (EV) technology, coupled with decreasing component costs, is contributing to the increasing popularity of EVs as a more environmentally friendly alternative to conventional vehicles. This study introduces a novel approach where the State of Charge (SoC) of EV batteries is continuously displayed, and the nearest charging stations are readily accessible on the vehicle's screen. The proposed system takes a step further by guiding the EV driver to a slot booking website from a curated list of nearby charging stations, streamlining the process of reserving a charging slot. As the commercial viability of EVs continues to rise, the demand for an effective slot booking system becomes imperative to alleviate the time-consuming nature of the charging process and accommodate the growing need for more charging stations. The presented model for the booking system aims to not only enhance efficiency but also establish a cost-effective solution, addressing the evolving requirements of the expanding electric vehicle ecosystem.

I. INTRODUCTION

The global transportation sector is shifting toward sustainable energy solutions, with Electric Vehicles (EVs) playing a pivotal role in reducing carbon emissions and reliance on fossil fuels. However, the rapid adoption of EVs has exposed significant challenges in charging infrastructure, such as long waiting times, uneven distribution of charging stations, and inefficient resource utilization. These issues hinder user convenience and discourage broader EV adoption.

To address these challenges, this study proposes an Optimized Electric Vehicle Reservation System powered by machine learning algorithms. The system integrates real-time monitoring of EV battery State of Charge (SoC) with a dynamic reservation platform, allowing drivers to locate and book charging slots seamlessly. By leveraging predictive analytics, the system forecasts charging station availability and optimizes slot allocation, ensuring minimal waiting times and efficient resource utilization.

The integration of machine learning enables the system to anticipate peak demand periods and allocate resources proactively, minimizing downtime and enhancing user experience. This research introduces a scalable and user-centric solution to EV charging management, addressing immediate challenges while laying the groundwork for future advancements in smart mobility. By combining real-time data analytics with machine learning, this study aims to create a robust framework that supports the sustainable growth of the EV ecosystem.

1.1 Data Collection

The development of the Optimized Electric Vehicle Reservation System relies on the collection and analysis of diverse datasets related to EV usage and charging infrastructure. Primary data sources include real-time EV telemetry data, charging station availability logs, and user behavior patterns. These datasets are collected from publicly available repositories, EV manufacturers, and charging network providers. Key data attributes include EV telemetry data such as State of Charge (SoC), battery health, location, and driving patterns. Additionally, charging station data such as station location, availability status, charging speed, and

historical usage trends are collected. User behavior data, including reservation patterns, preferred charging times, and feedback on station performance, are also incorporated.

To ensure data reliability, preprocessing techniques such as handling missing values, removing duplicates, and normalizing data are applied. The processed dataset is then used to train machine learning models, enabling the system to predict charging station availability and optimize slot allocation. This data-driven approach ensures the system's accuracy and scalability in real-world scenarios..

1.2 Preprocessing and Analysis

The collected datasets undergo rigorous preprocessing to ensure their suitability for training machine learning models. Missing values are addressed through imputation techniques, while duplicate entries are removed to eliminate redundancy. Feature selection is performed to retain only the most relevant attributes, such as State of Charge (SoC), charging station location, and user reservation patterns. Numerical features are normalized to maintain consistency across the dataset, and categorical variables are encoded into numerical formats to facilitate model training.

Exploratory Data Analysis (EDA) is conducted to uncover patterns and trends within the data. Visualization techniques such as histograms, heatmaps, and scatter plots are used to analyze feature distributions and their relationships with charging station availability. Insights from EDA guide the refinement of feature selection and help identify key predictors for accurate model training.

The preprocessed dataset is then split into training and testing sets to evaluate model performance. By applying these preprocessing and analysis steps, the dataset is optimized for machine learning, ensuring the system's ability to predict charging station availability and recommend optimal reservation slots effectively.

1.3 Modeling Approach

The proposed Optimized Electric Vehicle Reservation System employs machine learning algorithms to predict charging station availability and optimize slot allocation. Four models are evaluated for this purpose: Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost. These models are chosen for their ability to handle classification and regression tasks, making them suitable for predicting station availability and user behavior.

The dataset is split into training and testing sets, with k-fold cross-validation applied to ensure model robustness and prevent overfitting. Hyperparameter tuning is performed to optimize each model's performance. Logistic Regression is used for its interpretability and efficiency in binary classification tasks, while Random Forest and XGBoost are leveraged for their ensemble learning capabilities, which enhance prediction accuracy. SVM is employed for its effectiveness in handling non-linear data through kernel functions.

Model performance is evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. The best-performing model is selected for integration into the reservation system, ensuring reliable predictions and efficient slot allocation. This approach ensures the system's ability to adapt to dynamic charging demands and provide a seamless experience for EV users.

1.4 Model Evaluation

The performance of the machine learning models is evaluated using key metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. These metrics assess the models' ability to accurately predict charging station availability and optimize slot allocation. To ensure robustness, k-fold cross-validation is applied, dividing the dataset into multiple subsets for training and testing. This approach minimizes overfitting and ensures the models generalize well to new data.

Confusion matrices are used to visualize classification results, highlighting true positives, false positives, true negatives, and false negatives. ROC curves are plotted to analyze the trade-off between sensitivity and specificity, providing insights into the models' predictive capabilities. Feature importance analysis is conducted for ensemble models like Random Forest and XGBoost to identify the most influential predictors. Based on the evaluation results, the best-performing model is selected for integration into the reservation system. This model demonstrates high accuracy and reliability, ensuring efficient prediction of charging station availability and optimal slot allocation. The evaluation process confirms the system's ability to meet the dynamic demands of EV users and support the sustainable growth of charging infrastructure.

II. Research Methodology

This study follows a systematic methodology to develop a machine learning framework for the Optimized Electric Vehicle Reservation System. The process begins with data collection from multiple sources, including EV telemetry systems, charging station logs, and user behavior records. The gathered data undergoes preprocessing, including handling missing values, selecting relevant features, and normalizing data to improve model accuracy. The dataset is then divided into training and testing sets to evaluate model performance.

Multiple machine learning algorithms, such as Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost, are trained and tested on the processed data. Their effectiveness is measured using key evaluation metrics, including accuracy, precision, recall, and ROC-AUC, to identify the best-performing model. Finally, a graphical user interface (GUI) is integrated to provide an accessible platform for real-time charging slot reservations, ensuring the framework's practical application in real-world scenarios.

2.1 Theoretical framework

The theoretical framework of this study is built on the application of machine learning techniques for optimizing Electric Vehicle (EV) charging infrastructure. It leverages classification and regression algorithms to analyze EV telemetry data, charging station availability, and user behavior patterns. Supervised learning models, including Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost, are utilized to process structured datasets containing key features. These features typically encompass State of Charge (SoC), charging station location, historical usage trends, and user reservation patterns.

To enhance model efficiency, data preprocessing techniques such as feature selection, normalization, and handling missing values are implemented. The performance of different algorithms is assessed using statistical metrics like accuracy, precision, recall, and ROC-AUC. By integrating machine learning methodologies within this framework, the study aims to provide a data-driven approach to EV charging management, complementing traditional infrastructure planning for efficient and scalable solutions.

III. Model Development

The machine learning model development focuses on creating a framework for optimizing EV charging station reservations. The process begins with data preprocessing, including handling missing values, selecting relevant features, and normalizing data to enhance model accuracy. Four classification and regression algorithms—Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost—are trained on the processed dataset. These models undergo hyperparameter tuning to improve predictive performance.

Evaluation is conducted using key metrics such as accuracy and ROC-AUC to identify the most effective algorithm. Finally, a user-friendly graphical interface is integrated to facilitate easy access and real-time charging slot reservations.

3.1. Logistic Regression Model

Logistic Regression is a statistical model used for binary classification tasks, making it suitable for predicting charging station availability based on relevant input features. It predicts the probability of an instance belonging to a particular class using the logistic (sigmoid) function. In this study, Logistic Regression is employed to classify charging stations as available or occupied based on features such as State of Charge (SoC), location, and historical usage patterns. The model is trained on labeled datasets, allowing it to establish relationships between independent features and the target variable.

To enhance performance and prevent overfitting, regularization techniques such as L1 (Lasso) and L2 (Ridge) are applied. The model's effectiveness is assessed using key evaluation metrics, including accuracy, precision, recall, and ROC-AUC, ensuring its reliability for predicting charging station availability.

3.2. Random Forest Model

The Random Forest model is an ensemble learning technique that enhances classification accuracy by combining multiple decision trees. It works by training multiple trees on different subsets of data and making predictions based on majority voting. Each tree is built using randomly selected features and training samples, reducing overfitting and improving generalization.

During prediction, each tree in the forest provides an output, and the final decision is determined by aggregating the results. This method ensures robustness and higher accuracy compared to individual decision trees. The model is evaluated using metrics like accuracy, precision, recall, and ROC-AUC to assess its effectiveness in predicting charging station availability.

The prediction in Random Forest for classification is given by:

$$\hat{y} = \arg \max \sum_{t=1}^T h_t(x)$$

where $h_t(x)$ represents the prediction of the t th decision tree, and T is the total number of trees. The final output is the most frequently predicted class among all trees.

3.3. SVM Model

Support Vector Machine (SVM) is a supervised learning algorithm used for classification tasks. It identifies an optimal hyperplane that separates data points from different classes. SVM maximizes the margin between the closest data points, known as support vectors, to improve generalization and reduce classification errors.

For non-linearly separable data, SVM applies kernel functions such as linear, polynomial, and radial basis function (RBF) kernels. These functions transform the input space into a higher-dimensional feature space, enabling the application of a linear decision boundary. This adaptability makes SVM effective for complex classification tasks, including predicting charging station availability.

3.4. Comparison of the Models

Comparing multiple machine learning models is essential for identifying the most effective approach for early Autism Spectrum Disorder (ASD) detection. This study evaluates Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost using key metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.

Random Forest and XGBoost generally achieve higher accuracy due to their ensemble learning capabilities, while SVM performs well with non-linearly separable data using kernel functions. Logistic Regression offers interpretability but may struggle with complex patterns. The final model selection balances accuracy, efficiency, and interpretability, ensuring optimal integration into ASD detection systems.

3.5. Model Evaluation

Comparing multiple machine learning models is essential for identifying the most effective approach for optimizing EV charging station reservations. This study evaluates Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost using key metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.

Random Forest and XGBoost generally achieve higher accuracy due to their ensemble learning capabilities, while SVM performs well with non-linearly separable data using kernel functions. Logistic Regression offers interpretability but may struggle with complex patterns. The final model selection balances accuracy, efficiency, and interpretability, ensuring optimal integration into the EV reservation system.

IV. RESULTS AND DISCUSSION

The proposed system demonstrates high accuracy in predicting charging station availability, with XGBoost outperforming other models. Key features like State of Charge (SoC) and station location significantly improve predictions. The system reduces waiting times by dynamically allocating slots, confirmed by confusion matrices and ROC curves. This framework enhances user convenience and optimizes resource utilization, supporting sustainable EV infrastructure. Future work will focus on real-time data integration and scalability.

4.1 Results of Descriptive Statics of Study Variables

Table 4.1: Descriptive Statics

Variable	Mean	Standard Deviation	Minimum	Maximum
State of Charge (SoC) (%)	65.2	12.4	20	100
Charging Time (minutes)	45.6	10.3	15	120
Distance to Station (km)	8.7	4.2	1	25
Station Utilization (%)	72.5	15.6	30	100
User Satisfaction (1-10)	7.8	1.5	3	10

Table 4.1 The table below provides a detailed statistical summary of the key variables analyzed in the study. It includes the mean, standard deviation, minimum, and maximum values for each variable, which help in understanding the distribution and variability of data points.

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