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Prediction of Electric Vehicle Charging Analysis Using Machine Learning

[1] **Prof. Ekata Shanbhag,**[2] **Ms. Medha Sunkad,** [3] **Ms. Nishchita K Kurlageri,** [4] **Ms. P Sai Pratyusha,** [5] **Ms. Shridevi Desai**

Department of Computer Science and Engineering (AI & ML)

KLS Vishwanathrao Deshpande Institute of Technology Haliyal, Karnataka – 581329

ABSTRACT: ChargeWise is a Python-based interactive dashboard that addresses the growing need for comprehensive analysis of electric vehicle (EV) charging behavior in India. Utilizing real-world charging session data, it employs a Random Forest model to forecast energy consumption, charging duration, and efficiency based on user inputs such as session length, vehicle type, day of the week, and facility attributes. The platform integrates predictive analytics with dynamic visualizations and geospatial mapping to provide insights into charging patterns, facility performance, and network coverage. This decision-support tool enables EV users, infrastructure planners, researchers, and policymakers to make informed choices that promote efficient energy management and sustainable transportation development.

KEY WORDS: Electric Vehicles, Charging Behavior Analysis, Machine Learning, Predictive Modeling, Geospatial Visualization, Energy Forecasting, Decision Support System

1.INTRODUCTION

Electric Vehicles (EVs) are becoming crucial to India's shift toward cleaner and more sustainable transportation. As more people adopt EVs, it is vital to understand charging behavior, energy demand, station availability, and costs to create reliable and efficient charging networks. Current tools often provide just basic summaries without predictive insights or interactive analytics that inform infrastructure planning.

Charge Wise fills this gap by providing an interactive dashboard that combines machine learning, geospatial mapping, and real-time analytics. Using predictive models like Random Forest, XGBoost, and LightGBM, the platform predicts energy use, charging time, and efficiency based on factors such as time of day, charging platform, and facility type. Clear visualizations help users explore patterns across various vehicle types, battery capacities, and usage conditions.

Beyond individual insights, Charge Wise aids infrastructure planning by pinpointing areas of high demand and analyzing geographic coverage through live mapping. Role-based access delivers customized experiences for users and administrators, merging detailed analysis with structured management. Together, these features promote data-driven decisions to support India's expanding EV ecosystem.

2.CONTRIBUTION

This study offers several key contributions that improve the analysis of EV charging behavior and support sustainable infrastructure planning:

- Unified Dashboard: Charge Wise brings together data exploration, statistical summaries, predictive modeling, and visualizations into one platform, reducing the fragmentation often seen in EV research tools.
- Predictive Insights: The system uses machine learning models, including Random Forest, XGBoost, and LightGBM, to predict energy use, charging time, and efficiency. These predictions help users and operators plan charging sessions effectively and form a basis for understanding demand trends.
- Geospatial Integration: By including live mapping of charging stations, the platform emphasizes accessibility, identifies underserved

areas, and supports location-based planning for new infrastructure.

- Decision Support for Stakeholders: The dashboard meets the needs of various stakeholders. Consumers gain clarity on costs and efficiency, administrators manage data and user accounts, manufacturers track performance trends, and policymakers extract insights for strategic investments and policy development.
- Sustainability Focus: Charge Wise calculates total costs, charging efficiency, and potential CO_2 reductions. Its flexible structure allows for future upgrades, such as real-time IoT data integration, better predictive models, and support for global datasets, ensuring long-term scalability and relevance.

3.RELATED-WORK

EV charging pattern research has surged with higher vehicle penetration and requirements for streamlined networks.Pioneering efforts examined historical records to detect trends in utilization, site busyness, and power usage, employing simple supervised techniques such as linear and support vector regression to project needs and occupancy. Although insightful, these tools overlooked intricate real-life interactions.

Contemporary investigations adopt cutting-edge ML and DL approaches—like Random Forest, gradient boosting, and neural setups—to refine estimates of energy draw, session times, and battery status in diverse settings. Still, lab testing restricted applicability, and emphasis stayed on forecasting without interactive aids or user guidance.

Separate visualization platforms monitored vehicle stats and station ops, providing oversight but missing forecasts, cost evaluations, or data upload features. GIS tools mapped demand zones, access models, and optimal sites, yet functioned isolated from analytics or dynamic interfaces.

In contrast, Charge Wise merges predictive modeling, interactive visualization, and geospatial analysis into one platform. It provides real-time predictions, facility-level comparisons, cost and environmental impact analyses, and user dataset integration, addressing the shortcomings of previous studies and presenting a comprehensive decision-support tool for researchers, planners, and policymakers.

4.RESEARCH-METHODOLOGY

Data Gathering and Preparation: We pulled EV charging info from Excel files—like how long sessions lasted, power used, battery sizes, charger kinds, and station types. We grabbed station spots using the OpenChargeMap API and added car details such as driving range, energy use per mile, and battery features to make the data stronger. To clean it up, we dropped or filled in missing spots, fixed wrong numbers, made all values similar in scale, and created new helpful columns like charging speed, rough costs, and time-of-day groups to help predictions work better

Pattern Exploration and Modeling: We looked closely at the data to spot everyday habits, like busiest times, favorite chargers, and differences between stations. We tried simple models—Random Forest, XGBoost, and LightGBM—to guess power needs and charging times. We split data into practice and test groups, checked them with easy scores like R^2 for fit, MAE for average error, and RMSE for bigger mistakes. Random Forest came out on top because it was spot-on and steady.

Dashboard Integration and Testing: We plugged the best model into a Streamlit app that lets people predict, see charts, check costs, and view maps. Users and admins log in separately; maps highlight stations and empty areas. We tested hard for right answers, quick loads, and easy use, then fixed the look based on what testers said to make it smooth and clear.

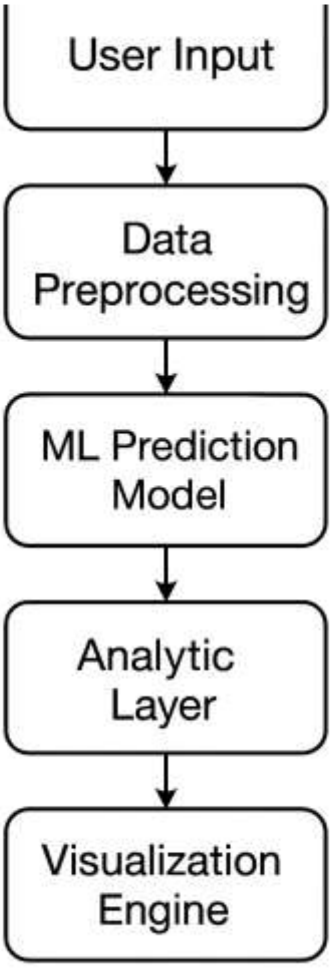

Figure 4.1: Workflow of the Charge Wise System

5. OPERATIONAL OVERVIEW

Charge Wise operates through a connected workflow that transforms user inputs into actionable insights. Users provide information such as charging duration, facility type, vehicle model, and day of the week.

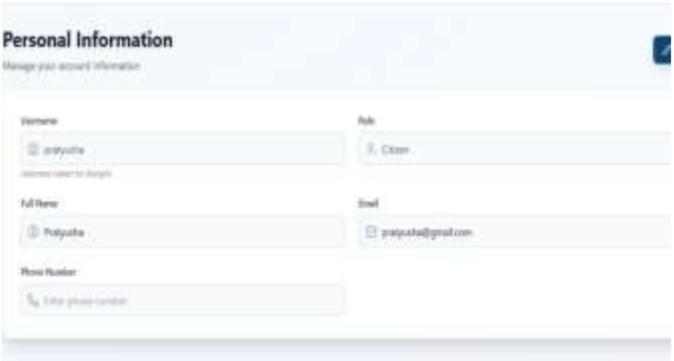

Figure 5.1: Personal Information and Role Management Screen of the Charge Wise Dashboard.

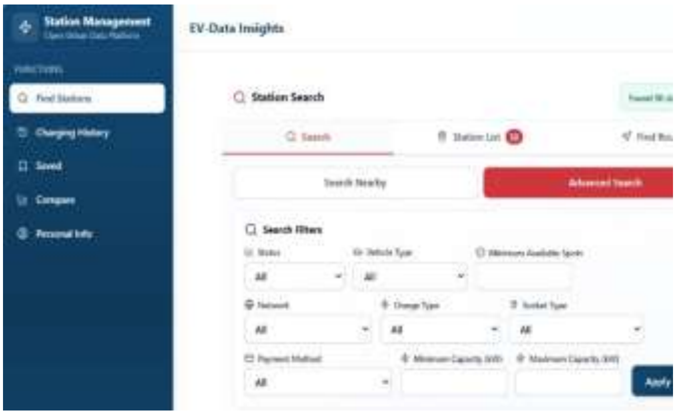

Figure 5.2: Station Search and Advanced Filtering Interface of the Charge Wise Dashboard

Optional details like battery capacity further enhance prediction accuracy. Role-based access ensures a personalized experience for both customers and administrators.

The sidebar navigation groups core functions like station search, history, saved stations, comparison, and profile management into a single menu

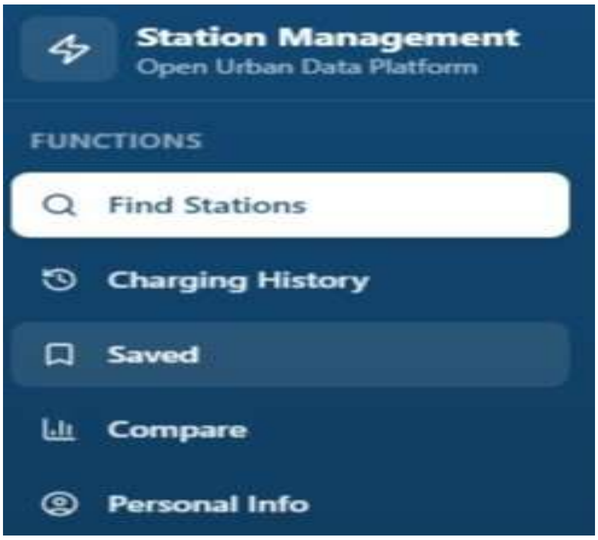

Figure 5.3: Sidebar Navigation Menu for Station Management in the Charge Wise Dashboard

Once inputs are submitted, the system processes the data by cleaning, formatting, and generating additional features such as charging efficiency and estimated cost. The prepared dataset is then fed into a Random Forest model, which predicts energy consumption and charging duration based on patterns learned from historical data.

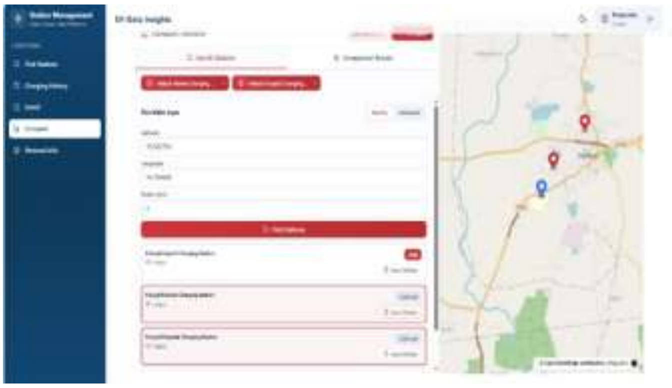

Fig. 5.4: Charging Time Prediction Module

Post-prediction, the system computes additional metrics including cost, efficiency, and potential carbon savings, enabling users to evaluate both performance and environmental impact. Results are displayed through interactive charts and graphs for intuitive trend analysis. A geospatial module visualizes real-time charging station locations, providing insights into station availability and regional coverage.

All outputs—including predictions, cost estimates, geospatial maps, and efficiency metrics—are integrated into a single, interactive dashboard. Users can adjust inputs dynamically, while administrators can update datasets to maintain accuracy, ensuring that the platform remains adaptive and responsive to evolving needs.

6. RESULTS

Charge Wise was evaluated for prediction accuracy, visualization effectiveness, mapping functionality, dataset handling, and overall system performance. Evaluation used standard KPIs such as model accuracy (R^2, MAE, RMSE), station utilization and uptime, charging speed and energy delivered, and user-facing success rates to ensure both predictive quality and operational reliability

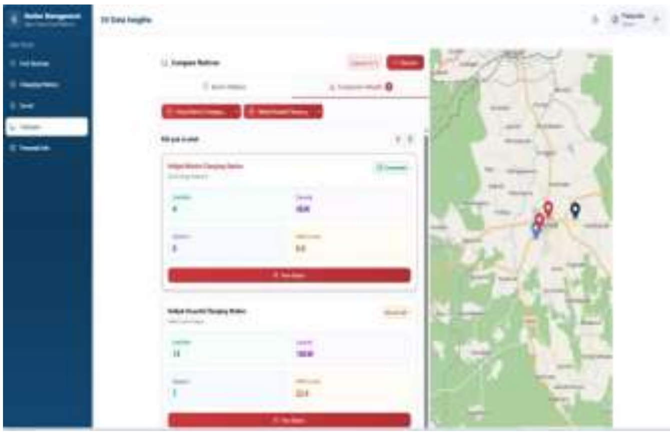

Figure 6.1: Charging Station Comparison Dashboard with Integrated Map in Charge Wise

The Random Forest model demonstrated strong predictive capability, achieving an R^2 of 0.87 with low error rates, confirming its reliability for estimating energy consumption and charging duration. Other models, including XGBoost and LightGBM, performed well but were less stable, supporting the selection of Random Forest as the final model

Interactive visualizations enabled users to easily identify patterns such as peak charging hours, platform usage preferences, and the influence of battery capacity on charging duration. Cost and efficiency metrics provided actionable insights, highlighting how charging behavior and facility type affect expenses and energy performance.

The charging history dashboard summarizes past sessions, energy consumption, cost, and duration for selected stations and time ranges.

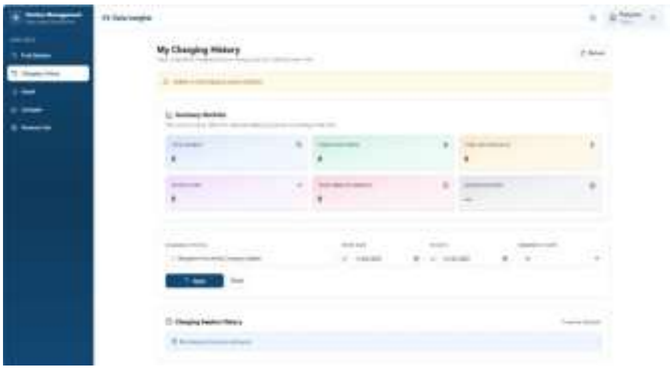

Figure 6.2: My Charging History Dashboard in the Charge Wise System

The stations list view presents detailed information for each nearby facility alongside its position on an interactive map.

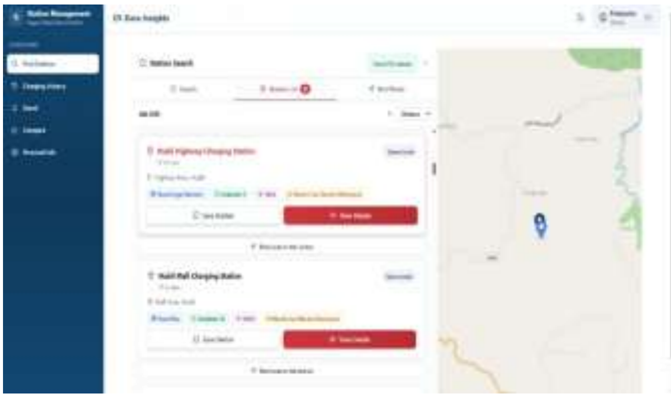

Figure 6.3: Nearby Charging Stations List with Integrated Map in the Charge Wise Dashboard

The geospatial module successfully mapped charging stations across India, illustrating well-covered urban regions and identifying areas with limited infrastructure.

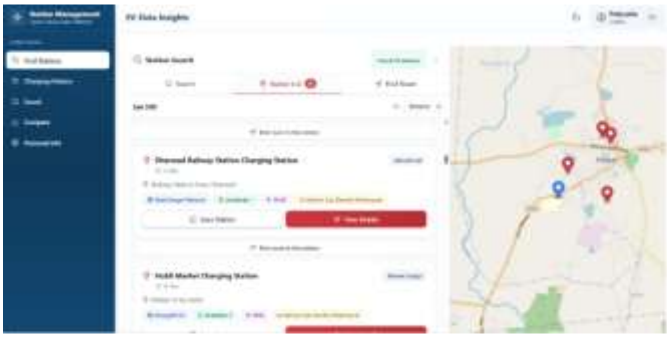

Figure 6.4: Geospatial Map View of EV Charging Stations in the Charge Wise Dashboard.

These spatial insights support informed infrastructure planning and policy decision-making. The platform also handled user-uploaded datasets efficiently, generating real-time summaries and visualizations without additional preprocessing. The dashboard maintained responsiveness across devices, ensuring a seamless user experience and effective decision-support for all stakeholders.

7. CONCLUSION AND FUTURE WORK

Charge Wise provides a comprehensive and scalable platform for analyzing Electric Vehicle (EV) charging behavior. By integrating machine learning with interactive visualizations and geospatial analysis, the system enables users to estimate energy consumption, evaluate charging efficiency, and identify usage patterns across different vehicle types, facilities, and regions. This unified approach supports informed decision-making for EV owners, infrastructure planners, researchers, and policymakers, facilitating the development of reliable and efficient charging networks.

There remains significant potential to enhance the platform. Incorporating real-time data from connected chargers would improve prediction timeliness and responsiveness. Integrating user feedback could enable personalized recommendations, while expanding to global datasets and adding multilingual support would broaden accessibility. Advanced modeling techniques could refine accuracy and reveal deeper insights, and additional modules focusing on environmental impact, carbon savings, and grid effects would strengthen its role in sustainable mobility planning.

Together, these improvements position Charge Wise as a dynamic, adaptive tool capable of evolving alongside the rapidly growing EV ecosystem, supporting both operational efficiency and strategic infrastructure development.

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