EV Charging Station Optimization Using AI and ML

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Team Guide
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Introduction

- Electric Vehicles (EVs) are key to sustainable transportation.
- Challenges: Station availability, long wait times, inefficient routing.
- This project uses AI and ML to optimize EV charging in urban areas like Chennai.
- Integrates real-time data, predictive analytics, and user-friendly interface.

Objectives

- Recommend optimal charging stations based on availability, cost, and distance.
- Predict station demand using LightGBM for efficient planning.
- Provide traffic-aware route optimization via HERE Maps API.
- Offer personalized recommendations using Google Gemini LLM.
- Deliver an interactive web app using Streamlit and DuckDB for data management.

Literature Survey

- Sharma et al. (2022): Hybrid model for station recommendations using clustering and gradient boosting.
- Liu et al. (2023): Multi-criteria optimization with real-time traffic and pricing data.
- Kaur and Singh (2021): Streamlit for smart city dashboards, validating UI choice.
- Zhang et al. (2020): Spatio-temporal forecasting using LSTM, inspiring geohash use.
- Behrens and Freitag (2021): DuckDB for efficient in-process analytics.
- Owusu et al. (2023): LLMs for natural language interfaces in transport systems.

Existing System

- Basic functionalities: Station locators, availability, navigation.
- Technologies: Google Maps, static databases, basic analytics.
- Limitations:
  - Lack of real-time data integration.
  - No predictive demand modeling.
  - Limited geospatial analysis or personalization.
  - Complex server-based databases.

Proposed System

- Comprehensive AI-driven platform for EV charging optimization.
- Key features:
  - Real-time station filtering (availability, cost).
  - Demand prediction using LightGBM.
  - Traffic-aware routing via HERE Maps API.
  - Conversational insights via Google Gemini LLM.
- Deployed on Streamlit Community Cloud for accessibility.

System Architecture

- **Inputs**: User location, station data, traffic, weather.
- **Preprocessing**: Label encoding, feature engineering (geohash, time-based).
- **Modules**:
  - Data simulation and API integration (HERE Maps).
  - ML model (LightGBM) for demand prediction.
  - Geospatial analysis (Voronoi, heatmaps).
  - Streamlit UI and Gemini LLM for user interaction.
- **Outputs**: Station recommendations, routes, demand forecasts.

Model Selection

- **Demand Prediction**: LightGBM Regressor
  - Mean Absolute Error (MAE): 3.21
  - Root Mean Squared Error (RMSE): 4.58
  - R^2 Score: 0.87
- Chosen for high accuracy and efficiency in handling large datasets.

Implementation

- **Environment**: Python, Streamlit, DuckDB, LightGBM, HERE Maps API.
- **Data**: Simulated dataset for Chennai, real-time API data.
- **Preprocessing**: Label encoding, normalization, geohash encoding.
- **UI**: Multi-page Streamlit app with interactive dashboards.
- **Integration**: Weather, traffic, and LLM via APIs.

Deployment

- Hosted on Streamlit Community Cloud.
- Linked to GitHub for automatic updates.
- Accessible on mobile, tablet, and desktop.
- No local installation required.
- URL:
  `https://ai-ev-charging-station-recommender.streamlit.app/`

Results and Evaluation

- **LightGBM Performance**:
  - MAE: 3.21
  - RMSE: 4.58
  - R^2: 0.87
- **DuckDB Query Performance**:
  - Station filtering: 45 ms
  - Voronoi analysis: 120 ms
  - Recommendation query: 70 ms
- **Real-World Test Case**: Recommended optimal station in Chennai with low wait time and cost.

Streamlit Web App Outputs

- Interactive dashboard showing nearby stations and LLM suggestions.
- Demand predictions with natural language explanations.
- Traffic heatmaps and Voronoi diagrams for station coverage.
- Optimized routes with estimated travel time.

Advantages

- High-accuracy demand prediction ($R^2 = 0.87$).
- Real-time traffic and weather integration.
- Lightweight DuckDB for serverless data management.
- User-friendly Streamlit interface with LLM insights.
- Scalable for multi-city expansion.

Limitations

- Relies on simulated data for initial testing.
- Limited by HERE Maps API data availability.
- No current support for EV-specific battery range or connector matching.
- LLM responses depend on prompt quality and API latency.

Conclusion

- Developed an AI-powered EV charging optimization platform.
- Integrates LightGBM, HERE Maps, DuckDB, and Google Gemini LLM.
- Provides accurate recommendations, demand forecasts, and routes.
- User-friendly and scalable for urban EV infrastructure.

Future Enhancements

- User feedback loop for continuous improvement.
- Multi-city expansion with real-world data.
- Battery range estimation and connector compatibility.
- LLM fine-tuning for better responses.
- Mobile app conversion and smart grid integration.

Our Web App Link

`https://ai-ev-charging-station-recommender.st`

Thank You!

Questions?