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AI-BASED BATTERY OPTIMIZATION AND PERFORMANCE MANAGEMENT IN ELECTRIC VEHICLES

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ABSTRACT:

Electric vehicles (EVs) are widely recognized as an effective solution for reducing environmental pollution and promoting sustainable transportation. However, the performance and reliability of EVs strongly depend on efficient battery management. Conventional Battery Management Systems (BMS) mainly monitor parameters such as voltage, current, temperature, and State of Charge (SoC), but they provide limited capabilities for predictive analysis and optimization.

This paper introduces an AI-powered battery optimization and performance management system for electric vehicles. In our implementation, we observed that machine learning models can effectively analyse battery usage patterns and estimate the State of Health (SoH) with consistent reliability. By analysing how the battery is used and how the car responds, the platform spots early signs of battery degradation and helps steer better maintenance choices.

What we found during development is that combining monitoring, prediction, and charging recommendations within a single platform makes the system more practical for real-world usage. It relies on explainable AI so users can actually understand the model’s predictions, seeing what factors really impact battery performance. With these insights, the system offers practical actions to improve battery operation and prevent unnecessary damage.

In short, this system highlights how artificial intelligence can transform EV battery management. Early feedback and intelligent advice help batteries last longer, boost performance, and make electric vehicles more reliable.

Keywords- Artificial Intelligence, Machine Learning, Electric Vehicles, Battery Management System, State of Health, Predictive Maintenance, Charging Optimization.

1. INTRODUCTION

In general, electric vehicles represent an environmentally sustainable alternative to traditional transportation systems. Due to the increasing worries about climate change and the over-exploitation of fossil fuels, there is a trend of adoption of EVs by different countries around the globe. Still, along with other apparent benefits, the key issue with electric cars is battery performance. The condition of batteries determines the operation efficiency of any vehicle. Hence, the need to monitor their condition.

One of the factors influencing battery performance negatively is degradation, poor management strategies, and lack of adequate battery monitoring capabilities. As mentioned above, the awareness of EV owners in regard to the condition of the battery installed in a car and optimal ways of managing it is rather low. Traditional BMS only gathers information related to such parameters as voltage, currents, temperature, and SoC, which is rather insufficient as the process of predictive analysis is still far from being implemented.

From our perspective, one major limitation of existing systems is not the lack of data, but the lack of meaningful interpretation of that data.

During initial analysis, we noticed that users often struggle to convert raw battery metrics into actionable decisions.

In recent years, the usage of AI and machine learning in the management of batteries became more popular. By analyzing large datasets, machine learning algorithms can identify hidden patterns in battery operational data. This means that with the help of predictive models, it is possible to identify future battery failures and evaluate battery health (SoH).

The global shift to sustainable transportation systems has seen electric vehicles emerge as an alternative to traditional transportation systems. However, there have been issues like battery degradation, low energy efficiency, and charging problems, all of which have affected the optimal performance of electric vehicles, thus emphasizing the importance of intelligent battery optimization techniques.[1] Recent developments in Artificial Intelligence (AI) and Machine Learning (ML) have significantly improved the capabilities of a Battery Management System (BMS). To be specific, AI and ML allow for an accurate prediction of state of health (SoH), fault detection, and predictive maintenance. Such "intelligent" systems optimize charging and usage efficiency, increasing the reliability and lifespan of batteries [2], [7].

2. LITERATURE SURVEY

Several research studies have explored the use of Artificial Intelligence (AI) and Machine Learning (ML) to improve battery management and optimization in electric vehicles. These studies highlight the importance of intelligent systems in predicting battery health, optimizing charging cycles, and improving overall performance.

Muhammed Cavus et al. [1] propose a comprehensive review of AI-driven predictive maintenance for EV batteries, showing that LSTM and GRU networks are more effective than traditional methods, and CNNs for State of Health (SoH) and Remaining Useful Life (RUL) estimation. Their analysis on voltage- current-temperature time series reveals that these recurrent models are better at capturing long-term degradation patterns, achieving lower RMSE values that validate their suitability for continuous battery health monitoring in real-world applications.

Kushal Lodha et al. [2] proposed a systematic evaluation of machine learning algorithms to predict SoH across multiple different operating conditions and situations, their focus mainly lands on straightforward performance evaluated through consistency. Among tested approaches, the Random Forest and Gradient Boosted Trees stands out due to their stable results exceeding 95% correctness when processing structured battery data. These ensemble methods prove suitable for building health assessment tools capable of combining various aging signals without losing clarity. Deployment readiness follows naturally from robustness observed during testing across scenarios.

G. Divya et al. [3] propose an explainable AI framework for battery diagnostics that reveals thermal stress impacts through transparent model outputs using SHAP analysis integrated with natural language explanations. By prioritizing user comprehension over raw predictions, their approach demonstrates how interpretable analytics builds trust while transforming complex degradation patterns into guidance that drivers can immediately apply.

Md. Tanjil Sarker et al. [4] proposed a mix of reinforcement learning and linear programming guides electric vehicle charging in homes using solar panels and battery storage. 31.5% less peak demand appears through tests on eight hundred units, along with steadier voltage levels. This method centers on power network needs. Our work focuses instead on drivers - predicting their habits, offering tailored feedback. Still, both approaches rely on machine learning to manage energy tasks in actual settings. One begins at the grid and another ends with user behavior.

Azadeh Kermansaravi et al. [5] proposed a full analysis covering artificial intelligence methods - deep learning, reinforcement approaches, neural structures, fuzzy reasoning, transfer techniques - applied to electric vehicle energy systems, grouping them by usage in consumption control, charge planning, battery oversight. Trends emerge through structured examination of published work, alongside hurdles such as processing demands and clarity gaps, countered with combined frameworks and explainable AI tools, placing weight on instant response ability when improving storage lifespan, energy flow, network coordination. That classification, along with findings about broadened AI application, shapes the foundation of our system's varied model setup, shifting their energy management emphasis toward personalized guidance for battery condition and efficiency.

K.G. Nagaraja et al. [6] proposed a working battery management system that was built around an Arduino Uno, integrating sensors for voltage, current, and heat, alongside MATLAB simulations for enabling dynamic cell balancing and overheating safeguards. While functional for fundamental safety checks and real-time charge alignment across cells, the method shows limitations in forecasting faults or adapting to large-scale deployments. Our solution improves upon this by incorporating machine learning techniques that anticipate degradation patterns, paired with a modular backend design allowing seamless expansion. Where earlier designs stop, new capabilities emerge - not through replacement, but evolution of structure and intelligence.

Md. Khaja Farman et al. [7] proposed deep learning solutions that combines LSTM and CNN architectures to detect thermal irregularities and prevent overheating in batteries. Their multi-model strategy shows the importance of thermal awareness for decision-making that supports both health monitoring and charging optimization by identifying critical temperature thresholds early in the degradation process.

From the literature review, it is clear that AI-based battery management systems offer significant advantages over traditional methods by enabling predictive maintenance, intelligent optimization, and improved performance. However, challenges such as data accuracy, model reliability, and system integration still need to be addressed. These studies provide a strong foundation for developing an AI-Based Battery Optimization and Performance Management System for electric vehicles.

3. METHODOLOGY

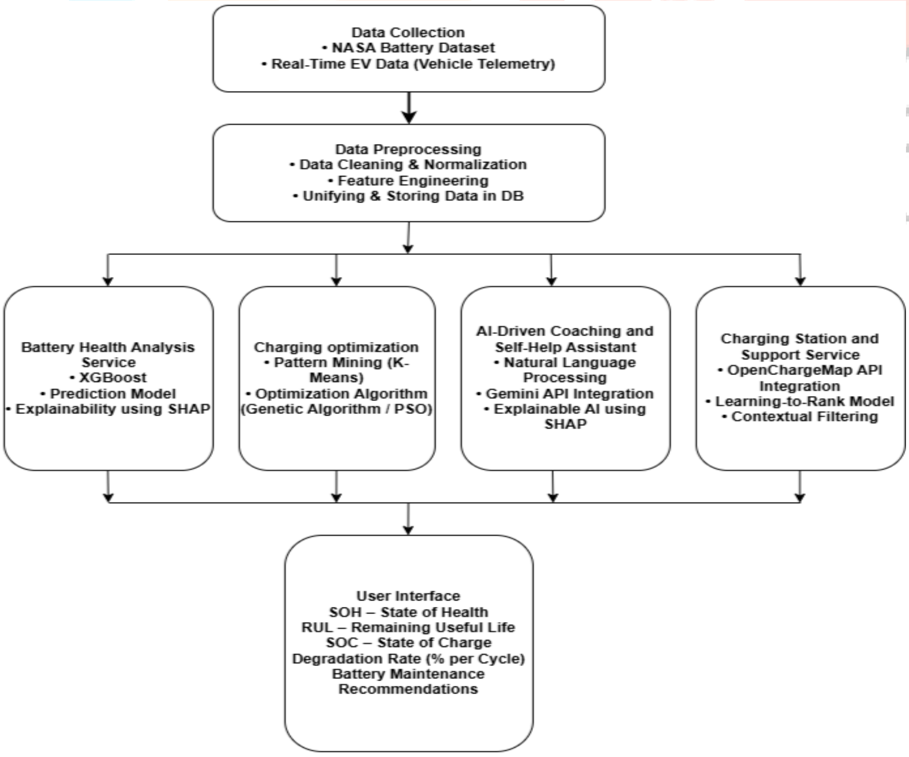


Fig. 3.1 System Architecture

An EV Battery Optimization Platform operates using artificial intelligence within a web-based structure. Built with Java Spring Boot for backend services, its interface runs on React.js while data storage relies on MySQL. Instead of simple reporting, it interprets live battery telemetry via machine learning models. Insights emerge continuously, supporting immediate assessment of battery condition. Predictions appear alongside clear reasoning, making outcomes transparent. Coaching suggestions originate from pattern recognition in usage behavior. Unusual activity triggers alerts based on learned norms over time. Recommendations for charging locations form dynamically according to multiple influencing factors. All capabilities integrate within a single cohesive environment. Functionality unfolds without reliance on external interpretation layers.

Data Layer Architecture:

Despite manual inputs, the system accepts battery telemetry via various paths. Through CSV files or by extracting details from PDFs and Word documents with tools like Apache PDFBox and POI, information enters steadily. Every entry holds a time marker along with state of charge, heat levels, electrical pressure, flow intensity, and usage cycles, each checked thoroughly. From external weather services, surrounding temperature conditions arrive continuously. Real-time insights into charging locations emerge from OpenChargeMap, delivering specifics on plug formats, energy output capacity, access status, and cost structure.

Structured data resides within MySQL, where thoughtfully indexed tables hold user credentials through JWT and OAuth2 systems. Vehicle details - such as battery size, chemical composition, and charge traits - are recorded systematically. Telemetry enters both unaltered and refined forms, forming part of broader time-based aggregations. Predictions related to system wellness appear alongside interpretative outputs using SHAP methodology. Notifications about irregular behavior are preserved with instructional interaction logs. Charging events complete the set, each entry arranged under a normalized design meant to support speed.

AI Layer Implementation:

Starting with feature inputs like cycle count and thermal extremes, a forest-style regressor estimates health status through ensemble averaging. Following temporal trends over one-month windows, memory-equipped neural nets project lifespan metrics forward in time units. Detection of irregular behavior emerges when deviations appear in heat profiles or energy flow sequences. Rather than relying on single indicators, outlier identification operates across multiple system signals simultaneously. Instead of fixed thresholds, adaptive boundaries respond to shifts in usage history. Forecast precision improves when past degradation paths inform future projections. Unusual charging rhythms trigger scrutiny only after consistent pattern baselines form.

From a different starting point, SHAP delivers clarity in artificial intelligence by measuring how much every variable shifts outcomes. Instead of grouping them, cycle frequency pulls down results at minus 0.025 per instance. Temperature plays contrasting roles - above twenty-five degrees Celsius, it reduces forecasts by zero point three per degree; below that mark, warmth adds zero point one each time. Fast charging behaves differently again, lowering scores steadily with each percentage rise. Voltage inconsistency matters too - a tenth of a volt off balance subtracts zero point two points overall. Depth beyond seventy percent discharge brings an additional penalty of zero point fifteen per unit increase. Each element appears structured not as raw numbers but shaped into labeled categories showing both size and influence direction. The outcome reads clearly because labels carry meaning along with signs indicating effect flow.

AI Coaching and User Assistance:

From user inquiries, purpose detection begins - separating standard battery concerns, explanations needing SHAP reasoning, or requests tied to geographic charging points. Vehicle details emerge gradually: condition rating, state of health, remaining lifespan, rapid charge usage, how often it occurs, how deeply batteries discharge, alongside behavioral patterns forming a complete profile.

When health drops below 60, the system flags a Critical issue. Severity between 60 and 75 triggers a Warning classification. Over half of charging cycles being fast marks Excessive Fast Charging. If habit scores fall under 60, it indicates Poor Habits. Each label allows focused follow-up actions.

Beginning with tailored guidance, the system forms replies through a triple-tier backup approach. When needed, it shifts to Gemini 1.5-flash as an alternate path. Built on vehicle details and SHAP elements, the primary layer uses Gemini 2.5-flash API. Friendly openings appear at start, followed by insights tied directly to user inputs. Three clear next steps show up each time, shaped by live information patterns. Encouragement closes every message, not as filler but as consistent structure.

Charging Optimization Service:

Last half-century of charging episodes gets examined. Through this review, speed-based recharge ratio emerges. Charge intensity on average appears next. How often each week stands revealed afterward. One figure follows another without addition signs. Frequency details come through clear measurement. Depth perception shifts toward practical insight. Patterns form around recurring values. Session count remains fixed at fifty entries. Results display without extra commentary.

The system calculates a behavior rating using three factors: half weight goes to rapid recharging speed, less emphasis on how deeply batteries drain, minor importance given to how often charging happens. When battery condition falls below eighty percent, maximum charge gets set lower; otherwise it allows more storage overnight. If quick top-ups exceed thirty percent of total sessions, alerts appear recommending change. Charging events per week above seven prompt suggestions to combine some into fewer instances. Importance level increases sharply whenever device health drops under seventy-five or routine quality scores beneath seventy. Decisions adjust automatically based on these thresholds without user input required at each step.

Still present within the system, suggestions remain stored alongside projected durability gains. Lifespan forecasts accompany each entry passively. Exposure happens without active initiation, maintained for retrieval readiness

Charging Station Recommendation Service:

Real-time information arrives through OpenChargeMap API. From that point, station positions are measured using the Haversine method. After measurement comes a ranking process shaped by multiple factors. Distance holds greatest influence at 40%. Power contributes one-fifth of total weight. Reliability adds another fifth. Compatibility fills the remaining portion equally. Weighted scores determine final order.

Battery health below seventy percent reduces compatibility with chargers exceeding one hundred kilowatts by thirty percent. This adjustment favors slower methods when degradation is present. Charging speed scales inversely with battery wear under high-power conditions. Lower capacity retention leads to modified station suitability ratings. A threshold at seventy percent triggers revised energy transfer recommendations. Fast charging effectiveness diminishes alongside battery condition decline. System response adapts based on measured cell fatigue levels.

Aiding users, the AI coach suggests leading stations alongside individualized justifications. From one perspective, location proximity influences choices, while charge rate plays a role too. Reliability metrics appear alongside cost details for balance. Instead of generic advice, clear follow-up actions emerge. Estimated durations accompany each option presented. Compatibility markers guide suitability checks. Through layered inputs, outcomes adjust accordingly.

4. IMPLEMENTATION

Dataset:

The battery health prediction model was trained using an experimental dataset packed with operational measurements from battery charging and discharging cycles. There are about 29,000 records, and each one reflects different battery usage conditions as time passes.

The dataset includes several parameters describing battery operating conditions, including voltage, current, temperature, State of Charge (SoC), State of Health (SoH), cycle count, and battery identification information. Together, these details basically describe how the battery performs both electrically and thermally during normal use.

From our analysis, voltage and current features turned out to be the most influential, as they provide a clearer picture of how energy flows and fluctuates during different operating conditions. Temperature gives you hints about any thermal stress that could affect performance. Cycle count and identification info help track the battery’s history, making it easier to spot patterns of wear and degradation.

This dataset is used to train machine learning models to recognize patterns related to battery degradation. By analyzing past battery behavior, the system can estimate battery health and deliver predictive analysis for the future.

Results:

The optimization process for the EV battery was done using various system module performances. Such systems are composed of battery condition prediction, optimization of the charging process, charging station suggestions, and AI coaching assistant.

This suggests that the model is not only accurate but also stable across different battery conditions, which is important for real-world deployment where data variability is high.

Battery Health Prediction module:

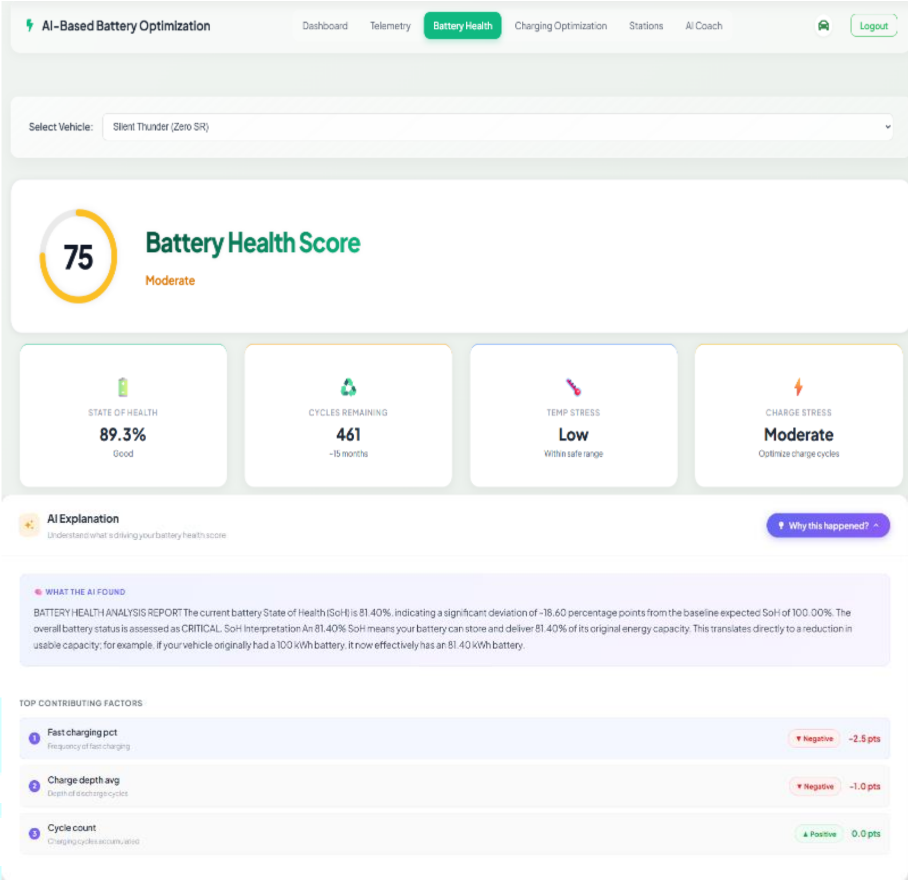


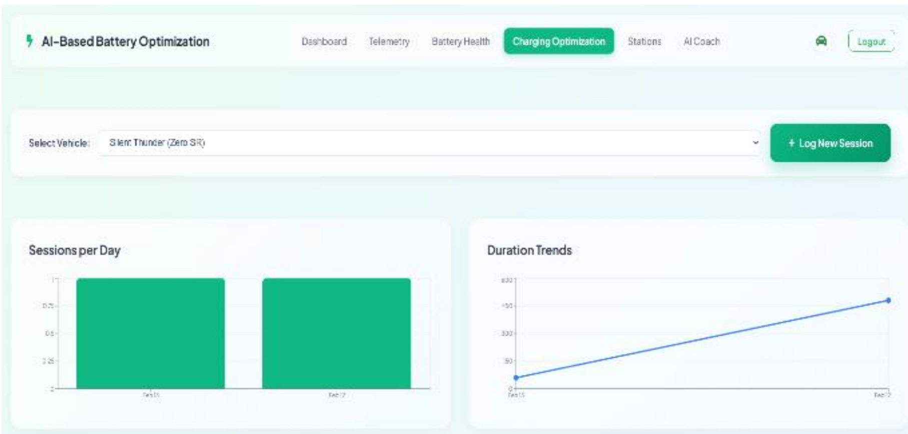
Fig. 4.1 Battery Health Prediction

The battery health prediction module relies on an XGBoost regression model to estimate the State of Health (SoH). The model processes multiple battery parameters including voltage, current, temperature, State of Charge (SoC), and cycle-related stress indicators.

Tests show the model's predictions stay solid across different battery conditions. Accuracy usually lands between 85% and 92%, depending on how much degradation the dataset has. Evaluation metrics reveal the mean absolute error sits somewhere between 2.6 and 3.4, and the root mean squared error falls between 3.3 and 4.5.

To make things more transparent, the system uses explainable AI techniques by integrating SHAP analysis. This makes it easier to see which input factors matter most for predicting battery health. That way, both technical and general users get a clearer picture of how the model comes up with its results.

Charging Optimization module:



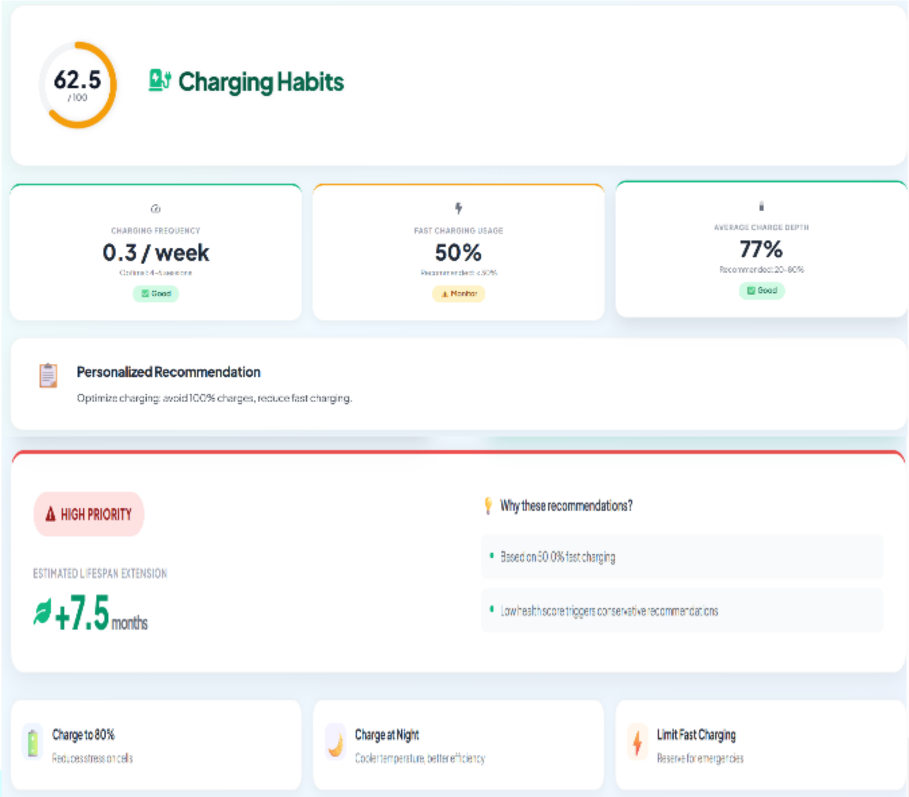


Fig. 4.2 Charging Optimization

In practice, the Charging Optimization module uses these predictions to design an adaptive charging strategy that reduces unnecessary battery stress, which can minimize avoidable stress while optimizing the efficiency of the utilization process. In the process of integration testing, the module has been seen to prefer battery-preserving options, which discourage avoidable high-stress charging patterns in favour of more stable operating periods under moderate stress conditions. While the results of short-horizon system tests do not directly indicate the extent of lifetime extension, the derived indirect indicators from simulated patterns of utilization cycles, along with the results of comparative schedules, do suggest the benefits of an adaptive optimization layer in the charging process, which can minimize degradation pressure when the suggested patterns are followed, particularly in the case of users whose charging patterns are irregular or those whose operating conditions are thermally challenging. In practical scenarios, this becomes particularly important when battery usage is inconsistent.

AI-Driven Coaching and Self-Help Assistant:

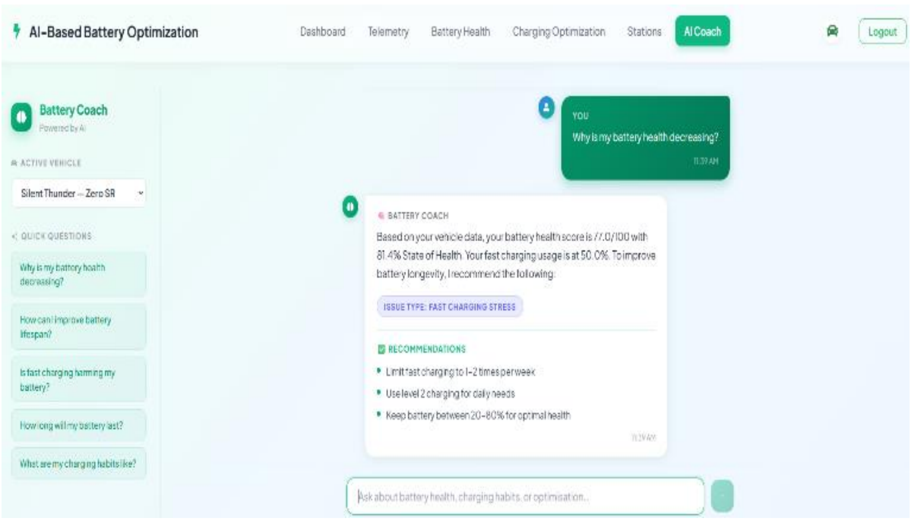


Fig. 4.3 AI-Driven Coaching

The AI-Driven Coaching and Self-Help Assistant provided users with personalized, conversational support, drawing on the battery's condition and the user's actions. Unlike traditional systems that simply provide fixed advice, this component will deliver adaptable, context-aware suggestions, tackling both everyday usage and problem-solving needs. The assistant frequently cautioned against frequent overcharging, suggested maintaining the battery within optimal temperature limits, and presented State of Charge (SoC) operating ranges designed to minimize the buildup of electrochemical stress.

The assistant also offered users explanatory guidance that associated observed symptoms with possible technical causes and recommended preventative measures, thus improving interpretability at the human decision layer. The assistant's NLG capabilities, along with contextual reasoning, were enabled through integration with the Gemini API, allowing users to generate model results, explanatory artifacts, and interaction history into coherent maintenance-oriented interactions. The usability and effectiveness of this interaction design, as determined through empirical testing, showed that users, especially non-experts, could benefit from this design, allowing gradual behavioral adaptations towards preventative battery care.

Charging Station and Support Service Recommendation module:

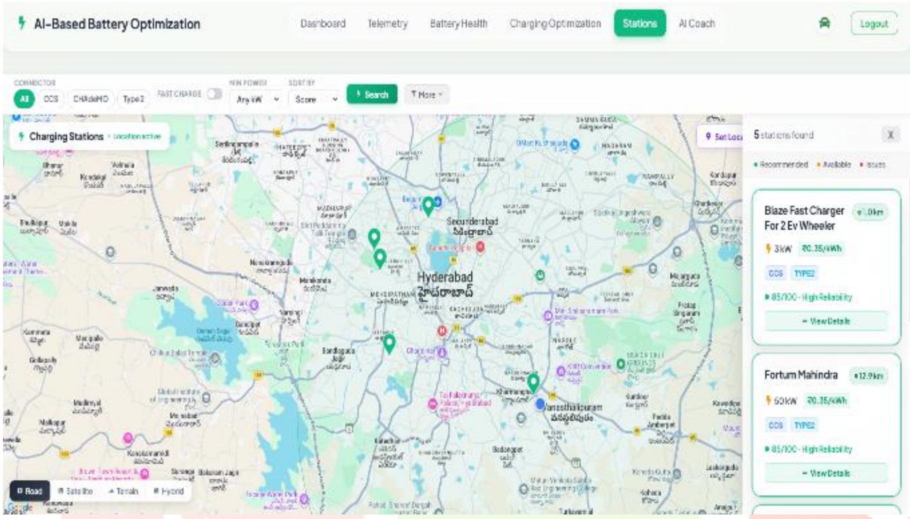


Fig. 4.4 Charging Station Recommendation

The charging station recommendation module helps users find the best charging stations based on where they are and how much battery they've got left. It pulls charging station data from the Open Charge Map, which keeps track of available charging infrastructure.

The system ranks nearby stations by looking at things like distance, charging power, reliability, and whether the station works with the user's vehicle. All these details help determine which station really fits the user's needs.

If a user's battery is running low or isn't in great shape, the system tends to recommend moderate charging speeds instead of going straight for the fastest ones. This way, it's easier on the battery but still pretty convenient for the user.

In the end, bringing together machine learning predictions, explainable AI, smart charging strategies, and user-friendly advice really improves battery management systems for electric vehicles.

5. CONCLUSION

In this work, we explored how artificial intelligence can be applied to improve battery management in electric vehicles beyond traditional monitoring systems. From our observations, integrating prediction with practical recommendations makes the system significantly more useful for everyday users. The system aims to boost battery efficiency by bringing prediction, monitoring, and user guidance together on one platform. Instead of just tracking battery data, it puts available information to better use and helps users make smarter decisions.

It relies on machine learning to estimate battery health and spot signs of possible degradation. By looking at things like temperature, charging habits, and how the battery gets used, the system offers insights that support battery maintenance. Explainable AI is also built in, which means the predictions actually make sense to both technical folks and people without a tech background.

Another key feature is the way the system guides users with practical advice. It gives tips on charging, how to use the battery, and which stations to pick, all aimed at taking unnecessary stress off the battery. Over time, this can boost battery performance and increase how long it lasts. One key takeaway from our implementation is that users benefit more from understandable insights than from raw data alone.

The results show that mixing predictions with real-life recommendations leads to better battery management. Still, how well the system works depends a lot on how good the input data is and how many different factors it covers. Out in the real world, batteries behave differently—things like the weather, how someone drives, and what type of battery it is all play a role.

Looking ahead, future work might include using real-time data from IoT-based battery systems and trying out more advanced deep learning models for better accuracy. Making the platform handle more varied operating conditions would also make it even more useful.

Overall, our findings indicate that combining machine learning with explainable and user-focused design can make battery management systems more effective in real-world scenarios.

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