REAL-TIME MACHINE LEARNING FRAMEWORK FOR BATTERY HEALTH ESTIMATION IN EV BATTERY SWAPPING

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ABSTRACT
The use of electric vehicles (EVs) is growing quickly, which calls for dependable and effective battery management systems, particularly in battery swapping infrastructures. In order to improve the effectiveness of EV battery swapping systems, this project offers a machine learning-driven web service for real-time battery health estimation. The system forecasts two crucial aspects of battery condition: State of Health (SoH) and remaining charge cycles. It was developed using Flask as the backend web framework and Python for data processing and machine learning. The application uses two potent ensemble learning algorithms, Random Forest Regression and XGBoost, which are trained on historical battery usage data, including charge/discharge current, voltage, temperature, and cycle counts, to produce accurate forecasts. The system allows for quick decision-making at battery changing stations by processing user input in real time and displaying the battery's health condition via an intuitive interface. By lowering the likelihood of premature battery disposal, this solution supports sustainable energy practices in addition to encouraging proactive maintenance and effective use of EV batteries. The application is scalable, effective, and appropriate for integration into actual EV infrastructure thanks to the combination of machine learning and a lightweight Flask-based deployment.
Keywords: XGBoost, Random Forest, Electric Vehicles, Battery Health Estimation, State of Health, Charge Cycles, Machine Learning, Decision Trees, Battery Swapping Stations.

1. INTRODUCTION

The need for creative and effective energy management systems is rising due to the quick development of electric vehicle (EV) technology. EV battery swapping is one such new option that enables customers to swap out drained batteries for fully charged ones, providing a rapid and practical substitute for conventional EV charging. However, maintaining swappable batteries' functionality and health is a major difficulty. It is crucial to precisely monitor and assess battery health in real time because frequent cycles of charging and discharging might deteriorate battery performance.

Conventional battery monitoring systems frequently rely on manual inspection, rule-based techniques, or predefined thresholds, which are insufficient to manage the complexity of battery deterioration over time. Hidden patterns or nonlinear correlations between several operational parameters, such as current, voltage, temperature, and cycle count, are not captured by these approaches. Because of this, batteries may be overused or thrown away too soon, which could have an impact on battery switching stations' performance, safety, and operating expenses. This study suggests a machine learning-driven strategy that makes use of predictive analytics to assess battery health parameters in real time in order to overcome these constraints. Flask is used as the backend web framework to make the solution easily accessible and interactive, while Python is used for data management and machine learning. To forecast important metrics like the State of Health (SoH) and remaining charge/discharge cycles, it integrates trained models like Random Forest Regression and XGBoost. To identify trends in battery deterioration under different circumstances, these models are trained using historical battery information.

EV station operators and technicians can make well-informed decisions fast thanks to the integration of this ML-powered system into an intuitive web interface. The technology guarantees improved battery lifetime management, lowers downtime, improves safety, and supports the sustainability objectives of the EV industry by forecasting the health state of batteries before designating them for reuse. In addition to demonstrating the usefulness of machine learning in energy systems, this initiative advances the creation of intelligent infrastructure for smart transportation.

2. EXISTING SYSTEM

The Remaining Useful Life (RUL) of batteries is estimated using single machine learning methods like XGBoost or Random Forest in the current system for managing EV battery swapping stations. In order to forecast battery health in real time, these models examine battery data such as voltage, current, temperature, and usage cycles. Operators can plan maintenance and effectively manage battery inventories with the aid of this RUL calculation. In order to guarantee that consumers are fairly compensated for battery replacements, a pricing plan based on the anticipated battery health is also put into place.

2.1 Limitations Of Existing Systems

While these models are reasonably accurate and computationally efficient, they frequently struggle to generalize predictions across different battery types and usage patterns. Relying on a single technique might reduce robustness, particularly when dealing with noisy or insufficient data, which can result in sporadic errors in RUL estimate and less-than-ideal pricing choices. User discontent and operational inefficiencies at exchanging stations may arise from this. It has disadvantages like Limited Precision, Diminished Sturdiness, Basic Pricing Structures

3. RELATED WORK

A thorough analysis of machine learning methods for estimating the State of Health (SoH) and Remaining Useful Life (RUL) of lead-acid batteries is provided in A Mapping Study of Machine Learning Methods for Remaining Useful Life Estimation of Lead-Acid Batteries by S. F. Chevtchenko, E. da Silva Rocha, B. Cruz, E. C. de Andrade, and D. R. Barbosa de Araújo (2023). Regression models, decision trees, ensemble learning methods, and other predictive techniques utilised in battery health monitoring are among the machine learning algorithms that the authors methodically examine. The paper assesses different techniques according to inference delay, computing efficiency, and prediction accuracy. The researchers also look at several sensor configurations that are frequently used in automotive battery management systems and pinpoint important issues and unmet research needs for upcoming electric car applications. The results demonstrate the increasing significance of machine learning in battery prognostics and offer insightful information for creating trustworthy battery health estimate systems.

A machine learning-based framework for battery State of Health (SoH) estimation that takes into account real-world driving behaviour data is proposed in Driving Behaviour-Guided Battery Health Monitoring for Electric Vehicles Using Machine Learning by N. Jiang, J. Zhang, W. Jiang, Y. Ren, J. Lin, E. Khoo, and Z. Song (2023). The study looks into a number of health markers and assesses them according to how easy it is to quantify them and how they relate to battery deterioration. To increase the accuracy of battery health forecasts, the authors present a scenario-based feature fusion approach in conjunction with probabilistic feature utility analysis. The suggested method strikes a balance between estimating accuracy and the convenience of obtaining pertinent features in electric vehicle systems by taking realistic driving situations into account. The study shows that including driving behaviour data can greatly improve battery health monitoring and lead to more effective battery management strategies.

4. PROPOSED SYSTEM

The suggested system is a platform for real-time battery health evaluation created especially for situations involving the swapping of EV batteries. Python is used for backend processing and machine learning integration, while Flask serves as the web framework. Users can enter battery parameters like temperature, cycle count, voltage, and charging/discharging current in real time. In order to assess if a battery is suitable for continued use or requires replacement, the application uses this input to estimate two critical characteristics of battery health: State of Health (SoH) and the remaining number of cycles. Compared to conventional threshold-based systems, the method guarantees more accurate predictions by integrating machine learning models. The backend hosts the trained models, which provide instantaneous results via an intuitive user interface. This makes it possible for EV station technicians or operators to make fast, data-driven choices about battery maintenance and allocation. All things considered, the suggested approach improves battery swapping operations' efficiency, prolongs battery life, and advances sustainability objectives by cutting down on needless battery waste.

4.1 Advantages Of Proposed System

- Real-Time Prediction of Battery Health with the help of accurately predicted State of Health and Remaining Useful Life.
- Increased Precision Through ML Models especially XGBoost that has high performance on non-linear data, with complex relationships.
- It facilitates predictive maintenance for the battery swapping stations, promoting efficient battery charging to reduce customer dissatisfaction.
- Scalable and portable, and can be easily deployed on battery swapping stations with easy to use interface.

5. MODULES

1. Data Collection & Preprocessing Module:

The raw battery dataset needed to train the machine learning models is gathered and prepared by this module. It comprises a variety of crucial metrics, such as temperature, voltage, charging/discharging current, and cycle count. Preprocessing entails cleansing the dataset by addressing inconsistent data, outliers, and missing values. In order to standardise the data and guarantee interoperability with machine learning methods, this module also performs scaling or normalisation. In order to save only the most pertinent inputs for forecasting State of Health (SoH) and remaining cycles, feature selection is also carried out here.

2. Machine Learning Model Training Module:

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This module uses the pre-processed data to train machine learning algorithms. It entails dividing the dataset into subsets for testing and training, training models like Random Forest and XGBoost, and assessing them using performance measures like R2 score, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). To minimise overfitting and maximise model accuracy, hyperparameter adjustment is carried out. This module produces a verified and well-trained model that is prepared for use.

3. Model Serialization Module:
This module is in charge of employing serialisation techniques to save the machine learning model that performs the best once it has been trained. The model is transformed into a file format (such as.pkl) that may be loaded later in the prediction module using libraries like joblib or pickle. By preventing the model from having to be retrained each time the program is executed, serialisation enhances scalability and performance.

4. Web Application Interface Module (Flask):
This module uses the Flask web framework to create the application's user interface. It has frontend pages that allow users to enter battery parameters in real time, such as temperature, voltage, and current. Flask routes manage form submissions, communicate with the backend model, and provide the user with the predictions. For EV station operators or technical staff, the module guarantees that the application is user-friendly, interactive, and accessible.

5. Prediction Module:
The main engine that loads the serialised machine learning model and utilises it to generate predictions in real time depending on user input is called the prediction module. This module receives battery data via the Flask form, processes it, formats it correctly, and then sends it to the model. The output, which includes the estimated State of Health (SoH) and the number of cycles left, is subsequently received and returned to the interface for display.

6. Result Analysis & Interpretation Module:
This module transforms the prediction model's raw output into insightful knowledge for the battery swapping station operatives, who can decide based on the predicted SoH and RUL whether the battery condition is good, bad, or critical. This enables consumers to comprehend the outcomes without requiring technical expertise. In order to facilitate improved decision-making in battery swapping procedures, it can also offer suggestions regarding whether to reuse, recharge, or retire the battery.

6. TECHNIQUES USED IN THIS RESEARCH

6.1. EXISTING TECHNIQUE:

In order to increase operational efficiency and user happiness, the current approach for electric vehicle (EV) battery swapping stations focuses on evaluating the Remaining Useful Life (RUL) of batteries. For real-time RUL prediction using battery data like voltage, current, temperature, and usage patterns, it usually uses specific machine learning methods like XGBoost or Random Forest. These techniques offer insightful information about the health of batteries, allowing for improved maintenance and replacement decisions.

In order to maintain fairness, the pricing method in current systems is frequently based on the forecasted RUL, charging customers based on the condition and anticipated lifespan of the switched battery. This strategy preserves consumer confidence and system sustainability by preventing overcharging for batteries with lower capacities and undercharging for healthy ones.

Nevertheless, the prediction accuracy and resilience may be limited when dealing with different battery types, climatic circumstances, and operational pressures because these current methods mostly rely on a single machine learning model. Additionally, their reliability in real-world applications may be impacted by their inability to handle noisy or missing data.

Despite these difficulties, the current systems are reasonably accurate, with error rates on typical datasets ranging from 3.5 to 3.8. In order to satisfy the expectations of real-time applications in battery swapping stations, there is still opportunity for improvement in the balance between accuracy, speed, and memory use, even though computational efficiency is acceptable.

6.2. PROPOSED TECHNIQUE USED:

This project analyses and forecasts battery health metrics using two potent ensemble machine learning techniques: Random Forest Regression and XGBoost. A bagging method called Random Forest creates several decision trees and aggregates their results to generate a prediction that is more reliable and accurate. It is appropriate for complicated battery datasets with numerous parameters including current, voltage, temperature, and cycles since it is very good at handling noisy data and minimizing overfitting.

In contrast, the boosting technique known as XGBoost (Extreme Gradient Boosting) is renowned for its accuracy and speed. It improves performance at every stage by constructing trees in a sequential manner, with each new tree fixing the mistakes of the preceding ones. Additionally, XGBoost handles missing data effectively and allows regularization, which improves the model's capacity for generalization. To ensure that both models were prepared for real-time deployment in the web application, they were evaluated using standard evaluation metrics and trained on historical battery performance data.

This research uses two machine learning approaches, Random Forest Regression and XGBoost, which are both renowned for their resilience and predictive power, to reliably evaluate battery health in real-time.

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These techniques are classified as ensemble learning, which combines several models to enhance overall performance. In order to handle nonlinear interactions and minimize overfitting in regression tasks like battery SoH prediction, Random Forest builds a large number of decision trees during training and outputs the average of their predictions.

6.2.1 SYSTEM ARCHITECTURE:

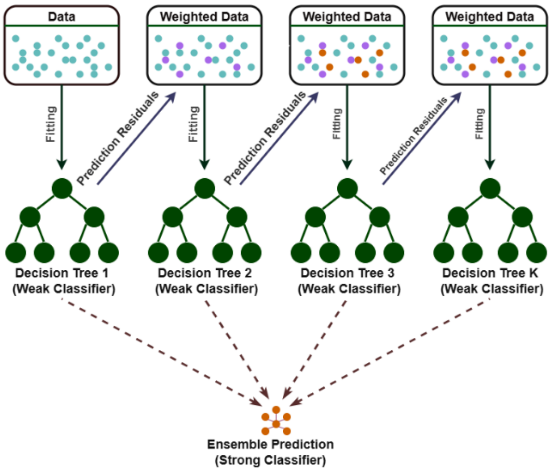

Fig 1: System Architecture

7. RESULTS

Fig 2: Models Performance Comparison

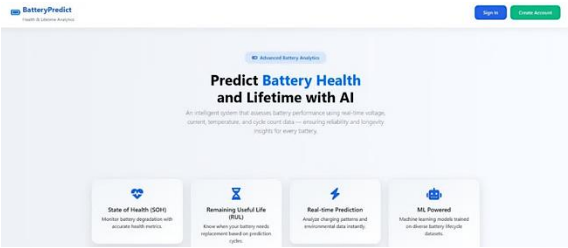

Fig 3: Main Website

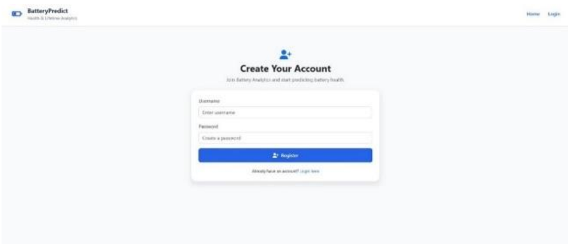

Fig 4: Account registration

Fig 5: Account Login

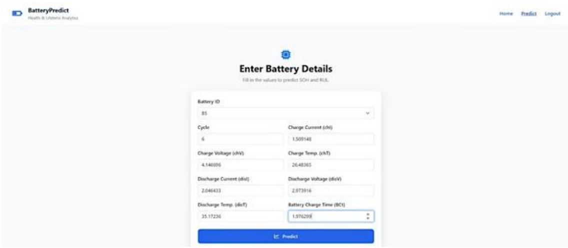

Fig 6: EV Health Predictions

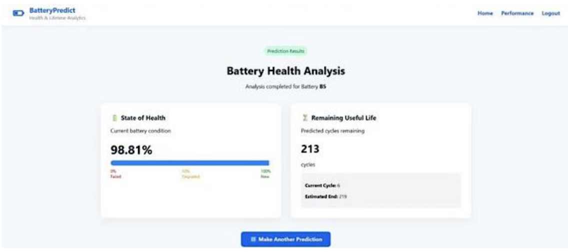

Fig 7: Prediction Results

8. DISCUSSION AND CONCLUSION

In summary, the suggested approach effectively illustrates how machine learning may be used to forecast the condition and remaining lifespan of electric vehicle (EV) batteries in real time. The system provides precise predictions of battery State of Health (SoH) and cycle life, which are essential for effective battery swapping operations, by utilizing models like Random Forest and XGBoost. By incorporating this model into a Flask-based web application, users can enter important battery characteristics and immediately obtain useful information, improving EV fleet management's dependability and simplicity. The project targets the increasing demand for intelligent energy systems in the e-mobility industry in addition to encouraging better use of EV batteries. The system is able to adjust to changing battery technologies and consumption patterns by retraining the model with updated datasets via an admin interface. By prolonging battery lifespan and encouraging smarter energy utilization, this clever, user-friendly technology has the potential to greatly decrease operational downtime, optimize battery usage, and support sustainability goals.

9. FUTURE ENHANCEMENT

By incorporating real-time sensor data collecting through IoT-enabled battery management systems, this system can be improved in the future. The application can obtain real-time voltage, current, and temperature information from EV batteries through cloud-connected devices, eliminating the need to manually enter battery parameters. This would remove human error and greatly increase accuracy. Furthermore, contextualizing battery health based on driving habits and ambient factors through the integration of GPS and usage data will enable more intelligent, flexible forecasts. Using deep learning models for time-series battery degradation prediction, such as LSTM or GRU networks, is another significant improvement. By learning temporal dependencies from usage data, these models can anticipate battery life cycles and health under various usage scenarios more accurately. Additionally, the platform might have battery recommendation engines that offer the best replacement or switch locations based on availability, present location, and SoH. For wider adoption, it might additionally include a mobile app version, a real-time alarm system for unusual degradation, and language support.

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