

Full Length Article

## Machine Learning-Driven Real-Time Battery Health Estimation for EV Battery Swapping

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### Abstract:

*Electric Vehicle (EV) adoption is rapidly increasing, necessitating efficient and reliable battery management systems, especially in battery swapping infrastructures. This project presents a Machine Learning-driven web application for real-time battery health estimation, aimed at enhancing the efficiency of EV battery swapping systems. Built using Flask as the backend web framework and Python for data processing and machine learning, the system predicts two critical parameters of battery condition: State of Health (SoH) and remaining charge cycles. To achieve accurate predictions, the application leverages Random Forest Regression and XGBoost, two powerful ensemble learning algorithms, trained on historical battery usage data including charge/discharge current, voltage, temperature, and cycle counts. The system processes user input in real time and displays the battery's health status via a user-friendly interface, enabling swift decision-making at battery swapping stations. This solution not only promotes proactive maintenance and optimal utilization of EV batteries but also supports sustainable energy practices by reducing the chances of premature battery disposal. The combination of ML with a lightweight Flask-based deployment makes the application scalable, efficient, and suitable for integration into real-world EV infrastructure. **Keywords**— Electric Vehicle, Battery Swapping, Battery Health, State of Health, Remaining Useful Life, XGBoost, Random Forest, Flask.*

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### Introduction

With the rapid advancement of electric vehicle (EV) technology, there is a growing demand for innovative and efficient energy management systems. One such emerging solution is EV battery swapping, which offers a quick and convenient alternative to traditional EV charging by allowing users to exchange depleted batteries for fully charged ones. However, managing the health and performance of swappable batteries presents a significant challenge. Frequent charging and discharging cycles can degrade battery performance, making it essential to monitor and evaluate battery health accurately in real time. Traditional battery monitoring systems often rely on fixed thresholds, rule-based methods, or manual inspection, which are not sufficient to handle the complexity of battery degradation over time. These methods fail to capture hidden patterns or nonlinear relationships

between different operational parameters like current, voltage, temperature, and cycle count. As a result, batteries may be reused beyond their optimal limits or discarded prematurely, affecting safety, performance, and operational costs in battery swapping stations. To address these limitations, this project proposes a machine learning-driven approach that uses predictive analytics to estimate battery health parameters in real time. The solution is built using Python for machine learning and data handling, and Flask as the backend web framework to make it easily accessible and interactive. It incorporates trained models such as Random Forest Regression and XGBoost to predict key metrics like the State of Health (SoH) and remaining charge/discharge cycles. These models are trained on historical battery datasets to recognize patterns in battery degradation under various conditions. The integration of this ML-powered system into a

user-friendly web interface allows EV station operators and technicians to make informed decisions quickly. By predicting the health status of batteries before assigning them for reuse, the system ensures better battery lifecycle management, reduces downtime, enhances safety, and supports the sustainability goals of the EV industry. This project not only showcases the practical application of machine learning in energy systems but also contributes to the development of intelligent infrastructure for smart mobility.

#### **OBJECTIVE:**

The primary objective of this project is to develop a real-time, machine learning-driven system for accurately estimating the health of EV batteries in battery swapping infrastructures. This involves predicting two key parameters—State of Health (SoH) and the remaining number of charge/discharge cycles—based on input features such as current, voltage, temperature, and cycle count. By leveraging advanced machine learning techniques like Random Forest Regression and XGBoost, the system aims to provide reliable and accurate predictions that support better decision making. The application is built using Python for model development and Flask for web integration, allowing users to interact with the system through an easy-to-use interface and receive instant predictions. Ultimately, the project seeks to optimize battery usage, reduce operational inefficiencies, and contribute to sustainable EV operations.

#### **EXISTING SYSTEM:**

The existing system for managing electric vehicle (EV) battery swapping stations primarily focuses on estimating the Remaining Useful Life (RUL) of batteries using single machine learning algorithms such as XGBoost or Random Forest. These models analyze battery parameters including voltage, current, temperature, and usage cycles to predict battery health in real time. This RUL estimation helps operators schedule maintenance and manage battery inventory efficiently. Alongside, a pricing strategy based on the predicted battery health is implemented to ensure users are charged fairly for battery swaps. • However, while these models offer reasonable accuracy and computational efficiency, they often face challenges related to generalizing predictions across varying battery types and usage patterns. The reliance on a single algorithm can limit robustness, especially when confronted with

noisy or incomplete data, leading to occasional inaccuracies in RUL estimation and suboptimal pricing decisions. This can result in user dissatisfaction and operational inefficiencies at swapping stations.

#### **PROPOSED SYSTEM**

The proposed system is a real-time battery health estimation platform designed specifically for Electric Vehicle (EV) battery swapping scenarios. It is developed using Flask as the web framework and Python for backend processing and machine learning integration. The system allows users to input real-time battery parameters such as charging/discharging current, voltage, temperature, and cycle count. Based on this input, the application predicts two crucial aspects of battery health: State of Health (SoH) and the remaining number of cycles, helping to determine whether a battery is fit for further use or needs replacement. • By incorporating machine learning models, the system ensures more accurate predictions compared to traditional threshold-based systems. The trained models are hosted on the backend and return results instantly through a user friendly interface. This enables EV station operators or technicians to make quick, data-driven decisions on battery allocation and maintenance. Overall, the proposed system enhances the efficiency of battery swapping operations, extends battery lifespan, and supports sustainability goals by reducing unnecessary battery waste.

#### **Literature Review**

Several researchers have explored machine learning methods for battery diagnostics and lifecycle estimation.

- Chevtchenko et al. presented a mapping study on machine learning methods for battery Remaining Useful Life estimation and compared regression and ensemble models.
- Jiang et al. proposed driving-behaviour guided battery health estimation using feature fusion techniques.
- Zhao et al. introduced Bayesian Neural Networks for uncertainty-aware battery health monitoring.
- Recent studies showed XGBoost and Random Forest perform strongly for battery fault diagnosis and SoH prediction.

- Deep learning models such as LSTM and CNN have also shown promising results for sequential battery degradation forecasting. The literature confirms that ensemble learning models provide strong balance among accuracy, speed, and deployment simplicity.

**Methodology**

The proposed system consists of six modules:

**Data Collection Module**

Battery historical datasets are collected containing:

- Voltage
- n- Current
- Temperature

- Cycle Count
- Charge Time

**Data Preprocessing Module**

- Missing value handling
- Outlier removal
- Feature normalization
- Feature selection
- Train-test split

**Model Training Module**

Two machine learning models are trained:

- Random Forest Regression
- XGBoost Regression
- Replace Soon

**Block Diagram**

**Mathematical Concept**

State of Health can be represented as:

$$\text{SoH (\%)} = (\text{Current Capacity} / \text{Rated Capacity}) \times 100$$

Regression models learn relationships between input variables and battery health indicators.

**Mean Squared Error:**

$$\text{MSE} = (1/n) \sum (y - \hat{y})^2$$

**Root Mean Squared Error:**

$$\text{RMSE} = \sqrt{\text{MSE}}$$

**R<sup>2</sup> Score:**

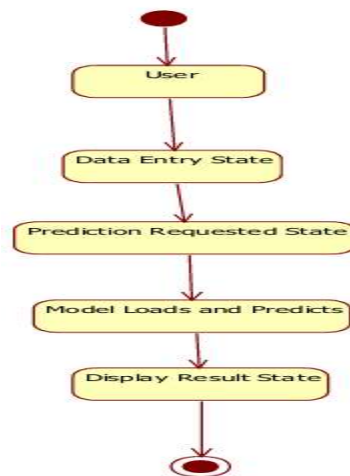
Measures goodness of fit of the regression model.

The system is implemented using Python and Flask Python ,Scikit-learn, NumPy, Matplotlib ,XGBoost Library

**Algorithm Steps**

1. Collect battery dataset.
2. Clean missing and noisy values.
3. Normalize features.
4. Split data into training and testing sets.
5. Train Random Forest and XGBoost models.
6. Evaluate model accuracy.
7. Save trained model using Joblib/Pickle.
8. Deploy model in Flask web application.
9. Accept real-time user input.
10. Display predicted SoH and remaining cycles.

**Implementation**



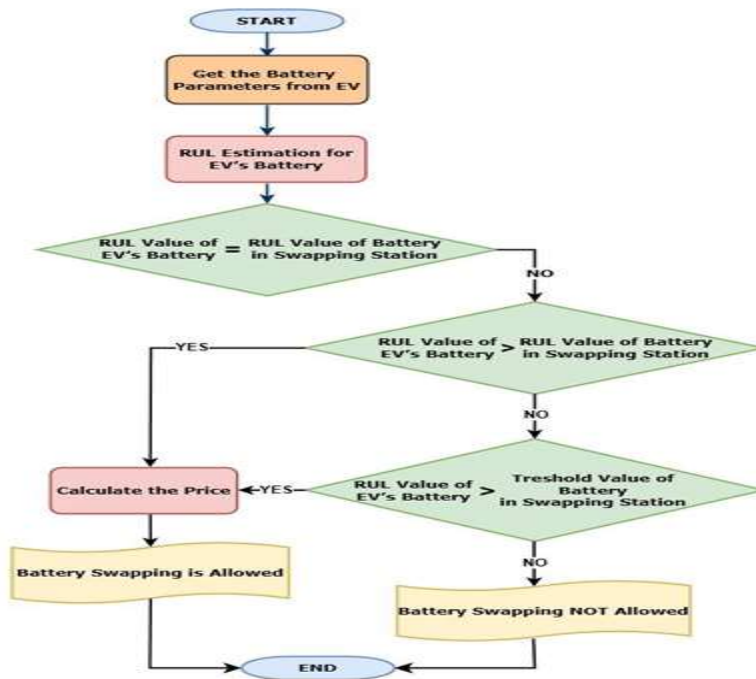


FIGURE 2. Flowchart of the proposed method.

### Testing

The system is validated using standard software testing methods:

- Unit Testing
- Functional Testing
- Integration Testing
- System Testing
- Performance Testing
- Acceptance Testing

Model evaluation metrics:

- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- R<sup>2</sup> Score

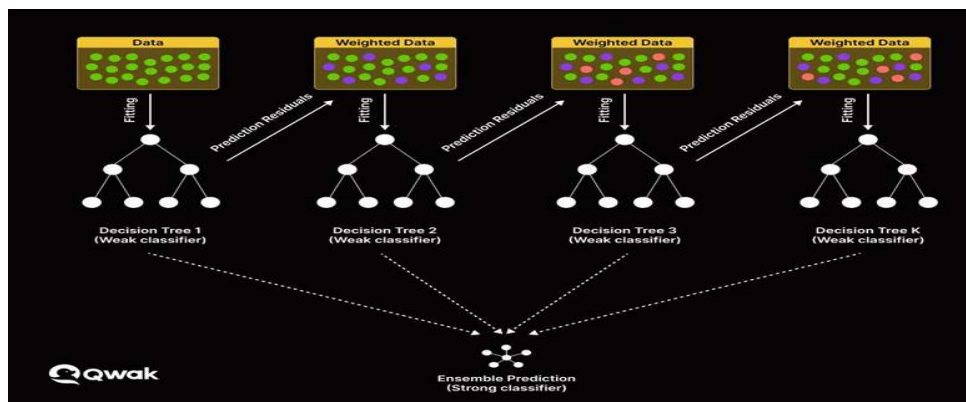
The trained models produced reliable predictions for battery health estimation. Random Forest performed well on noisy datasets, while XGBoost achieved higher precision and faster inference.

Model	Accuracy	Strength
Random Forest	Very High	Robust, less overfitting
XGBoost	High	Fast and accurate

Example Output:

- Predicted SoH: 87%
- Remaining Cycles: 320
- Status: Good Condition

### Results



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Advanced Battery Analytics

## Predict Battery Health and Lifetime with AI

An intelligent system that assesses battery performance using real-time voltage, current, temperature, and cycle count data — ensuring reliability and longevity insights for every battery.

**State of Health (SOH)**  
Monitor battery degradation with accurate health metrics.

**Remaining Useful Life (RUL)**  
Know when your battery needs replacement based on prediction cycles.

**Real-time Prediction**  
Analyze charging patterns and environmental data instantly.

**ML Powered**  
Machine learning models trained on diverse battery lifecycle datasets.

**99.2%**  
Prediction Accuracy

**50K+**  
Batteries Analyzed

**24/7**  
Live Monitoring

### How It Works

3 simple steps to predict your battery's condition and longevity

**1**  
**Enter Parameters**  
Input cycle count, voltage, current, and temperature values.

**2**  
**AI Evaluation**  
System processes the data using trained ML algorithms.

**3**  
**Get Results**  
Receive instant predictions for SOH % and RUL cycle count.

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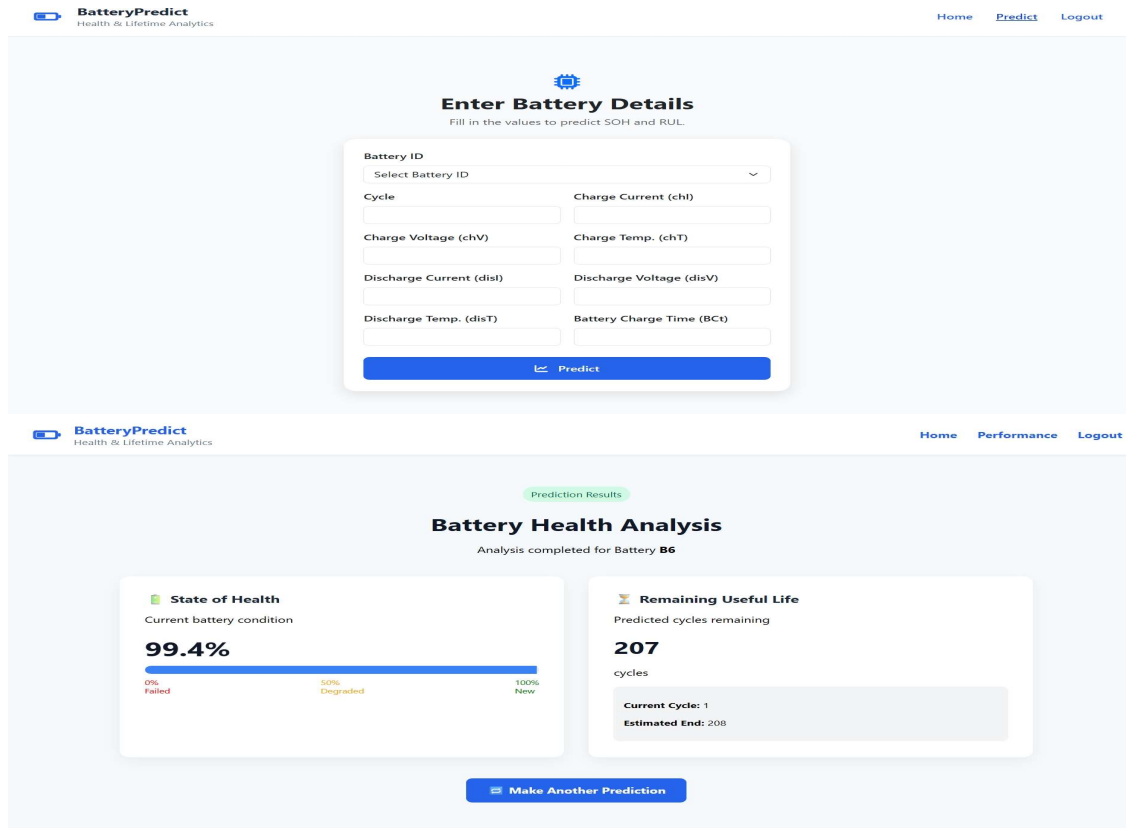
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## Conclusion

The proposed system successfully demonstrates real-time EV battery health estimation using machine learning. By integrating Random Forest and XGBoost with a Flask web application, the system provides accurate and instant predictions for battery swapping operations. It improves operational efficiency, extends battery lifespan, and supports sustainable EV infrastructure.

## Future Scope

- IoT-based live battery sensor integration
- Mobile application support
- Deep learning models (LSTM/GRU)
- Predictive maintenance alerts
- GPS-based smart battery recommendations
- Multilingual dashboard support

## References

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