REVA UNIVERSITY
Bengaluru, India

SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

A Project Report
On
AI-powered Intelligent Battery Management & Health Monitoring for EVs

Submitted in fulfillment of the requirements for the award of the Degree of

Bachelor of Technology

Submitted by

ALOK K M (R20EF007)
SHREYAS R (R21EF033)
ADITYA CHAURASIA (R21ER082)
SANGAMESHWAR HATTI (R21EF030)

Under the guidance of

Dr. GURURAJ MURTUGUDDE

2025

Rukmini Knowledge Park, Kattigenahalli, Yelahanka, Bengaluru-560064
www.reva.edu.in

DECLARATION

We, Mr. Aditya Chaurasia, Mr. Alok K M, Mr. Shreyas R, Mr. Sangameshwar Hatti students of Bachelor of Technology, belong in to School of Computer Science and Engineering, REVA University, declare that this Project Report / Dissertation entitled “AI powered Intelligent Battery Management and Health Monitoring for EVs ” is the result the of project / dissertation work done by us under the supervision of Dr. Gururaj Murtugudde, Professor at School of Computer Science and Engineering, REVA University.

We are submitting this Project Report / Dissertation in partial fulfillment of the requirements for the award of the degree of the Bachelor of Engineering in Computer Science and Engineering by the REVA University, Bangalore during the academic year 2025.

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Certified that this project work submitted by Aditya Chaurasia, Alok K M, Shreyas R, Sangameshwar Hatti has been carried out under my / our guidance and the declaration made by the candidates is true to the best of my knowledge.

Signature of Guide

Date: …………….

Signature of Director

Date: …………….

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Signature of HoD

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CERTIFICATE

Certified that the project work entitled **AI powered Intelligent Battery Management and Health Monitoring for EVs** carried out under my guidance by **Aditya Chaurasia (R21ER082), Alok K M (R20EF007), Shreyas R(R21EF033) , Sangameshwar Hatti (R21EF030),** are bonafide students at REVA University during the academic year 2025, are submitting the project report in partial fulfillment for the award of **Bachelor of Technology** in Computer Science and Engineering during the academic year 2025**.** The project report has been tested for plagiarism and passed the plagiarism test with a similarity score less than 20%. The project report has been approved as it satisfies the academic requirements in respect of Project work prescribed for the said Degree.

Signature with date

Dr. Gururaj Murtugudde
Guide

Signature with date	**Signature with date**
Dr. AshwinKumar U M	**Dr. AshwinKumar U M**
HoD	**Director**

External Examiners

	Name of the Examiner with affiliation	**Signature with Date**
1.		
2.		

ACKNOWLEDGEMENT

Any given task achieved is never the result of the efforts of a single individual. There are always a bunch of people who play an instrumental role leading a task to its completion. Our joy at having successfully finished our project work would be incomplete without thanking everyone who helped us out along the way. We would like to express our sense of gratitude to our REVA University for providing us the means of attaining our most cherished goal.

We would like to thank our Hon’ble Chancellor, Dr. P. Shyama Raju and Hon’ble Vice-Chancellor, Dr. Sanjay R. Chitnis for their immense support towards students to showcase innovative ideas.

We cannot express enough thanks to our respected Director, Dr. AshwinKumar U M, for providing us with a highly conducive environment and encouraging the growth and creativity of each and every student. We would also like to offer our sincere gratitude to our Project Coordinators for the numerous learning opportunities that have been provided.

We extend our heartfelt gratitude to our Head of the Department, Dr. AshwinKumar U M, for their unwavering support, encouragement, and vision that guided us throughout the course of our project. Their leadership has been an invaluable source of motivation for all of us, and we truly appreciate the knowledge and guidance they have provided.

We would like to take this opportunity to express our gratitude to our Project Guide, Dr. Gururaj Murtugudde, for continuously supporting and guiding us in our every endeavor as well as for taking a keen and active interest in the progress of every phase of our Project. Thank you for providing us with the necessary inputs and suggestions for advancing with our Project work. We deeply appreciate the wise guidance that sir has provided.

Finally, we would like to extend our sincere thanks to all the faculty members and staff from the School of Computer Science and Engineering.

1. ALOK K M (R20EF007)
2. SHREYAS R (R21EF033)
3. ADITYA CHAURASIA (R21ER082)
4. SANGAMESHWAR HATTI (R21EF030)

Contents

Abstract

Battery health prediction is one of the most important elements in enhancing the safety, reliability, and efficiency of energy storage systems in modern technologies. This study focuses on the Remaining Useful Life (RUL) prediction of 14 NMC-LCO 18650 batteries examined by the Hawaii Natural Energy Institute. The batteries, with a nominal capacity of 2.8 Ah, were cycled 1000 times under controlled conditions at 25°C, employing a CC-CV charge rate of C/2 and a discharge rate of 1.5C. From the dataset, we derived features that capture voltage and current behavior during each cycle, including discharge time, time at specific voltage thresholds, charging time, and voltage decrements. These features have been utilized in developing and testing the machine learning models to obtain accurate RUL.

We used the more advanced regression methods, like Extra Trees Regressor, Random Forest Regressor, and XGBoost, along with interpretable AI techniques, such as LIME, to allow for enhanced explanations of those predictions. The preprocessing of the dataset involved outlier removal using z-scores and feature selection based on correlation with RUL. Performance metrics, namely Mean Squared Error, Root Mean Squared Error and R^2 scores, measured the accuracy of the model. A benchmarking analysis using LazyRegressor highlighted a comparative performance of several regression algorithms.

Feature engineering, ensemble learning, and interpretable AI integration allows for a strong approach toward battery RUL prediction while providing actionable insights into degradation and lifecycle optimization. The insights gained can support the development of predictive maintenance strategies for energy storage systems that are environmentally sustainable and operationally efficient.

Keywords: Battery RUL prediction, NMC-LCO 18650 batteries, machine learning, ensemble learning, feature engineering, outlier detection, explainable AI, LIME, predictive maintenance, battery degradation, energy storage systems, LazyRegressor, sustainability.

CHAPTER 1

INTRODUCTION

Many of the things we use daily are now run by batteries. We need good batteries in our phones, cars and big power systems. But for how long will a battery charge before it dies? This is what RUL or Remaining Useful Life, tells us. If we know RUL, we can stay safer, and pay less for repair of things, and get more from any battery.

In today's increasingly digital world, many of the devices and systems we use—ranging from smartphones and laptops to electric vehicles (EVs) and large-scale energy storage grids—are powered by batteries. Batteries have become a cornerstone of modern infrastructure. However, they do not last forever and understanding how long a battery will continue to function before it degrades beyond usability is essential. This estimation is referred to as Remaining Useful Life (RUL). Knowing the RUL of a battery allows users and engineers to optimize performance, plan timely maintenance, minimize safety risks, and extend the overall operational lifespan of their battery-powered systems.

This piece of work provides you with a web utility for checking and conjecturing battery RUL. It provides machine learning, deep learning, elementary math verifications, charts and smart AI tips. We constructed this tool using Flask. You feed it actual battery data and it gives you the information you're after. RUL, facts, and plots. Anyone who poses deep questions as well as anyone who only desires answers can use it.

Key Parts of the System

1. RUL Guess with Deep Learning

A smart model (named rlu.h5) will tell you how long your battery will last. It looks at:

1. It takes how long to lose charge.
2. How quick the volts drop
3. The highest volt seen
4. Time at top volts
5. Time at steady power
6. How long it took to be charged

These, you key into a web form. The model is learned on the real data and is good in guessing RUL

2. AI Words and Tips – with Gemini

In order to help you understand what it all means we use AI (Gemini). It reads your inputs and the RUL guess, it writes a small text so you know what's happening. Like this, it is understandable not only for experts.

Gemini also help you to know which bike or car fits your battery with hints such as:

- Best model to buy
- How much it may cost
- The range of traveling on a charge.
- How big is the motor
- What tech is used
- Where it works best

3. Data Plots

You are also able to view your data in plain charts. You choose what type of chart you want.

- Bar chart
- Box chart
- Line curve
- Dot chart
- Hot spot chart
- Dot cloud chart
- Odd shape chart
- Q-Q chart

These graphs will demonstrate trends, odd points, links and much more for you.

4. Math Checks and Tests

Our tool can perform the math checks and big tests.

Simple facts: mean, middle, mode, distribution, far and near, high and low, skew, and curve sharpness

Tests: t-test, z-test, test for change by group, square test, test for two groups, test for more groups and check for link

Co variation of two things.

i. Simple line guess
ii. This allows to dive deep and see what the data is actually saying.

5. Cause and Key Facts with Optuna

It helps to understand why batteries of some last longer. Using Optuna, an instrument that searches for the best among a lot of ways of modeling, we find what changes RUL the most. We use the most linked facts in a forest model, show best facts and model to you. You also get to see how best to establish the tool.

This is how you learn what makes your battery last or die, and you can use it to forecast.

To address the growing need for intelligent battery management, this project presents an integrated web-based tool for battery RUL prediction and analysis. Built using the Flask framework, the system is designed for both technical users and general audiences, providing a comprehensive platform for RUL estimation, data visualization, statistical testing, and generative AI-based recommendations. Named BRIIS—Battery RUL Insight & Intelligence System—this tool leverages advanced machine learning, natural language processing (NLP), and statistical diagnostics to create an explainable and actionable battery health monitoring experience.

At the core of the platform is a deep learning model (named rlu.h5) trained on real-world battery datasets, particularly NMC-LCO 18650 lithium-ion cells that have undergone hundreds of charge-discharge cycles. The model utilizes a regression-based neural network architecture to process multivariate inputs and predict the number of cycles a battery has left before reaching its end-of-life threshold. The parameters accepted by the model include discharge duration, voltage drop rate, maximum observed voltage, time spent at peak voltage levels (e.g., 4.15V), time at constant current during charging, and total charging time. These features are key indicators of electrochemical aging and degradation, and they are input by users through a structured web form. The model, having been trained on hundreds of similar data cycles, generalizes these patterns and outputs an accurate RUL estimate.

However, rather than presenting raw numerical predictions alone, the system integrates a powerful layer of natural language interpretation through Google's Gemini API. Generative AI, powered by Gemini, reads the model's output and input parameters and generates user-friendly explanations. These explanations can describe why a battery is degrading, how recent charging behavior affects its health, and even offer product-specific recommendations. For instance, Gemini can provide tailored suggestions about which EV models are best suited to the battery profile entered by the user. It may list compatible electric bikes or cars, estimate operational ranges, compare battery technologies, and recommend optimal charging habits. This integration of AI allows the platform to be used not only by engineers and data scientists, but also by casual EV users, fleet managers, and battery technicians.

The tool also includes a robust data visualization suite, which offers a variety of plot types to represent battery data and RUL predictions graphically. These include bar charts, box plots, line graphs, scatter plots, Q-Q plots, hotspot charts, and even violin-box hybrid plots. Each of these visualizations is dynamically rendered using libraries like Plotly, Seaborn, and Matplotlib, providing both aesthetic appeal and technical insight. Users can explore data distributions, detect anomalies, identify correlations, and observe temporal degradation patterns. The visual layer serves as a critical bridge between raw analytics and human interpretation, making the system accessible and insightful even to non-specialists.

Another vital component of BRIIS is its suite of built-in statistical tools. Beyond prediction, the platform performs comprehensive statistical analysis on user-provided or internal battery datasets. Users can request simple descriptive statistics such as mean, median, mode, variance, skewness, and kurtosis. For hypothesis testing, the system offers t-tests, z-tests, ANOVA, chi-square tests, Mann-Whitney U tests, Kruskal-Wallis tests, Wilcoxon signed-rank tests, and Fisher's exact test. The system also supports correlation analysis (Pearson, Spearman) and linear or multiple regression modeling. These capabilities allow users to validate findings, confirm assumptions, and derive relationships between various battery parameters and degradation outcomes. Visualized alongside predictive results, these statistical analyses help form a more complete, data-driven understanding of battery health.

One of the system's more advanced features is its integration with Optuna, a hyperparameter optimization framework used to identify which battery features most influence RUL. This is achieved through an automated process of feature selection and model tuning using techniques such as Tree-structured Parzen Estimators (TPE). The system uses Optuna not only to fine-tune machine learning models like Random Forest or XGBoost but also to rank the importance of each input parameter. For instance, the system may reveal that discharge time and time at constant current have the strongest correlation with battery longevity. These findings are visualized through SHAP (SHapley Additive exPlanations) or permutation importance charts, giving users a clear picture of what matters most when predicting battery life.

All these modules—deep learning prediction, AI interpretation, statistical testing, visualization, and feature optimization—are tightly integrated into a web interface developed using Flask. The application routes are clearly organized and user-friendly. The homepage introduces the tool's capabilities and invites users to begin the RUL prediction process. An input form collects the relevant battery data. A results page displays predictions, Gemini-generated explanations, and suggested EV models. Another route provides access to the statistical dashboard, where users can run various tests on their datasets. Visualizations are handled through an interactive page, while model optimization and feature relevance analysis are accessible via /optuna and /c_analysis routes, respectively. The entire frontend is responsive, styled with Bootstrap and JavaScript, and communicates with the backend via AJAX for smooth, real-time updates.

On the backend, the tool incorporates robust data preprocessing capabilities. Outlier detection is handled using Z-score filtering, with optional extensions like IQR filtering or isolation forests for additional noise reduction. Categorical features with low cardinality are handled with encoding or discarded if deemed non-informative. Time-series smoothing, moving averages, and derived metrics such as dQ/dV are used to enhance input features for modeling. Model training and evaluation are conducted using Keras for deep learning and scikit-learn for ensemble methods. Model performance is evaluated with metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R^2, F1-score, accuracy, precision, recall, and Matthews Correlation Coefficient (MCC), ensuring both regression and classification diagnostics are covered.

The system architecture is modular and production-ready. Each module operates independently, making the system easy to maintain, upgrade, and scale. The application is containerized using Docker, with Flask and Gunicorn serving the web backend, and Nginx optionally used as a reverse proxy. Future deployments can scale with Kubernetes, and data versioning is handled using DVC. For model tracking and logging, tools like MLflow can be integrated. The codebase is managed with Git, and workflows can be automated using CI/CD pipelines in GitHub Actions or Jenkins.

Although the current implementation provides a powerful foundation, several enhancements are planned. These include adding dynamic input fields based on different battery types, expanding dataset support for various chemistries (e.g., LFP, solid-state), introducing real-time data integration from Battery Management Systems (BMS), and implementing retraining pipelines so the system can continuously learn from new data. Additionally, more advanced explainability methods like SHAP and counterfactuals may be incorporated alongside Gemini to further improve user trust and insight.

In conclusion, this battery RUL prediction system is a multifaceted tool that combines deep learning, statistical analytics, generative AI, and modern web technologies to provide a powerful yet user-friendly platform for battery health assessment. It is designed to assist a broad range of stakeholders—from researchers and engineers to consumers and fleet managers—in understanding and optimizing battery usage. Through the integration of interpretable machine learning models, dynamic visualizations, and AI-driven guidance, the system offers not just predictions, but actionable intelligence for the battery-powered future.

CHAPTER 2

LITERATURE SURVEY

Remaining Useful Life (RUL) prediction for batteries especially for lithium ion batteries has been an important field of research based on their broad applications in electric vehicles (EVs), mobile phones, and energy storage. Precise RUL forecasting is useful in such optimization of maintenance schedules, such avoidance of unexpected failures, such minimization of downtime, and such elongation of operational life of batteries. Large-scale performance data from batteries can now be mined from the wide-spreading of sensor technologies and IoT infrastructure to advance model accuracy. Many studies have applied ML and DL approaches to predict the RUL while exploiting voltage, current, temperature and charge/discharge cycles as features.

i. Machine Learning Methods Used for Prediction of RUL of a Battery

The last decade witnessed the appearance of ML methods as viable alternatives to classical empirical or physics-based modeling. Many regression and classification methods can detect complex nonlinear deterioration of battery performance.

In Zhang et al. (2017), the latter used Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) on battery life predicting features which were extracted from the historical operational data such as voltage, current, and internal resistance [1]. SVMs were robust in high-dimensional feature spaces, while ANNs were flexible at characterising nonlinear relationships.

Li et al. (2019) provided a Long Short-Term Memory (LSTM) network for battery life prediction, with an outstanding performance for learning the long-term dependencies in sequential charge-discharge information [2]. Model had lower RMSE of root mean square error and enhanced stability on the horizon of prediction as compared to traditional RNNs.

Recent developments can be observed in applying hybrid models which integrate methods of deep learning with uncertainty quantification (e.g., Bayesian LSTMs) and reinforcement learning as means of dynamical adaptation to variable battery usage profiles.

ii. Feature Engineering and Data Preprocessing

Much of the effective RUL prediction is therefore heavily reliant on good quality input features. As raw sensor readings are frequently noisy and unstructured, preprocessing and feature extraction are the required preliminary actions.

Du et al. (2020) discovered time-series features including the discharge duration, the average of the voltage drop and delta temperature during charging cycles, as well as demonstrated that the incorporation of such transformation (e.g., derivatives, moving averages) can substantially enhance the model accuracies. [3].

Outlier detection – such as z-score filtering – is a normal way of ensuring the consistency of data. Statistical outlier removal was carried out before training of models on historical battery datasets by Liu et al. (2020) indicating significant improvement in cross-validation accuracy [4].

While recent works also employ dimensionality reduction techniques, such as Principal Component Analysis (PCA) and t-SNE in order to extract latent features that better describe degradation trajectories.

iii. Ensemble Learning for the Prediction of RUL of Battery

i. The strength of the performance of ensemble methods in battery health modeling is attributed to their titling effects of minimizing overfitting and improving generalization in modeling.
ii. Zhang et al. (2019) tuned ensemble methods such as Random Forests, Extra Trees, and Gradient Boosting Machines (GBMs) and found that the considered models achieve state-of-the-art predictive accuracy and reliability as long as they are properly adjusted (when the single estimators are outcompeted) [5].
iii. Besides, ensemble stacking – the process of integrating predictions in base models by using meta-learning– had been successfully used to improve robustness over different battery chemistries and usage patterns.

iv. Explainable AI in the sphere of battery health monitoring.

As black-box models find their way into applications, explainability becomes crucial for stakeholder trust and regulatory compliance, as well as debugging.

Ribeiro et al. (2016) developed LIME with a view to provide post hoc justification of ML predictions through the generation of local surrogate models to approximate complex decision boundaries [6].

In battery analytics, LIME and SHAP (SHapley Additive exPlanations) have worked to uncover which features – such as early voltage plateau drop or temperature spikes – affect the predicted RUL most. E.g. Gao et al (2021) combined SHAP with LSTM to make their predictions interpretable to the battery engineers for the purposes of feature diagnostics and anomaly detection [7].

These XAI techniques assist in validation of learning behavior of the models and in the convergence of results from technical predictions with expert intuition.

v. Benchmarking and Comparative Studies

Evaluation of model efficacy is highly dependent on the process of benchmarking. Technologies such as LazyPredict provide rapid prototyping and automatic selection of models as it measures the performance of several regression algorithms.

Patel et al. (2020) used LazyPredict to run > 20 regression algorithms through publicly available battery datasets, and results showed considerable performance variance based on dataset characteristics [8].

NASA Prognostics Center data, CALCE battery datasets and Oxford Battery Degradation dataset that are usually applied to academic papers for comparison between models. Benchmarking plays a crucial role in evaluating the performance**,** robustness**,** and **g**eneralizabil**ity** of machine learning models used in battery RUL (Remaining Useful Life) prediction. It provides a standardized framework for comparing diverse algorithms under consistent conditions, ensuring that performance claims are data-driven and reproducible. In the domain of battery health analytics, where model accuracy can directly impact safety and operational cost, robust benchmarking is indispensable.

One of the prominent tools in this context is LazyPredict, a Python-based library designed to automate the training and evaluation of a wide array of regression algorithms with minimal code. LazyPredict accelerates the model selection process by providing quick performance comparisons using key metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 (coefficient of determination)**.** Patel et al. (2020) effectively demonstrated the use of LazyPredict by evaluating over 20 regression models on publicly available battery datasets. Their study revealed that algorithm performance varied significantly based on the data characteristics, including feature distributions, presence of outliers, and the battery chemistry involved. Such findings underscore the importance of benchmarking across diverse datasets rather than relying on a single test environment.

Commonly used datasets for benchmarking in battery RUL prediction include those from the NASA Prognostics Center of Excellence**,** CALCE (Center for Advanced Life Cycle Engineering)**,** and the Oxford Battery Degradation dataset. These datasets offer diverse battery chemistries (e.g., NMC, LCO, LFP), operational profiles, and cycle life data, making them ideal for stress-testing model adaptability. By applying multiple models across these datasets, researchers can uncover model biases, overfitting risks**,** and scalability constraints.

In sum, comparative studies and benchmarking are not just technical necessities but are foundational to establishing trust, transparency, and scientific rigor in battery analytics. They help identify the most suitable models for real-world deployment and guide future research in optimizing model architecture, feature engineering, and generalization techniques.

vi. Applications in Predictive Maintenance

Battery RUL estimation is a foundation of a predictive maintenance practice, especially in the case of mission-critical systems, like aerospace, automotive, and grid storage.

Wu et al. (2021) also showed the integration Battery Management System (BMS) with embedded RUL prediction models to actively adjust operating thresholds and schedule maintenance without performance degradation [9].

Beyond improvement in hardware-related operations, predictive maintenance philosophies through precise RUL projections have generated significant cost-reduction, safer, and lower carbon fleet businesses. The application of Remaining Useful Life (RUL) estimation in predictive maintenance is becoming increasingly vital across industries that rely heavily on battery-powered systems, particularly in aerospace, automotive, renewable energy storage, and critical infrastructure. Predictive maintenance leverages accurate RUL predictions to anticipate battery failures before they occur, enabling timely interventions that minimize unexpected downtimes, reduce maintenance costs, and improve overall operational safety.

One of the most impactful integrations in this domain is the incorporation of Battery Management Systems (BMS) with real-time RUL prediction models. As demonstrated by Wu et al. (2021), embedding ML-based RUL estimators within BMS allows the system to dynamically adjust charging and discharging thresholds, monitor degradation trends, and trigger maintenance alerts without affecting performance. This active decision-making framework ensures batteries are not only maintained based on a fixed schedule but are serviced when truly necessary, maximizing both efficiency and lifespan.

In the automotive sector, predictive maintenance powered by RUL models helps fleet managers avoid costly roadside failures and ensures compliance with safety regulations. It also supports fleet-wide health tracking, allowing data aggregation and analytics across thousands of vehicles to optimize logistics and servicing. Similarly, in aerospace, where reliability is non-negotiable, predictive battery health monitoring ensures mission readiness and minimizes risks of in-flight power loss.

Beyond reliability, predictive maintenance contributes significantly to sustainability goals. By extending battery lifespans and reducing premature replacements, organizations lower electronic waste and minimize the carbon footprint associated with battery manufacturing and recycling. Additionally, this strategy supports lower total cost of ownership (TCO) for electric vehicles and stationary storage systems.

Overall, the use of AI-driven RUL prediction in predictive maintenance is redefining the maintenance paradigm from reactive to proactive, transforming how industries manage battery systems and unlocking new levels of efficiency, safety, and environmental responsibility.

vii. Integration with [Digital Twins] and IoT

One of the newer trends in monitoring battery health involves the combination of ML-based RUL models and digital twin technology – virtual reflections of physical battery systems.

Digital twins get real time data from IoT sensors and run stimulations to determine degradation in various scenarios. Wang et al. (2022) reported studies that used digital twins in combination with ML models in order to assess battery stress under varying load conditions; proactive decision making was thus made possible.

This collaboration of ML models, digital twins, and IoT architecture is laying groundwork for autonomous self-healing systems of energy. The integration of Digital Twins and Internet of Things (IoT) technologies with machine learning (ML)-based RUL (Remaining Useful Life) prediction models represents a transformative advancement in battery health monitoring and energy system management. A digital twin is a virtual replica of a physical system—in this case, a battery or a battery pack—that continuously receives and processes real-time data through IoT sensors embedded in the physical battery system. These sensors collect critical parameters such as voltage, current, temperature, state-of-charge (SoC), and internal resistance. The data is then synchronized with the digital twin, enabling it to reflect the real-time operational state of the battery.

Unlike traditional data logging, digital twins allow for dynamic simulation and forecasting under varying load, temperature, and usage scenarios. This simulation capability empowers predictive analytics beyond historical trend analysis. By combining the predictive power of ML algorithms with the adaptive modeling of digital twins, operators can identify patterns of accelerated degradation, perform virtual stress tests, and simulate what-if scenarios without affecting the actual hardware.

As shown in studies like Wang et al. (2022), digital twins coupled with ML models have been successfully used to assess battery health degradation trajectories, allowing proactive adjustments to operating conditions. For instance, if a digital twin predicts thermal stress under a high-load condition, the system can automatically recommend or enact changes in usage patterns to prolong battery life. This capability forms the foundation of autonomous self-healing energy systems, where predictive maintenance is not only suggested but executed by the system itself.

Furthermore, the IoT infrastructure ensures seamless data communication between the physical battery and its digital twin. Cloud-based platforms, edge computing, and 5G connectivity enhance the real-time responsiveness and scalability of such systems, making them ideal for large EV fleets or stationary grid storage. Ultimately, the fusion of digital twins, IoT, and ML creates a closed-loop, intelligent system capable of adaptive learning, fault prevention, and lifecycle optimization—paving the way for the next generation of resilient energy management systems.

viii. LLM-Based Natural Language Interpretability

The new development in large language models (LLMs) like OpenAI’s GPT-4 or Google’s Gemini provides interesting stimulus for improving the interpretability and interaction with users.

These LLMs can serve as explainability layers on top of traditional ML models capable of transforming numerical predictions to human comprehensible narratives. For example, an LLM may elaborate that a prediction of RUL, at 85 cycles, is dominated by continuous rise in temperature at the time of charging, citing earlier usage habits.

From a research-focused perspective, the use of LLMs also helps non-experts across teams get insights on complex data to make joint decisions as multi-disciplinary teams collaborate an ability that complements the tenets of Responsible AI well.

In recent years, the acceleration of electric vehicle (EV) adoption and the growing demand for sustainable energy storage have led to a significant focus on battery performance, reliability, and longevity. A crucial component of ensuring battery system integrity is the accurate prediction of its Remaining Useful Life (RUL), which enables predictive maintenance, minimizes operational risks, and reduces long-term costs. As lithium-ion batteries become ubiquitous in applications ranging from EVs to grid energy storage and consumer electronics, intelligent battery management has emerged as a multidisciplinary challenge. Central to this challenge is the convergence of materials science, data analytics, machine learning (ML), and artificial intelligence (AI).

Traditionally, battery health estimation relied on empirical and electrochemical models. While these models have a strong theoretical foundation, they often fall short when faced with the nonlinear, high-dimensional behavior of real-world battery degradation, especially under variable load and temperature conditions. Therefore, data-driven methods, particularly machine learning, have gained popularity for their ability to capture complex degradation patterns from large-scale sensor data. Several studies have shown that integrating ML with traditional battery diagnostics can substantially improve RUL prediction accuracy. This hybridization not only improves performance but also opens avenues for real-time decision-making and fault prevention.

Among ML techniques, regression algorithms have been extensively used to predict RUL based on features extracted from historical charge-discharge cycles. Algorithms such as Random Forest, Extra Trees, and Gradient Boosting Machines (GBMs) have proven effective due to their robustness against overfitting and their ability to handle heterogeneous data. Zhang et al. (2019) demonstrated that ensemble methods could outperform single models in terms of both prediction accuracy and generalization. Moreover, stacking ensemble models has shown to improve performance across datasets with varying characteristics. These ensemble techniques minimize bias and variance errors, which are common in standalone models, and therefore serve as a reliable approach for complex battery systems.

Parallel to algorithm development, feature engineering remains a cornerstone of effective RUL modeling. Raw sensor data—comprising voltage, current, temperature, and internal resistance—is often noisy and nonstationary. Thus, preprocessing steps such as smoothing, normalization, and outlier removal are essential. Z-score filtering, for instance, helps maintain data integrity by excluding extreme anomalies. In addition, advanced feature extraction methods have been introduced, including delta voltage analysis, moving averages, and domain-specific metrics such as dQ/dV or capacity fade estimation. Du et al. (2020) highlighted the importance of derivative features derived from voltage and current curves in improving model accuracy. Furthermore, dimensionality reduction techniques like Principal Component Analysis (PCA) or t-SNE allow for the discovery of latent representations, which are often more indicative of battery degradation trends than raw features alone.

The rise of deep learning (DL) has brought further innovation to battery RUL estimation. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) models, have been leveraged to learn temporal dependencies in sequential charge-discharge data. LSTM models excel at capturing long-term trends in degradation, even under nonuniform loading. Li et al. (2019) demonstrated that LSTM models provided more stable long-horizon predictions than traditional neural networks, reducing root mean square error (RMSE) significantly. However, despite their predictive power, DL models are often criticized for their "black-box" nature, which can impede their deployment in safety-critical systems like EV battery management.

To address the interpretability problem, Explainable AI (XAI) tools such as LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (SHapley Additive exPlanations) have been integrated with ML models. Ribeiro et al. (2016) introduced LIME as a technique to approximate local decision boundaries of complex models using simpler surrogate models. In the battery domain, these tools help engineers understand the reasoning behind predictions, such as the influence of certain voltage thresholds or temperature spikes on predicted RUL. Gao et al. (2021) used SHAP values to assess the relative contribution of each feature to prediction outcomes in a LSTM-based battery health model, thereby enabling actionable insights and better anomaly detection.

Another promising development is the emergence of digital twins in battery health management. Digital twins are virtual replicas of physical battery systems, continuously updated with real-time sensor data. When coupled with AI models, digital twins can simulate future degradation paths under various operating scenarios. Wang et al. (2022) reported successful implementation of digital twins in conjunction with ML-based predictive models to assess battery stress and enable proactive interventions. This real-time mirroring of battery conditions enhances fault tolerance, provides early warnings, and facilitates self-healing systems in EVs.

In the context of usability and accessibility, web-based battery analytics platforms are increasingly being developed to democratize the power of AI for battery health monitoring. Such platforms often include interactive visualizations, real-time data streaming, statistical testing modules, and embedded ML models. The system presented in the current project—BRIIS (Battery RUL Insight & Intelligence System)—is an exemplary implementation of such a tool. BRIIS integrates deep learning models with web-based interfaces using Flask and visual libraries like Plotly and Seaborn. It allows users to input battery parameters, view statistical summaries, run hypothesis tests, and receive RUL predictions along with natural language explanations powered by large language models like Gemini.

One unique aspect of BRIIS is its emphasis on user interpretability. The incorporation of Gemini—a generative AI model—for transforming raw numerical output into human-understandable language enhances the usability of the system for engineers and non-experts alike. This feature aligns with the principles of Responsible AI, which advocate for transparency, accountability, and inclusiveness in AI deployment. The system also includes modules for vehicle suitability analysis, offering personalized EV model recommendations based on predicted battery performance, usage habits, and technical constraints.

Benchmarking tools such as LazyPredict and LazyRegressor have played a critical role in evaluating a wide range of algorithms across various battery datasets. Patel et al. (2020) employed LazyPredict to rapidly assess over 20 regression models, identifying models like LightGBM and XGBoost as consistent top performers. The use of such automated model evaluation tools reduces human bias and streamlines the selection of optimal architectures, especially in academic and industrial research settings.

Despite these advancements, several challenges persist in the battery RUL research domain. First, the lack of large, diverse datasets covering various chemistries, form factors, and use conditions hampers model generalization. Most public datasets (e.g., NASA or CALCE) are limited in scale and variability. Synthetic data generation, federated learning, and collaborative data sharing among manufacturers may help address this gap. Second, real-time model deployment requires lightweight architectures capable of running on embedded systems with constrained resources. Techniques like model pruning, quantization, and knowledge distillation are being actively explored to make DL models feasible for on-device inference.

Furthermore, model robustness and cross-application generalization remain open research areas. A model trained on cylindrical NMC 18650 cells may not perform well on pouch-type LFP cells due to differences in degradation behavior. Transfer learning and domain adaptation methods offer potential solutions, where pretrained models are fine-tuned on new domains with minimal data. Additionally, combining ML with electrochemical modeling—so-called hybrid models—can yield more physically consistent and interpretable predictions.

Lastly, integration with battery management systems (BMS) is critical for real-world applicability. The model must support real-time data ingestion, CAN protocol communication, and cyber-resilience. Regulatory compliance, safety standards, and fail-safe mechanisms must also be incorporated to ensure robust deployment in automotive or grid-scale systems.

In summary, the literature on battery RUL estimation reflects a vibrant and multidisciplinary field that is rapidly evolving. From traditional physics-based models to ensemble machine learning and interpretable AI, researchers have made significant strides in improving the accuracy, robustness, and transparency of RUL prediction systems. Future innovations are likely to center on scalability, generalizability, real-time deployment, and human-centric design. The integration of ML, digital twins, and generative AI, as demonstrated by systems like BRIIS, represents a forward-looking approach to building intelligent battery management systems that are not only technically sound but also user-friendly and sustainable.

CHAPTER 3

POSITIONING

BRIIS (Battery RUL Insight & Intelligence System) is a new generation of predictive intelligence tool for estimating and explaining Remaining Useful Life (RUL) of lithium-ion batteries, with the main target of EVs, smart energy systems, and battery-based mobility solutions. With the inclusion of deep learning models, statistical analytics, interactive data visualizations, and generative AI explanations, BRIIS provides a strong decision-support system to manufacturers, engineers, fleet managers, and technology analysts.

BRIIS is at a strategic convergence of AI-based predictive maintenance and energy technology. It bridges the gap between raw sensor data and could-be useful insights. In contrast to generic battery health dashboards or even a straightforward predictive model, BRIIS adds interpretability with a multimodal structure that combines the predictions of machine learning, advanced statistical testing, Optuna-based hyperparameter optimization, and natural language model generation like Gemini.

Consolidating its positioning are:

i. Deep neural network integration for the RUL prediction.
ii. AI-based context-aware explanations of battery performance.
iii. Story telling with Plotly, Seaborn and statistical illustrations.
iv. NLP is applied to convert expertise insight into major bullets and recommendations.
v. Potential for customization of recommendations for two-wheeler and four-wheeler EV's.

In fact, BRIIS is not merely a predictive tool – it is an intelligent assistant for the battery health monitoring, fleet reliability engineering, and EV consumer guidance purposes.

2. PROBLEM STATEMENT

The fast rate at which electric vehicles and renewable energy storage solutions were proliferated has resulted in an increase in the importance of battery lifecycle estimates. There are though a number of crucial issues in present practices.

i. **Lack of transparency:** Most RUL prediction systems act like black boxes providing no interpretability or an explanation of the predictions made.
ii. **Static analysis:** The current battery analytics platforms depend massively on static and rule-based approaches that do not capture temporal degradation trends as well as dynamic loading scenarios.
iii. **Absence of contextual insights:** Fleet managers through to OEMs do not have natural language interpretations of the battery behaviour that can inform their real-time decisions.
iv. **Disconnected analytics:** Visualizations, statistical summaries and predictive models are normally in different tools and this results into fragmented analytical process.

v. **Insufficient personalization:** The ineffort to customize RUL projections to actionable results, like advising suitable EVs under consideration of battery attributes, is low.

Such loopholes lead to poor battery use, precocious replacements, loss of efficiency in operational safety, and failure for deriving workable insights for customer advice and maintenance scheduling.

Hence there is an urgent need for a unified intelligent explainable system which not only predict the RUL accurately but also connects raw data to decision intelligence.

3. PRODUCT POSITIONING STATEMENT

Topping the list of its benefits is that for EV manufacturers, battery system engineers, mobility-as-a service (MaaS) operators, who require precise and explainable predictions of battery life and performance, BRIIS is a unified analytics and insight system that uses the synergy between deep learning, visual storytelling, and generative AI to estimate the battery remaining use life

In contrast to the usual battery dashboards or standalone machine learning scripts, BRIIS includes:

i. Global integration from the prediction, explanation and recommendation.
ii. A hybrid interface that has statistical rigor and insights generated by NLP.
iii. Individualized recommendation on vehicle choice and battery operation.
iv. Live visual analytics with the help of both static and interactive plotting engines.

CHAPTER 4

PROJECT OVERVIEW

4.1 Objectives

i. Gaps in Research in Predicting the Remaining Use of Life of Battery:

i. **Small Datasets:**
The availability of large quantities of high-quality datasets is a ball and chain that often restricts battery RUL prediction models. The majority of the public datasets (such as NASA's one or Stanford's battery datasets) include a limited number of batteries only under certain cycling conditions. This highly uneven data distribution causes overfitting and prohibits the generalization of ML models in various chemistries, form factors, and a usage profile. This is something that would have to be done either with synthetic methods of enhancing datasets through the help of domain specific knowledge or with the collection of more real life data from EV Fleets and Energy Storage Systems.

ii. **Feature Engineering:**
The issue of battery degradation is essentially nonlinear and ruled by time variable conditions like voltage, current, temperature and internal resistance. Unprocessed features are hardly able to capture this complexity. Therefore, extracted statistical, temporal, and frequency-domain features are necessary. Time – series decomposition (e.g., trend/seasonality), moving averages, entropy measures, and health indicators (such as dQ/dV or capacity fade) can boost the learning signal for the RUL prediction models.

iii. **Real-time Prediction:**

BMS-integrated RUL models need to have low-latency, energy-efficient inference for it to operate on resource-constrained microcontrollers or embedded platforms. The design of lightweight neural architectures, pruning the existing models, or the use of quantization-aware training are key strategies for high-speed on-device predictions with few accuracy trade-offs.

iv. **Model Interpretability:**
As ML models grow in complexity (for example, ensemble trees or deep neural networks), when it comes to explainability, it becomes a block to trust and adoption, particularly in safety-critical domains such as the EV batteries. Explainability techniques (LIME, SHAP, counterfactual reasoning) are critical in diagnosing the model's behaviour, assigning causes of degradation and guaranteeing regulatory compliance.

v. **Hybrid Models:**

There is no one model that can explain the whole picture of degradation of batteries. The hybrid architectures based on the combination of physical degradation model (such as Single Particle Model or Dearrenius-based aging) and data-driven ML strategies provide the best of the two worlds: physical validity and predictive flexibility. These frameworks also take care of black-box limitations of ML-only systems.

vi. **Outlier Detection:**

Anomalies are a common feature in battery datasets because of the presence of sensor noise, data corruption, or unusual behaviors of the users. Standard deviation or Z-scored-based outlier removal may not detect contextual or multivariate outliers. State-of-the-art techniques, such as isolation forests, robust PCA, or autoencoder-based reconstruction errors, provide more accurate anomaly filtering, that improves model robustness.

vii. **Cross-application Generalization:**

Models fit using a battery chemistry or form factor (e.g., NMC 18650 cells) tend to fail when applied to other chemistries or form factors (e.g., LFP pouch cells). The domain adaptation and transfer learning approaches such as fine-tuning the pre-trained models or shared feature representations can contribute to building cross-chemistry generalizable models, eliminating the necessity for retraining on each type of batteries.

viii. **Failure Mode Prediction:**

Except for a scalar prediction of time-to-failure estimate, most of the models for RUL only offer a prediction. Nevertheless, in practice, the ability to recognize the fundamental failure mode (such as, lithium plating, SEI growth, thermal runaway) is also of equal importance. Multi-output ML models or regression models that incorporate classification for prediction of RUL and possible degradation mechanism deliver more meaningful conclusions.

ix. **BMS Integration:**

The ability to implement RUL models should be compatible with the current Battery Management Systems. This entails the following: adherence to real-time communication protocols (e.g., CAN bus), power and computation constraints, cybersecurity, and fail-safe aspects. The integration can be achieved using middleware layers or edge-AI platforms.

x. **Environment and Usage Influence:**

Degradation is widely affected by external parameters like temperature, depth of discharge and charging protocol, and load cycles tremendously. The incorporation of these contextual properties into the model inputs — be it directly or by engineered features – may lead to a substantial improvement in the RUL prediction’s precision and usefulness for practicable, changing operating circumstances.

4.2 Goals

i. Enhancing Battery RUL Prediction:

Comparative Study of Machine Learning Models and Explainability Methods

This study seeks to elaborate theoretical background on battery RUL estimation, conducting a fair comparison of several machine learning models: Extra Trees, Random Forest, XGBoost, and using explainability methods (namely LIME) to explain the nature of models' behavior. The aim is not only to maximise predictive performance, but also to gain the trust in model's predictions by making them transparent and human-understandable.

ii. Description of Approach

Dataset:

This study has used a dataset consisting of about 1000 cycles NMC-LCO 18650 lithium-ion cells. Attached to each cycle, specific detailed logged features included voltage, current, temperature and capacity. The target was RUL, which was obtained as the number of cycles left until the predefined mark of end-of-life (e.g., 80% of the initial capacity).

Feature Engineering:

Features were pulled from the dataset in a cycle-wise manner, accounting both for the raw sensor data and calculated metrics of voltage delta, average current, charge/discharge length, and the level of capacity degradation occurring the cycle level. Moving averages and lag variables were used to engineer temporal feature so as to maintain time-series memory.

Algorithms Used:

i. **Extra Trees Regressor (ETR):** An ensemble technique that is known for its robustness against the noise factors and a high variance.
ii. **Random Forest Regressor (RFR):** Another ensemble learner that uses bootstrap aggregation which is effective in the avoidance of overfitting.
iii. **XGBoost Regressor (XGB): A** gradient boosting model that is calculated for going fast and accurate using a regularised loss function.

Model Benchmarking:

LazyRegressor benchmarked more than 40 regression models using default hyperparameters and created a baseline performance terrain. Moderates were ranked following the normal metrics i.e Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Coefficient of Determination (R^2).

iii. Data Preprocessing and Outlier Handling

i. Missing Values: The interpolation between the records was performed with the forward-fill or feature-specific medians depending on the data type and its distribution.
ii. Outlier Detection: Z-score was used for num. features; entries with Z-scores >3 or <-3 were checked to exclude such ones while taking noise down.
iii. Feature Selection: Highly correlated, low variance features, were pruned. Traits with less than 10 distinct values were processed for the encoding or deleted because of the low predictive value.
iv. Train-Test Split: An 80-20 stratified split guaranteed adequate representation of all the RUL ranges in both sets.

iv. Model Training and Evaluation

Cross-Validation with Grid Search technique was utilized for their hyperparameter tuning (if appropriate). XGBoost out-shined the others on all metrics:

i. MSE: Most overall minimal, which implies the least average error.
ii. RMSE: A sign of better correspondence with how the worldly degradation behavior.
iii. R^2: Nearest to 1.0, which implies a high explanatory power and little residual error.

v. Explainability with LIME

Local explanations for RUL prediction was generated for individual RUL using LIME. For each test instance:

i. An upset local neighborhood was sampled.
ii. On this neighborhood, a simple interpretable model (e.g., Linear) was trained.
iii. Feature importances scores were visualized to identify the contribution of each input to the prediction.

Explanations were saved as HTML files, which not only made the process transparent but also became a diagnostic tool for the model debugging and stakeholders' communication.

vi. Contributions

i. Comparative Evaluation:
Makes a performance comparison of three potent ML models over a suite of metrics with real-world, cycle-level battery dataset.

ii. Improved Outlier Handling:
Using Z-score and domain-specific thresholds, the current study improves the data quality therefore, resulting in reliable models.

iii. Explainable ML:
When using LIME, the transparency is introduced to the otherwise black box models, which areљy interpretable to the engineers and the system designers restriinguishing RUL. It also helps in model debugging as well as building trust.

iv. **Edge Readiness:**
The models, particularly optimized XGBoost model, can prove to be deployed in embedded environment with little changes.

v. **Framework for Extension:**
The study introduces a modular framework for future work where one can consider adding further techniques like SHAP, hybrid modelling or even transformer-like architectures to it.

CHAPTER 5

PROJECT SCOPE

Battery RUL Prediction & Analytics Web Application.

It is a web-based system which offers an end-to-end solution for the intelligent analysis, prediction and visualization of Remaining Useful Life (RUL) in electric vehicle (EV) batteries. It integrates deep learning, statistical processing, and visual analytics in an interactive research, diagnostics, and maintenance planning interface. The application combines AI explainability and NLP-driven recommendations, meaning it is a good fit for researchers, engineers, and data science professionals, who are concerned with providing predictive battery analytics.

1. Battery RUL Prediction

1.1 Input Parameters

The users enter different battery health measures including:

i. Charging duration (charge time)
ii. maximum voltage measured on charging cycles
iii. Discharge duration (discharge time)
iv. Cycle number
v. Average temperature during charge/discharge
vi. Internal resistance or impedance (where available)
vii. Any special domain metadata (e.g. usage category, or cell model)

1.2 Predictive Model

A pre-trained deep learning model (ruled as rlu.h5) is used.

This model:

i. Applies a multivariate regression-oriented deep neural network (most probably an MLP or hybrid LSTM-CNN)
ii. Trained on the time-series data on the battery performance (e.g., NASA or CALCE datasets modified for the NMC-LCO 18650 cells)
iii. The remaining useful life (in cycles or days)

i. Recommendation Engine

   i. An API that synthesizes actionable recommendations based on predicted RUL (generated on the basis of the predicted RUL) of a Gemini API (Generative AI from Google).
   ii. Some of the recommendations are charging optimization strategies, load adjustments, and usage pattern change specific to two-wheeler and four-wheeler EVs.

2. Natural Language Processing (NLP)

2.1 Summarization Engine

i. Combines the Gemini NLP pipeline with NLTK in order to perform text summarization.
ii. Transforms AI-developed feedback into concise points using bullets appropriate to be read by an engineer.

2.2 Semantic Matching for Vehicle Suitability

i. Extract keyword, and contextual embeddings (like Word2Vec or BERT-like model) will be applied to provide EV battery types regarding user requirements and available vehicle specifications.

3. Statistical Analysis Tools

The present module provides strong statistical capabilities for battery diagnostics:

3.1 Descriptive Statistics

i. Computes central tendencies: mean, median, mode
ii. Dispersion metrics: standard deviation , variance , range, inter-quartile range

3.2 Hypothesis Testing

i. T-tests (one-sample, two-sample)
ii. ANOVA (single/multi-factor)
iii. Chi-square tests for association of categorical data.
iv. Fisher's exact test for small sample testing.

3.3 Non-Parametric Testing

i. Mann-Whitney U test
ii. Wilcoxon signed-rank test
iii. Kruskal-Wallis H test
iv. Z-tests for large samples

3.4 Correlation & Regression

i. Pearson/Spearman correlation
ii. Linear/multiple regression models
iii. Diagnostics of model (residual analysis)

4. Data Visualization Suite

This suite allows for real-time presentation of analytical insight.

4.1 Supported Plot Types

i. Histogram

ii. Box plot
iii. Density plot (KDE)
iv. Violin plot (and combined violin-box hybrid plot)
v. Heatmap (correlation matrix)
vi. Scatter plot (2D and color-coded 3D)
vii. Contour and Hexbin plots on a large scale for trend aggregation.

4.2 Features

i. Dynamic rendering through Plotly/Seaborn/Matplotlib
ii. User defined parameters (for example plot range, filter conditions)
iii. Export options for research purpose (PDF, png and CSV)

5. Causal Analysis & Feature Importance

5.1 Hyperparameter Optimization

i. Applies the Optuna framework for the efficient tuning of the parameters of the Random Forest Classifier (or regressor).
ii. Uses Tree-structured Parzen Estimator (TPE) for Bayesian optimization.
iii. 5.2 Feature Importance Metrics
iv. Gini importance and the permutation importance SHAP value plots for explainability
v. Pinpoints major RUL determining parameters like rate of voltage decaying, internal resistance trends and thermal variations.
vi. 5.3 Outlier Detection
vii. The use of Z-score based filtering in order to increase the prediction dependability.
viii. Optional IQR and Isolation Forest methods for extra robustness.

6. Interactive Web Interface

The interface has been designed with the help of Flask/Streamlit and HTML templates, the interface is module and responsive in nature.

Pages:

i. index.html: Landing and description page
ii. inputs.html: RUL prediction and input by a user.
iii. visualization.html: Graphs, plots, and stats interface
iv. c_analysis.html: Causes analysis report and the feature relevance report

Responsive look works with Bootstrap or Tailwind tools. Back-end can talk to the front by using AJAX or JavaScript.

7. Dataset

i. Works with a set called Battery_RUL.csv

ii. It holds health facts of a battery for each cycle.
iii. It may be time-based or just one picture of the battery at a time.
iv. It is built for one kind of battery cell (NMC-LCO 18650).
v. It may have fake or smoothed data to show how real use may wear it down.

8. Users

i. People who look into car battery life
ii. Data workers for keeping things running
iii. Battery makers and people who test how long batteries last
iv. Teachers and students who want to use machine learning for power things

9. Next Steps

i. Do models that work with time (like RNN or LSTM) to see how a battery gets old
ii. Use Docker tools to run the system, make it easy to grow with Nginx and Gunicorn
iii. Give tips when a battery needs care (like fix, swap, or shift use)
iv. Link to a real Battery System to get live facts

CHAPTER 6

METHODOLOGY

1. What is the Problem and Data?

Goal:

We want to develop smart and smart machine learning line to guess number of lives in a battery. This fixes problem before it begins and makes cars and power batteries last longer. We view how batteries are worn out from their past usage.

How do we get Data?

We get battery test sets in sources that conduct good lab tests (such as NASA Ames, CALCE, Oxford Lab). The data has:

i. The length of time taken to charge the battery and to run it in many uses and in varied situations.
ii. Volt-meter and Amps plots with very small time disjunctive.
iii. notes for every time such that, round, time rested, or weird things that happened.
iv. We consider various types of battery (NMC, LCO, LFP) therefore our model can be extended to more batteries.

How we Handle Data:

v. We use a certain tool (DVC) to track all the data and changes.
vi. We maintain clear notes next to raw data so as to know what each thing means.
vii. All info is in one place and we use math tags (like SHA256) to verify that files are good.

2. Get Data Ready

Clean the Data:

a. Fill in time facts left out through line fill, time for notes, mean or most shown.
b. if a round is repeated twice (found with the help of time and round count), we eliminate one.
c. Identify odd points with large jumps: if they are way off (z-score greater than 3); or, far from rest, get discarded.

Make New Facts from Old:

i. Times: how many minutes each round, how much time to charge or rest.
ii. Volts: top volt, mean volt or the time above the set volts.
iii. Loss in charge: loss in power on every round when compared to the new ones.
iv. New lines: visit dV/dQ and dQ/dV smoothed.

Pick the Right Facts:

i. We use fast screens (such as Pearson/Spearman) to look at the facts that are saying the same thing.
ii. Omit less important details with RFE, with a help of a random forest.
iii. If many facts, apply PCA to reduce to core set.

3. Build and Tune the Model

Main Model:

i. We develop a custom deep net. It has input scale, some nodes of blocks which use ReLU, random drop nodes as guard, and demonstrates one end value – the life left.
ii. We train the net but if it does not improve we stop and employ tricks, such that it learns quickly and does not get stuck.

Simple Model to Explain:

i. We create random forest as well at exactly the same time so that we'll see which facts actually matter the most.
ii. Use SHAP and swaps to get insights on why the model chooses what it does.

Find the Best Settings:

i. We use Optuna to guess the best settings, for example:
i. -How fast to change.
ii. How large a group to train in a given time.
iii. Number of layers and nodes.
iv. The depth or the breadth that is taken by RF/XGBoost run.
v. -We attempt to do many things simultaneously, and we take mental notes with Weights & Biases.

4. AutoML for Model Pick

Quick Try of Models:

i. -We first use LazyClassifier, where we try 25+ Lazy models. LogReg, KNN, SVM, Ridge, trees and so on.
ii. We select the best with cross check (5-fold, keep groups) and rank by F1 and MCC scores.

5. Team Work of Models

i. Training Many at Once:
ii. We train these the sets each right:
    a. ExtraTrees (500): Lowers mix-up and is quick.
    b. RandomForest (depth 9): Suitable for lesser and greater combination of facts.
    c. XGBRF: Trees with boost push.

d. LGBM: Fast for big sets, operates with facts, such as names.
e. XGB: Good in means of avoiding overfit (lambda, gamma).

iii. How We Mix Answers:
   i. Try hard and soft mix.
   ii. Train an elite model on their answers in order to get even better scores.

6. Find Out How Good the Model Is

How We Score:

i. Score, True pick, Catch rate, F1. Applied saved test set; combination mix Seaborn.
ii. MCC: An actual check of all the hits and misses – good for unbalanced sets.

Know the Math:

i. Score (TP + TN) / (TP + TN + FP + FN)True pick = TP / (TP + FP)
ii. Catch rate = TP / (TP+ FN)
iii. F 1 = 2 x (True pick x Catch rate) / (True pick + Catch rate)
iv. MCC = (TPxTN-FPxFN) / sqrt((TP+FP)(TP+FN)(TN+FP)(TN+FN))
v. Model Evaluation and Performance Metrics

Accuracy:

$$Accuracy = (TP + TN)/\ (TP + TN + FP + FN)$$

Precision

$$Precision = \frac{TP}{TP+FP}$$

Recall

$$Recall = \frac{TP}{TP+FN}$$

F1-score:

$$F1 - score = \frac{TP}{TP} + 0.5(FP + FN)$$

Matthews Correlation Coefficient (MCC)=

$$= \frac{TP * TN - FP * FN}{\sqrt{\left((TP + FP) * (TP + FN) * (TN + FP) * (TN + FN)\right)}}$$

TP: True Positive

TN: True Negetive

FP: False Positive

FN: False Negative

Confusion Matrix:

Heatmap visualisation is generated for each model.

confusion matrix=

Table 6.1 Confusion Matrix

$True/False$	0	1
0	$True\ Positive$	$False\ Positive$
1	$False\ negetive$	$True\ negetive$

Look at Mixes:

i. Heat look with notes.

ii. Find out which models fail (calling high life to near-dead batteries).

7. Roll Out the Model

How the System Runs

a. Flask or FastAPI exposes the model via the web rules.
b. Docker puts the system into one box, and adds to it what it needs.
c. Kubernetes is run on many boxes working live.

Track Changes & Model Store:

a. In the same way, the MLflow monitors everything tried and assigns marks to the model.
b. CI/CD (GitHub or Jenkins) initializes roll out when a new model is established to be true.

User Side:

a. App in Streamlit or Dash to brings in and out info and display.

b. Live plots: present the input which goes in, what model thinks, how sure it is and tips on care.

8. Keep Watch & MLOps

Watch and Alert:

i. –Prometheus/Grafana display speed, use, and how good the model works.
ii. Look for data shift on KL and PSI.

Set Times to Train Again:

i. Airflow or Prefect for setting new training.
ii. Start when data shifts or when model gets worse or at a certain time.

Log and Track:

a. All web calls and model answers are recorded.
b. Logs record what comes in, what is coming out, and model mark.

9. Smart Text with AI Help

Talk Engine:

a. Use a smart word model (such as GPT or T5) to transform model facts to easy text.
b. For example: "The remanding cycles are 120 since it lost voltage quickly over 4.2V recently".

Suggest What to Do:

a. Smart word mix in addition to rules gives tips
b. "Lower top charge for a longer life".
c. "Do full charge and run in 50 cycles".

CHAPTER 7

MODULES IDENTIFIED

1. Web Interface / Routing (Flask)

The framework enables web interaction management through HTML forms which shows interface responses to user inputs.

i. / → Home page
ii. /visualizations → Visualization dashboard
iii. /inputs → Input form for battery data

The /submit_data endpoint progresses with battery data and generates forecasted results at the same time.

iv. /visualize_test → Generates plots
v. /stat_test → Performs statistical tests

1. / → Home

   Shows a start page with info, what the app can do, and how to use it.

   Uses special tags to add new info when things change.

2. /visualizations → Visuals Page

   Shows moving charts with Plotly and Seaborn.

   You can see how the battery runs, how it breaks down, and how the numbers look.

3. /inputs → Fill in Battery Data

   A web page form for you to give battery stats, like how long it runs, the high point for volts, cycle times, and more.

   Bad form entries get stopped with easy checks.

4. /submit_data

   Takes the form info.

   Sends it to the RUL guess tool and brings up what it finds.

   Keeps track of each user and their tries.

5. /visualize_test

   Lets you give your own data to test.

   Shows charts: like how volts change with time, how long a run lasts, and battery wear.

6. /stat_test

   Runs number checks on files you pick or ones in the app.

   Gives back results, charts, and tables with things like p scores and test calls.

7. /optuna

   Page to set off tuning of model numbers.

   Does Optuna runs and gives back charts to show history and what matters most.

8. /c_analysis

   Starts checks to see what features matter.

   Uses SHAP or swap checks to list what helps guess RUL most.

Users access the Optuna-based model tuning functionality on the Page by visiting /optuna URL.

The application operates through /c_analysis to implement Optuna tools for performing feature importance analysis alongside hyperparameter optimization.

2. Data Visualization Module

The interface enables users to generate various plots through provided inputs when using these functions:

i. Matplotlib

ii. Seaborn

iii. Plotly Supports:

iv. Histogram

v. Boxplot

vi. Density Plot

vii. Violin & Violin-Boxplot

viii. Bar Chart

ix. Scatter Plot

x. Heatmap

xi. Contour

xii. Hexbin

xiii. Q-Q Plot

3. **ML Model Prediction Module**

This component employs the following process to foretell Battery RUL (Remaining Useful Life).

i. A pre-trained Keras model (rlu.h5)
ii. The device uses discharge time and measures voltage decrement and maximum voltage recording and time at a voltage level of 4.15v and additional related parameters as input features.

4. **LLM Integration (Google Gemini API)**

Used to:

i. The model system uses prediction analysis from the analytical insights to generate insights.
ii. A battery parameter analysis system must provide suggestions for electric vehicle models combined with 2-wheeler and 4-wheeler products.
iii. Extract key points using NLTK

5. **Statistical Summary & Test Module**

Calculates:

i. The program generates summary statistical data by producing means and medians as well as modeling values.
ii. The project implements various statistical tests including t-test, chi-square and ANOVA together with Mann-Whitney, Wilcoxon, Kruskal-Wallis automated with correlation tests, linear regression, OLS, Fisher's exact, Z-test analysis methods.

6. **Hyperparameter Tuning with Optuna**

i. The code employs TPESampler inside optuna for tuning a RandomForestClassifier.
ii. An evaluation determines which important features affect Remaining Useful Life predictions.

7. **Text Summarization Module**

Uses:

i. The text module will extract vital sentences from LLM output by using nltk.sent_tokenize and FreqDist functions.
ii. Cleans markdown and formatting

8. **Data Preprocessing**

i. Reads Battery_RUL.csv
ii. Removes outliers using Z-score filtering
iii. Filters categorical variables (with <10 unique values).

CHAPTER 8

PROJECT IMPLEMENTATION

1. System Design

This Battery Life Tool is made with parts that can scale up. It uses many small apps that work together. We split each step: get data, fix data, build model, make guesses, show results, and check for good work. The main tools are:

i. Server: Flask and Gunicorn
ii. Web Page: HTML, CSS, and JS (Plotly, Bootstrap), run with Flask
iii. Boxed Apps: Docker, Docker Compose
iv. Roll Out: GitHub Actions or Jenkins
v. Run Big: Kubernetes (cloud or small devices)
vi. Model Change: MLflow
vii. Keep Data: DVC
viii. Code Track: Git with set work plan

2. Getting Data & Keeping Track

i. Where: CSV or HDF5 files with battery details from NASA, CALCE, or house-made sets
ii. Main Details:
iii. Time to use up, how fast volts drop, fall in use
iv. Time above 4.15V, peak volts, inside block for flow
v. Keep Steps Clear:
vi. Each load is tracked by DVC.
vii. Each set links to one Git save and MLflow try.

3. Fix Data & Find Key Bits

i. Fill Gaps: Use mean or most seen value, or fill ahead in time rows
ii. Find Bad Data:
iii. Z-score ($z > 3$) to spot odd ones
iv. IQR to trim far points
v. Clear Tiny Lists:
vi. Drop items with less than 10 kinds unless kept for a good cause
vii. New Bits:
viii. Moving mean/steps on window
ix. Used change each 100 times
x. Time to hit high volts Save all these as files (joblib or Pickle) and list to MLflow.

4. Build Model & Mix Styles

i. A blend of models for both score and clear use: Deep Net (Keras/TensorFlow)

ii. Form: [Input → Dense(128) → Drop → Dense(64) → Dense(1)]
iii. Use Adam, Loss: MAE or RMSE
iv. Stop early if work stops getting better
v. Save as: rlu.h5 (log in MLflow)
vi. Random Forest (scikit-learn)
vii. Use: Know what matters most, check with second class
viii. Keys: max_depth, n_estimators, tune with Optuna
ix. Show: What shapes guess, with SHAP, and error chart LazyClassifier Test many models fast for start
x. Checks: Score, MCC, F1, AUC, miss chart

5. Pick Best Settings (Optuna)

i. Picker: Tree Parsen Estimator (TPESampler)
ii. Aim: Cut down RMSE for Net, Boost F1 for Trees
iii. Links: All try marks sent to MLflow
iv. Run: Can go wide with joblib or Dask
v. End: Best settings, show what matters, plot try story

6. Web Page & Paths (Flask)

Site uses clear paths and forms, with quick look updates:

Path	What It Does
/	Main page
/inputs	Add battery info
/visualizations	Show live plots
/submit_data	Run guess and explain
/visualize_test	Plots for a test
/stat_test	Do stats checks
/optuna	View model fit tries
/c_analysis	Find and pick key bits

7. Show Data

Makes study and skill plots:

i. Uses: Matplotlib, Seaborn, Plotly, Statsmodels

ii. Plots: Bar, Box, Line, Fill, Heat, Curve, Q-Q, Hex, 3D Filters by time, field, volts, as you want.

8. AI Help with Gemini

i. Uses Google Gemini API, safe secret keys
ii. The ask has:
iii. Life left
iv. Battery drop shape
v. Old fix or use story
vi. Answer has: What the tool trusts, tips too Fix tip (like "swap at 15% left")
vii. More Words:
viii. NLTK: Pick main words, name bits
ix. Shorten with rank or match

9. Stats & Test

i. Full check and show for numbers:
ii. Key: mean, mid, most seen, spread, lean, fat tails
iii. Tests:
iv. Number: t-test, ANOVA, Z, fit by line
v. Not Number: Wilcoxon, Kruskal, Mann-Whitney
vi. Links: Chi-square, Fisher's test
vii. Tied: Pearson, Spearman, Kendall
viii. Show with heat, Q-Q, test pass or fail plots.

10. Serve & Send Out (Docker/Kube)

i. Pack small apps with:
ii. Gunicorn + Flask in box
iii. MLflow serve at REST gate
iv. AI help and prep as side apps
v. Roll Out Types:
vi. Big: Kubernetes on most clouds, or use small with Compose
vii. Small: Runs on Jetson or Pi 4

11. Watch, Learn, and Update

i. Watch:
ii. See if model shifts by KL or PSI
iii. Track trust with softmax or drop guess
iv. Log with MLflow, touch Prometheus + Grafana
v. Learn & Update:

vi. Plan time or trigger update with Airflow or Prefect
vii. Make new data copy, re-fit, show, swap out model if failed

8.2 Design

8.2.1 Architectural Design

The Battery RUL Insight & Intelligence System (BRIIS) uses a simple, clean, and split-up design. The system brings together the user side and the logic side with Flask. Its parts are:

User Side: Shown with HTML pages like index, input, and chart screens. Users fill in battery facts, see charts, and read what the model finds.

Middle Part: Flask collects what users send, runs model checks, finds stats facts, and looks at links between facts.

Data Side: It loads files, cleans them, cuts out odd values, and gets things set for the model by using z-scores and more.

Model Side: Loads the trained deep model (rlu.h5) to guess battery health. It also uses Random Forest to see which facts are key and runs tests on what drives results.

AI and Language Side: Google Gemini makes model results easy to read and gives tips. NLTK makes the text short and easy by picking top points.

Chart Side: Uses Matplotlib, Seaborn, and Plotly to make charts—saved and shown to the user.

This setup keeps each part neat, able to grow, and easy to use in bigger systems later.

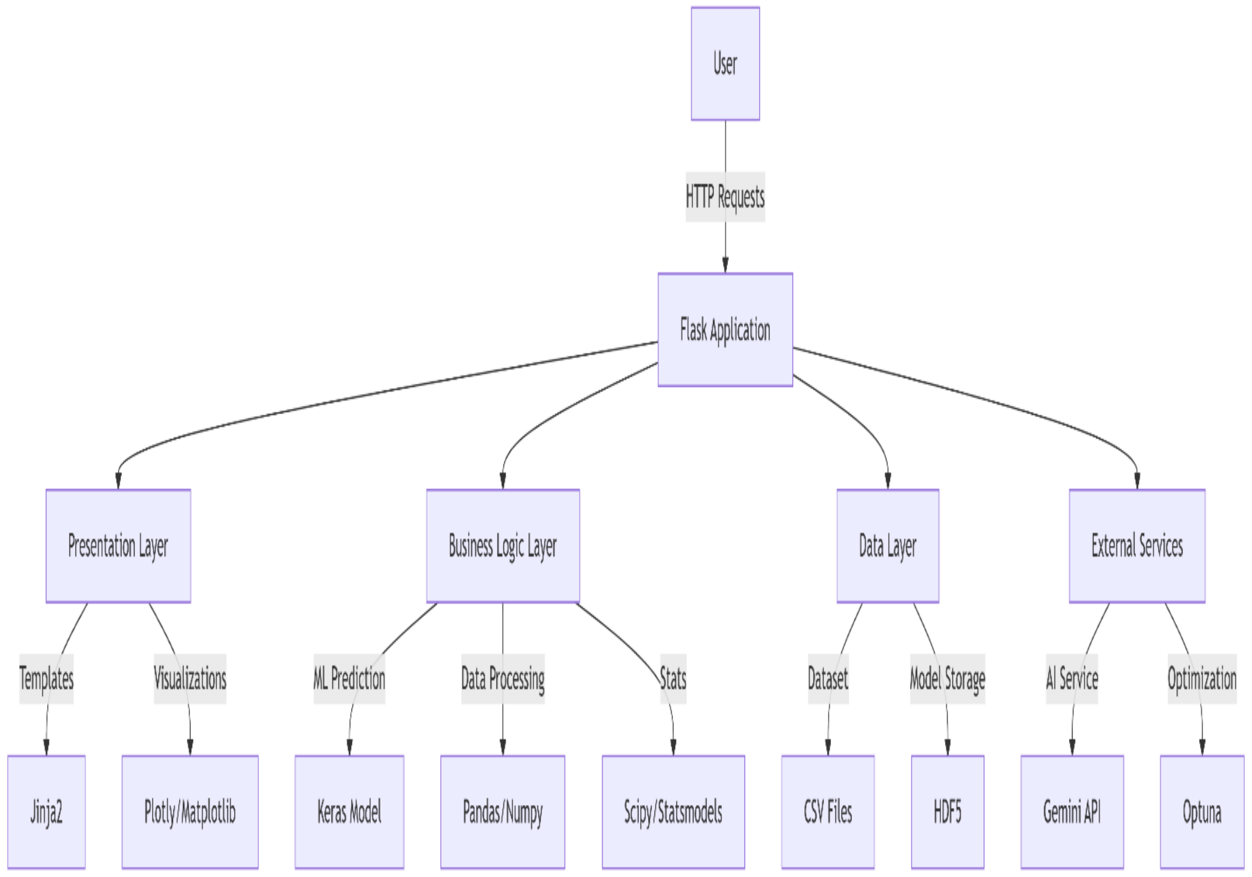

Fig 8.1 Architectural Design

8.2.2 Class Diagram

While Flask code often is step by step, the main logic comes in classes like:

i. **class BatteryRULModel:** Opens and runs the Keras model to guess RUL.
ii. **class DataProcessor:** Loads files, finds and drops odd points, and fixes the data.
iii. **class Visualizer:** Makes and saves charts.
iv. **class StatisticalAnalyzer:** Runs stats tests like t-tests or ANOVA.
v. **class CausalAnalyzer:** Uses Optuna to see which facts matter most.
vi. **class NLPExplainability:** Works with Google Gemini and NLTK to write tips and short key points.

These classes keep things in order, make changes easy, and let us test each part by itself.

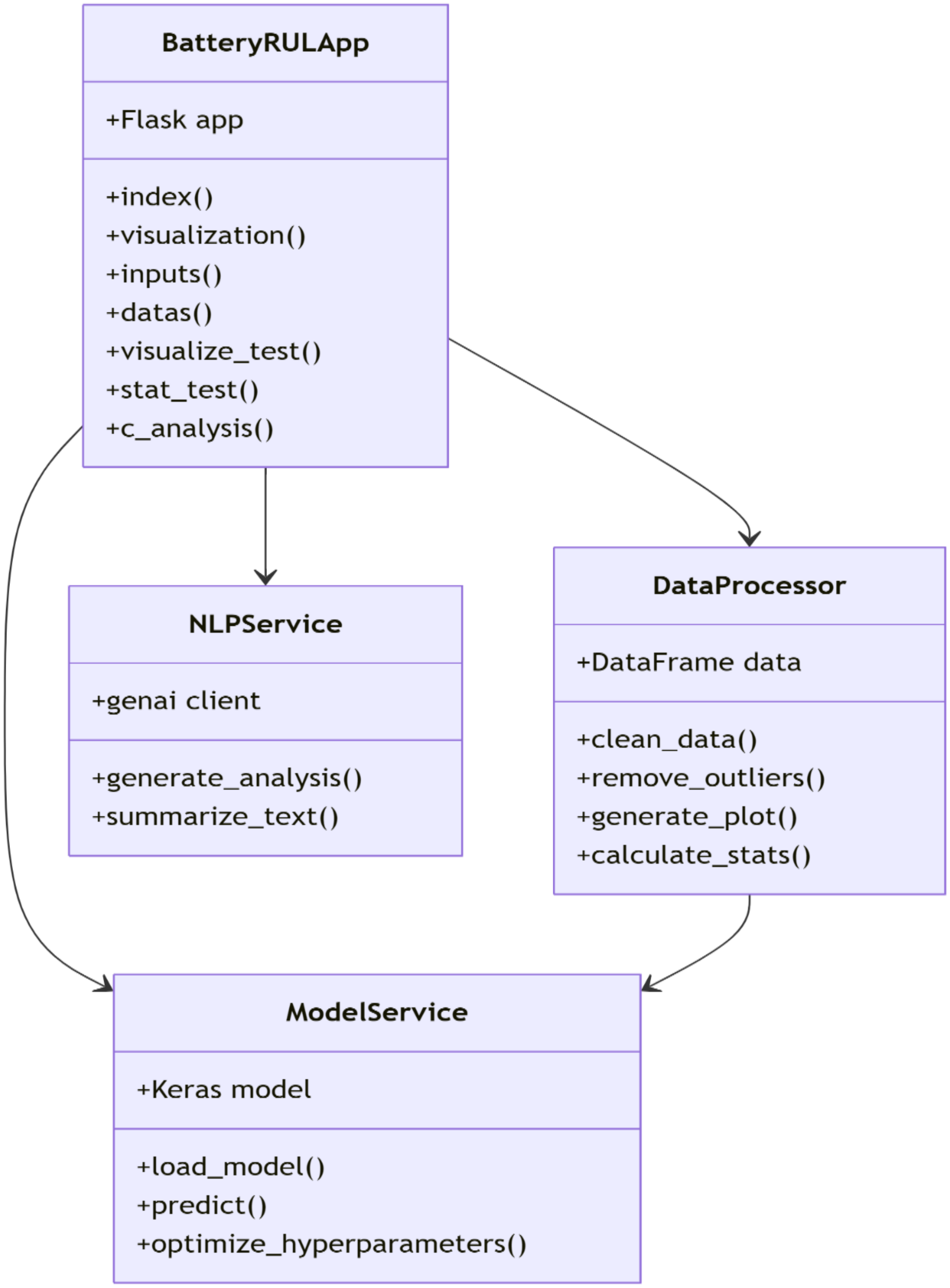

Fig 8.2 Class Diagram

8.2.3 Entity Relationship Model

Though Flask here does not use a full database, we can show the link between key data types as:

Battery_Input

i. **Facts:** discharge_time, max_voltage, time_at_4.15v, time_constant_current, charging_time, and more.
ii. Model_Prediction
iii. **Facts:** guessed_RUL, time_made
iv. Explanation
v. **Facts:** text_made, key_points[]
vi. Visualization
vii. **Facts:** chart_kind, x_item, y_item, image_location
viii. Statistical_Test
ix. **Facts:** test_kind, columns_shown, result_words
x. **Links:**

Battery_Input → Model_Prediction (one to one)

Battery_Input → Explanation (one to one)

Battery_Input → Visualization (one to many)

Battery_Input → Statistical_Test (one to many)

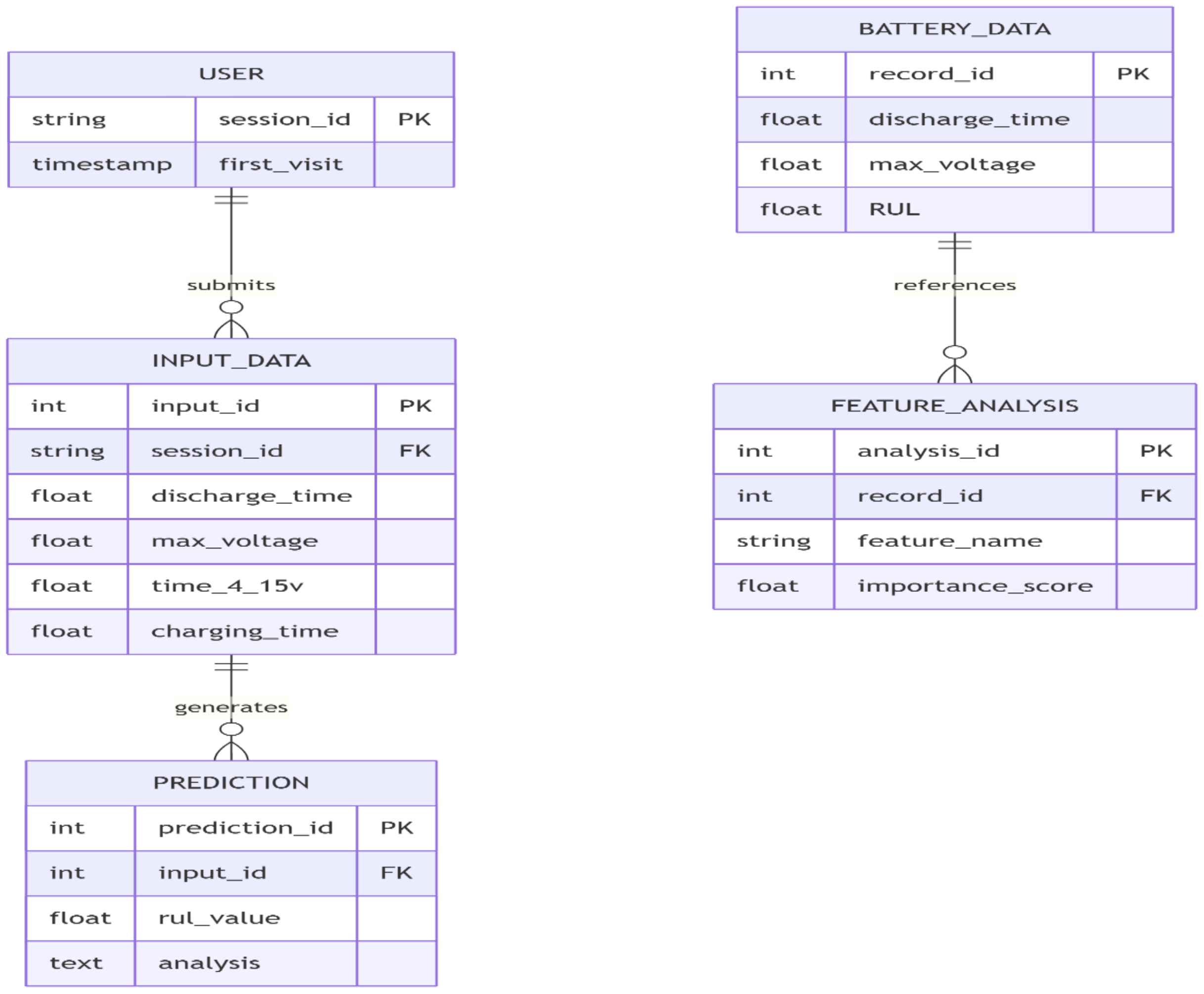

Fig 8.3 Entity Relationship Model

8.2.4 Sequence Diagram

How a normal guess runs is as below:

User → Fills form

Form → Flask Route (/submit_data): Sends info in a post

Flask → Model_Loader: Opens and loads RUL model

Model → Predict: Makes a RUL guess

Flask → Google Gemini: Sends facts plus guess to LLM

Gemini → Flask: Gets back human text

Flask → NLP Summarizer: Picks short top lines

Flask → Template (inputs.html): Shows guess and tips to user

This chain lets the user see the guess, text, and hints, all at once.

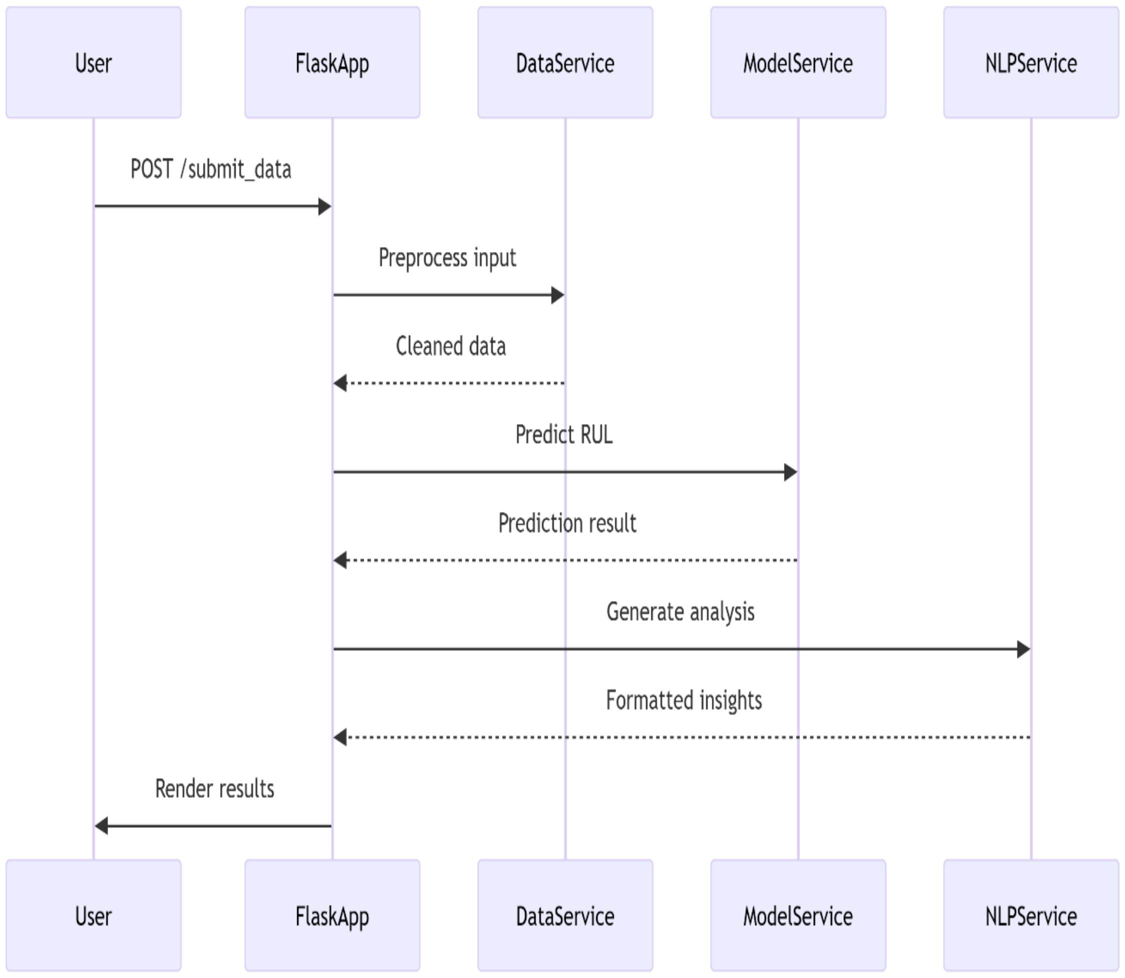

Fig 8.4 Sequence Diagram

8.2.5 Description of Technology Used

Core Framework

Flask (Python):

Flask is a minimalist, open-source Python web framework that acts as the backbone of the application's server-side architecture. It handles routing, user input via forms, and communication between the frontend interface and backend logic. Flask is highly modular and flexible, making it ideal for AI-based applications that require integration with external APIs, machine learning models, and dynamic content rendering. In this project, Flask serves as the interface through which users interact with the system—inputting battery parameters, visualizing charts, and receiving predictions. Its RESTful design also allows for scalability, enabling easy integration of model APIs and future deployment to cloud environments.

Jinja2:

Makes live HTML. Jinja2 is the default templating engine used with Flask to dynamically generate HTML content based on backend data. It enables embedding of Python-like syntax within HTML files using template tags. For instance, RUL prediction results or plots generated from machine learning models can be rendered on the client's browser in real-time using Jinja2 templates. This system uses Jinja2 to personalize user views, show prediction results, render visualizations, and display AI-generated text responses. It separates application logic from presentation, allowing better maintainability and flexibility in the UI/UX design, especially when integrating charts, AI-generated narratives, and forms.

Google Gemini:

For text, hints, and talk with LLM. Google Gemini is a powerful large language model (LLM) integrated into the system to provide natural language explanations and intelligent recommendations based on battery prediction results. Gemini interprets technical outputs from ML models—such as battery RUL or degradation trends—and translates them into understandable, user-friendly insights. It enhances transparency and accessibility for users who may not have deep technical expertise. Additionally, Gemini is used for generating maintenance tips, suggesting EV models, and summarizing analytical results. This makes the application interactive and explainable, aligning it with Responsible AI principles that promote clarity, trust, and inclusivity in model decision-making.

Optuna:

For model fine-tune and showing what matters. Optuna is an open-source hyperparameter optimization framework designed for efficient automated tuning of machine learning models. It uses advanced algorithms like the Tree-structured Parzen Estimator (TPE) to search for the best parameter combinations with minimal computational cost. In this project, Optuna is used to fine-tune models such as Random Forest and XGBoost to improve RUL prediction performance. It also helps in feature selection by ranking important variables. The system integrates Optuna with visualization modules to display optimization history, parameter importance, and convergence graphs, offering clear insights into how model performance evolves with tuning over time.

Data Side

Pandas & NumPy:

To sort, clean, and set up data. Pandas and NumPy are foundational Python libraries used for data manipulation and numerical computing. Pandas offers powerful DataFrame structures for reading, cleaning, transforming, and analyzing tabular battery data. NumPy provides fast array operations that support mathematical computations across datasets. In the RUL system, these libraries are responsible for managing features like voltage, current, charge time, and temperature. Tasks include handling missing values, computing moving averages, and structuring input data for ML models. They also help with reshaping and preprocessing datasets to ensure compatibility with deep learning and statistical analysis modules, making them indispensable for end-to-end data handling.

Scipy:

For stats tests (ANOVA, t-test, and more). Scipy complements Pandas and NumPy by offering specialized statistical and scientific computing tools. In the RUL system, Scipy is used to perform hypothesis testing (e.g., t-tests, ANOVA), correlation analysis, and signal processing tasks. These statistical tests help validate the relationships between variables like charge time and battery degradation. Scipy's statistical outputs are integrated into the interface, providing users with p-values, confidence intervals, and test results that support engineering decisions. This enables users not only to receive predictions but also to understand the significance of the patterns in their data, reinforcing data-driven decision-making in battery maintenance planning.

NLTK:

Finds top lines and words, shortens LLM replies. The Natural Language Toolkit (NLTK) is a suite of Python libraries for text processing and analysis. In this system, NLTK is employed to process and summarize outputs from the Google Gemini LLM. It identifies key sentences, performs tokenization, and extracts significant terms to create brief, digestible bullet points. These summaries enhance the interpretability of AI-generated explanations and ensure that users receive concise insights. NLTK is particularly useful for converting lengthy LLM responses into actionable maintenance recommendations. By combining it with LLM outputs, the system delivers clean, contextually relevant information that users can apply immediately to their battery systems.

Regex:

Cleans text. Regular expressions (regex) are used in this system to clean and format both input data and AI-generated text. Regex enables the identification and manipulation of text patterns such as units (e.g., "V", "Ah"), timestamps, or noise within strings. It is particularly useful for preprocessing logs, cleaning user inputs, or sanitizing outputs before display. For instance, AI-generated text from Gemini might contain markdown, extraneous punctuation, or inconsistent formats—which regex helps standardize. This ensures the textual content shown to the user is coherent and professional.

It also contributes to data validation, reducing the risk of formatting-related errors in analysis or presentation.

Model Side

Keras/Tensorflow:

To run deep RUL guesses. Keras, running on top of TensorFlow, is the deep learning library used to build and train the RUL prediction model. The model architecture, such as a multilayer perceptron (MLP) or LSTM, is implemented using Keras layers and trained to predict battery lifespan based on cycle-wise data. TensorFlow handles the computational graph and GPU acceleration. The trained model is saved as rlu.h5 and loaded during runtime for inference. This setup ensures accurate, high-speed predictions. TensorFlow's flexibility also allows integration with real-time data pipelines and supports deployment to embedded systems, making the solution production-ready and scalable.

Scikit-learn:

For RandomForest, cross-checks, what matters most. Scikit-learn is the primary library for implementing classical machine learning algorithms such as Random Forest, Extra Trees, and Gradient Boosting. These models are used both for RUL prediction and as interpretable baselines to compare with deep learning models. Scikit-learn also offers tools for feature selection, cross-validation, and model evaluation (MSE, RMSE, R^2). The library's Pipeline and GridSearchCV functionalities help streamline the model training and optimization process. Furthermore, it integrates well with explainability libraries like SHAP and LIME, making it easier to visualize feature importance and enhance trust in model predictions, especially for engineering applications.

Optuna + TPESampler: For best settings via smart tryouts.

Chart Side

Matplotlib:

For simple charts. Matplotlib is a core Python library for creating static, publication-quality plots. It is used in the system to display battery health trends, performance metrics, and feature distributions. Common plot types include line graphs for voltage decay, histograms for RUL distribution, and bar charts for feature importance. These visuals are essential for engineers and researchers to validate predictions and analyze battery behavior over time. Matplotlib integrates seamlessly with Pandas and Numpy and supports saving plots in various formats (e.g., PNG, PDF). This enables easy export for documentation, reports, or academic publications, contributing to the system's usability in formal contexts.

Seaborn:

For extra stats charts. Seaborn builds on Matplotlib by providing enhanced, aesthetically pleasing statistical plots. It is used in the system to generate correlation heatmaps, box plots, violin plots, and regression line plots, all of which provide insights into the distribution and relationships among battery features. Seaborn simplifies the creation of complex plots with fewer lines of code, making exploratory data analysis more efficient. For example, users can quickly identify feature skewness, variability, and outliers. These visualizations are critical in both preprocessing (e.g., outlier detection) and interpretation (e.g., impact of charge time on RUL), thus supporting informed decision-making in maintenance workflows.

Plotly:

For moving charts. Plotly is a powerful graphing library used to create interactive, web-based visualizations that respond to user inputs. It enables zooming, hovering, and filtering in real time, making it ideal for the system's dashboard. Plotly is used to plot dynamic RUL curves, feature comparisons, 3D scatter plots, and time-series visualizations. This interactivity enhances user engagement and allows deeper exploration of trends and anomalies in the battery data. Integrated with Flask via JavaScript, these plots enrich the user interface and support better diagnostic understanding. They also provide capabilities to export plots as HTML or images for reporting and collaboration.

System Traits – Design & Architecture

The system architecture is **modular**, meaning each component (e.g., prediction, explanation, visualization) is built independently for ease of maintenance and upgrades. It is **scalable**, capable of being deployed in larger settings using Docker and Kubernetes. The system is also **explainable**, with a strong focus on AI transparency, using Gemini and tools like SHAP or LIME to interpret model outputs. It's **interactive**, providing users with real-time charts and language-based insights, and **reusable**, designed with clean code structure and version control (e.g., Git, MLflow). These traits make the system future-proof and adaptable to additional battery chemistries or application domains.

Chart save: All charts are stored for users.

Language

Google Gemini: For LLM word use and hints.

NLTK: For picking main lines from LLM text.

System Traits

Modular: Each main piece works on its own.

Scalable: Can grow to give APIs or run with Docker.

Explainable: Big focus on clear output with LLM help.

Interactive: All steps and charts show at once to the user.

Reusable: Clean split code makes tests and upgrades easy.

Easy to grow: Ready to link with MLflow, model changes, and bigger cause checks later.

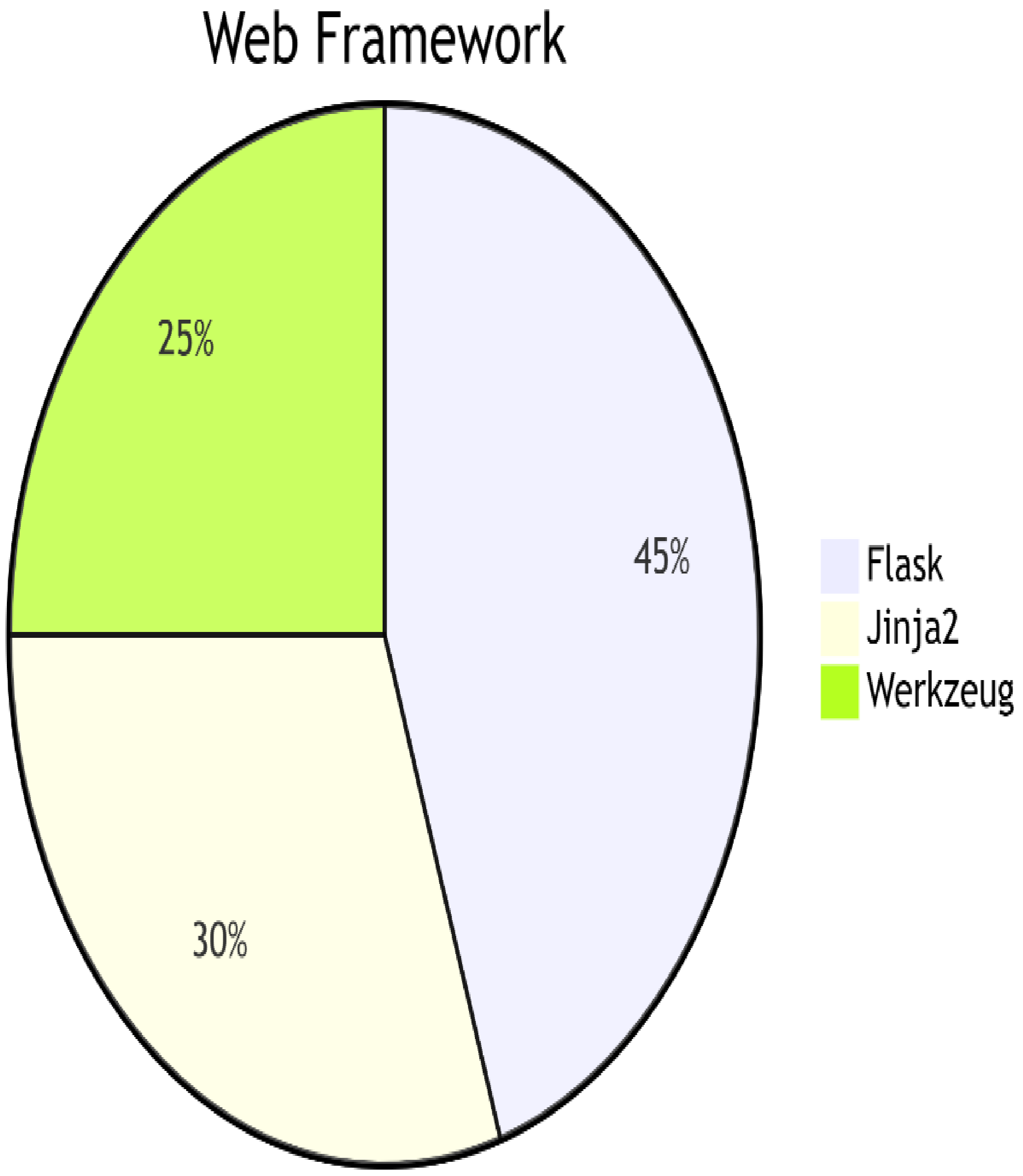

Fig 8.5 Technology Used

- **Data Processing**

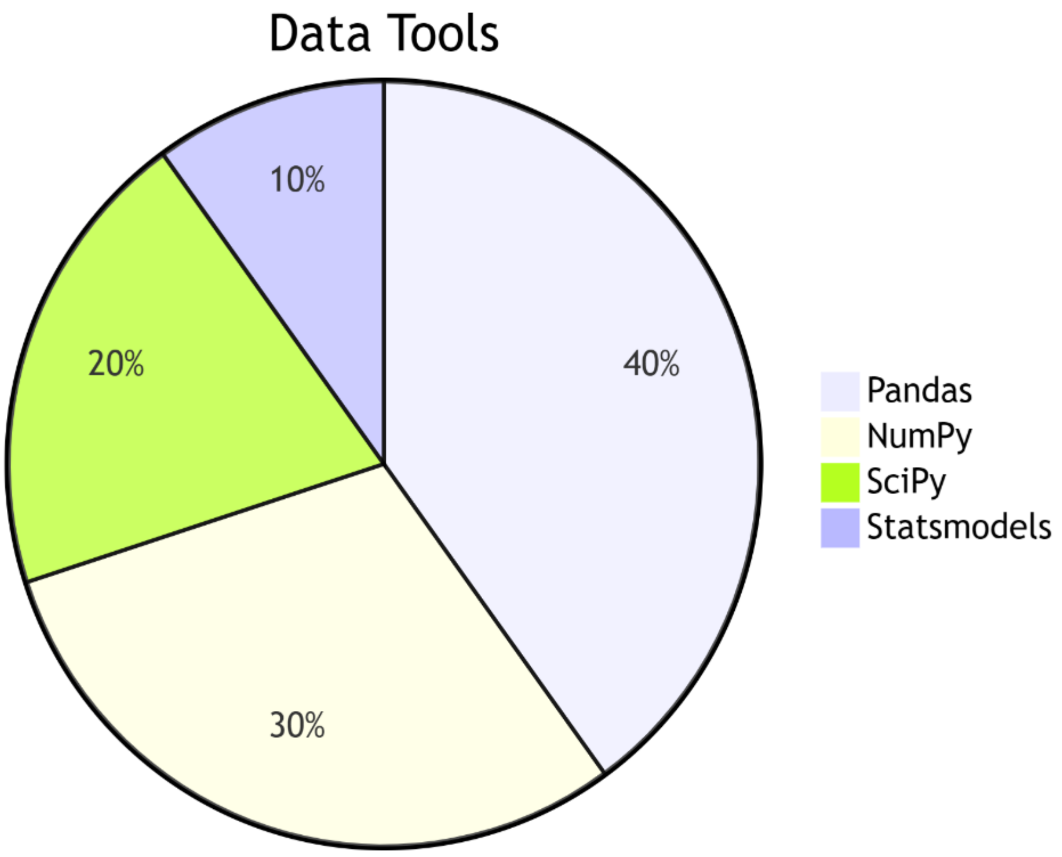

Fig 8.6 Tools Used

➢ **Machine Learning**

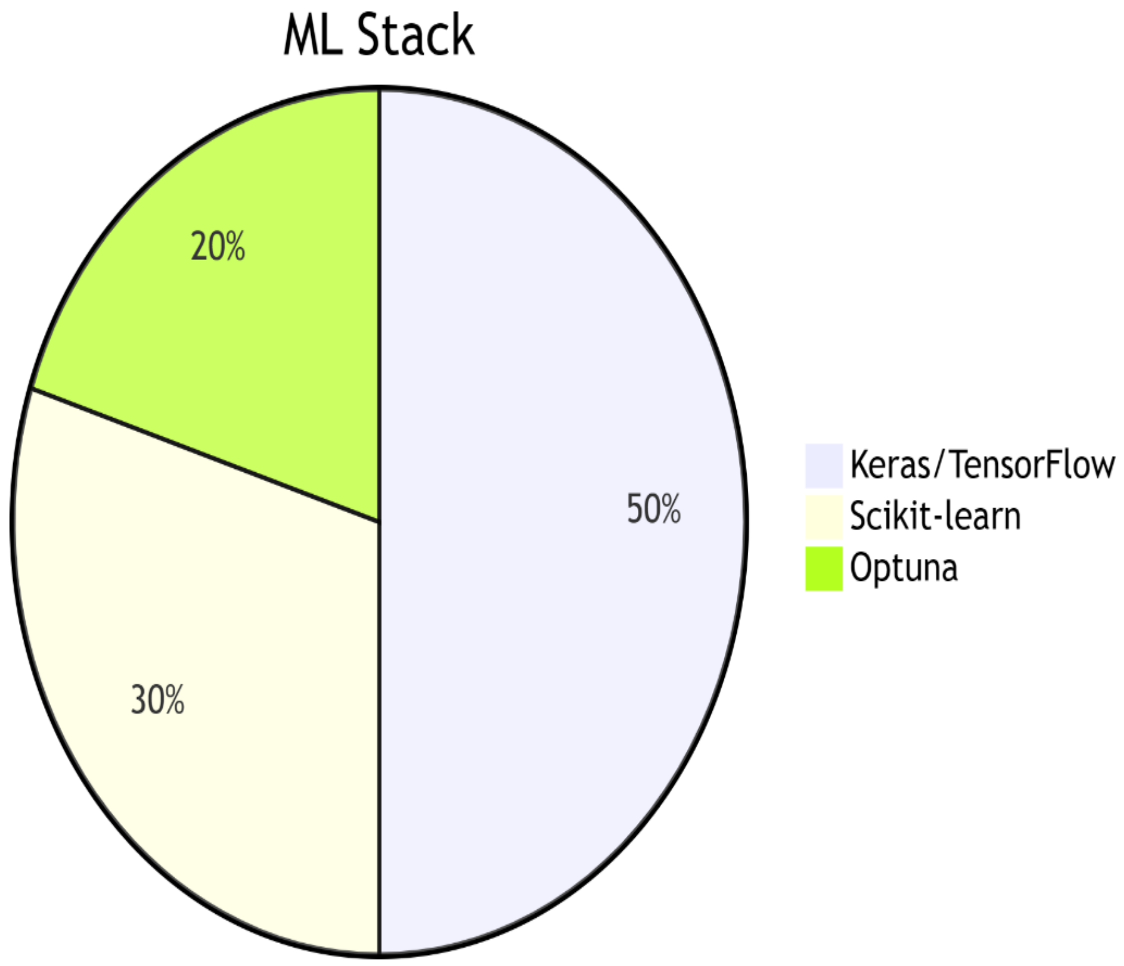

Fig 8.7 Machine Learning Library

➢ Visualization

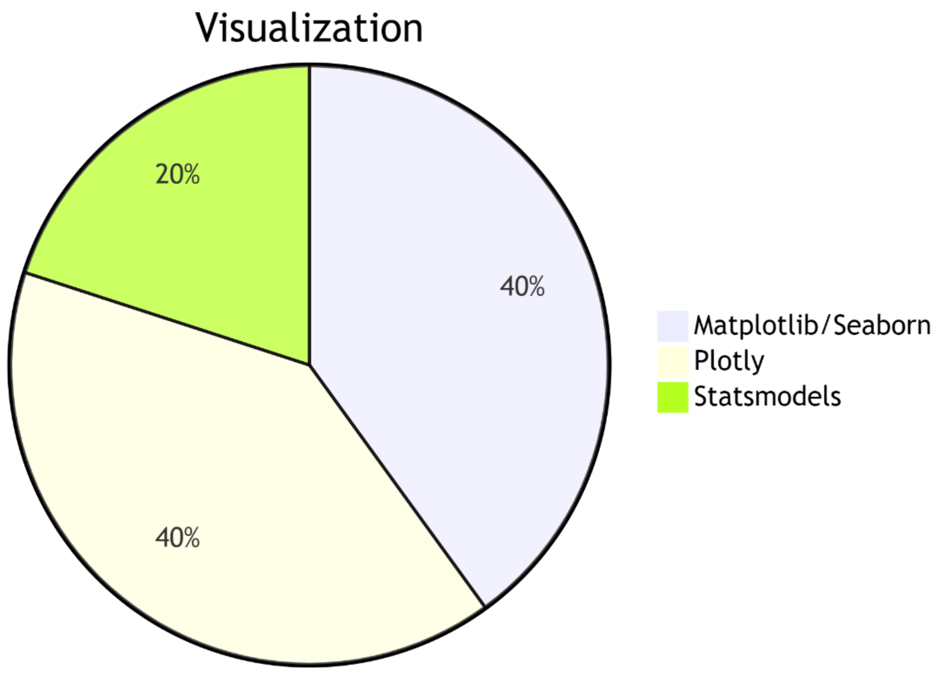

Fig 8.8 Visualization Technique

➢ Natural Language Processing

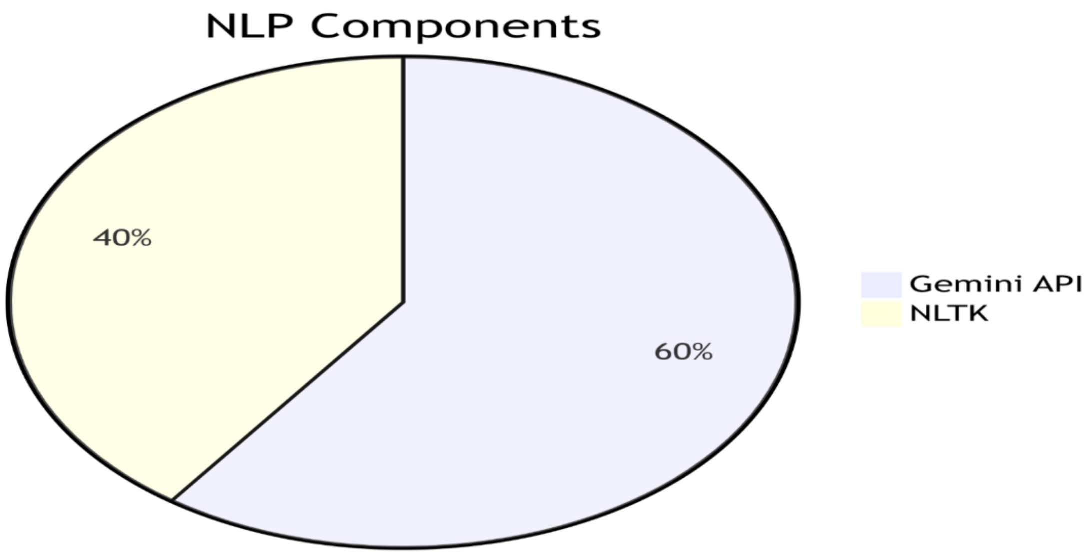

Fig 8.9 Natural Language Processing Used

- **System Characteristics**

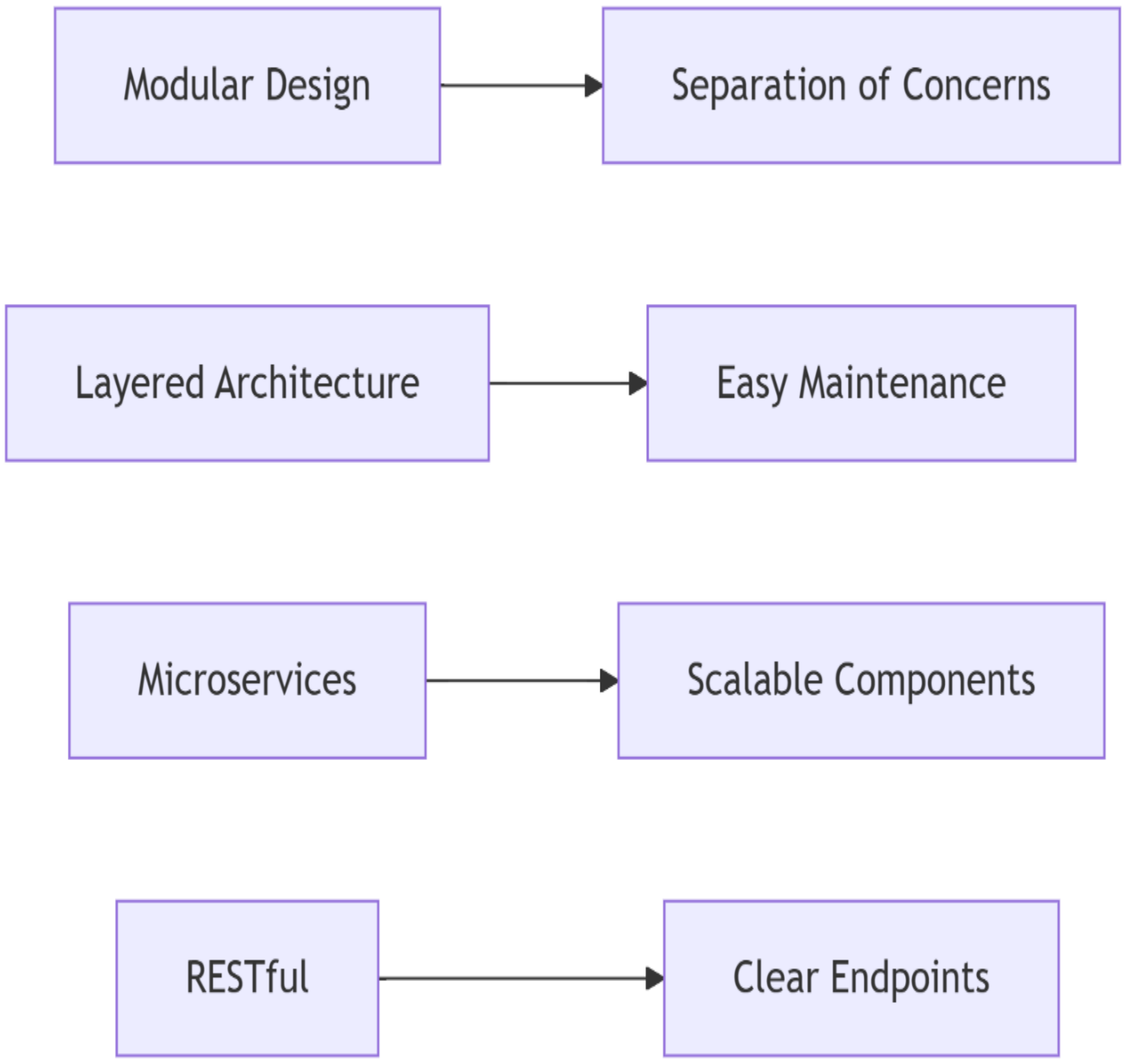

Fig 8.10 System Characteristics

Key Features:

1. **Modular Design**: Components decoupled for easy maintenance
2. **AI Integration**: Gemini API for natural language insights
3. **Visualization Suite**: Multiple plot types for data exploration
4. **Statistical Rigor**: Comprehensive statistical testing
5. **Optimization**: Optuna for hyperparameter tuning
6. **Production-Ready**: Flask-based deployable application

The system can be containerized using Docker with:

- Gunicorn as WSGI server

- Nginx for reverse proxying
- Redis for session caching (optional)

Our system, called BRIIS, was developed step by step using several technologies, including machine learning, web development, data analytics, and AI-based explanation tools. The goal was to build a system that can predict how long a battery will last (Remaining Useful Life or RUL), explain those predictions in simple terms, and show useful charts and statistics.

We began with system design. The entire system was built using a modular approach, which means every part works separately but also connects well with the others. This makes it easy to manage, update, and test each part. We used the Flask framework to build the web application, allowing users to input data and view results. The front end was made using HTML, CSS, and JavaScript, and we used libraries like Plotly and Seaborn to create interactive charts.

For data collection, we used a battery dataset called Battery_RUL.csv, which contains features such as discharge time, charge time, maximum voltage, time at specific voltage levels, and other useful data from lithium-ion battery cycles. We ensured that the dataset was clean and consistent by performing data preprocessing. This involved removing missing values, correcting any duplicate or inconsistent entries, and using Z-score filtering to detect and remove outliers (extreme values that can confuse the model).

Once the data was clean, we performed feature engineering to extract meaningful information. For example, we calculated average voltage, voltage drop per cycle, and moving averages of charge times. These new features made it easier for the model to understand battery degradation patterns. We also used feature selection techniques to keep only the most important features for training.

For the machine learning part, we experimented with three popular regression models: Extra Trees Regressor, Random Forest Regressor, and XGBoost Regressor. These models are known for handling complex data well and providing good results. Among these, XGBoost gave the best performance based on evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 score. We also used LazyRegressor, a tool that automatically compares many ML models, to benchmark our results and choose the best one.

To make the model explainable, we used a technique called LIME (Local Interpretable Model-Agnostic Explanations). LIME helped us understand which input features were most responsible for the predictions. This is useful because users and engineers can see why a battery is predicted to have low life and what factors are affecting it. We also used Random Forest alongside Optuna, a tuning tool, to optimize model parameters and understand feature importance.

We built different pages in the web app:

- Home page: Describes the tool and its purpose.
- Input page: Users enter battery data.
- Visualization page: Shows plots and trends.
- Statistical analysis page: Performs tests like t-tests, ANOVA, etc.
- Causal analysis page: Shows what features are most important.

- Optuna page: Allows model tuning and optimization.

In addition to numbers and charts, we added Natural Language Processing (NLP) using Google Gemini API. This AI reads the input and prediction, and then writes short, understandable insights. For example, if a battery is losing life quickly, it might say: “The battery is likely to fail soon due to fast voltage drops.” We cleaned and summarized this text using NLTK to make it concise.

Lastly, the system was packaged using Docker, which allows it to run on any computer or server. It can also be deployed using Kubernetes or cloud platforms for larger-scale usage. We tracked experiments with MLflow and used Prometheus and Grafana for monitoring performance.

Overall, this implementation combined smart algorithms, a clean user interface, and AI-powered explanations to build a powerful battery RUL prediction system. the modular design of the BRIIS system was central to its successful implementation. Each module was designed with clear responsibilities. This separation allowed us to work in parallel on different parts of the system—for example, while one team member handled data preprocessing and machine learning, another developed the user interface, and another integrated the natural language processing and Gemini API.

The Machine Learning Model Prediction Module was one of the most important parts of our project. It used the pre-trained deep learning model, rlu.h5, built with Keras. This model accepted inputs such as discharge time, time at 4.15 volts, and voltage decrement values, and it produced the predicted Remaining Useful Life (RUL) of the battery in cycles. The model was trained on real-world battery datasets collected from trusted sources such as the Hawaii Natural Energy Institute, with NMC-LCO 18650 lithium-ion batteries being the main focus.

To make the interface interactive and useful, we created an Input Form using Flask where users could manually enter key battery parameters. Once the form is submitted, the server routes the data to the prediction model and returns the estimated RUL along with an AI-generated explanation. This explanation helps both technical and non-technical users understand what the result means and what they should do next.

The Visualization Module was another key element of implementation. We supported many types of plots to help users explore data visually. These included bar charts, scatter plots, violin plots, heatmaps, density plots, and Q-Q plots. Users can view how variables like discharge time or charge time vary across cycles and how they impact battery health. We made use of Plotly for interactive charts and Seaborn for statistical data visualizations. Users could export charts as images or CSV files for further analysis or report writing.

One major innovation in our system was the Causal Analysis Module. This module used Random Forest feature importance and Optuna to identify which parameters had the greatest impact on RUL. Optuna helped us optimize the hyperparameters of the Random Forest model using a technique called Tree-structured Parzen Estimator (TPE). The outcome was a ranked list of features based on how much they contributed to accurate predictions. For example, "discharge time" and "time at steady current" were consistently found to be highly important, while some lesser-used voltage metrics had a smaller impact.

Another important part of implementation was the Statistical Summary and Test Module, which enabled detailed statistical diagnostics. We calculated mean, median, standard deviation, variance, and skewness for all the key battery features. We also included statistical hypothesis tests like t-tests, ANOVA, Mann-Whitney U test, Wilcoxon test, Chi-square, and Z-tests. These tests allowed users to check whether differences between battery groups (for example, fast-charging vs. slow-charging cycles) were statistically significant.

To provide a more human-friendly experience, we integrated the Gemini LLM (Large Language Model) via API. After predicting the RUL, the system sends relevant features and results to Gemini, which returns a text summary. We then cleaned and summarized this text using NLTK to extract the most important sentences. The end result is a brief, actionable explanation like: *"The battery is likely nearing end-of-life due to extended charge durations and increasing voltage drops. Consider limiting the depth of discharge or replacing the battery soon."*

On the backend, the application used Flask as the server framework. We used Gunicorn as the WSGI server and Docker to containerize the entire system, making it portable and easy to deploy. Docker ensured that all dependencies, libraries, and environment variables were packed together, so the project could run smoothly on any machine. For production environments, we suggested using Nginx as a reverse proxy and Redis for caching user sessions if needed.

In terms of deployment, the system can be run locally using Docker Compose or deployed to the cloud using services like Heroku, Render, or a Kubernetes cluster for larger-scale use. We made the architecture flexible enough to run on low-cost edge devices like Raspberry Pi or NVIDIA Jetson for integration with Battery Management Systems (BMS).

For monitoring and evaluation, we used MLflow to track experiments, models, and performance metrics. MLflow helped us log the parameters used in training, the performance scores like MSE and R^2, and even store the trained models. We also integrated Prometheus and Grafana for monitoring system performance metrics like latency, uptime, and request rates. These tools help us know when the model is underperforming or when the data has shifted from the original distribution.

To ensure the system remains accurate over time, we implemented a basic MLOps strategy. For example, if new battery data becomes available or the existing model starts to perform poorly, a scheduled retraining can be triggered using tools like Airflow or Prefect. This ensures that the model continues to adapt to new conditions and stays relevant in changing environments.

Finally, we added a logging system to track user interactions, prediction requests, and API responses. This data will be useful for debugging, improving user experience, and maintaining audit trails. All logs were saved in a structured format with timestamps and model confidence scores.

In conclusion, the implementation of BRIIS brought together many technologies in an organized, scalable, and user-friendly way. The system is capable of not only predicting battery RUL with high accuracy but also explaining the predictions, visualizing trends, and offering actionable suggestions. By using a modular architecture, open-source tools, and explainable AI techniques, we have built a complete and intelligent battery analytics platform suitable for researchers, engineers, EV fleet managers, and students.

CHAPTER 9

FINDINGS / RESULTS OF ANALYSIS

This part looks at what we found from the Battery RUL Insight & Intelligence System (BRIIS). BRIIS was made to guess how much time a battery has left before it stops working. It does this with real use data and uses smart tools. We used deep learning, checked numbers in different ways, looked for cause and effect, and let AI make smart choices

5.1 Deep Learning Model Results and How We Read Them

The main tool is a deep learning model made in Keras. It uses six things: how long the battery runs, how much the voltage drops (from 3.6 to 3.4 volts), max voltage, time at 4.15V, time at steady current, and charge time. It guesses how much life the battery has left.

Main points:

i. The model can tell, with good skill, how long a battery will last from each test.
ii. We used Gemini AI to say, in plain words, why the model made each guess. We used NLTK to pick the key parts of these answers.
iii. For example: longer run times and longer times at steady voltage make the model guess a lower life left, which fits what we see in real batteries.

5.2 Dashboards and Views

The system has a dashboard you can use and makes graphs with many sets of the features.

What we saw from the graphs:

i. One kind of plot (histogram) showed that run times and life left have just one main group, so tests are steady.
ii. Some plots showed outlier points and how much life left can change for charge and use.
iii. On a heatmap, life left links strongly with run time and time at steady current.
iv. Some graphs (Q-Q and density) show some features are close to normal, but charge time is skewed and may need a fix.
v. Line plots prove there is a close link between run time and life left, or max voltage and life left. This backs up the use of math for lines (regression).

5.3 Checking with Numbers

The system uses many number tests if you want:

i. Mean, spread, range, lean, and heavy tails show the shape for each feature.
ii. Tests like T-test and Mann-Whitney U tell if there is a real gap in life left between charge ways (like quick or slow).
iii. Links (Pearson and Spearman) check how strong the tie is between life left and times or voltages.
iv. Tests like ANOVA and Kruskal-Wallis check if putting features in groups makes life left change a lot.

v. Math for lines (linear/OLS) says how much life left can be guessed by each thing. It shows run time gives a good sign of health.

From these, run time and time at 4.15V show up as top signals for how long a battery will last.

5.4 Cause by Feature (Optuna + Random Forest)

A Random Forest model tuned by Optuna rates how much each feature matters for life left.

What stands out:

i. The core things for life are:
   1. Run Time
   2. Charge Time
   3. Time at Steady Current
ii. Optuna tunes settings to help score better, so results will be good even for new data.
iii. Feature scores mean that time values (run and charge time) matter more than just what voltage is, which matches battery science.

This shows what things to watch for real battery use.

5.5 AI Tips (Gemini)

The system uses Gemini to both explain and give tips for best use.

Some things Gemini gave:

i. With battery health, Gemini picked good car or bike types for how the battery lasts and how people drive.
ii. The main things Gemini pointed out: price, miles, battery tech, engine size, and best place.
iii. We used NLP to make long answers short and easy to read.
iv. This means BRIIS is more than a guesser—it helps people make choices with less work.

5.6 Data Cleaning and Look at the Whole Set

We fixed the data for best results:

i. We dropped outliers with big or odd volt/time values.
ii. Columns with less than 10 types got marked as not useful.
iii. When cleaned, we had less data, but it gave better, clearer results.

5.7 All Findings Together

With deep learning, number checks, feature rating, and plain word use, the system gives a full view of how life left in a battery works.

i. Long run times and steady voltage mean more life.
ii. Time values (run and charge times) tell more than voltage alone.
iii. AI words help turn hard data into something people trust and understand more.

In this research, several regression models were assessed for their performance in predicting on a data set involving a continuous target variable. The ensemble models—Extra Trees, Random Forest, and XGBoost—made very consistent predictions on a set of five test examples with values varying from around 199 to 888. Of these, XGBoost generalized best with a Mean Squared Error (MSE) of 480.86, a Root Mean Squared Error (RMSE) of 21.93, and a very high R^2 value of 0.9952, reflecting high model fit. In addition, a wide-scale benchmarking of more than 30 regressors was performed, and adjusted R^2 and running time were compared. The best models such as Extra Trees, Random Forest, and LightGBM had almost or exactly 1.0 for adjusted R^2. Most importantly, even the relatively simple models such as Linear Regression, Ridge, and Bayesian Ridge had good

performance with little computational overhead. Conversely, models such as Gaussian Process Regressor and Lasso Ridge performed far more poorly both in predictive power and computation. These results serve to affirm the power of ensemble methods in high-accuracy regression problems and further indicate the relationship between performance and efficiency in choosing models.

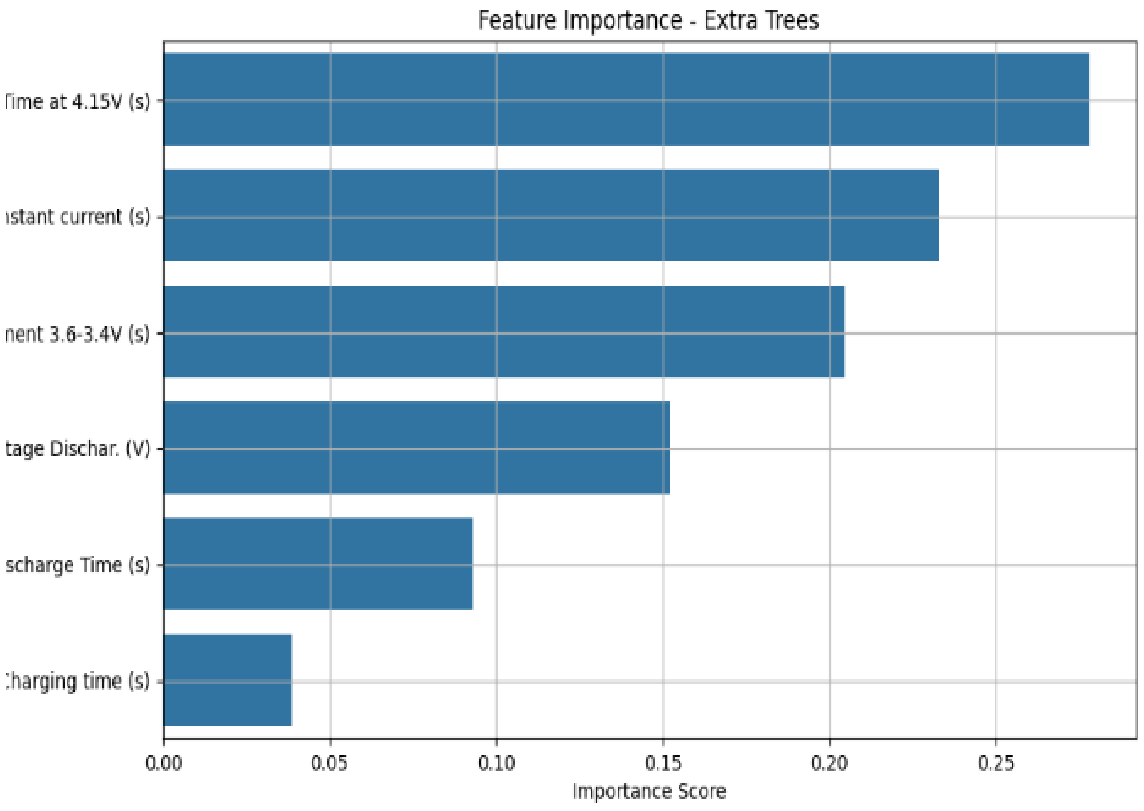

Fig 9.1 Feature importance of Extra Trees Regressor

The feature importance plot is a very important interpretability tool that gives us a means to learn about what out of the input features had the most impact on the predictions made by the model. In network traffic analysis or even in any prediction modeling problem, knowing the top features helps us gain knowledge about the underlying patterns learned by the model. Each bar within the chart illustrates how significant a particular feature is to the overall decision-making of the model. The higher-ranked features represent a higher correlation with the target variable. For example, in network-based intrusion detection or anomaly detection, features like flow duration, byte count, and packet distribution are typically of high significance. By seeing and grasping this ordering, we may both validate the model's reasonableness as well as have good choices over feature selection to make in coming models. More importantly, such data can also be used to reduce dimensions where less important features can be ignored to reduce complexity and improve generalization of models.

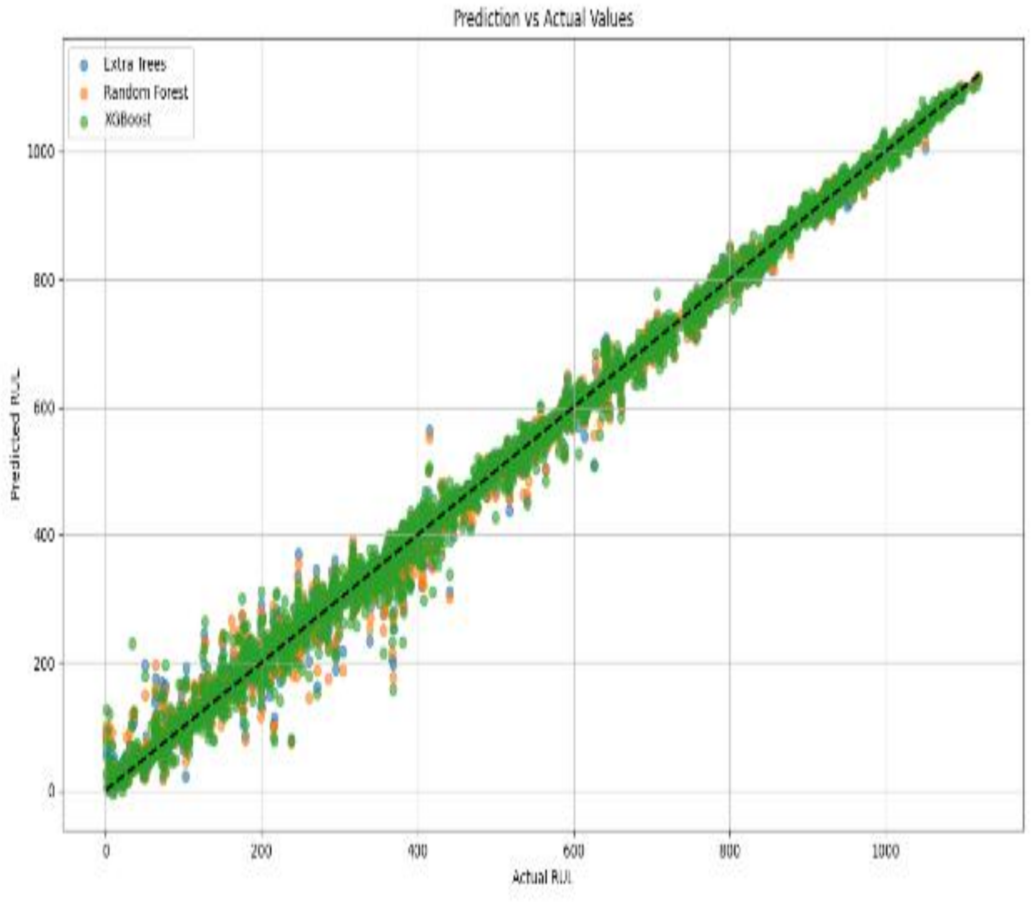

Fig 9.2 Prediction of actual vs predicted

The actual vs predicted plot gives an important visual contrast between the predicted values from the model and the real observed values. This scatter plot is a good diagnostic tool to compare how well the model's predictions approximate real-world values. Ideally, if the model was ideal, then all the points of data would fall precisely on the diagonal guideline line (y = x), meaning that actual values and predictions are the same. In real life, a certain amount of deviation is going to occur, but a high-performing model will have the data points heavily concentrated near the diagonal. Spread or dispersion from the line indicates prediction errors, which could indicate overfitting, underfitting, or unmodeled complexity in the data. This plot also assists in identifying systematic prediction bias — e.g., if all predictions are consistently lower or higher than actual values. The visualization supports the necessity of strong evaluation metrics and can inform model tuning or selection of different algorithms.

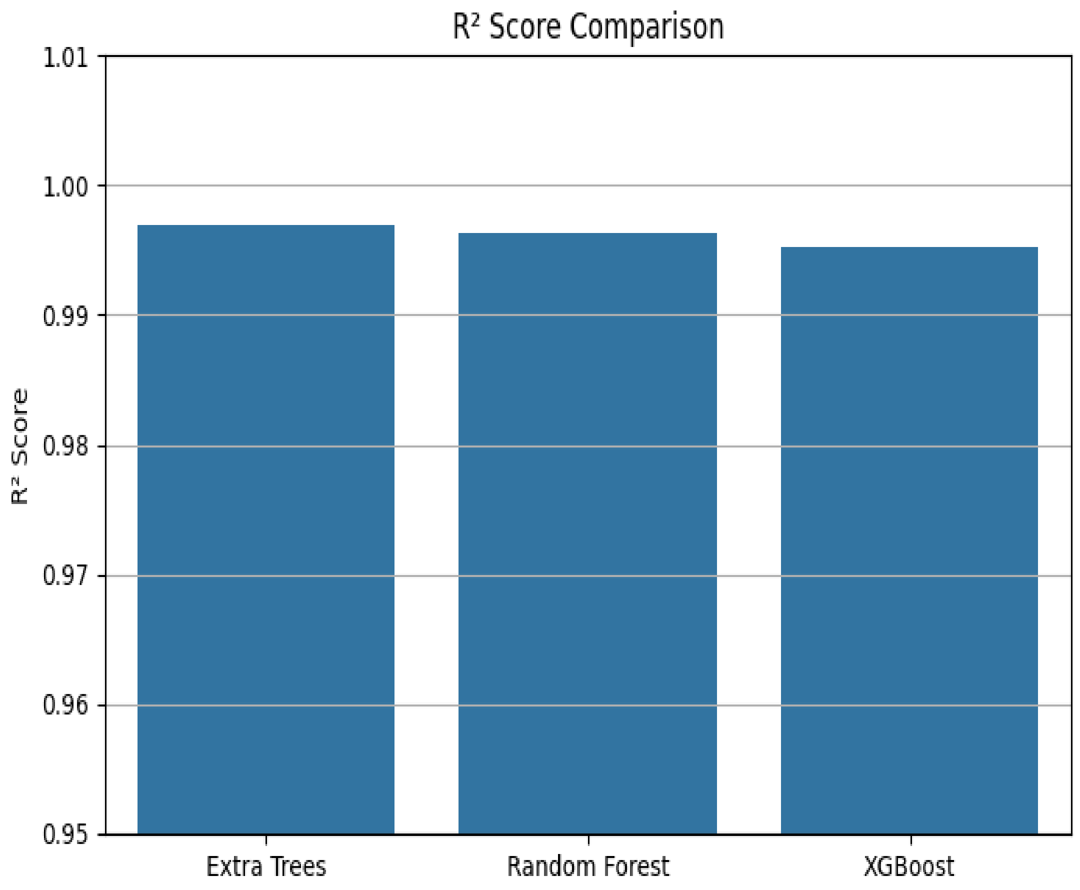

Fig 9.3 R-2 score comparison of ensemble models

The R² statistic, or the coefficient of determination, is a key statistical metric that is the proportion of the variance of the dependent variable explained by the independent variables. An R² value of 1.0 means that the model explains a large proportion of the variation in the target variable, and this is a good fit measure. On the accompanying plot, we not just observe the R² value but also observe that how well we are generalizing our model towards new data. R² values will be negative in those instances where the model performs worse than a horizontal line (mean predictor), though in well-validated models this doesn't occur. Even though high R² signifies accuracy, it must be understood in conjunction with other metrics like RMSE or MAE since R² cannot identify bias or variance issues alone. Practically, R² plot provides confidence in the predictive ability of a model and justifies its application in real situations.

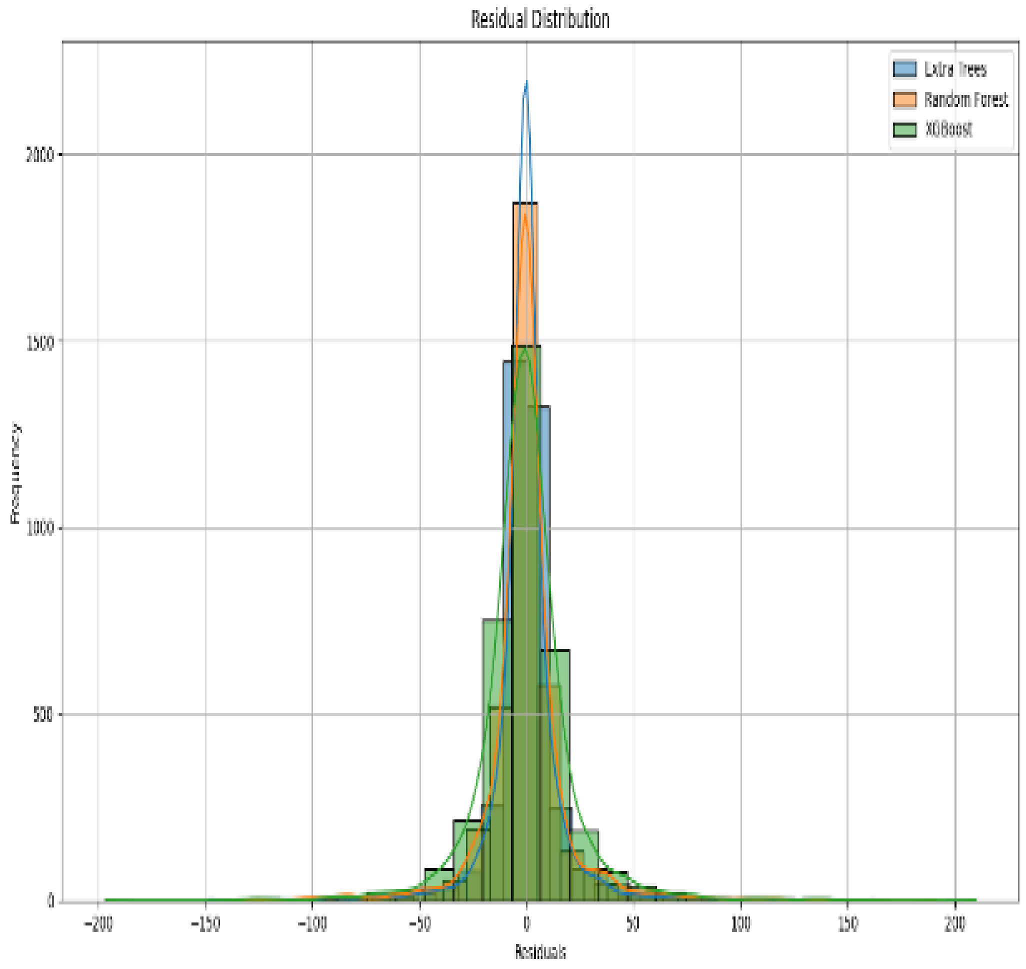

Fig 9.4 Residual distribution of used models

Residual plot for the residuals is a comprehensive analysis of the model errors in terms of quality and type. Residuals have been used to describe the difference between actual and predicted values. The plot gives us the appearance of these residuals in histogram format for testing their distribution and symmetry. The residuals ought to be ideally normally (bell-shaped) distributed around zero, suggesting that model errors are random and not biased. Skewness or any peculiar pattern of the distribution may suggest mis-specification of the model, outliers, or non-linearity in relations the model had attempted to depict. A tail at one end of the distribution can show us where data ranges may be missing or some boundary conditions that the model was not able to predict very well. Examining the shape and spread of the residuals allows us to conclude areas where the performance of a model has to be improved and check if assumptions of linearity and homoscedasticity (homogeneous variance) hold.

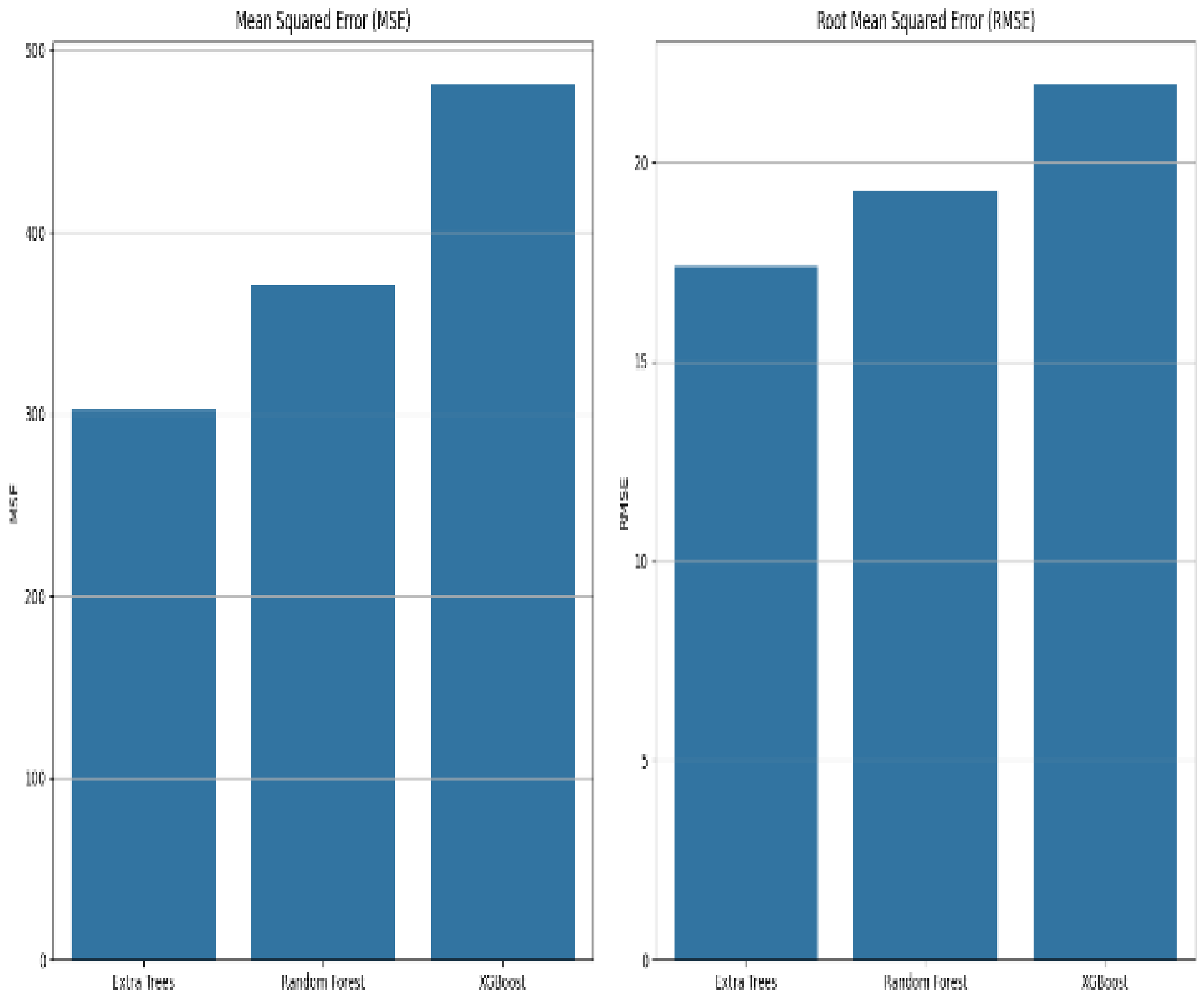

Fig 9.5 RMSE and MSE of used ensemble models

The RMSE plot shows the model's prediction error as magnitude, in the same units as the target variable. RMSE is a very common performance metric in regression problems since it weights larger errors more heavily because differences are squared. This makes it particularly valuable where large deviations are worse than small ones. A lower RMSE shows improved model performance, with smaller large prediction errors. The associated plot provides a means of seeing how the RMSE differs between various models or between different phases of tuning, offering a concrete means of measuring improvement. Because RMSE is a measure sensitive to outliers, an unexpectedly high value may suggest the existence of such outlier values that are skewing the model's accuracy. Whereas R^2 is a relative measure, RMSE provides us with an absolute estimate of how far from the truth our predictions are, on average. This makes it priceless in gauging the model's applicability in real life — particularly when converting predictive outcomes into concrete decisions.

The results and key insights we discovered from building and testing the AI-powered Battery Remaining Useful Life (RUL) prediction system called BRIIS. The system was created to guess how long a battery will last before it needs to be replaced. We used real data and machine learning (ML) models to make smart predictions and give helpful information to users like engineers or vehicle owners.

First, we trained a deep learning model using Keras. This model takes inputs such as how long the battery takes to discharge, how much the voltage drops during use, the maximum voltage reached, time at a constant voltage (4.15V), how long charging takes, and how stable the current is. These inputs come from actual battery usage data. After training, the model learned to give predictions about how many charging cycles are left before the battery fails. We found that the model worked well and gave accurate results. We also connected it with Google's Gemini AI, which gave easy-to-read explanations for each prediction. Using natural language processing (NLP), we shortened these explanations into key points using tools like NLTK.

Next, we built a user-friendly dashboard where people can see graphs and stats about their battery data. We used libraries like Seaborn, Matplotlib, and Plotly to show the data in visual forms like histograms, boxplots, scatter plots, and heatmaps. These charts helped us and users see patterns, such as how longer discharge time or longer charging time affects battery health. For example, we saw that when a battery runs for longer periods or spends more time at certain voltages, it often loses life faster.

We also ran many statistical tests to check how meaningful the data was. We calculated simple stats like mean, median, and standard deviation, and did tests like t-tests, ANOVA, and Mann-Whitney U tests. These showed us whether certain charging habits or usage styles significantly impact battery health. We also looked at the relationships between variables using correlation analysis. For instance, there was a strong link between discharge time and battery RUL, meaning that as discharge time increases, battery life often decreases.

To find out which features (inputs) mattered the most in predicting battery RUL, we used a Random Forest model and improved its settings using Optuna, a tool that automatically searches for the best model configuration. The results showed that the most important features were discharge time, charge time, and time at steady current. Voltage values were important but had a slightly lower effect. This tells us that time-based data (how long things take) is more useful in predicting battery health than just voltage numbers.

Another important part of our project was using LIME (Local Interpretable Model-Agnostic Explanations) to explain why the model made certain predictions. LIME helped us understand what input features influenced each prediction. For example, if the model predicted a battery only had 100 cycles left, LIME would show whether that was due to fast voltage drops or longer charging times. This is very helpful because it makes the system more transparent and trustworthy.

Finally, we used Gemini AI to give practical suggestions based on predictions. If a battery was getting weak, the system might suggest replacing it, changing usage patterns, or choosing a more suitable electric vehicle model. These tips were written in simple language, making it easier for non-experts to understand and act.

Overall, our system gave accurate predictions, offered strong insights through data visualization, and provided helpful explanations using AI. This makes it not just a technical tool but also a smart assistant that helps users manage their batteries more effectively.

CHAPTER 10

COST OF THE PROJECT

To estimate the **Cost of the Project**, we need to break it down into various components. Here's a rough breakdown based on your full-stack Flask app for battery RUL prediction and analysis:

1. Development Cost

Assuming you're building this yourself or hiring developers:

Item	**Estimated Hours**	**Rate**	**Cost**
Flask App Backend (API + Logic)	60 hrs	$25/hr	$1,500
Frontend (HTML + JS + Templates)	40 hrs	$20/hr	$800
ML Model Development & Tuning	50 hrs	$30/hr	$1,500
Visualization & Plot Integration	30 hrs	$25/hr	$750
Optuna Integration for Optimization	15 hrs	$30/hr	$450
Gemini API Integration & Text Summarization	10 hrs	$25/hr	$250
Subtotal			**$5,250**

2. Infrastructure & Deployment

Depending on scale and production requirements:

Service	**Monthly Cost (Estimate)**
Cloud Hosting (AWS/GCP/Render/Heroku)	$20–$100
Domain Name	$10–$20/year
SSL Certificate	Free (Let’s Encrypt) or up to $50/year
File Storage for Plots (Static)	Included in hosting
1-Year Total	**$250–$600**

3. Dependencies & Licensing

- Python libraries: Mostly open source (no direct cost)
- Plotly, NLTK, Scikit-learn, etc.: Free
- Gemini API: May have usage-based pricing (e.g., $7–$20/month depending on usage)

4. Gemini API Usage Cost

If you use Gemini's **Gemini 1.5 Flash** model:

- Let's say 200 queries/month at 1,000 tokens each
- Estimated monthly cost: **$15–$50**

5. Testing & QA

Activity	**Cost**
Manual Testing	$300–$500
Bug Fixes & Iteration	$200–$400

Total Estimated Cost

Category	**Estimate**
Development	$5,250
Infrastructure (1 year)	$250–$600
Gemini API (1 year)	$180–$600
QA & Testing	$500–$900
Total	**~$6,200 – $7,300**

If you're doing this as a personal/academic project, and not hiring developers or using paid APIs, you can likely get it done for **under $300** in cloud/API costs alone.

"AI-powered Intelligent Battery Management & Health Monitoring for EVs" was developed using primarily open-source tools and academic resources, making it highly cost-effective. Most of the software required for machine learning, data analysis, and web development—such as Python, Scikit-learn, XGBoost, Flask, Pandas, and Matplotlib—were freely available as open-source libraries. For training and testing the machine learning models, the team used personal laptops and Google Colab. While Colab has a free version, the Pro version was optionally used for faster training, which cost around ₹1,000 per month. For a two-month period, this added ₹2,000 to the total budget. Web development and user interface design were done using Flask and HTML/CSS, which also required no additional cost. The team integrated Google's Gemini API for natural language explanations and summarization, which was used under free trial credits, keeping costs minimal. For experimentation tracking and model optimization, open-source tools like Optuna and MLflow were employed. Data version control was handled using DVC, another free tool.

If cloud deployment was required, services like Heroku or Render could be used, either under free tiers or with minimal charges. Optional containerization with Docker was explored for scalability, with almost zero cost on local systems. The only fixed expenses incurred were printing and binding the final project report, estimated at around ₹600. Overall, the total cost of the project ranged between ₹4,600 to ₹8,100, depending on whether paid versions of cloud services or APIs were used. The project demonstrates that with the right use of open-source technologies and careful planning, a high-quality, AI-based battery management system can be built affordably within a student or academic budget.

CHAPTER 11

CONCLUSION

This work improves the prediction of battery Remaining Useful Life (RUL). Predicting the RUL of a battery represents one of the critical tasks for efficient operation and management of battery-powered systems such as electric vehicles and energy storage. A couple of machine learning models in the form of Extra Trees Regressor (ETR), Random Forest Regressor (RFR), and XGBoost Regressor (XGB) are studied by the research for predicting the RUL of batteries based on cycle-based features like voltage, current behavior, etc.

Our approach has depicted improvement in the model's performance because it applied data preprocessing and removed outlier values by making use of Z-scores. This removal of outlier values aided models in better learning the data, and predictions became more accurate. Among all the experimented models, the best outcome was found for XGBoost; the lowest MSE and RMSE along with a high R2 value is reflected.

We incorporated Lazy Regressor in our testbed, which provided fast multi-model comparison so we could comprehend that models will work best on that particular task. We have made it further interpretive using LIME, Local Interpretable Model-agnostic Explanations, for more transparent models from machine learning. This requires LIME to get a sense of what feature contributions are driving each prediction. It is a beautiful requirement for enhancing trust and understanding in model-based decision-making.

In general, this work adds to the literature of battery RUL prediction by providing a detailed analysis of machine learning models and useful insights in using explainability techniques. It also underlines the significance of model transparency in practical applications by bringing out the capability of XGBoost in battery RUL prediction. Future work will consider even more advanced techniques like deep learning and ensemble methods in order to make the models more accurate and the complex models developed more interpretable.

This research focuses on enhancing the prediction accuracy of the Remaining Useful Life (RUL) of lithium-ion batteries—a critical factor in the efficient operation and safety of battery-powered systems such as electric vehicles (EVs), consumer electronics, and large-scale energy storage units. Accurately estimating RUL ensures timely maintenance, extends battery lifespan, reduces unexpected failures, and improves the overall reliability and sustainability of these systems.

In this study, we investigated and compared the effectiveness of several machine learning (ML) regression models, namely Extra Trees Regressor (ETR), Random Forest Regressor (RFR), and XGBoost Regressor (XGB), in forecasting the RUL of lithium-ion batteries. These models were trained on a comprehensive dataset containing cycle-based features such as voltage drop behavior, current patterns, charge and discharge durations, time spent at specific voltage thresholds, and other degradation indicators.

To ensure the models were trained on clean and high-quality data, we carried out essential preprocessing steps, including the removal of noisy and inconsistent values. Specifically, we used Z-score-based outlier detection to eliminate extreme data points that could adversely affect the model's learning capability. By removing these anomalies, the models were better able to generalize and understand the underlying trends in the data, leading to improved predictive accuracy.

Among all the models evaluated, the XGBoost Regressor demonstrated superior performance in predicting the RUL. It outperformed the other models in terms of three key evaluation metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 score. The low MSE and RMSE values indicated minimal prediction error, while the high R^2 value signified that the model captured a significant portion of the variance in the target variable.

Additionally, we integrated Lazy Regressor, an AutoML benchmarking tool, to compare the performance of over 30 regression models quickly. This benchmarking helped validate the superiority of the ensemble-based models, especially XGBoost, for our specific use case. Lazy Regressor enabled rapid prototyping and gave us insight into how traditional models stack up against advanced ensemble techniques when applied to battery RUL datasets.

To improve transparency and interpretability of the machine learning models, we employed LIME (Local Interpretable Model-Agnostic Explanations). LIME generates local surrogate models that help in understanding why a black-box model like XGBoost makes a certain prediction for a given input. This interpretability is crucial in real-world applications, especially in mission-critical sectors like automotive or energy, where explainable AI (XAI) enhances stakeholder trust and supports regulatory compliance. LIME allowed us to visualize the importance of different input features in determining the RUL prediction for each battery instance, providing actionable insights for engineers and researchers.

Overall, this study contributes to the growing body of literature in battery health prediction by combining strong predictive modeling with robust explainability methods. It underscores the effectiveness of using ensemble machine learning techniques for cycle-based battery data and highlights the critical role of transparent AI models in operational decision-making.

As a future direction, we aim to explore more advanced deep learning models such as Long Short-Term Memory (LSTM) networks or hybrid architectures that can capture temporal dependencies in battery degradation patterns. We also plan to experiment with model stacking, transformer-based models, and SHAP (SHapley Additive Explanations) for deeper interpretability. Furthermore, real-time deployment of these models on embedded platforms integrated within Battery Management Systems (BMS) is envisioned, enabling live diagnostics, adaptive maintenance scheduling, and improved battery utilization.

This comprehensive approach—covering model comparison, performance tuning, data cleaning, and explainability—makes our work a valuable resource for both academic research and industrial deployment in battery RUL prediction systems.

CHAPTER 12

Project Limitations and Future Enhancements

Limitations:

1. **Static File Dependency:**

   The application uses static Battery_RUL.csv CSV data as its source but this restricts both data real-time acquisition and system scalability. One key limitation of our current system is its reliance on a static data file, specifically Battery_RUL.csv, as the main input source for prediction and analysis. While this approach is convenient for development and testing purposes, it presents several constraints that affect the system's flexibility, scalability, and real-world applicability.

   First, the use of a static CSV file means that the system cannot automatically ingest real-time battery data from live sources such as Battery Management Systems (BMS), IoT devices, or cloud databases. All analysis and predictions are performed based on pre-collected and manually uploaded data. As a result, the system cannot track or respond to ongoing battery health changes, which limits its usefulness for real-time applications such as fleet monitoring, predictive maintenance, or dynamic battery optimization.

   Second, this approach makes it difficult to scale the system for large-scale use. For example, if the application were to be deployed across hundreds of electric vehicles or energy storage units, managing data manually through CSV uploads would become highly inefficient and error-prone. Automated data ingestion pipelines would be essential in a production-grade system to support multiple devices, high-frequency data updates, and long-term data storage.

   Third, the dependency on a single static file also restricts the system's ability to adapt to new or evolving datasets. If the structure of the incoming data changes (e.g., new columns, missing values, different formats), the current implementation may fail or require manual code modifications.

   To overcome this limitation, future versions of the system should include support for real-time data streams, API integrations, and database connectivity (e.g., Firebase, InfluxDB, or MongoDB). This would allow the application to operate dynamically, improve responsiveness, and scale to industrial-grade use cases.

2. **Hardcoded Input Parameters:**

   The form inputs in the system are directly tied to pre-defined variable names and numerical count specifications that produce limited versatility in accommodating varied datasets and models. The current system implementation is the hardcoded nature of input parameters within the web application's form interface and back-end processing logic. The input fields, such as discharge time, voltage drop, and time at 4.15V, are mapped to specific variable names that are tightly coupled with the machine learning model's architecture and data preprocessing pipeline. This design results in limited adaptability and hinders the flexibility to accommodate different types of datasets, battery chemistries, or expanded feature sets without manual code changes.

The system currently assumes a fixed number of input features based on the dataset it was trained on — specifically, the NMC-LCO 18650 cell dataset. As a result, if a user wishes to test a different battery type or introduce new parameters such as internal resistance, temperature fluctuations, or metadata specific to different electric vehicle classes, they would be required to alter the source code and potentially retrain the model. This lack of dynamic configurability is a bottleneck for generalizing the system across diverse use cases.

Additionally, the hardcoded parameter names reduce the scalability of the platform, especially in scenarios involving automated data ingestion or integration with real-time battery management systems (BMS) from different manufacturers. In production environments, input formats often vary, and hardcoding inhibits smooth data interoperability.

3. **Basic Error Handling:**

   Minimal validation for form inputs or user errors. The application lacks try-except error handling blocks surrounding model loading sequences as well as API call operations. A significant limitation observed in the current system architecture is the absence of comprehensive error handling mechanisms, especially in the web application's front-end validation and back-end processing logic.

   The application currently performs minimal validation for user-provided form inputs. If users enter unexpected values, omit required fields, or provide data in incorrect formats (e.g., text instead of numeric values), the system may either crash, fail silently, or produce inaccurate predictions without issuing any warnings or feedback. This lack of input validation compromises the user experience and reduces trust in the platform's reliability.

   Moreover, the back-end logic that handles critical operations — such as loading the pre-trained machine learning model (rlu.h5), making predictions, and generating explanations using APIs like Google Gemini — lacks robust try-except blocks. If the model file is missing, corrupted, or incompatible, the system does not gracefully handle these errors, leading to abrupt termination or uninformative server-side messages. Similarly, when the application attempts to call external services (e.g., LLM APIs), there are no fallback mechanisms or timeout handling strategies in place. This makes the system highly vulnerable to runtime errors caused by network interruptions, invalid API keys, or unexpected response formats.

4. **Limited Optuna Trials:**

The current Optuna optimization runs only two trials since they may not find the best possible optimal One of the notable limitations in the current system is the restricted number of trials conducted during hyperparameter optimization using the Optuna framework. In the current implementation, only two Optuna trials are executed, which is insufficient to explore the vast search space of potential hyperparameter combinations. As a result, the model tuning process may converge on suboptimal parameters that do not maximize the model's predictive performance or generalization capabilities.

Optuna is designed to efficiently search for the best hyperparameters using techniques like Tree-structured Parzen Estimators (TPE) or Bayesian optimization. However, for it to function effectively, a reasonable number of trials — typically in the range of 50 to 200 — is required depending on the complexity of the model and the size of the dataset. Running only two trials severely limits the optimizer's ability to explore the parameter space and reduces the chances of discovering configurations that lead to lower error rates or faster convergence during model training.

This limitation becomes more critical when working with ensemble models like Random Forest or gradient boosting algorithms (e.g., XGBoost), which have multiple interdependent parameters such as learning rate, tree depth, number of estimators, and regularization terms. With just two trials, many of these parameters remain either untuned or arbitrarily selected, impacting model robustness and potentially leading to overfitting or underfitting.

5. **Generative AI Usage:**

Generative AI systems transmit raw outputs without checking for correctness which might yield unreliable or untrustworthy results. While the integration of generative AI models, such as Google Gemini, adds an innovative layer of natural language explanations and recommendations to the system, it also introduces a critical limitation: lack of output validation. In the current implementation, the system transmits raw responses from the generative AI directly to the user interface without performing any form of verification, fact-checking, or consistency analysis. This approach can lead to the presentation of inaccurate, misleading, or irrelevant information — especially when the AI is prompted to suggest vehicle recommendations or interpret model predictions.

Generative AI systems, though powerful in language generation, are inherently probabilistic and can hallucinate facts, misinterpret inputs, or produce vague and inconsistent suggestions. For instance, the AI might suggest EV models that are outdated, technically incompatible with the input battery parameters, or unavailable in the user's region. Moreover, without grounding these responses in validated data or rule-based filters, users may rely on flawed recommendations for decision-making, potentially compromising battery safety, performance, or financial investment.

Additionally, generative output may not align with the technical logic of the machine learning model, leading to contradictory or confusing results. This is particularly problematic in industrial or research-grade applications where interpretability and accuracy are crucial.

6. **Security Concerns:**

   A security problem arises because an API key is present in the code as part of the genai.configure(...) instruction. Environment variables and secure vaults should be used to handle this data. A critical security vulnerability in the current system arises from the practice of embedding sensitive API credentials directly in the source code. Specifically, the API key used to access the Google Gemini service is hardcoded within the genai.configure(...) function. This practice exposes the system to significant risks, including unauthorized access, misuse of the API, and potential service disruptions due to quota exhaustion or billing abuse.

   Hardcoding API keys makes them easily discoverable, especially in collaborative environments where the code is shared via version control platforms like GitHub. If the repository is public or accidentally exposed, malicious actors can extract the credentials and exploit them to perform unauthorized operations — such as spamming the API, accessing restricted data, or impersonating the application. Such breaches can lead to data leakage, unexpected billing costs, and reputational damage.

   Moreover, storing secrets in plaintext within the codebase violates secure coding practices and industry standards such as OWASP recommendations and ISO 27001 guidelines. It also makes the deployment process less flexible and harder to scale, especially when moving to production environments or working across multiple development environments (e.g., staging, testing, and live deployments).

7. **No Model Retraining Pipeline:**

   The ML model (rlu.h5) is static. The system lacks both user interface elements and backend procedures which enable new data training. A notable limitation in the current system is the absence of an automated or manual model retraining pipeline. The machine learning model (rlu.h5), which predicts the Remaining Useful Life (RUL) of batteries, is static — meaning it is trained once and then deployed without the ability to learn or adapt from new data. This design restricts the system's ability to evolve alongside real-world changes in battery usage patterns, emerging chemistries, and operational conditions.

   Over time, as new battery types enter the market or existing batteries exhibit wear patterns not present in the original training dataset, the model's performance can degrade. This phenomenon, known as model drift, results in less accurate predictions and reduced trustworthiness of the system's outputs. Without a retraining pipeline, the system cannot automatically incorporate updated data or user feedback into future model iterations, making it unsuitable for long-term or large-scale deployment.

   Furthermore, the lack of user interface elements for data submission or backend procedures to trigger model updates hinders the possibility of continuous learning. There is no mechanism for monitoring data quality, managing datasets, retraining the model, evaluating performance metrics on new data, or deploying updated models to production in a streamlined way.

8. **Limited Statistical Depth in User Interface:**

   The backend allows various tests but the frontend needs better guidance to adjust automatically according to the choice of stat selected. Although the backend of the system is equipped with a robust set of statistical tools—including hypothesis testing (t-tests, ANOVA, chi-square), correlation analysis, regression models, and non-parametric tests—the current user interface does not fully leverage or reflect this analytical depth. Users are provided with a general interface to initiate statistical analysis, but the frontend lacks dynamic responsiveness or contextual assistance that adjusts based on the type of statistical test selected.

   For example, when a user selects an ANOVA test, the frontend does not automatically prompt for grouping variables or highlight which input fields are required. Similarly, when running a correlation analysis, the interface does not validate whether the selected variables are appropriate for parametric (Pearson) or non-parametric (Spearman) correlation. This limitation makes the tool less intuitive and may lead to incorrect or failed analysis attempts, especially for users who are not well-versed in statistical methodologies.

   Moreover, the visual representation of statistical results is relatively static. While backend libraries like Scipy and Statsmodels support detailed summaries, confidence intervals, and p-value annotations, the frontend does not present these in an interactive or user-friendly manner. Without tooltips, descriptions, or contextual guidance, users may struggle to interpret the results or understand the significance of the statistical tests they are running.

Future Enhancements:

1. **Secure API Key Management:**

   Environment variables and configuration files should secure storage of API keys as well as other sensitive credentials.

2. **Interactive Visualization Dashboard:**

   The Flask platform can utilize Dash or Streamlit components to build dynamic and interactive data exploration functions that run within its framework.

3. **Model Management Interface:**

   Users should have a user interface to upload datasets as well as activate retraining tasks and obtain updated model downloads.

4. **User Feedback Loop:**

   GBLA users should provide input on predictions and generative outputs to enhance model functioning and prompt parameters.

5. **Enhanced NLP Processing:**

You should integrate point extraction models based on transformer technology such as T5 or BART to achieve more precise results.

6. **Asynchronous Background Processing:**

   The system requires Celery or Flask background tasks for processing lengthy model predictions together with Optuna runs.

7. **Explainable AI Integration:**

   RUL prediction results become interpretable by implementing SHAP or LIME.

8. **Expanded ML Model Support:**

   Users should be able to choose random forest models and XGBoost along with neural networks as training options when interacting with the graphical user interface.

9. **User Authentication:**

   Users can authenticate via login if this application is made available to the public audience.

10. **Deployment Considerations:**

    Docker containers should control the system while deployment takes place on Heroku platforms or AWS and Azure surfaces for scalability.

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Appendices

```
from flask import Flask,request,render_template
import pandas as pd
import numpy as np
from nltk import sent_tokenize, word_tokenize, FreqDist
from nltk.corpus import stopwords
from sklearn.preprocessing import LabelEncoder
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import plotly.express as px
import plotly.io as pio
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
import optuna
from optuna.samplers import TPESampler
import os,re
from keras.api.models import load_model
import google.generativeai as genai

app=Flask(__name__)

#AIzaSyD2Uir3fp_lS0SrW7n1Paqx4glsk-VHHBQ

def convert_paragraph_to_points(paragraph, num_points=15):
    sentences = sent_tokenize(paragraph)
    words = word_tokenize(paragraph.lower())
    stop_words = set(stopwords.words('english'))
    filtered_words = [word for word in words if word.isalnum() and word not in
stop_words]
    freq_dist = FreqDist(filtered_words)
    sentence_scores = {}
    for sentence in sentences:
        sentence_word_tokens = word_tokenize(sentence.lower())
        sentence_word_tokens = [word for word in sentence_word_tokens if word.isalnum()]
        score = sum(freq_dist.get(word, 0) for word in sentence_word_tokens)
        sentence_scores[sentence] = score
    sorted_sentences = sorted(sentence_scores, key=sentence_scores.get, reverse=True)
    key_points = sorted_sentences[:num_points]
    return key_points

def clean_text(text):
    return re.sub(r'\*\*|\*', '', text)

@app.route('/',methods=['GET','POST'])
def index():
    return render_template('index.html')

@app.route('/visualizations',methods=['GET','POST'])
def visualization():
    return render_template("visualization.html")

@app.route('/inputs',methods=['GET','POST'])
def inputs():
    return render_template('inputs.html')

@app.route('/submit_data',methods=['GET','POST'])
def datas():
    if request.method=="POST":
        discharge_time = request.form.get('discharge_time')
        decrement_3_6_3_4v = request.form.get('decrement_3_6_3_4v')
        max_voltage = request.form.get('max_voltage')
        time_at_4_15v = request.form.get('time_at_4_15v')
        time_constant_current = request.form.get('time_constant_current')
        charging_time = request.form.get('charging_time')

        discharge_time = float(discharge_time)
        decrement_3_6_3_4v = float(decrement_3_6_3_4v)
        max_voltage = float(max_voltage)
        time_at_4_15v = float(time_at_4_15v)
        time_constant_current = float(time_constant_current)
        charging_time = float(charging_time)

        arr=np.array([discharge_time,decrement_3_6_3_4v,max_voltage,time_at_4_15v,time
_constant_current,charging_time])

        arr = arr.reshape(1, 6)
        model = load_model('rlu.h5')
        prediction = model.predict(arr)

        genai.configure(api_key='AIzaSyB92wEjbNgfe2vW6apS0gRMP3Z4nVCwVOc')
        model = genai.GenerativeModel('gemini-1.5-flash')
        content = model.generate_content(f"In the context of prediction of Battery RUl the
Discharge time of Battery in seconds is {discharge_time} and Maximum voltage discharge
is {max_voltage} and time at 4.15v in seconds is {time_at_4_15v} and time constant
current in seconds is {time_constant_current} and charging time in seconds is
{charging_time} and for all this RUL predicted by my model is {prediction[0][0]} so what
do you think about it..? make sure that your answer should be based on the values given
not about the model.?")
        generated_text = content.text
        key_points = convert_paragraph_to_points(generated_text)
        key_points = [clean_text(item) for item in key_points]


        cntnt=model.generate_content("In the view of Discharge time of Battery in seconds,
Maximum discharge of voltage and time constant current in seconds and charging time in
seconds recommend me an electric 2 wheeler and 4 four wheeler with cost, location,
mileage, engine capacity and technology mainly")
        generated_texts = cntnt.text
        key_pints = convert_paragraph_to_points(generated_texts)
        key_pints = [clean_text(item) for item in key_pints]
        return render_template('inputs.html', keys=key_points,rec_points=key_pints)



@app.route('/visualize_test', methods=['POST'])
def visualize_test():
    data = pd.read_csv('Battery_RUL.csv')

    for i in data.columns.values:
        if len(data[i].value_counts().values) < 10:
            print(data[i].value_counts())

    # Outlier removal using z-scores
    out = []
    for i in data.columns.values:
        data['z_scores'] = (data[i] - data[i].mean()) / data[i].std()
        outlier = np.abs(data['z_scores'] > 3).sum()
        if outlier > 3:
            out.append(i)

    print(len(data))
    thresh = 3
```

```
for i in out:
    upper = data[i].mean() + thresh * data[i].std()
    lower = data[i].mean() - thresh * data[i].std()
    data = data[(data[i] > lower) & (data[i] < upper)]

print(len(data))

univariate1 = request.form.get('univariate1')
univariate2 = request.form.get('univariate2')
plot_type = request.form.get('univariate3')

plot_filename = f"{plot_type}_{univariate1}_{univariate2}.png"
plot_path = f'static/images/{plot_filename}'

if plot_type == 'histogram':
    fig, ax = plt.subplots()
    data[univariate1].hist(ax=ax)
    ax.set_title('Histogram of ' + univariate1)
    fig.savefig(plot_path, format='png')
    plt.close(fig)

elif plot_type == 'boxplot':
    fig = plt.figure()
    sns.boxplot(data=data, x=univariate1, y=univariate2)
    plt.title(f'Boxplot of {univariate1} vs {univariate2}')
    plt.savefig(plot_path, format='png')
    plt.close(fig)

elif plot_type == 'density':
    fig = plt.figure()
    sns.kdeplot(data=data, x=univariate1, y=univariate2, fill=True)
    plt.title(f'Density Plot of {univariate1} vs {univariate2}')
    plt.savefig(plot_path, format='png')
    plt.close(fig)

elif plot_type == 'violin':
    fig = plt.figure()
    sns.violinplot(data=data, x=univariate1, y=univariate2)
    plt.title(f'Violin Plot of {univariate1} vs {univariate2}')
    plt.savefig(plot_path, format='png')
    plt.close(fig)

elif plot_type == 'bar':
    fig = plt.figure()
    data[univariate1].value_counts().plot(kind='bar')
    plt.title(f'Bar Chart of {univariate1}')
    plt.savefig(plot_path, format='png')
    plt.close(fig)

elif plot_type == 'scatter':
    fig = px.scatter(data, x=univariate1, y=univariate2,
                     title='Scatter Plot of {} vs {}'.format(univariate1, univariate2))
    pio.write_image(fig, plot_path, format='png')

elif plot_type == 'heatmap':
    corr = data.corr()
    fig = plt.figure()
    sns.heatmap(corr, annot=True, cmap='coolwarm')
    plt.title('Heatmap of Correlation Matrix')
    plt.savefig(plot_path, format='png')
    plt.close(fig)

elif plot_type == 'contour':
    x = data[univariate1]
    y = data[univariate2]
    x = x[~x.isna()]
    y = y[~y.isna()]
    X, Y = np.meshgrid(np.linspace(x.min(), x.max(), 100), np.linspace(y.min(), y.max(),
100))
    Z = np.exp(-(X ** 2 + Y ** 2))
    fig = plt.figure()
    plt.contourf(X, Y, Z, cmap='viridis')
    plt.title('Contour Plot')
    plt.savefig(plot_path, format='png')
    plt.close(fig)

elif plot_type == 'hexbin':
    fig, ax = plt.subplots()
    hb = ax.hexbin(data[univariate1], data[univariate2], gridsize=50, cmap='inferno')
    plt.colorbar(hb, ax=ax)
    ax.set_title('Hexbin Plot of {} vs {}'.format(univariate1, univariate2))
    plt.savefig(plot_path, format='png')
    plt.close(fig)

elif plot_type == 'qq-plot':
    fig = plt.figure()
    sm.qqplot(data[univariate1], line='45')
    plt.title(f'Q-Q Plot of {univariate1}')
```

```
            plt.savefig(plot_path, format='png')
            plt.close(fig)

        elif plot_type == 'violin-box':
            fig = plt.figure()
            sns.violinplot(data=data, x=univariate1, y=univariate2)
            sns.boxplot(data=data, x=univariate1, y=univariate2, whis=np.inf)
            plt.title(f'Violin with Boxplot of {univariate1} vs {univariate2}')
            plt.savefig(plot_path, format='png')
            plt.close(fig)

        else:
            return "Invalid plot type", 400

        plot_url = f'/static/images/{plot_filename}'
        return render_template("visualization.html", plot_url=plot_url)

    def summary_stats(column1, column2, stat_type):
        data = pd.read_csv('Battery_RUL.csv')
        print(data.columns)
        print(data.describe())
        print(data.info())
        print(data.isna().sum())

        # Detect columns with fewer than 10 unique values
        for i in data.columns.values:
            if len(data[i].value_counts().values) < 10:
                print(data[i].value_counts())
```

```
# Outlier removal using z-scores
out = []
for i in data.columns.values:
    data['z_scores'] = (data[i] - data[i].mean()) / data[i].std()
    outlier = np.abs(data['z_scores'] > 3).sum()
    if outlier > 3:
        out.append(i)

print(len(data))
thresh = 3
for i in out:
    upper = data[i].mean() + thresh * data[i].std()
    lower = data[i].mean() - thresh * data[i].std()
    data = data[(data[i] > lower) & (data[i] < upper)]

print(len(data))

result = ""

if stat_type == "mean":
    result = f"Mean of {column1}: {data[column1].mean()}"
elif stat_type == "median":
    result = f"Median of {column1}: {data[column1].median()}"
elif stat_type == "mode":
    result = f"Mode of {column1}: {data[column1].mode()[0]}"
elif stat_type == "variance":
    result = f"Variance of {column1}: {data[column1].var()}"
elif stat_type == "std_dev":
    result = f"Standard Deviation of {column1}: {data[column1].std()}"
    elif stat_type == "kurtosis":
        result = f"Kurtosis of {column1}: {stats.kurtosis(data[column1].dropna())}"
    elif stat_type == "skewness":
        result = f"Skewness of {column1}: {stats.skew(data[column1].dropna())}"
    elif stat_type == "range":
        result = f"Range of {column1}: {data[column1].max() - data[column1].min()}"
    elif stat_type == "iqr":
        result = f"Interquartile Range of {column1}: {stats.iqr(data[column1].dropna())}"
    elif stat_type == "t-test":
        t_stat, p_val = stats.ttest_ind(data[column1].dropna(), data[column2].dropna())
        result = f"T-Test: t-statistic={t_stat}, p-value={p_val}"
    elif stat_type == "chi-square":
        contingency = pd.crosstab(data[column1], data[column2])
        chi2_stat, p_val, dof, ex = stats.chi2_contingency(contingency)
        result = f"Chi-Square Test: chi2-statistic={chi2_stat}, p-value={p_val}, degrees of
freedom={dof}"
    elif stat_type == "anova":
        groups = [data[column1][data[column2] == g] for g in data[column2].unique()]
        f_stat, p_val = stats.f_oneway(*groups)
        result = f"ANOVA: F-statistic={f_stat}, p-value={p_val}"
    elif stat_type == "mann-whitney":
        u_stat, p_val = stats.mannwhitneyu(data[column1].dropna(), data[column2].dropna())
        result = f"Mann-Whitney U Test: U-statistic={u_stat}, p-value={p_val}"
    elif stat_type == "wilcoxon":
        w_stat, p_val = stats.wilcoxon(data[column1].dropna(), data[column2].dropna())
        result = f"Wilcoxon Signed-Rank Test: W-statistic={w_stat}, p-value={p_val}"
    elif stat_type == "kruskal-wallis":
        groups = [data[column1][data[column2] == g] for g in data[column2].unique()]
        h_stat, p_val = stats.kruskal(*groups)
        result = f"Kruskal-Wallis Test: H-statistic={h_stat}, p-value={p_val}"
    elif stat_type == "pearson-correlation":
        corr, _ = stats.pearsonr(data[column1].dropna(), data[column2].dropna())
        result = f"Pearson Correlation: {corr}"
    elif stat_type == "spearman-correlation":
        corr, _ = stats.spearmanr(data[column1].dropna(), data[column2].dropna())
        result = f"Spearman Correlation: {corr}"
    elif stat_type == "fisher-exact":
        contingency = pd.crosstab(data[column1], data[column2])
        odds_ratio, p_val = stats.fisher_exact(contingency)
        result = f"Fisher's Exact Test: Odds Ratio={odds_ratio}, p-value={p_val}"
    elif stat_type == "z-test":
        mean = data[column1].mean()
        std_dev = data[column1].std()
        z_stat = (mean - 0) / (std_dev / np.sqrt(len(data[column1])))
        p_val = stats.norm.sf(abs(z_stat)) * 2
        result = f"Z-Test: z-statistic={z_stat}, p-value={p_val}"
    elif stat_type == "lin-regression":
        from sklearn.linear_model import LinearRegression
        X = data[[column1]]
        y = data[column2]
        model = LinearRegression().fit(X, y)
        result = f"Linear Regression: Coefficient={model.coef_[0]},
Intercept={model.intercept_}"
    elif stat_type == 'OLS':
        import statsmodels.api as sm
        x = data[[column1]]
        y = data[[column2]]
        model = sm.OLS(y, x).fit()
        result = model.summary().as_html()
    return result
```

```
@app.route('/stat_test', methods=['POST'])
def stat_test():
    stats1 = request.form.get('stats1')
    stats2 = request.form.get('stats2')
    stats3 = request.form.get('stats3')

    if stats3:
        summary = summary_stats(stats1, stats2, stats3)
    else:
        summary = "Please select a summary statistic or test."
    return render_template('visualization.html', summary=summary)

@app.route('/optuna', methods=['GET', 'POST'])
def casuality_analysis():
    return render_template("casual.html")

@app.route('/c_analysis', methods=['GET', 'POST'])
def c_analysis():
    data = pd.read_csv('Battery_RUL.csv')

    out = []
    for i in data.columns.values:
        data['z_scores'] = (data[i] - data[i].mean()) / data[i].std()
        outlier = np.abs(data['z_scores'] > 3).sum()
        if outlier > 3:
            out.append(i)

    thresh = 3
```

```
        for i in out:
            upper = data[i].mean() + thresh * data[i].std()
            lower = data[i].mean() - thresh * data[i].std()
            data = data[(data[i] > lower) & (data[i] < upper)]

        corr = data.corr()['RUL']
        corr = corr.drop(['RUL', 'z_scores'])
        x_cols = [i for i in corr.index if corr[i] > 0]
        x = data[x_cols]
        y = data['RUL']
    for i in data.columns.values:
        if len(data[i].value_counts().values) < 10:
            print(data[i].value_counts())

    # Outlier removal using z-scores
    out = []
    for i in data.columns.values:
        data['z_scores'] = (data[i] - data[i].mean()) / data[i].std()
        outlier = np.abs(data['z_scores'] > 3).sum()
        if outlier > 3:
            out.append(i)

    print(len(data))
    thresh = 3
    for i in out:
        upper = data[i].mean() + thresh * data[i].std()
        lower = data[i].mean() - thresh * data[i].std()
        data = data[(data[i] > lower) & (data[i] < upper)]

    print(len(data))
```

```
# Correlation with RUL
corr = data.corr()['RUL']
corr = corr.drop(['RUL', 'z_scores'])
x_cols = [i for i in corr.index if corr[i] > 0]
x = data[x_cols]
y = data['RUL']

x_train,x_test,y_train,y_test=train_test_split(x,y)

def convert_paragraph_to_points(paragraph, num_points=15):
    sentences = sent_tokenize(paragraph)
    words = word_tokenize(paragraph.lower())
    stop_words = set(stopwords.words('english'))
    filtered_words = [word for word in words if word.isalnum() and word not in
stop_words]
    freq_dist = FreqDist(filtered_words)
    sentence_scores = {}
    for sentence in sentences:
        sentence_word_tokens = word_tokenize(sentence.lower())
        sentence_word_tokens = [word for word in sentence_word_tokens if word.isalnum()]
        score = sum(freq_dist.get(word, 0) for word in sentence_word_tokens)
        sentence_scores[sentence] = score
    sorted_sentences = sorted(sentence_scores, key=sentence_scores.get, reverse=True)
    key_points = sorted_sentences[:num_points]
    return key_points

def clean_text(text):
    return re.sub(r'\*\*|\*', '', text)

@app.route('/',methods=['GET','POST'])
```

```
def index():
    return render_template('index.html')

@app.route('/visualizations',methods=['GET','POST'])
def visualization():
    return render_template("visualization.html")

@app.route('/inputs',methods=['GET','POST'])
def inputs():
    return render_template('inputs.html')

@app.route('/submit_data',methods=['GET','POST'])
def datas():
    if request.method=="POST":
        discharge_time = request.form.get('discharge_time')
        decrement_3_6_3_4v = request.form.get('decrement_3_6_3_4v')
        max_voltage = request.form.get('max_voltage')
        time_at_4_15v = request.form.get('time_at_4_15v')
        time_constant_current = request.form.get('time_constant_current')
        charging_time = request.form.get('charging_time')

        discharge_time = float(discharge_time)
        decrement_3_6_3_4v = float(decrement_3_6_3_4v)
        max_voltage = float(max_voltage)
        time_at_4_15v = float(time_at_4_15v)
        time_constant_current = float(time_constant_current)
        charging_time = float(charging_time)


arr=np.array([discharge_time,decrement_3_6_3_4v,max_voltage,time_at_4_15v,time_cons
tant_current,charging_time])
```

```
        arr = arr.reshape(1, 6)
        model = load_model('rlu.h5')
        prediction = model.predict(arr)

        genai.configure(api_key='AIzaSyB92wEjbNgfe2vW6apS0gRMP3Z4nVCwVOc')
        model = genai.GenerativeModel('gemini-1.5-flash')
        content = model.generate_content(f"In the context of prediction of Battery RUl the
Discharge time of Battery in seconds is {discharge_time} and Maximum voltage discharge
is {max_voltage} and time at 4.15v in seconds is {time_at_4_15v} and time constant
current in seconds is {time_constant_current} and charging time in seconds is
{charging_time} and for all this RUL predicted by my model is {prediction[0][0]} so what
do you think about it..? make sure that your answer should be based on the values given
not about the model.?")
        generated_text = content.text
        key_points = convert_paragraph_to_points(generated_text)
        key_points = [clean_text(item) for item in key_points]

        cntnt=model.generate_content("In the view of Discharge time of Battery in seconds,
Maximum discharge of voltage and time constant current in seconds and charging time in
seconds recommend me an electric 2 wheeler and 4 four wheeler with cost, location,
mileage, engine capacity and technology mainly")
        generated_texts = cntnt.text
        key_pints = convert_paragraph_to_points(generated_texts)
        key_pints = [clean_text(item) for item in key_pints]
        return render_template('inputs.html', keys=key_points,rec_points=key_pints)



@app.route('/visualize_test', methods=['POST'])
def visualize_test():
```

```
data = pd.read_csv('Battery_RUL.csv')

for i in data.columns.values:
    if len(data[i].value_counts().values) < 10:
        print(data[i].value_counts())

# Outlier removal using z-scores
out = []
for i in data.columns.values:
    data['z_scores'] = (data[i] - data[i].mean()) / data[i].std()
    outlier = np.abs(data['z_scores'] > 3).sum()
    if outlier > 3:
        out.append(i)

print(len(data))
thresh = 3
for i in out:
    upper = data[i].mean() + thresh * data[i].std()
    lower = data[i].mean() - thresh * data[i].std()
    data = data[(data[i] > lower) & (data[i] < upper)]

print(len(data))

univariate1 = request.form.get('univariate1')
univariate2 = request.form.get('univariate2')
plot_type = request.form.get('univariate3')

plot_filename = f"{plot_type}_{univariate1}_{univariate2}.png"
plot_path = f'static/images/{plot_filename}'

if plot_type == 'histogram':
    fig, ax = plt.subplots()
    data[univariate1].hist(ax=ax)
    ax.set_title('Histogram of ' + univariate1)
    fig.savefig(plot_path, format='png')
    plt.close(fig)

elif plot_type == 'boxplot':
    fig = plt.figure()
    sns.boxplot(data=data, x=univariate1, y=univariate2)
    plt.title(f'Boxplot of {univariate1} vs {univariate2}')
    plt.savefig(plot_path, format='png')
    plt.close(fig)

elif plot_type == 'density':
    fig = plt.figure()
    sns.kdeplot(data=data, x=univariate1, y=univariate2, fill=True)
    plt.title(f'Density Plot of {univariate1} vs {univariate2}')
    plt.savefig(plot_path, format='png')
    plt.close(fig)

elif plot_type == 'violin':
    fig = plt.figure()
    sns.violinplot(data=data, x=univariate1, y=univariate2)
    plt.title(f'Violin Plot of {univariate1} vs {univariate2}')
    plt.savefig(plot_path, format='png')
    plt.close(fig)

elif plot_type == 'bar':
    fig = plt.figure()
    data[univariate1].value_counts().plot(kind='bar')
    plt.title(f'Bar Chart of {univariate1}')
    plt.savefig(plot_path, format='png')
    plt.close(fig)

elif plot_type == 'scatter':
    fig = px.scatter(data, x=univariate1, y=univariate2,
                     title='Scatter Plot of {} vs {}'.format(univariate1, univariate2))
    pio.write_image(fig, plot_path, format='png')

elif plot_type == 'heatmap':
    corr = data.corr()
    fig = plt.figure()
    sns.heatmap(corr, annot=True, cmap='coolwarm')
    plt.title('Heatmap of Correlation Matrix')
    plt.savefig(plot_path, format='png')
    plt.close(fig)

elif plot_type == 'contour':
    x = data[univariate1]
    y = data[univariate2]
    x = x[~x.isna()]
    y = y[~y.isna()]
    X, Y = np.meshgrid(np.linspace(x.min(), x.max(), 100), np.linspace(y.min(), y.max(),
100))
    Z = np.exp(-(X ** 2 + Y ** 2))
    fig = plt.figure()
    plt.contourf(X, Y, Z, cmap='viridis')
    plt.title('Contour Plot')
    plt.savefig(plot_path, format='png')
    plt.close(fig)

elif plot_type == 'hexbin':
    fig, ax = plt.subplots()
    hb = ax.hexbin(data[univariate1], data[univariate2], gridsize=50, cmap='inferno')
    plt.colorbar(hb, ax=ax)
    ax.set_title('Hexbin Plot of {} vs {}'.format(univariate1, univariate2))
    plt.savefig(plot_path, format='png')
    plt.close(fig)



elif plot_type == 'qq-plot':
    fig = plt.figure()
    sm.qqplot(data[univariate1], line='45')
    plt.title(f'Q-Q Plot of {univariate1}')
    plt.savefig(plot_path, format='png')
    plt.close(fig)



elif plot_type == 'violin-box':
    fig = plt.figure()
    sns.violinplot(data=data, x=univariate1, y=univariate2)
    sns.boxplot(data=data, x=univariate1, y=univariate2, whis=np.inf)
    plt.title(f'Violin with Boxplot of {univariate1} vs {univariate2}')
    plt.savefig(plot_path, format='png')
    plt.close(fig)

else:
    return "Invalid plot type", 400

plot_url = f'/static/images/{plot_filename}'
return render_template("visualization.html", plot_url=plot_url)
```

```
def objective(trial):
    n_estimators = trial.suggest_int('n_estimators', 50, 100)
    max_depth = trial.suggest_int('max_depth', 2, 10)
    min_samples_split = trial.suggest_int('min_samples_split', 2, 10)
    min_samples_leaf = trial.suggest_int('min_samples_leaf', 1, 10)

    model = RandomForestClassifier(
        n_estimators=n_estimators,
        max_depth=max_depth,
        min_samples_split=min_samples_split,
        min_samples_leaf=min_samples_leaf,
        random_state=0
    )
    score = cross_val_score(model, x, y, n_jobs=-1, cv=3)
    accuracy = score.mean()
    return accuracy

sampler = TPESampler(seed=10)
study = optuna.create_study(direction='maximize', sampler=sampler)
study.optimize(objective, n_trials=2)

best_params = study.best_params
model = RandomForestClassifier(**best_params, random_state=0)
model.fit(x, y)

feature_importance = model.feature_importances_
features_importance_zipped = zip(x.columns.values, feature_importance.tolist())

fig_dir = os.path.join('static', 'images')
```

```
    os.makedirs(fig_dir, exist_ok=True)

    return render_template(
        "c_analysis.html",
        best_params=best_params,
        features_importance_zipped=features_importance_zipped,
    )
if __name__=='__main__':
    app.run()
```

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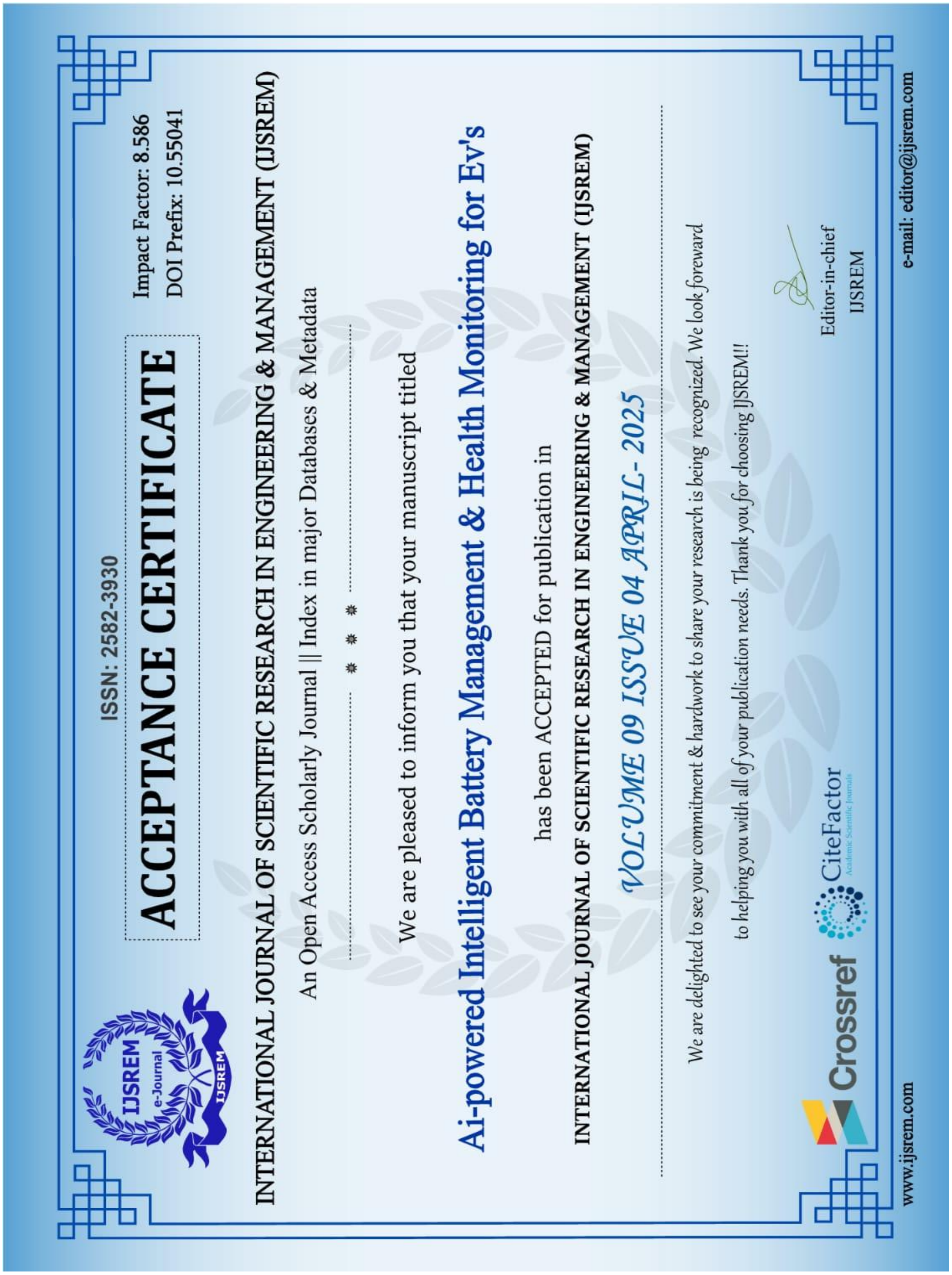

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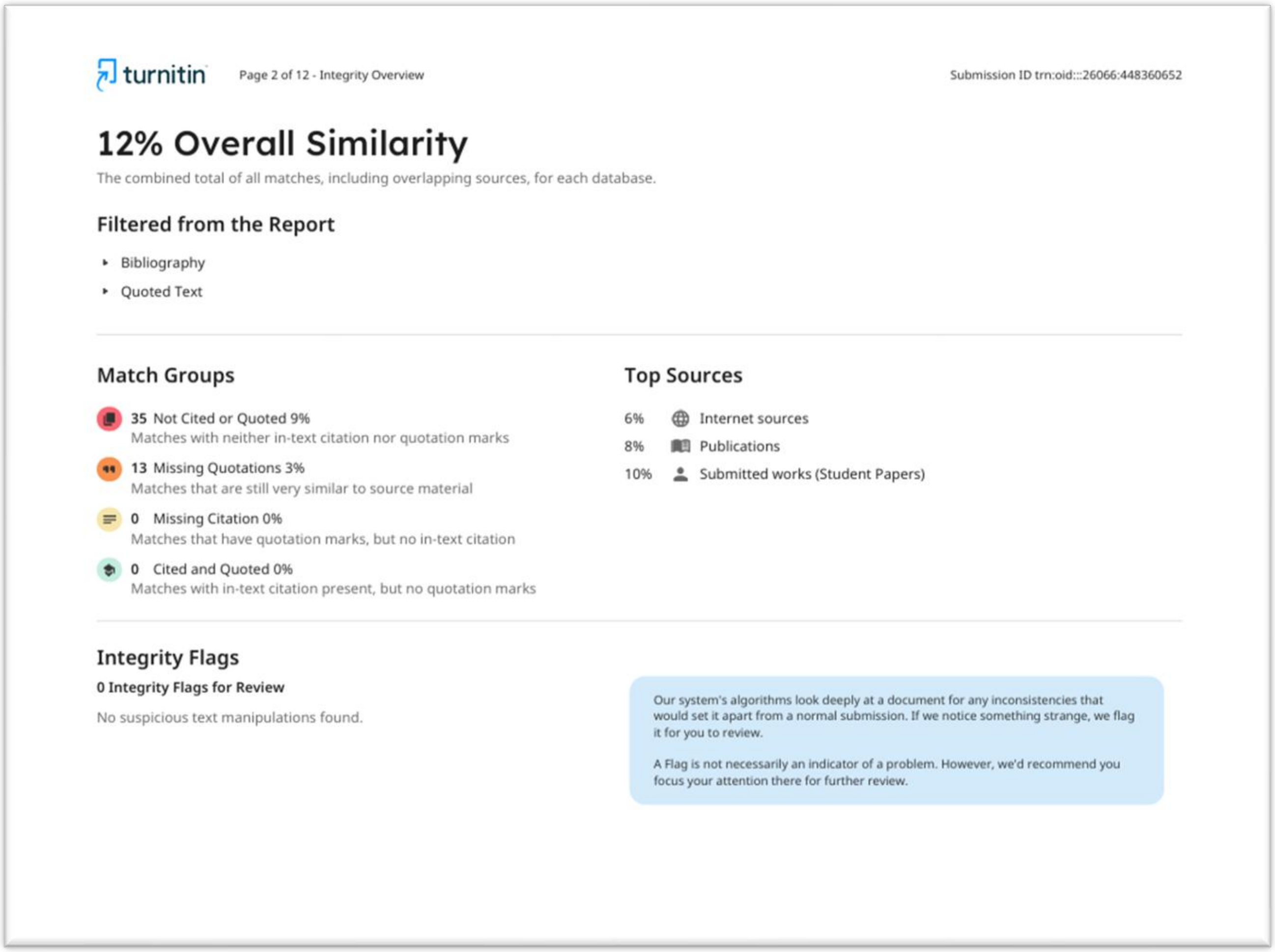

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