A PROJECT REPORT ON

Explainable AI for Predictive Maintenance of EV Batteries.

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Abstract

Increasing demand for Electric Vehicles further emphasized the importance of efficient Battery management solutions. The field of predictive maintenance battery health involves identifying potential battery failures in the future. This research proposes a solution framework based on Explainable AI to make correct predictions for the maintenance of batteries and to ensure Transparency on Artificial Intelligence simultaneously The proposed system relies on historical battery data, including parameters such as battery voltage, current, temperature, and state of health, to predict battery degradation and remaining useful life(RUL).For handling complex nonlinearities in battery degradation, machine learning and deep learning algorithms are used. As artificial intelligence techniques encompass the 'black-box problem' in model interpretation, feature attribution and model interpretability methods are also used.Through experimental analysis, the proposed method has been shown to offer valid prediction results, as well as a valid explanation on the basis of the decision. This increases the validity, accountability, and usability of the method in a real-life application in EVs. It helps in proactive maintenance, decreases the number of sudden EV battery breakdowns, as well as increases the overall EV battery life. The project proves the significance of the explanation of artificial intelligence in forward-thinking intelligent

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Chapter 1

Introduction

Electric Vehicles are widely accepted owing to their green attributes. In all EV components, the battery system is the most essential one and has a tremendous impact on EV performance and costs. Battery deterioration is dependent on factors such as variations in temperature conditions, number of charge/discharge cycles, loading conditions, and age factors. Unintentional failure of batteries would result in failure of EVs, rise in maintenance costs, and a depreciating customer base.

In order to deal with such challenges, it is important to adopt effective battery health management. Predictive maintenance is being used to help manage battery degradation based on trends noted by data-driven approaches, thereby performing condition-based maintenance, as opposed to time-based maintenance.

Recent developments in Artificial Intelligence and Machine Learning techniques allow for reliable estimation of battery status and RUL using existing and operating data. It is essential to predict the RUL accurately for maintenance and improvements in battery safety and overall lifespan. This proposed project aims at building an AI predictive maintenance system for the battery in an electric vehicle with a focus on RUL.

1.1 Aim

The aim of this project is to develop an explainable AI–based predictive maintenance system that accurately estimates battery degradation and remaining useful life while providing clear and interpretable insights into the factors affecting battery health. The system aims to improve trust, reliability, and decision-making by enabling timely maintenance, enhanced safety, and extended battery lifespan.

1.2 Traditional vs XAI-Integrated Models

Table 1.1: Comparison Between Black-Box Models and XAI-Integrated Models

Black-Box Models	**XAI-Integrated Models**
Operate as opaque systems with no explanation of predictions	Provide human-understandable explanations for predictions
Decision logic is hidden and difficult to interpret	Decision-making process is interpretable using SHAP and LIME
Limited user trust due to lack of transparency	Higher user trust due to explainable and verifiable outputs
Feature contribution to prediction is not visible	Important features such as temperature, voltage, and current are highlighted
Not suitable for informed maintenance decisions	Supports explainable and data-driven maintenance planning
Errors are difficult to analyze and correct	Errors can be easily diagnosed and corrected
Limited usage in safety-critical EV applications	Well-suited for real-world EV battery management systems
Focuses only on improving prediction accuracy	Enables proactive, transparent, and reliable predictive maintenance

1.3 Objective

- To collect and preprocess battery performance data relevant to electric vehicle operation.
- To develop machine learning models for predicting battery degradation and remaining useful life(RUL).

- To identify key factors influencing battery health under different operating conditions.
- To integrate explainable AI techniques to interpret and justify model predictions.
- To enhance trust and transparency in predictive maintenance decisions.
- To support timely maintenance actions that improve battery safety and lifespan.

1.4 Scope of the Project

The scope for this project will be limited to the software-based predictive maintenance of Electric vehicle batteries are the focus of this system, which estimates the Remaining Useful Life(RUL) of batteries using machine learning techniques. Hardware Implementation and deployment on board in real time are beyond the scope of current work.

1.5 About XAI

Explainable Artificial Intelligence (XAI) is concerned with ensuring the interpretability of predictions made by machine learning models. This is because conventional black-box approaches lack transparency. XAI techniques are used to provide reasons why an outcome is obtained from the model, which helps to determine the factors that affect the final result. There are several techniques that can be applied in XAI. They are divided into global and local explanation methods. In model agnostic and model-specific techniques. For this project, SHAP and LIME are adopted because they are straightforward and widely accepted methods. They are also not redundant. SHAP is preferred because it renders stable attributions to factors. It is applicable at the global and instance level. It is very helpful in tree-based models. LIME is preferred because it provides understandable explanations at the local level. This is done by approximating the model close to the outcome.

Table 1.2: Comparison between SHAP and LIME

SHAP	**LIME**
SHapley Additive exPlanations	Local Interpretable Model-agnostic Explanations
Fairly distributes contribution of each feature using game theory	Approximates model behavior locally around one prediction
Provides both local and global explanations	Provides only local explanations
Consistent and stable explanations	Explanations may vary across runs
High accuracy and reliability	Approximate and less reliable
Computationally expensive	Faster and less computationally intensive
Model-agnostic	Model-agnostic
Clear feature contribution values	Feature importance for a single instance
Highly suitable for EV Battery RUL due to stable explanations	Less suitable due to variability

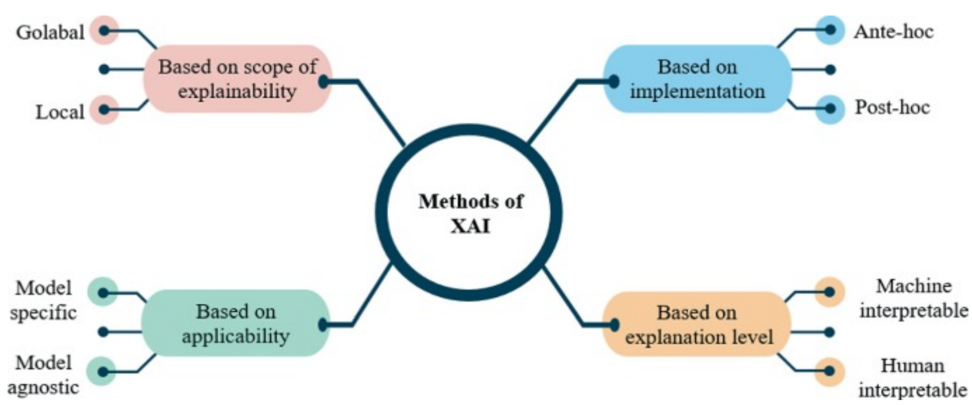


Figure 1.1: XAI$_{M}ethods$

1.6 Summary

In this chapter, the relevance of health status monitoring in electric vehicle batteries and the use of Artificial Intelligence in predictive maintenance were asserted.

The purpose, goals, and the range of the research project were also covered in this chapter. The proposed project essentially revolves around estimating the Remaining Useful Life (RUL) values for electric vehicle batteries.

Chapter 2

Literature Survey

2.1 Introduction

This chapter focuses on the review of the existing research work on battery health monitoring, degradation analysis, and RUL prediction in electric vehicle batteries. Different machine learning-based approaches on data required for battery RUL prediction have been dealt with in this chapter. The weaknesses of the previous research work in the domain justify the need for the research work in this chapter.

2.2 Battery Health and Degradation Studies

Some research has been conducted on the degradation characteristics of lithium-ion batteries, especially those used in Electric Vehicles. Aging of batteries is affected by parameters like temperature, discharge/charge cycles, depth of discharge, and the current on which it is being discharged. Some research studies have demonstrated that high temperatures accelerate chemical reactions, thereby reducing battery life.

Experimental research has proved that fast charging cycles with high current loads strongly affect battery life. Depth of discharge is the next factor that plays an important role, as the deeper the discharge cycles, the sooner the battery fails. These are the basics for the creation of predictive models for battery maintenance according to battery health metrics.

2.3 Remaining Useful Life(RUL) Prediction Techniques

RUL estimation is the process of predicting the number of cycles or the time remaining until the battery's end of life. The existing solutions for this problem are based either on electrochemical equations or degradation models. The main problem associated with these models is the requirement for precise battery parameters, which is not feasible in practical scenarios.

Data-driven solutions have become popular with the availability of data on battery sensor readings. These solutions use the past voltage, current, and temperature trends to train the predictions. Statistical modeling and probabilistic solutions have become very prominent within RUL predictions.

2.4 Machine Learning Approaches for Battery RUL

There has been recent interest in how machine learning algorithms such as Support Vector Machines(SVM), Random Forests, Gradient Boosting, and Neural Networks can be used for RUL predictions of batteries. These algorithms are capable of capturing non-linear relationships existing between battery variables and their degradation modes. Deep learning methods based on recurrent neural networks or 'long short-term memory (LSTM) networks have proved to improve their results in time series battery modeling. In fact, LSTM models tend to need big data and occupy high computation costs; thus, their application might be restricted in an actual EV system.

2.5 Limitations of Existing Systems

Even though there have been proposed various methods related to battery Remaining Useful Lifetime prediction, there is still room for improvement, as most current battery RUL estimation models lack adaptability and are often based on an ideal lab environment. Some methods require knowledge of specific parameters known only to the manufacturer.

Moreover, most models are black-box models and lack detailed information concerning their prediction capabilities. The above-mentioned characteristics imply a need for efficient and practical models capable of working under real-life settings and offering accurate predictions concerning RUL estimation.

2.6 Summary

In this chapter, exploration of existing literature regarding battery deterioration in electric vehicles, as well as methods to calculate Remaining Useful Life (RUL), has been discussed by comparing conventional techniques with machine learning methods, which are indeed more efficient, with pros and cons mentioned wherever necessary.

Table 2.1: Summary of Literature Review

Title of Paper	**Year**	**Description**
Explainable Artificial Intelligence for State of Charge Estimation of Lithium-Ion Batteries	2025	This article proposes a data-driven, explainable artificial intelligence (xAI) approach based on deep learning models such as LSTMs, GRUs, CNN-LSTMs, and hybrid models for accurate State of Charge (SoC) estimation of lithium-ion batteries in real-world electric vehicle datasets.The article proposes the integration of global and local explainable AI approaches in order to discover feature contributions and redundancies.In summary, the article provides practical insights into the application of explainable deep learning models in accurate battery state estimation in real-world electric vehicle applications.
Explainable AI for Battery Degradation Prediction in EVs: Toward Transparent Energy Forecasting	2025	The study focuses on data collection, feature selection using SHAP, and model training using LightGBM and other machine learning algorithms. Model performance is evaluated using metrics such as MSE, R^2, and 5-fold cross-validation to ensure reliable prediction accuracy.
XAI-Driven Prognostics For Lithium-Ion Battery Management Systems	2025	this paper focuses on developing a framework for lithium-ion battery prognostics based on Explainable Artificial Intelligence (XAI), specifically on accurate and interpretable prediction of SOH and RUL in battery management systems.incorporated SHAP global explanations, LIME instance-level explanations, and attention analysis to identify those aspects of temporal degradation dynamics that are most informative and thus of primary interest.

Chapter 3

Specifications

3.1 System Specifications

1. **Input Data:**

   (a) The operational data of the battery consists of voltage, current, temperature, and charge–discharge cycles.

   (b) Historical battery degradation data for training and validation.

   (c) Derived health indicators such as State of Charge (SOC) and State of Health (SOH).

   (d) Time-series data representing battery usage under different operating conditions.

2. **Model Architecture:**

   (a) Predictive Model: A data-driven machine learning model designed for battery health prognostics.

   (b) Feature Extraction Module: Extracts temporal patterns and degradation trends from historical battery data.

   (c) SOH Estimation Module: Estimates State of Health (SOH) as an intermediate signal representing the current degradation level of the battery.

   (d) RUL Predictive Module: establishes RUL as the primary prediction target for RUL by examining SOH (Degradation History) and its correlation with RUL.

(e) Develops SoH Estimation and RUL Prediction Interpretations via XAI (Explainable AI) Techniques.

3. **Evaluation Metrics:**

    (a) MAE : Mean Absolute Error for prediction accuracy.

    (b) RMSE : Root Mean Square Error to measure deviation in RUL prediction

    (c) R^2 score : To evaluate model reliability and goodness of fit.

    (d) Explanation Consistency: Validation of feature importance stability across predictions.

4. **Implementation:**

    (a) Framework: Python-based machine learning libraries.

    (b) Training Configuration: Model trained on multiple battery cycles with optimized hyperparameters.

    (c) Learning Strategy: Supervised learning with time-series forecasting.

    (d) Output: Predicted battery health, remaining useful life, and explainable AI insights.

3.2 System Description

The proposed system aims at offering reliable and explainable predictive maintenance for the electric vehicle battery using the concept of Explainable Artificial Intelligence. The technique uses past and current performance data of the battery in order to make predictions concerning its degradation and life span. this is done while considering the issue of non-linear degradation and changing conditions. In a measure aimed at improving explainability and interpretaibility, the proposed system utilizes explainable artificial intelligence that identifies the most important data features in each prediction. The efficiencyof the proposed approach can be measured by using common regression scores such as MAE, RMSE and R^2values.

3.3 Summary

The proposed system utilizes an Explainable AI predictive maintenance approach to predict the degradation and lifetime of the electric vehicle batteries. The predictive maintenance approach is capable of solving the disadvantages presented by other predictive maintenance approaches with respect to reliability and interpretability. The proposed approach utilizes techniques such as degradation and explanation. The proposed approach is capable of solving the disadvantages presented by predictive maintenance. The performance evaluation of the proposed approach utilizes performance metrics.

Chapter 4

Methodology

In its proposed approach, it aim at the prediction of the RUL for Lithium-ion batteries, the proposed scheme is required to apply an explainable machine learning approach takes an extended pipeline from raw data given by the discharge process of battery current to the interpretable prediction output relative to the prediction task related to the prediction task related to the RUL of lithium-ion battery cells.

4.1 Data Collection and Organization

The experimental data employed in this research work has been extracted from the NASA Prognostic Center of Excellence (PCoE) dataset for the lithium-ion battery type. The dataset was collected with several lithium-ion batteries being cycled in a controlled environment with extensive information being collected about their discharging, charging, and impedance measurements.

The batteries are given a distinctive identifier based on a normalized battery identifier that relies on the file naming convention. The discharge cycles are seen as the key sources of degradation information since they intuitively relate to the capacity degradation and aging process of the batteries. The degradation information is supplemented by charge information/measurements and impedance information/measurements to provide a multimodal dataset.

Data on impedance measurements are more sparse, yet important data on internal resistance development, and all discharge, charge, and impedance data relevant to the battery are systematically collected, building a unified battery life cycle model based on them.

4.2 Data Cleaning

Raw discharge files often contain missing values, duplicated cycle records, and inconsistent measurements resulting from logging interruptions and sensor noise. To address these, the following cleaning was done:

- Removal of incomplete, missing, or corrupted discharge records.
- Identification and elimination of duplicate battery cycle entries.
- Sorting of battery discharge cycles in proper chronological order.
- Consistent re-indexing of cycles across merged discharge datasets.

This process allows the collected data on discharge from each of the batteries to actually inform about its degradation trajectory.

4.3 Cycle-Level Aggregation and Multimodal Feature Construction

The preprocessed data series is then aggregated at the cycle level. This enables the extraction of the more representative cycle-level features. Electrical and temperature parameters such as voltage, current, discharge capacity, temperature, and internal resistance are part of the aggregated features.

Discharge cycles are used as a baseline for aggregation. The charge features, impedance features, and discharge cycles are matched on a per-cycle basis in order to create a multimodal feature representation. When there are sparse measurements in the impedance data, linear interpolation between the cycles could be done, excluding extrapolation outside the observed range. However, a binary feature is maintained in order to distinguish between measured and interpolated values.

4.4 SOH and RUL Computation

The State of Health (SOH) of each battery is computed on a per-cycle basis by normalizing the discharge capacity with respect to the initial rated capacity of the corresponding battery. This normalization yields a dimensionless SOH metric that consistently characterizes battery degradation over time. In the proposed framework, SOH is used as an intermediate health indicator to support degradation analysis and lifecycle boundary determination, rather than as a direct prediction target.

End of Life (EOL) is defined as the first cycle at which the SOH value falls below a threshold of 70%. This threshold is widely adopted in battery health assessment literature and industrial practice, as it signifies a substantial loss in usable capacity and practical performance. If a battery does not reach this threshold within the observed cycling data, the final available cycle is treated as a censored EOL.

The Remaining Useful Life (RUL), which serves as the primary target variable for model training, is subsequently calculated as the difference between the EOL cycle and the current cycle number. All cycles occurring beyond the EOL point are removed from the dataset to ensure the validity, monotonicity, and physical consistency of the RUL labels.

4.5 Data Sanitization and Leakage Prevention

In order to address the issue of information leakage, stringent validation is carried out to verify that the generation of all the features is on the basis of the present or former cycle data. Features with an implicit expression involving future degradation patterns or RUL features are eliminated. None of the operations involving smoothing, clipping, or outlier removal are carried out to ensure realism in the battery degradation process.

4.6 Data Normalization and Feature Scaling

All continuous input variables are standardized through z-score standardization to avoid any stability issues during learning. The parameters for standardization are calculated based on the training data and used uniformly for validation and test data. In this way, there is no dominance by variables with high magnitudes.

4.7 Sequence Construction for Temporal Modeling

Battery degradation is a temporal concept by nature. To address the sequential relationships, fixed-size sliding window sequences are extracted from the data at the cycle level. A sequence is a historical perspective of a few cycles in the battery life, and a target is the Normalized Remaining Useful Life (RUL) fraction corresponding to the last cycle in the sequence.

4.8 Model Training Strategy

To determine the best approach regarding the prediction task for the Remaining Useful Life (RUL), various modeling methods were examined. To begin with, the more powerful tabular machine learning methods, such as XGBoost and LightGBM, had been employed using cycle-level engineered features. These methods had been used as a baseline because such methods are capable of handling nonlinear relationships.

However, battery degradation always has a temporal nature, with the information in each consecutive cycle playing a significant role. To model the temporal battery health degradation patterns, a hybrid deep learning technique has been proposed. In this case, a simple LSTM encoder model has been used for the task of battery health representation learning. The resulting embeddings from the LSTM model have been used as inputs to a regularized XGBoost regressor for final remaining useful life prediction.

These comparative experiments were carried out using the same split of train, validation, and test datasets, and all experiments were evaluated using the MAE, RMSE, and R^2 metrics. Though XGBoost and LightGBM performed well as the benchmarking models, the hybrid model of LSTM and XGBoost performed better in generalization and resulted in the selection of this method as the best fit for this research.

4.9 Hybrid Learning for RUL Prediction

For improving the accuracy of prediction, a hybrid learning strategy is employed. Latent degradation embeddings obtained from the trained LSTM encoder are combined with direct contextual features like the normalized progress in the cycle (cycle fraction). The hybrid representation leverages the strong temporal insights obtained from deep learning with meaningful lifecycle information. Using the hybrid representation, an XGBoost regression algorithm predicts the Remaining Useful Life in fractional form.

4.10 Model Evaluation

The effectiveness of the proposed approach is evaluated using standard regression metrics:

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Coefficient of Determination (R^2)

Evaluation is conducted on unseen test batteries to assess the model's ability to generalize to new degradation profiles.

4.11 Explainable AI Integration

To improve the interpretability and understandability of the predicted Remaining Useful Life (RUL) values, an Explainable AI approach has been embedded into the proposed framework. SHAP (SHapley Additive exPlanations) is used as the technique for explaining the results to determine the global and local importance of features that affect the predicted values of RUL produced by the hybrid lst+XGBoost algorithm. SHAP values give an understanding of the importance drawn from learned LSTM degradation and cycle-related features.

Besides SHAP, LIME, which stands for Local Interpretable Model-agnostic Explanations, is employed to provide instance-level explanations for selected samples from the test dataset. Using LIME, it is possible to approximate the complex prediction behavior of the hybrid model using an interpretable model to identify the salient features contributing to either the positive or negative impact of RUL prediction of an individual battery.

Together, SHAP and LIME make it possible to have global explanations regarding the patterns of degradation as well as local explanations to ensure the transparency and trustworthiness of the model's predictions regarding battery degradation and predictive maintenance.

4.12 Summary

The proposed methodology is capable of delivering a well-structured framework for battery Remaining Useful Life prediction. The methodology is the result of incorporating robust preprocessing techniques for battery data, temporal models for battery performance, hybrid learning for battery algorithms, as well as explainable AI in battery solutions.

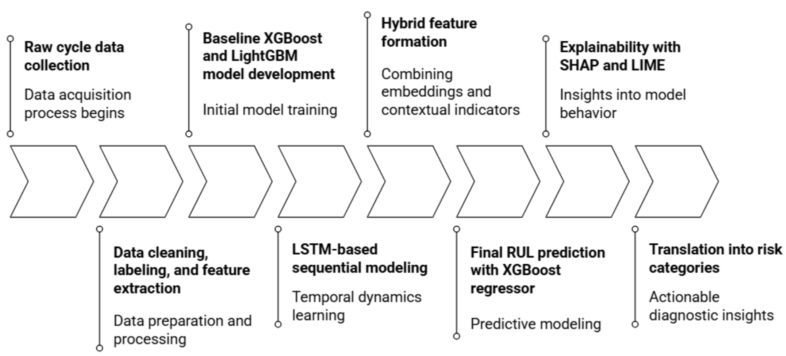


Figure 4.1: Flow Diagram

Chapter 5

Detail Design

5.1 System Architecture Overview

The proposed approach is developed as a modular pipe that is capable of processing raw discharge information from batteries and then providing a precise RUL estimation. The modular structure is developed with a sequential processing workflow that includes raw data processing, extraction of temporal features from batteries, hybrid modeling of the extracted features, and explainability analyses.

5.2 Data Preprocessing Module

5.2.1 File Scanning and Battery Identification

The preprocessing module uses recursion to scan the nested directories to find the discharge files based on the defined name format. IDs related to the batteries are derived from the names to correctly group the discharge logs related to the batteries.

5.2.2 Discharge Data Cleaning

Every discharge file is cleaned to eliminate invalid data, deal with missing data, and adjust inconsistent readings. Duplicate cycles caused by having more than one discharge log are removed.

5.2.3 Cycle-Level Aggregation

Cleaned discharge data is aggregated at the cycle level to generate representative statistics: average voltage, current, temperature, and capacity. Aggregation smooths noise and produces stable features which should be used in degradation modeling.

5.2.4 SOH and RUL Recalculation

The health indicators, SOH and RUL, are recomputed across a full lifecycle after merging all discharge segments of a battery. This ensures consistency of health indicators across merged datasets.

5.3 Dataset Consolidation Module

The processed data for each battery is stored in a separate file. Also, a master dataset is generated by combining all batteries' datasets and arranging them according to battery number and cycle number. The master dataset is used as input for the upcoming stages of modeling.

5.4 Feature Engineering Module

The task of feature engineering is handled by the feature engineering module and aims to convert the raw cycle-level battery data into a useful format for modeling battery degradation. The battery degradation modeling task requires appropriately selected features to capture the electrical, thermal, and aging characteristics of Li-ion batteries. The list includes statistical descriptors obtained using discharge cycle data and Health Indicators such as capacity, State of Health (SOH), and Remaining Useful Life (RUL).

For numeric stability during training and optimal training of the model, all continuous variables are processed for z-score normalization. During this process, all variables are normalized such that their mean is zero with a unit variance, which avoids dominance of variables with large magnitude during the training process of the model. The normalization is done without using information from validation and testing datasets; therefore, information leakage does not occur.

Firstly, besides using static characteristics, dynamic degradation characteristics are described using lag feature construction. The difference in terms of capacity, SOH, and RUL values regarding two sequential cycles is calculated to show degradation rates. The proposed model thus obtains information regarding battery degradation characteristics using temporal features.

5.5 Sequence Generation Module

Temporal dependencies are incorporated by the use of the sliding window mechanism in order to create fixed-size sequences from cycle-level data. A target will represent the point of change in RUL, while the sequences will embody cycles of the past. Temporal degradation learning is thus achieved.

5.6 Machine Learning Model Architectures

5.6.1 XGBoost Architecture (Level-wise Gradient Boosting)

Overview XGBoost is a regularized gradient boosting framework, which aims to be robust and generalized. Unlike LightGBM, XGBoost takes a level-wise (depth-wise) tree expansion strategy.

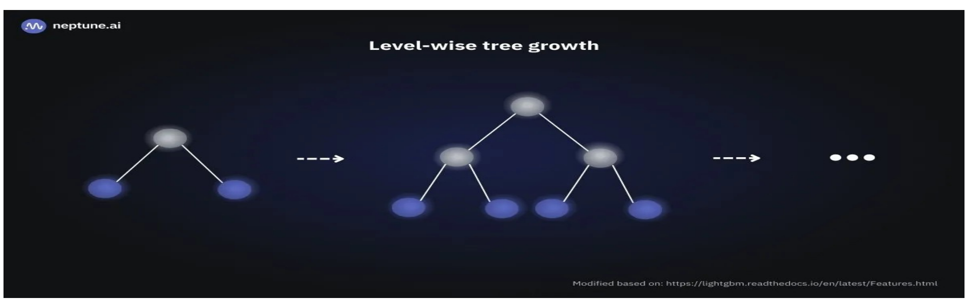


Figure 5.1: XGBoost architecture

Core Architecture The model takes in raw or engineered input features; native support for sparse and missing data. Trees are added one by one, with each tree learning the residuals of the previous ensemble. During construction, all nodes at a given depth are split simultaneously, and the resultant trees are balanced. While attempting to optimize its objective, XGBoost relies on a second-order Taylor series approximation to its loss. This is accomplished through its use of information about the gradient as well as the Hessian. This is further supplemented by L1 and L2 regularization terms. There is additionally use of shrinkage and column sub-sampling. The output is calculated through the summation of predictions made by all trees. Major Features XGBoost is known to offer good management of bias and variance.

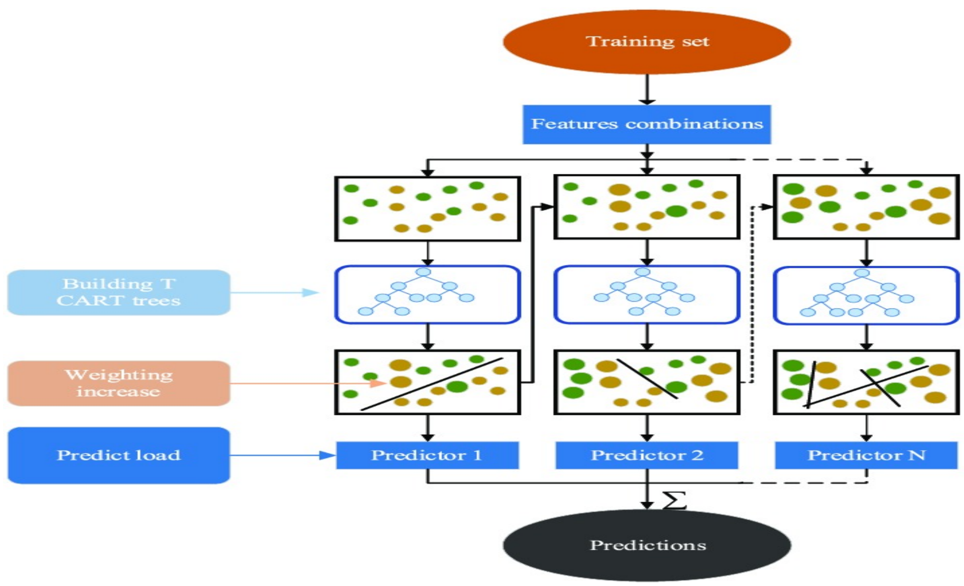


Figure 5.2: XGBoost architecture

5.6.2 LightGBM Architecture (Leaf-wise Gradient Boost)

Overview LightGBM is based on decision trees and is primarily known as an efficient and scalable tool. There is a difference in LightGBM and other boosting algorithms in terms of histogram binning and leaf-wise tree growth.

Core Architecture The model accepts engineered numerical inputs, supporting native handling of missing data. Continuous inputs are converted to discrete bins through histogram-based learning, conserving memory resources and improving the efficiency of split evaluations. Tree growing is carried out in a leaf-wise manner, splitting the leaf for which the greatest reduction in loss is obtained at each stage, promoting the growth of deeper possibly asymmetrical trees. The model is trained in a sequential gradient boosting scheme, optimizing the objective with respect to both first- and second-order gradients. The model complexity is constrained through the use of depth, the number of leaves, as well as the minimum samples per leaf. The final prediction is obtained through the sum of all weights of trees. Key Characteristics Leaf-wise growth allows for good modeling of complex patterns, whereas histogram-based learning enables fast learning processes. Nonetheless, strict constraints are required for learning processes involving leaf-wise growth so as to avoid overfitting.

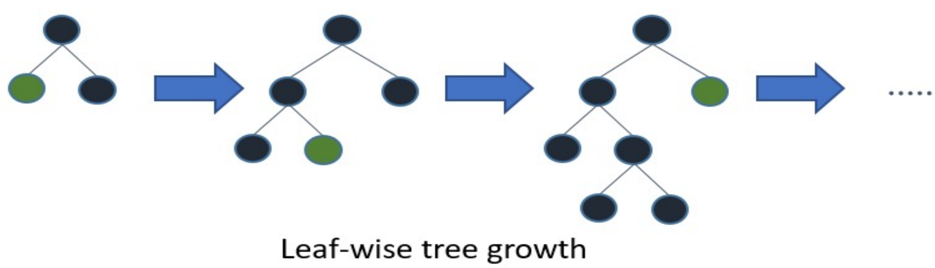


Figure 5.3: lightgbm

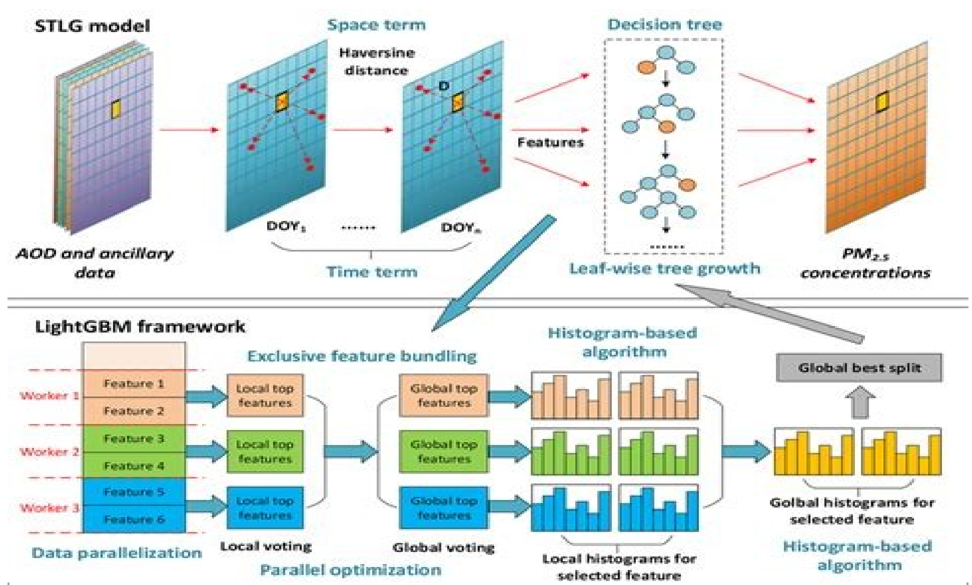


Figure 5.4: lightgbm architecture

5.6.3 Hybrid LSTM + XGBoost Architecture

Overview The combined LSTM-XGBoost architecture connects the ability to process temporal sequences to the powers of the gradient boosting method for prediction.

Architecture Pipeline The sequential input data is initially processed by an LSTM network. This is because LSTM is able to capture long- and short-term dependencies using its memory units. The output feature representation is then derived using extractions based on its output, usually its last hidden state. This output feature representation is supplemented by other statistical features. The output is then used as input to an XGBoost regressor or classifier. The XGBoost regressor or classifier is able to capture nonlinear relationships among features, thus generating predictions. Architectural Rationale The LSTM module learns the dynamics in the data, which cannot be modeled in tree models, while the XG-Boost handles the nonlinear boundary between the decisions in the tabular data. The rationale behind this work is to improve the generalization capability.

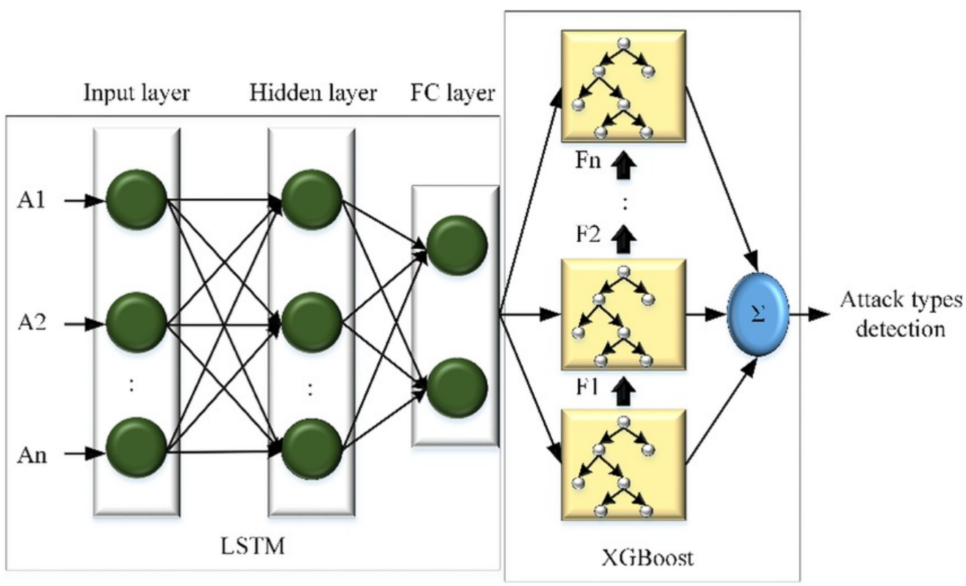


Figure 5.5: hybrid architecture

5.7 Explainable AI (XAI) Module

To ensure transparency and trustworthiness, explainability techniques are integrated into the prediction pipeline.

5.7.1 SHAP (SHapley Additive exPlanations)

Overview SHAP is a model interpretability tool that explains model predictions by attributing a fair share of the prediction to each input feature, depending on its contribution to the final result. SHAP is developed using notions from cooperative game theory. It is both reliable and stable.

Core architecture Given a trained model and a test instance, SHAP values each feature by looking at how much the result is changed by including versus excluding a feature. A feature is a participant in a team effort, so how much a feature contributes is its average impact given a combination of features. In the case of tree-based methods such as XGBoost and LightGBM, the TreeSHAP method is used in the implementation of the SHAP technique for the computation of exact feature values in decision trees. The results are globally accurate and locally precise. The explanation technique has both global interpreting capability and instance-level interpreting ability. The computational complexity might be relatively high when handling large models involving complex models that are not based on trees.

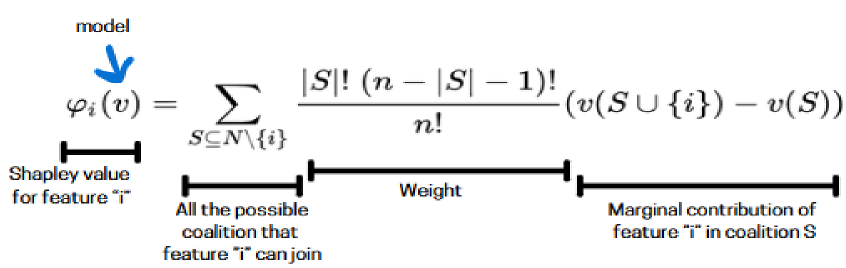


Figure 5.6: SHAP Formula

5.7.2 LIME (Local Interpretable Model-agnostic Explanations)

Overview -LIME explains individual predictions by creating a simple, easy-to-understand model that behaves like the original complex model in the neighborhood of a specific data point.

Core Architecture -For a given instance, LIME begins by producing many versions that are very similar to the instance but with small perturbations. The new instances are then used to produce predictions using the original black-box model. The instance is assigned a weight according to its distance to the original instance. Based on the weights obtained, LIME builds an interpretable model, for example, a linear model, which approximates the original black box function model for the particular given data only. The weights of the interpretable model illustrate the importance of the feature in predicting the specific data point. LIME is flexible and model-independent and very efficient with regard to explanation tasks for specific predictions. Nevertheless, it might happen that explanations provided by LIME are not similar in various runs.

$$\xi(x_i) = \arg\min_{g \in G} L(f, g, \pi_x) + \Omega(g)$$

Figure 5.7: LIME Formula

5.8 Summary of Detailed Design

This chapter has explained the internal implementation details of the battery Remaining Useful Life prediction system. The system integrates the preprocessing module, the temporal deep learning model, the hybrid regression model, and the explainable AI framework. The integrated system enables the creation of precise models for battery health assessment in the context of electric vehicles.

Chapter 6

Results

The current chapter focuses on experimental results obtained from the proposed hybrid approach to SOH and RUL prediction using the proposed framework and analyses of its behavior through the use of explainable AI. The main significance of the proposed approach is its ability to provide high predictive accuracy and explanations.

6.1 SHAP Global Feature Importance Analysis

Figure 6.1 illustrates the SHAP global feature importance using a beeswarm plot for Remaining Useful Life (RUL) prediction. The plot summarizes the contribution of each input feature for all validation samples. The horizontal axis represents the SHAP value, which shows the magnitude and direction of a feature's influence on the predicted RUL, while the color scale indicates the feature values ranging from low to high.
From the figure, the cycle fraction (*cycle_frac*) appears to have the greatest impact feature, suggesting that battery life progress is more prominent in RUL estimation.Higher cycle fraction values generally tends the predictions toward lower remaining life, which aligns with expected battery degradation behavior which matches the expected battery performance decay. In addition, several learned degradation embeddings (*deg_embed_**) significantly contribute to the prediction by describing complex degradation patterns over time and learned through the LSTM encoder. The relatively compact distribution of SHAP values for these embeddings indicates stable and consistent influence across samples.

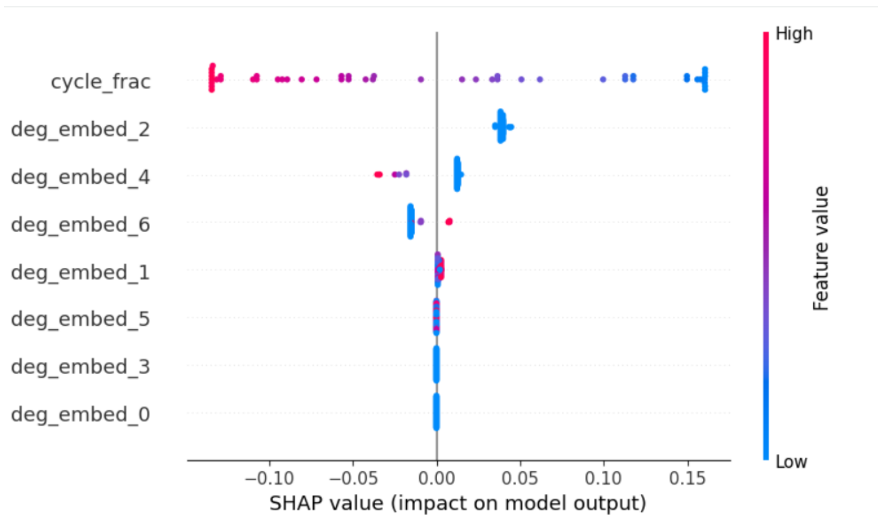


Figure 6.1: SHAP Global Feature Importance (Beeswarm Plot) for RUL Prediction

6.2 SHAP Local Explanation for a Single Prediction

In figure 6.2, a SHAP waterfall chart is presented for interpreting an individual RUL prediction.It illustrates the role of individual factors on the moving of (Prediction): baseline to final estimated RUL.The base value is an average value for RUL throughout the dataset. In this for example, the cycle fraction term makes a positive contribution, suggesting that the battery and therefore The battery is in an earlier stage of its lifecycle hence, there is a higher prediction probability of impending failure.remaining lifetime. Certain degradation embeddings are negatively contributing, embodying learned degradation pattern features that have a slightly lower effect on estimating the Remaining Useful Life. This graph indicates that the clearly demonstrates how lifecycle information and degradation characteristics are jointly considered by the model

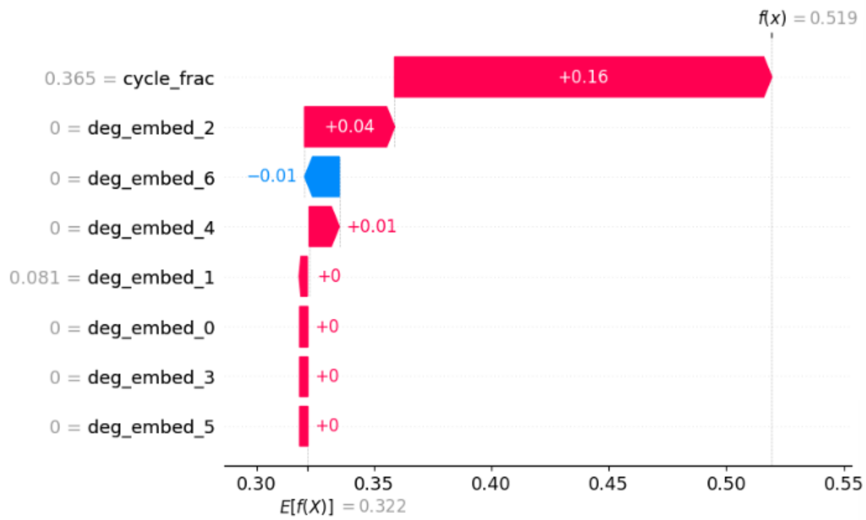


Figure 6.2: SHAP Waterfall Plot for a Single RUL Prediction Instance

6.3 LIME-Based Local Feature Importance for a Training Sample

Figure 6.3 LIME explanation for a training data point.LIME approximates the complex model locally with a simpler model It establishes a model and determines the key factors which influence a given prediction.The results reveal that cycle fraction is still the pre-eminent factor with a strong positive contribution to the predicted RUL. Several degradation embeddings are utilized in the model.

The contribute with smaller positive or negative weights. This verifies again that while lifecycle progressions that control the overall prediction, degradation patterns that refine the estimate based on their behavior patterns over time. The consistency between SHAP values and their behavior patterns for and LIME explanations further proves the dependability of the interpretability model.

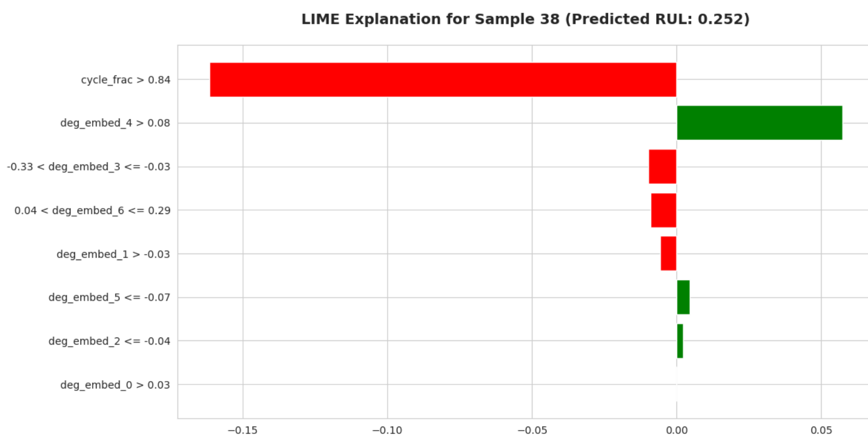


Figure 6.3: LIME-Based Local Feature Importance for Training Sample

6.4 Correlation Analysis of Degradation Embeddings with Physical Battery Features

Linear coefficient magnitude analysis explaining the relationship between learned degradation embeddings and physical battery parameters that different embeddings are capturing different aging and degradation characteristics.

6.5 XGBoost Model Training and Performance Metrics

The training configuration and testing results of the XGBoost Regression model based on the LSTM-degradation embeddings for MAE, RMSE, and R^2 performance on the training, validation, and test sets.

6.6 Battery-Wise RUL Prediction and Maintenance Recommendation

Battery-Wise RUL Prediction and Maintenance Suggestion Predicted Remaining Useful Life (RUL) percentages in the case of sample batteries, along with their respective risk classification and maintenance recommendations. This represents the applicability of the proposed predictive maintenance approach.

6.7 Overall Interpretation of Results

The explainability analysis confirms that the proposed hybrid framework successfully:

- Accurately predicts battery Remaining Useful Life,
- Captures meaningful and realistic degradation patterns,
- Provides transparent and consistent explanations using SHAP and LIME.

The alignment of SHAP and LIME values improves confidence in a model and confirms its effectiveness for use in real-world systems for battery status analysis and predictive maintenance in electric vehicles.

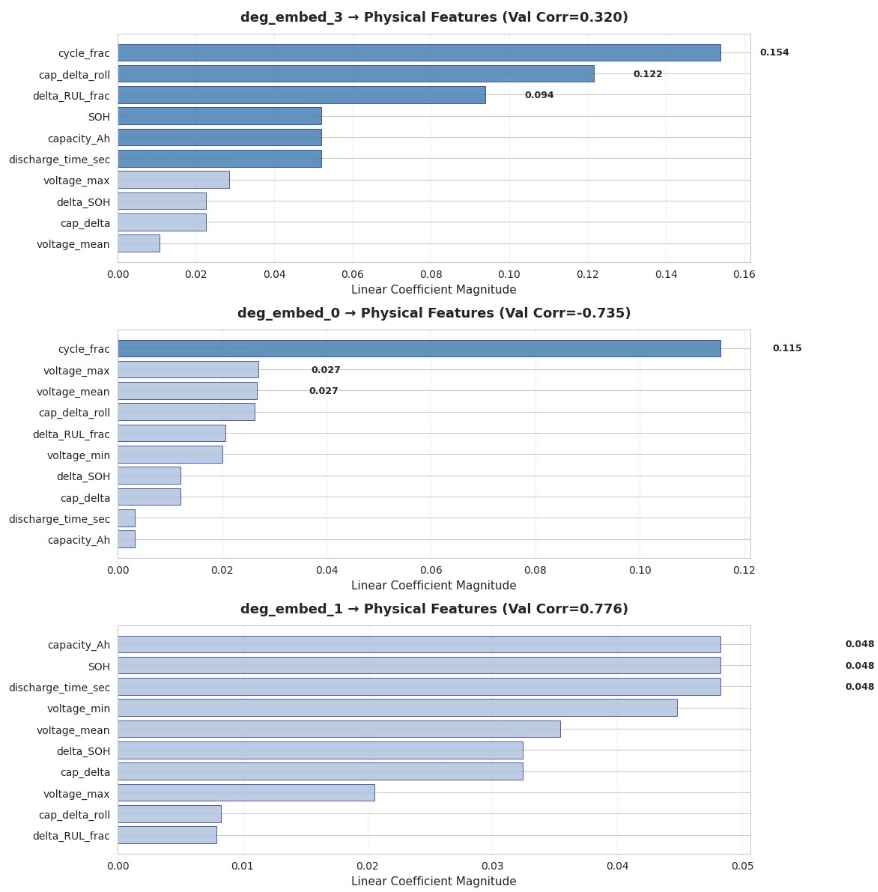
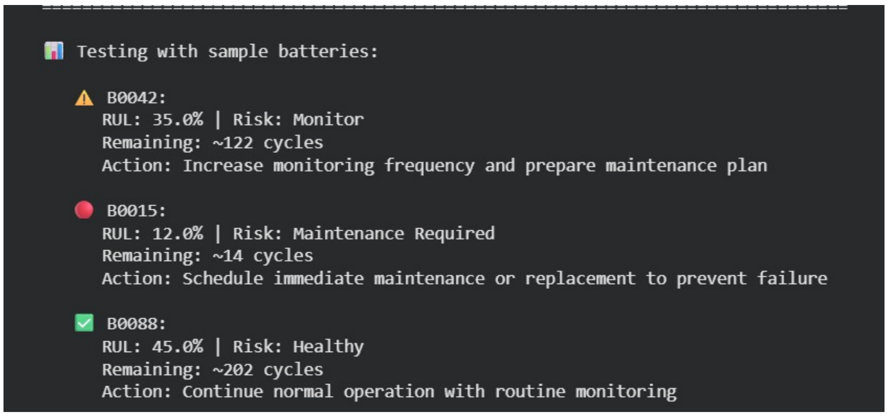


Figure 6.4: Correlation Analysis of Degradation Embeddings with Physical Battery Features : (a) Degradation embedding `deg_embed_3` showing medium correlation with cycle fraction, rolling capacity degradation, and Remaining Useful Life (RUL); (b) Degradation embedding `deg_embed_0` exhibiting negative correlation with key voltage-related features, indicating voltage-sensitive degradation behavior; (c) Degradation embedding `deg_embed_1` demonstrating strong positive correlation with capacity, State of Health (SOH), and discharge characteristics, representing long-term battery aging patterns.



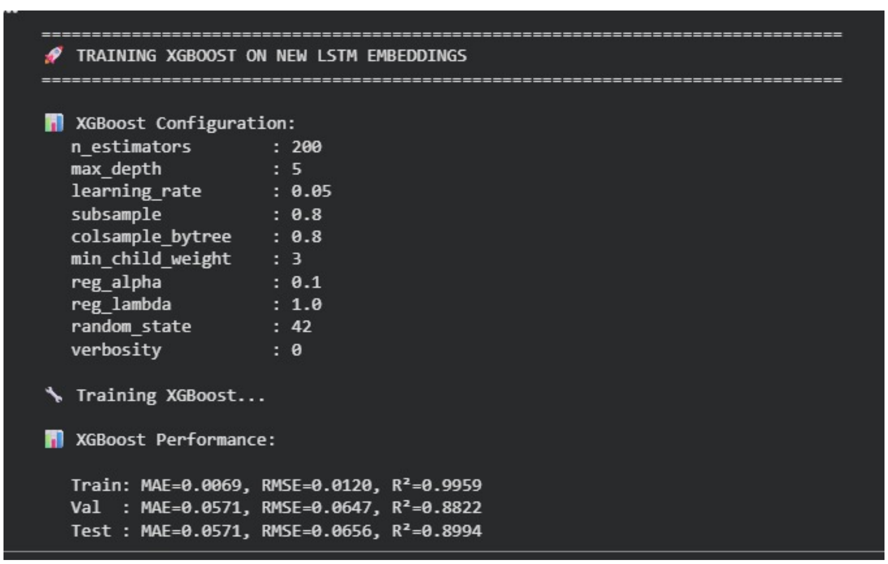
```
📊 Testing with sample batteries:

   ⚠️ B0042:
     RUL: 35.0% | Risk: Monitor
     Remaining: ~122 cycles
     Action: Increase monitoring frequency and prepare maintenance plan

   🔴 B0015:
     RUL: 12.0% | Risk: Maintenance Required
     Remaining: ~14 cycles
     Action: Schedule immediate maintenance or replacement to prevent failure

   ✅ B0088:
     RUL: 45.0% | Risk: Healthy
     Remaining: ~202 cycles
     Action: Continue normal operation with routine monitoring
```

Figure 6.5: XGBoost Model Training and Performance Metrics



```
================================================================================
🚀 TRAINING XGBOOST ON NEW LSTM EMBEDDINGS
================================================================================

📊 XGBoost Configuration:
   n_estimators        : 200
   max_depth           : 5
   learning_rate       : 0.05
   subsample           : 0.8
   colsample_bytree    : 0.8
   min_child_weight    : 3
   reg_alpha           : 0.1
   reg_lambda          : 1.0
   random_state        : 42
   verbosity           : 0

🔧 Training XGBoost...

📊 XGBoost Performance:

   Train: MAE=0.0069, RMSE=0.0120, R²=0.9959
   Val  : MAE=0.0571, RMSE=0.0647, R²=0.8822
   Test : MAE=0.0571, RMSE=0.0656, R²=0.8994
```

Figure 6.6: Battery-Wise RUL Prediction and Maintenance Recommendation

Chapter 7

Conclusion

7.1 Conclusions

The proposed work considers the predictiion of Remaining Useful Life (RUL) of Li-ion batteries, leveraging a hybrid machine learning model coupled with explainable AI approaches. In the proposed approach, temporal feature learning by deep learning techniques and robust regression by ensemble models are included. SHAP and LIME are applied for interpretability.

7.2 Features

The proposed system incorporates the following key features:

- Cycle-level electrical features extracted from charge and discharge profiles.
- Derived battery health indicators, including SOH and fractional RUL.
- Temporal degradation features such as:
  - Change in capacity between consecutive cycles
  - Change in SOH and RUL over time
- Long Short-Term Memory (LSTM) learned degradation embeddings that capture long-term temporal patterns in battery aging.
- Cycle progression feature (*cycle_frac*) providing contextual information about the battery's life stage.

- Hybrid feature representation combining deep learning-based embeddings with physically interpretable battery indicators.
- Model explainability enabled through SHAP for global feature importance analysis and LIME for instance-level explanations.

These features collectively enable the model to capture both short-term operational variations and long-term degradation behavior, resulting in improved prediction accuracy and interpretability.

7.3 Limitations

Despite promising results, the proposed project has certain limitations:

- Impedance data was excluded due to misalignment with aggregated cycle-level data, which may limit the capture of detailed electrochemical behavior.
- The model was trained on offline historical datasets, restricting its applicability for real-time or on-board deployment.
- Computational complexity increases due to the integration of deep learning–based embeddings with ensemble machine learning models.
- Explainability techniques such as SHAP can be computationally expensive when applied to large-scale datasets.
- Model performance may vary when applied to batteries with different chemistries or operating conditions not represented in the training data.

7.4 Future scope

Several extensions can further enhance this work:

- Integration of impedance spectroscopy features through improved alignment techniques or multi-resolution data aggregation.
- Deployment of the proposed model within a real-time Battery Management System (BMS) for on-board health monitoring and prediction.

- Exploration of Transformer-based architectures to improve long-term temporal dependency modeling.
- Development of online or incremental learning mechanisms to enable adaptation to evolving battery degradation patterns.
- Extension of explainability methods to include causal analysis and uncertainty estimation for more robust decision support.
- Validation of the model across diverse battery chemistries and real-world electric vehicle (EV) datasets.
- Optimization of the model for edge or embedded deployment to support real-time inference in electric vehicles.

Bibliography

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[3] ACN Data Working Group, “Adaptive Charging Network (ACN) Datasets,” University of California, Los Angeles (UCLA), 2018.

Appendix

Note: Contents to be included : -
a) Work Plan
b) Project Expenses (Bill of Materials Table)
c) Tables
d) Proofs
e) Test cases
f) Data sheets of Significant components ONLY
g) USER MANUAL : - A SIMPLE STEP- BY-STEP PROCEDURE for demonstrating the working of the Project set-up , should be given .
(A VIDEO file showing the same should be submitted alongwith the Soft-copy of the Report. This is Applicable ONLY for SELF –Sponsored and COLLEGE-Sponsored Projects.)
In case of Hardware Projects the instructions should begin from the POWER – ON step.
In case of Software projects the instructions should begin from the step mentioning the location and name of the .exe file to OPEN the GUI , if any or any other applicable .exe file .