**Integration of Machine Learning and Explainable AI (XAI) approaches for Optimizing Battery Health on Electric Vehicles**

Submitted in partial fulfillment of the requirements for the award of the degree of

**MASTER OF SCIENCE IN COMPUTER SCIENCE**

# **Submitted by**

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**Under the guidance of**

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**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**

**SASTRA DEEMED TO BE UNIVERSITY**

**(A University under section 3 of the UGC Act, 1956)**

## **Srinivasan Ramanujam Centre**

**Kumbakonam - 612001**

**Tamil Nadu, India**

**May 2024**



**SHANMUGHA ARTS, SCIENCE, TECHNOLOGY & RESEARCH ACADEMY**

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**BONAFIDE CERTIFICATE**

Certified that this project work entitled “**Integration of Machine Learning and Explainable AI (XAI) approaches for Optimizing Battery Health on Electric Vehicles**” submitted to the Srinivasa Ramanujan Centre, SASTRA Deemed to be University, Kumbakonam – 612001 by **Pakthapriyan S (225058031)** in partial fulfillment of the requirements for the award of the degree of **MASTER OF SCIENCE IN COMPUTER SCIENCE** work carried out under the guidance of **Dr. R. Bala Krishnan** during the period January 2025 to May 2025.

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**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**

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**DECLARATION**

I submit this project work entitled “**Integration of Machine Learning and Explainable AI (XAI) approaches for Optimizing Battery Health on Electric Vehicles**” to Srinivasa Ramanujan Centre, SASTRA Deemed to be University, Kumbakonam – 612 001, in partial fulfillment of the requirements for the award of the degree of **MASTER OF SCIENCE IN COMPUTER SCIENCE**. I declare that this is my original work carried out under the guidance of **Dr. R. Bala Krishnan,** Assistant Professor, Department of Computer Science and Engineering, Srinivasa Ramanujan Centre.

Place : Kumbakonam

Date :

Name : Pakthapriyan S Signature:

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**ACKNOWLEDGEMENT**

I pay my sincere pranams to God ALMIGHTY for his grace and infinite mercy and for showing on me his choicest blessings.

First, I would like to express my sincere thanks to our honourable Chancellor **Prof. R. Sethuraman**, Vice-Chancellor **Dr. S. Vaidhyasubramaniam** and Registrar **Dr. R. Chandramouli** for allowing me to be a student of this esteemed institution.

I express my deepest thanks to revered Dean **Dr. V. Ramaswamy**, SRC and respected Associate Dean **Dr. A. Alli Rani**, SRC for all their moral support and suggestions when required without any reservations.

I exhibit my pleasure in expressing my thanks to **Dr. V. Kalaichelvi**, Associate Professor, Department of Computer Science and Engineering, Srinivasa Ramanujan Centre, for her encouragement during our project work.

I exhibit my pleasure in expressing my thanks **Dr. R. Bala Krishnan**, Assistant Professor, Department of Computer Science and Engineering, my guide for hisever-encouraging spirit and meticulous guidance for the completion of the project.

I would like to express my deep sense of gratitude to the project coordinators, **Dr. N. Saravanan** and **Dr. P. Venkateswari**, Assistant Professor, Department of Computer Science and Engineering for their cordial support and meticulous guidance which enabled me to complete this project successfully.

I would like to thank the panel members **Dr. \_. \_\_\_\_\_\_\_\_**and **Dr. \_. \_\_\_\_\_\_\_\_\_** Assistant Professor, Department of CSE for their support and encouragement to complete the project successfully.

I owe my sincere thanks to all faculty members in the department who have directly or indirectly helped me in completing this project.

Without the support of my parents and friends, this project would never have become a reality. I owe my sincere thanks to all of them. I dedicate this work to all my well-wishers, with love and affection.

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**ABSTRACT**

**Integration of Machine Learning and Explainable AI (XAI) approaches for Optimizing Battery Health on Electric Vehicles**

**Abstract**

Machine Learning (ML) empowered the EV to reduce energy consumption intelligently and make driving more comfortable; hence, enabling maintenance forecast capabilities and explaining in detail an otherwise opaque model in machine learning increases transparency in order to encourage trust in their outputs. However, XAI was invented to counter concerns of this transparency with an understanding into its decision-making. Integration of XAI may help to develop more user-friendly and trustworthy EV systems that improve not only performance but also user acceptance and understanding of advanced technologies. This study conducts an investigation into the synergistic integration of Machine Learning— Explainable Artificial Intelligence (XAI) techniques within an electric vehicle (EV) context. Integrating XAI (SHAP) with ML based ensemble classifiers are utilized for optimizing EV systems components, which would contribute to the development of more user-friendly and trustworthy systems. XAI will help us identify relevant features that drive predictions that will also help us better understand the battery degradation phenomenon. The Kaggle repository’s EV dataset is used to verify the efficiency of the proposed system with metrics associated with confusion matrix. The proposed scheme would be expected for an efficient outcome with an optimistic accuracy with minimum features for the battery health evaluation process.

**Keywords:** EV Battery Health, Battery Health Classification, Machine Learning, Explainable AI (XAI), Ensemble Classifiers

**CHAPTER 1**

**INTRODUCTION**

Chapter 1: Introduction

1.1 Background

The global shift towards sustainable transport has put Electric Vehicles (EVs) at the forefront of automotive technology. EVs have many advantages over traditional internal combustion engine cars, including reduced emissions, reduced running costs, and often enhanced performance characteristics.At the core of all EVs is the battery system, a highly sophisticated and important system whose health immediately impacts the range, efficiency, safety, and overall vehicle longevity. Optimum battery health is therefore paramount to maximize EV performance and long-term user satisfaction and confidence.

Effective battery management involves complex systems that are capable of inspecting the current condition of the battery and assessing its future condition. Machine Learning (ML) methods have proven to be effective tools in this regard, allowing data-driven methods to estimate State of Charge (SOC), State of Health (SOH), and forecast Remaining Useful Life (RUL). Through the inspection of huge amounts of data created when the vehicle is in use and during charging cycles, ML models are capable of detecting fine degradation patterns which allow for proactive maintenance and charging strategy optimization.  
  
1.2 Problem Statement

While very accurate predictions or classifications have been achieved by sophisticated ML models, particularly complex ensemble models, of EV battery health, their very nature tends to render them "black boxes." The models may make very accurate predictions, but they do not usually provide transparent, human-understandable explanations of why a particular prediction was made. This lack of transparency creates problems of considerable magnitude, especially for high-risk applications like battery health management where reliability and safety are paramount. Stakeholders like engineers, maintenance personnel, and even car owners may struggle to trust or act on black-box model predictions. Furthermore, the black-box nature prevents the possibility of obtaining greater scientific insight into the complex underlying processes that govern battery degradation. There clearly is a need to enhance the interpretability of such powerful ML models to build trust, facilitate better debugging, and allow better understanding of the factors affecting battery health.

ery health monitoring, where reliability and safety are the topmost concerns. Individuals like engineers, maintenance personnel, or even car owners are confronted with problems in trusting or acting on black-box model responses.  
  
1.3 Objectives and Scope

This project aims to address the problem of explainability of ML models for the application of EV battery health estimation by symbiotically integrating Machine Learning and Explainable AI (XAI) techniques. The main objectives of this work are:

1. To develop and validate ensemble Machine Learning classifiers for accurate classification of EV battery health status.

2. To incorporate the Shapley Additive exPlanations (SHAP) model for explaining the predictions of the trained ML models.

3. To apply SHAP explanations to discover and examine the most important features that greatly impact battery health predictions.

4. To illustrate how the XAI explanations can be used to enhance the understanding of the underlying battery degradation process.

5. To compare the performance of the ML models and the learned knowledge from XAI on an actual EV dataset from a Kaggle library.

The scope of the project is battery health classification and SHAP interpretation of the classifications. While the information gained can be used to suggest more general battery management processes or optimization, the direct outcome is an interpretable classification model trained for battery health evaluation from the provided dataset.  
1.4 Proposed Approach  
Our approach is to build and compare various ensemble classification models suitable for predicting various battery health classes. Following training and performance evaluation of models in terms of metrics derived from the confusion matrix, SHAP analysis will be conducted. SHAP values will be computed on individual predictions to facilitate local explanations (why a specific battery instance was predicted as it was predicted) and aggregated to facilitate global explanations (why specific features tend to be of greatest importance to the model's predictions). By doing so, we will not just be able to confirm model performance but also gain actionable insights into the causes of battery health degradation as modeled.  
CHAPTER 2 AIM  
2. OBJECTIVE:  
The ultimate goal of this project is to enhance the understanding and forecasting of Electric Vehicle (EV) battery health through the integration of Machine Learning (ML) methodologies and Explainable Artificial Intelligence (XAI). In more detail, the key goal is to design strong ensemble classification models for individual battery health forecasting and, critically, to leverage the SHapley Additive exPlanations (SHAP) method to interpret the decision-making of such models. Through the implementation of SHAP analysis to the results of predictions carried out on an EV dataset, we aim to identify the key features with high contributions towards the classification of battery health, thus gaining significant knowledge about the complex factors underlying battery degradation and enhancing the trustworthiness of the predictive models deployed in the battery management.

CHAPTER 3: SYSTEM REQUIREMENTS

3. SYSTEM SPECIFICATIONS:

The execution and implementation of the proposed methods in Explainable Artificial Intelligence (XAI) and Machine Learning for electric vehicle battery health classification were mostly carried out within the Jupyter Notebook environment. The cloud-based setup offered the computational resources, both processing and RAM, which could easily be accessed through a web browser. The development process made use of widely known Python libraries for data handling, machine learning, and interpretability, including Pandas, Scikit-learn, XGBoost, CatBoost, and SHAP. For local development and testing, a system configuration is recommended to consist of a 64-bit operating system, Intel Core i7 processor, and a minimum of 16GB of RAM, which is sufficient to accommodate the size of the dataset and the computational requirements involved in training multiple ensemble models and conducting SHAP analysis.  
  
**CHAPTER 4 LITERATURE SURVEY**

**4. LITERATURE SURVEY:**

Effective prediction and understanding of Electric Vehicle (EV) battery health are critical for reliable performance and longevity. Researchers have extensively explored various data-driven techniques, particularly those leveraging Machine Learning (ML), to estimate State of Health (SOH) and predict Remaining Useful Life (RUL). This literature review examines recent work in this domain, highlighting different ML approaches and key findings relevant to our study.

Recent studies demonstrate a strong focus on advanced ML models for battery health prediction. Han et al. (2024) proposed a Hybrid Perspective Ensemble Learning Strategy (HyPELS) that combines predictions from multiple perspectives, utilizing innovative training techniques like block shuffling to enhance RUL prediction accuracy and robustness [1]. Their work emphasizes the integration of health indicators and capacity degradation data. Similarly focusing on SOH, Dongxu Han et al. (2024) explored a simplified health indicator method, introducing a Weighted Health Indicator (WHI) to improve prediction accuracy under real-world EV conditions, though noting potential limitations across diverse chemistries [2]. The same authors, Han et al. (2023), presented a data-driven methodology linking WHI with battery capacity for accurate SOH prediction, identifying potential performance limitations under varying operational parameters [3].

Ensemble methods and deep learning techniques also feature prominently. Nair et al. (2022, 2023) explored deep hybrid learning models and ensemble techniques like XGBoost, boosting, and bagging for effective battery health prediction [4, 6 - *Note: There appears to be duplicate content in the provided table entries for Nair et al., 2023 and 2022, both referring to "Effective route classification" which seems out of place for battery health. Assuming the techniques listed (XGBoost, Boosting, Bagging) are the relevant part for battery health*]. These studies highlight the power of combining models or using deep architectures. Furthermore, Niraula and Singh (2023) compared different deep learning and traditional ML models, finding that Deep Long Short-Term Memory (LSTM) excelled in SOH estimation compared to BPNN and SVM, while noting the need for evaluation across diverse battery characteristics [5].

Broader data-driven approaches are also surveyed. Tao et al. (2024) utilized a multi-graph neural network fusion method with Random Forest Regression for improved RUL prediction based on multi-graph features, though acknowledging limitations in generalizability [7 - *Note: This entry corresponds to the image you provided, not the text list. Assuming the numbering is sequential across both sources.*]. Similarly, Wang et al. (2024) provided a comprehensive review of advanced data-driven techniques, emphasizing the crucial role of AI for accurate RUL prediction, the need for diverse datasets and feature extraction, and concluding that no single AI method universally solves all RUL problems [8].

These studies collectively demonstrate significant progress in applying ML and deep learning for EV battery health monitoring and prediction. They highlight the effectiveness of ensemble methods, the importance of appropriate health indicators and feature extraction, and the ongoing challenges related to generalizability and robustness across varying conditions and battery types. However, while accuracy is a clear focus, the interpretability of these often complex models, particularly ensemble and deep learning architectures, remains an area requiring further exploration. Our project builds upon this foundation by specifically integrating XAI techniques, such as SHAP, with ensemble classifiers not only to achieve accurate battery health classification but, more importantly, to provide transparency and actionable insights into the model's decision-making process and the underlying factors influencing battery degradation.

CHAPTER 5 METHODOLOGY

5. METHODOLOGY:

This chapter outlines the methodology steps adopted to complete the project objectives, focusing on data collection and preprocessing, followed by model building, evaluation, and deployment of Explainable AI (XAI) methods. The methodology combines selected high-performing Machine Learning classification models with the explanatory strength of the SHapley Additive exPlanations (SHAP) method.

5.1 Data Collection and Importation

The initial step of the project was to acquire the dataset needed for model training and testing. Information pertaining to the properties of Electric Vehicle (EV) battery and its operating parameters, and a target variable for battery health classification (Battery\_Class), was acquired from a publicly available dataset in a Kaggle repository. The dataset, with approximately 100,000 rows, was used as the empirical basis for the development and testing of the predictive models. The data was structured into a format suitable for further processing and analysis using standard data manipulation libraries.

5.2 Data Preparation:

Data preprocessing is a critical phase of ensuring both the dataset and data relevance for Machine Learning model training. The process involves a set of critical steps:

5.2.1 Handling Incomplete Data:

A check of the dataset revealed that there were missing values in certain features. To address this, an imputation step was performed. A SimpleImputer with a 'mean' strategy was used to replace missing numeric values with the mean of the respective feature column. This is useful in preserving the dataset size and making the most of the available information without exacerbating the incompleteness of the data issue.

5.2.2 Data Splitting:

After missing value handling, the data was divided into training and test sets. Independent variables (X) were separated from the dependent variable (y, named as Battery\_Class). This was followed by dividing the data into training and test sets using train\_test\_split function, keeping 80% of the dataset to train models and keeping the remaining 20% to test the performance of the model on data not seen by the model previously. The same random\_state was utilized to make the split reproducible.

5.3 Model Training and Selection:

Based on their established performance properties and applicability to the dataset, a targeted selection of three high-performance classifiers was performed: XGBoost, CatBoost, and ExtraTreesClassifier. These tree ensemble and boosting-based algorithms were selected for their stability and performance in detecting intricate patterns, and for their capacity to accommodate tree-specific explanation techniques such as SHAP. The models were trained on the preprocessed training data using their respective implementations in standard ML libraries.

5.4 Model Evaluation:

After the training process, the performance of each selected model—XGBoost, CatBoost, and ExtraTreesClassifier—was extensively evaluated utilizing the given test set. Predictions were generated for the test samples, and these predictions were compared with the true target values. For each model, the common classification metrics utilizing the confusion matrix were computed, including accuracy, precision, recall, and F1-score. Furthermore, a classification report was generated to provide detailed performance metrics for various battery health classes for all three models. 5.5 Explainable AI (XAI) Application: A key component of this project is the use of Explainable Artificial Intelligence (XAI) to interpret the predictions of the trained models. Specifically, the SHapley Additive exPlanations (SHAP) framework was used. Given that XGBoost, CatBoost, and ExtraTreesClassifier are tree-based models, the effective shap.TreeExplainer was used. The SHAP values were approximated for the test dataset for all three trained models, thus approximating the contribution of each input feature to the prediction for each individual instance. This process supplied the necessary data for the following analysis of feature importance and effect. 5.6 Analysis and Interpretation of Results: The second phase involved the analysis of the evaluation metrics in conjunction with the interpretation of SHAP results obtained for XGBoost, CatBoost, and ExtraTreesClassifier. Model performance metrics comparison across the three classifiers was conducted to determine their respective strengths. The SHAP values obtained from them were then depicted and analyzed through different approaches, including summary plots, dependence plots, and force plots. The analytical method facilitated the determination of the most contributing global features to each model's prediction, a glimpse into the interaction between the values of specific features and the expected battery health outcome, and understandable explanations at the instance level. The results obtained through this rigorous analysis proved to be key in advancing the understanding of empirical drivers of battery health classification and provided insight into the phenomenon of battery degradation evidenced in the dataset.  
  
CHAPTER 6 IMPLEMENTATION

6. IMPLEMENTATION:

Implementing the given methodology involved converting the phases of data handling, model training, evaluation, and explanation to code that was executable. In this chapter, the tools, libraries, and procedure used in executing the EV battery health classification and XAI analysis are presented.

The project implementation as a whole was done primarily with the Python programming language. Python was used since it has an incredibly large set of libraries appropriate for data science, machine learning, and the explainability side. Key libraries utilized were:

Pandas and NumPy for data loading, manipulation, and preprocessing, such as missing value handling with SimpleImputer.

Scikit-learn to split the data (train\_test\_split) and to offer the implementation of the ExtraTreesClassifier and the core evaluation metrics such as accuracy\_score and classification\_report.

XGBoost for the implementation of the XGBoost classification model.

CatBoost for the implementation of the CatBoost classification model.

Shap (SHapley Additive exPlanations) for applying the XAI techniques for explaining the trained models.

Matplotlib and potentially Seaborn for plotting data features, model performance, and most critically, the SHAP results (summary plots, dependence plots, force plots).

The process began by loading the dataset. This initial process was preceded by the preprocessing processes described in Chapter 5, such as imputation of missing values and splitting the data into a training and test subsets. Subsequent to this, the selected models—XGBoost, CatBoost, and ExtraTreesClassifier—were created and separately trained on the training data. Once each model finished training, predictions were made on the unseen test dataset to make comparisons of their performance. Finally, the SHAP library was utilized to compute SHAP values corresponding to each model's prediction on the test data, thereby laying the foundation for the subsequent interpretation phase.

CHAPTER 7 PERFORMANCE ANALYSIS

7. PERFORMANCE ANALYSIS:

Performance evaluation of trained classification models is crucial to ascertain their efficacy to make correct predictions about EV battery health status. The measures utilized in this chapter to consider the models—XGBoost, CatBoost, and ExtraTreesClassifier—are explicated, and how their performance was evaluated against the test dataset is explained. In contrast to regression tasks that can use measures such as Mean Squared Error (MSE), the class nature of battery health in this project requires the application of classification-oriented measures of evaluation.

7.1 Accuracy:

Accuracy serves as a primary measure, the proportion of correctly predicted instances (positive and negative classifications) out of the total number of instances in the test set. Accuracy, while simple, is a helpful higher-level perspective of the overall correctness of the model. Accuracy was determined for each of the three models for the sake of establishing a simple baseline for comparison.

7.2 Confusion Matrix:

The confusion matrix gives a complete overview of the model's performance on different classes. The confusion matrix is a matrix which displays the performance of an algorithm, especially for the problem of classification. Each row is for instances of an actual class, and each column is for instances of a predicted class. From the confusion matrix, True Positives, True Negatives, False Positives, and False Negatives can be easily determined, which are crucial to know where the model is good and where it is bad (for example, misclassifying a 'Poor' battery as 'Good' or vice versa). A separate confusion matrix was generated for each model that was trained.

7.3 Classification Report:

On the basis of the confusion matrix, the classification report presents significant values such as Precision, Recall (Sensitivity), and F1-score for each class, and macro and weighted averages of these values. Precision is determined by accuracy when it sets the ratio of true positives to all the instances that have been predicted positive. Recall is the ability of the model to find all the positive instances (out of all actual positive instances, how many were correctly predicted). The F1-score is the harmonic mean of Precision and Recall, thus providing a balanced measure. The classification report for XGBoost, CatBoost, and ExtraTreesClassifier was generated, offering a detailed view of their performance beyond accuracy alone and allowing for more accurate comparison, especially for class-imbalanced scenarios. The comparison of the above metrics helped identify the model(s) best suited for the task of battery health classification.