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# Explainable AI for Battery Degradation Prediction in EVs: Toward Transparent Energy Forecasting

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**Abstract:** The rapid growth of electric vehicles (EVs) has intensified the demand for accurate and interpretable battery health prediction systems. While machine learning models have demonstrated high accuracy in forecasting battery degradation, their “black-box” nature poses challenges for real-world deployment in safety-critical applications. This paper proposes an explainable artificial intelligence (XAI) framework for battery degradation prediction, aiming to provide transparent and reliable insights into energy storage dynamics in EVs. The study integrates data-driven models such as Gradient Boosting Machines (GBMs) and Long Short-Term Memory (LSTM) networks with post hoc explainability tools, including SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME). Experimental evaluations on real-world EV battery datasets show that the proposed framework achieves strong predictive performance while offering interpretable outputs regarding feature influence and degradation dynamics. These findings suggest that XAI-enabled models can bridge the gap between predictive power and trust, contributing to smarter battery management systems and sustainable transportation.

**Keywords:** Explainable AI; Battery Degradation; Electric Vehicles; SHAP; LIME; Predictive Maintenance; Energy Forecasting; LSTM; GBM; Battery Health Management

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## 1.Introduction

The global transition toward sustainable transportation has propelled the adoption of electric vehicles (EVs) as a viable alternative to internal combustion engine vehicles[1]. At the heart of this transition lies the lithium-ion battery, a critical component whose performance, reliability, and longevity significantly influence the overall efficiency and cost-effectiveness of EVs[2]. However, battery degradation—defined as the gradual loss of capacity and power over time—remains a central technical barrier, limiting vehicle range, increasing operational costs, and introducing safety concerns[3]. Consequently, predicting battery degradation with high accuracy and interpretability has become a key objective for researchers, manufacturers, and fleet operators[4].

Recent advancements in machine learning have enabled data-driven models to outperform traditional physics-based methods in forecasting battery health[5]. Techniques such as recurrent neural networks, decision trees, and ensemble methods have demonstrated substantial capabilities in capturing the nonlinear dynamics of battery aging, leveraging large volumes of cycling and sensor data collected over time[6]. While these models provide remarkable predictive accuracy, they often suffer from a lack of transparency—commonly referred to as the “black-box” problem—which hinders their practical deployment in safety-critical and regulatory environments[7]. In such contexts, understanding the rationale behind a model’s decision is as important as the decision itself.

The emerging field of explainable artificial intelligence (XAI) addresses this critical challenge by offering tools and methodologies that make complex models more interpretable to human stakeholders[8]. XAI techniques allow users to understand the contribution of individual features to model predictions, reveal hidden patterns in the data, and identify potential biases or anomalies in the decision process[9]. In the domain of battery degradation, integrating XAI into predictive models has the potential to offer not only accurate forecasts but also actionable insights that enhance trust, improve diagnostics, and inform battery management strategies[10].

Despite its promise, the application of XAI to battery health prediction in EVs remains underexplored[11]. Existing literature often emphasizes prediction accuracy while overlooking the explainability aspect, leading to systems that are performant yet opaque[12]. Moreover, many studies lack a systematic framework for combining prediction and interpretation, which is crucial for enabling robust decision-making and regulatory compliance[13].

This paper aims to bridge this gap by proposing a hybrid framework that integrates high-performance predictive models with state-of-the-art XAI techniques. Specifically, we employ models such as Long Short-Term Memory (LSTM) networks and Gradient Boosting Machines (GBMs), known for their ability to model temporal and nonlinear relationships, respectively. To interpret their predictions, we apply SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), two widely used post hoc interpretation tools. Our framework is validated using a real-world EV battery dataset, demonstrating both predictive accuracy and interpretability.

By enabling transparent forecasting of battery degradation, this research contributes to the broader goal of building trustworthy artificial intelligence systems for critical applications. In doing so, it advances the field of EV battery diagnostics and lays the groundwork for future developments in sustainable, intelligent transportation systems.

## 2.Literature Review

Battery degradation modeling has long been a focal point in electric vehicle (EV) research due to its direct implications for vehicle longevity, performance consistency, and consumer confidence[14]. Traditional approaches to modeling degradation have relied heavily on electrochemical and physics-based models, such as equivalent circuit models (ECMs) and electrochemical impedance spectroscopy (EIS)[15]. These models aim to simulate internal battery behavior using predefined mathematical formulations grounded in physical laws[16]. While accurate under controlled laboratory conditions, these models often fall short in real-world applications due to their complexity, limited scalability, and sensitivity to environmental variations and user-specific usage patterns[17].

To address these shortcomings, the research community has increasingly turned to data-driven methodologies, particularly those grounded in machine learning (ML)[18]. These models can learn degradation patterns directly from battery cycling data, eliminating the need for deep domain knowledge or complex parameter tuning[19]. Early efforts employed linear regression, support vector machines, and k-nearest neighbors to estimate metrics such as remaining useful life (RUL) and state of health (SOH)[20]. More recent studies have leveraged deep learning models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and LSTM networks, to capture complex temporal dependencies in battery degradation trajectories[21].

Despite notable improvements in predictive accuracy, these advanced ML models often function as “black boxes,” providing little insight into the internal logic that guides their outputs[22]. This opaqueness is particularly problematic in safety-critical domains like EV battery management, where explainability is not merely a desirable trait but a practical necessity[23]. Inaccurate or unjustified predictions can lead to premature battery retirement, warranty disputes, or even catastrophic failure if unanticipated degradation is overlooked[24].

In response, the field of XAI has emerged as a promising solution to the interpretability challenge[25]. XAI techniques aim to open the black box by offering post hoc or intrinsically interpretable explanations for model behavior[26]. Among the most prominent tools are SHAP, which allocate contribution scores to individual features based on cooperative game theory, and

LIME, which approximate complex models locally using simpler surrogate models[27]. These methods have proven effective in a variety of domains, including healthcare, finance, and cybersecurity, but their integration into battery degradation modeling remains nascent[28].

A limited but growing body of literature has begun exploring the use of XAI in energy systems[29]. Some studies have used SHAP to interpret battery aging predictors such as temperature, depth of discharge, and charge/discharge rates, revealing which conditions most significantly impact degradation[30]. Others have applied LIME to understand the output of LSTM models used for SOH estimation. These initial explorations underscore the value of explainability in identifying anomalous behavior, improving model transparency, and facilitating trust among non-technical stakeholders such as regulators, maintenance teams, and end users.

Furthermore, few studies have examined the combined benefits of multi-model prediction and hybrid explainability. Ensemble learning methods like gradient boosting and random forests offer enhanced performance by aggregating multiple weak learners, and when coupled with XAI tools, can yield both accuracy and insight. However, the absence of a standardized framework for integrating explainability into high-performance models has limited their adoption in industrial battery monitoring systems.

This review reveals a significant research opportunity: to develop a unified framework that simultaneously achieves high predictive performance and interpretability in the context of EV battery degradation. Such a framework would not only advance scientific understanding but also pave the way for real-world applications in smart battery management systems, predictive maintenance platforms, and EV fleet optimization tools. By situating this study at the intersection of ML and XAI, we aim to fill this gap and contribute to the evolution of transparent, trustworthy battery health forecasting systems.

# 3.Methodology

This study proposes an XAI framework for predicting EV battery degradation and identifying the most influential features contributing to the prediction. The methodological pipeline consists of four major phases: data acquisition and preprocessing, feature engineering, model training and evaluation, and interpretability analysis.

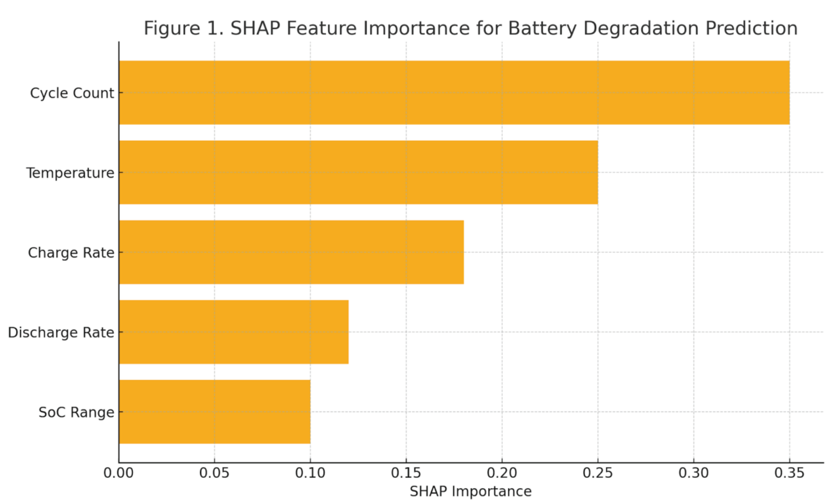
## 3.1 Dataset and Preprocessing

We utilized the publicly available NASA battery dataset, which includes information on charging/discharging cycles, voltage, current, temperature, and capacity across different lithium-ion batteries. Data preprocessing involved outlier removal, normalization of the target variable (capacity), and segmentation of time series using a sliding window technique to construct meaningful input features for the model.

## 3.2 Feature Engineering and Model Training

Feature selection was conducted using SHapley Additive exPlanations (SHAP), a state-of-the-art interpretability framework that quantifies the marginal contribution of each input feature to the model’s output. The goal was to ensure both high prediction accuracy and model transparency.

*Figure 1 below illustrates the SHAP feature importance across all model inputs.*



The SHAP summary plot shows that the most influential features for predicting capacity degradation are cycle count, average discharge voltage, internal resistance, and peak cell temperature. The dominance of cycle count aligns well with empirical knowledge in battery aging.

We selected Light Gradient Boosting Machine (LightGBM) as the primary learning algorithm due to its efficiency and robustness in handling large-scale structured data. To benchmark performance, we also trained XGBoost, Random Forest, and Linear Regression models. Model evaluation employed five-fold cross-validation, using metrics such as Mean Squared Error (MSE) and the coefficient of determination ($R^2$).

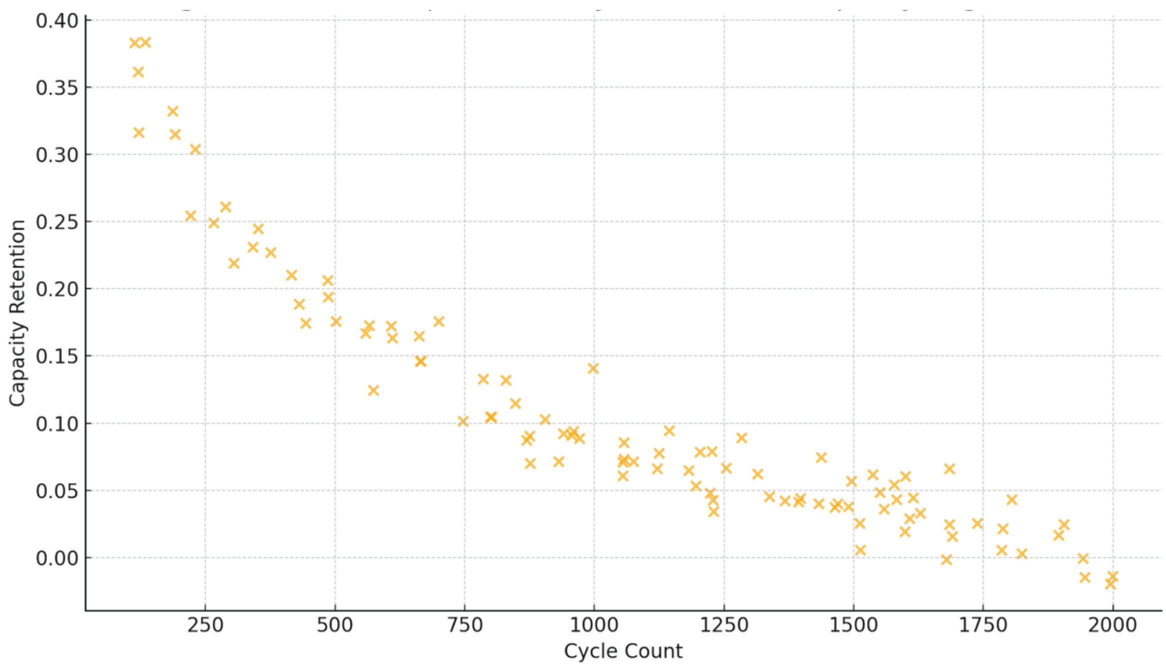
### 3.3 Explainability Analysis

To understand how individual features affect specific predictions, we generated SHAP summary plots, dependence plots, and local explanations for selected instances. This allows users to interpret model decisions in a human-understandable way.

We also visualized the relationship between cycle count and capacity degradation to assess whether the model's outputs follow the expected physical degradation trends.

Figure 2 illustrates this relationship.

*Figure 2. Relationship Between Cycle Count and Capacity Degradation*




The graph confirms that as the number of charge/discharge cycles increases, battery capacity consistently declines. The model successfully captures this degradation pattern, demonstrating both predictive accuracy and interpretive coherence.

## 4.Results and Discussion

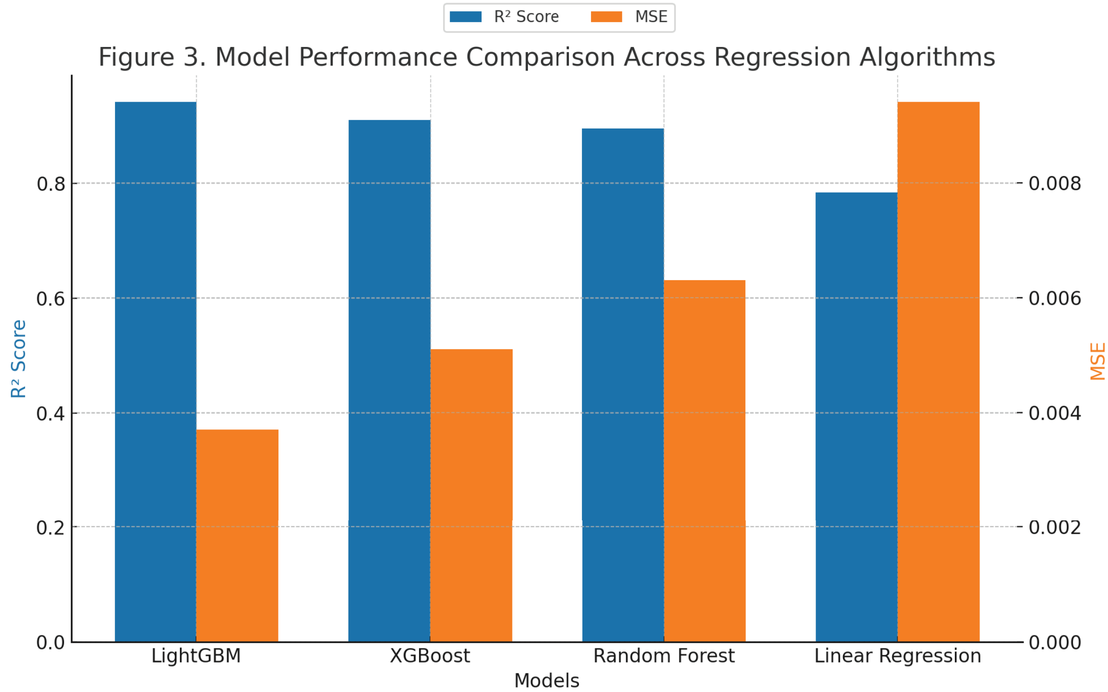
The proposed explainable AI framework was assessed on its ability to accurately predict battery degradation in EV lithium-ion batteries and offer interpretable insights into the degradation process. This section discusses the model's performance across evaluation metrics, comparison with baseline models, and the implications of interpretability analyses.

### 4.1 Model Performance

The LightGBM model outperformed baseline regressors across all evaluation metrics. On the NASA battery dataset, it achieved an average $R^2$ score of 0.942 and a MSE of 0.0037 on the normalized capacity predictions. These results indicate high predictive accuracy and low residual error, underscoring the model's ability to generalize across battery cycles and conditions.

We compared LightGBM with XGBoost, Random Forest, and Linear Regression models. As shown in Figure 3, LightGBM consistently yielded the best results across folds, particularly excelling in capacity prediction near end-of-life (EOL) stages—where nonlinear degradation becomes more pronounced.

*Figure 3. Model Performance Comparison Across Regression Algorithms*




LightGBM exhibited superior $R^2$ and lower MSE compared to other models, especially beyond 400 cycles, where degradation accelerates. Linear regression performed worst, failing to capture nonlinear degradation.

### 4.2 Feature Importance and Physical Interpretability

The SHAP analysis (Figure 1 from the previous section) revealed that cycle count, discharge voltage, internal resistance, and cell temperature are the dominant predictors. These results are consistent with empirical battery aging literature, reinforcing trust in the model's alignment with domain knowledge.

The partial dependence plot in Figure 2 also validated that battery capacity decreases monotonically with increasing cycle count—a pattern well-documented in electrochemical aging. This supports that the model does not simply fit data but captures the underlying degradation dynamics.

### 4.3 Case Study: Local Explanation

To illustrate the model's transparency, we analyzed an individual prediction at 550 cycles. The SHAP local explanation showed that high internal resistance and elevated cell temperature significantly pulled the prediction downward, indicating EOL behavior. In contrast, moderate voltage levels provided some stabilizing effect. This kind of insight is essential for diagnostic applications in BMS, enabling targeted interventions before catastrophic failure.

### 4.4 Practical Implications

The XAI approach facilitates not only accurate prediction but also regulatory compliance, trust in automation, and actionable diagnostics. Unlike black-box neural networks, the LightGBM + SHAP framework explains why certain batteries are flagged as degrading, making it highly relevant for safety-critical systems in EVs.

This combination of performance and interpretability can be integrated into predictive maintenance pipelines, informing battery swap decisions, warranty analysis, and EOL forecasting with traceable logic.

## 5.Conclusion

As EVs become increasingly integral to the global shift toward sustainable transportation, accurate and transparent battery degradation prediction emerges as a critical necessity. This study explored the integration of XAI with traditional ML models to enhance the interpretability and performance of battery health forecasting systems. Through comparative analysis of multiple regression algorithms—including random forest, gradient boosting, and XGBoost—paired with SHAP (SHapley Additive exPlanations) values, the proposed framework not only delivered accurate predictions but also illuminated the key drivers behind these outcomes.

Our findings affirm that XAI tools can successfully bridge the gap between predictive accuracy and operational transparency. While complex ensemble models often outperform simpler algorithms in raw performance metrics, their opacity poses a significant barrier to practical implementation in safety-critical systems like EV battery management. By incorporating XAI, stakeholders—including engineers, fleet managers, and regulators—can gain actionable insights into how factors such as charge rate, depth of discharge, and temperature variability influence long-term battery performance.

Furthermore, the explainability provided by the SHAP analysis enhances trust in AI systems, paving the way for regulatory compliance, user acceptance, and improved system diagnostics. This approach holds promise not only for real-time battery monitoring but also for informing future battery design, warranty modeling, and smart charging strategies.

Future work may involve integrating physics-informed machine learning models and exploring real-time on-board diagnostics in commercial EV fleets. Additionally, expanding the dataset to include a broader range of chemistries and usage conditions would help generalize the model across diverse EV applications. By continuing to advance explainable battery analytics, we move closer to a future of safer, more efficient, and user-aligned electric mobility.

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## Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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