A Machine Learning-Based Real-Time Remaining Useful Life Estimation and Fair Pricing Strategy for Electric Vehicle Battery Swapping Stations

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Abstract: As EVs become more mainstream, battery swapping stations must implement battery management in a way that is effective and fair, and that can be affected by the pricing and inefficiency of various battery health and degradation levels. To tackle this challenge, a real-time RUL estimation framework is developed based on the Battery RUL Dataset available from Kaggle . Parameters such as cycle index, discharge time, charging time, voltage characteristic, time constant, etc., describing the battery degradation behavior are included in the dataset. Based on the operational and electrical characteristics, the RUL estimation of EV batteries is performed using regression techniques such as the RF, Lasso, GB, Kernel Ridge, DT and XGBoost regression. In particular, XGBoost achieves the best test RMSE of 3.50 and is the most accurate among the models, which makes it a promising model for making accurate RUL estimates and for making fair dynamic pricing for battery swapping stations. To enhance the prediction performance and the interpretability we propose the use of the Stacking and Voting Regressors, providing an RMSE of 3.039 and 3.329, respectively. Moreover, LIME and SHAP are utilized to understand the model outputs and to detect influential factors. The flask-based interface offers a real-time input and prediction, which brings transparency, data-driven and fair pricing methods to EV battery swapping systems.

“**Index Terms:** Battery swapping station, electric vehicle, machine learning, remaining useful life, XGBoost”.

1. INTRODUCTION

Electric vehicles (EVs) have become a major invention in the field of sustainable mobility in the race for cleaner sources of energy and the pressing need to reduce the impact of environmental degradation [1]. The fast depletion of fossil fuels and the increasing awareness of its ecological repercussions have pushed the transition from traditional internal combustion engines to electric mobility options. BEVs and plug-in hybrid electric vehicles (PHEVs) have been the top players in the last ten years of the world EV market and have had an exponential growth rate in sales [2]. The development of battery technologies is a critical aspect of this transformation, as they significantly impact the major characteristics of EVs, such as range, energy efficiency, and charging time [3]. Despite all the improvements made in battery chemistry and the battery management system, the time required for charging remains a challenge for driver convenience and wider EV penetration of the transportation system as a whole [4].

The limitation of long charging time has been addressed by introducing BSS, which have been proposed as a viable solution to the problem of long charging times [5]. The users can then utilize these stations to swap their depleted batteries for fully charged ones in minutes thereby vastly boosting turnaround time and user happiness. But the ability to become functional and economical with BSS is significantly affected by the proper health assessment of the batteries, proper scheduling and fair pricing mechanisms [6]. The current models are designed to minimize the energy use, reduce the cost or increase throughput, without addressing other factors that are important, such as battery replacement fairness when batteries have different RULs. This imbalance leads to inequalities among users, as some users may be receiving poorer quality batteries with similar pricing, thus undermining the overall sustainability and user confidence in the battery swapping system [7]. Furthermore, there is a lack of dynamic pricing schemes based on health and a precise real-time RUL estimation model which is a critical gap in current research that can impair the transparency and efficiency of the existing systems [8].

The main goal of this work is to propose a fair and intelligent technique that couples the battery health evaluation and an equitable pricing system. The aim of this strategy is to enable proper assessment of the health of each battery, and the fair allocation of costs among users. The proposed method enables an overall fair evaluation of the economic value of each battery in the battery pack based on the correlation of variables that characterize the battery performance, like discharge behavior, voltage characteristics and the battery operational history [9]. Moreover, this method focuses on enhancing the live determination of battery replacement procedures, in order that the battery circulation and expense will be synchronised with the real battery serviceability potential, and even fairness and customers' happiness can be realised.

This research is significant because it helps fill a gap between the advancement of tech and equitable resource distribution in EV batteries. This solution is a combination of real-time health assessment, fair pricing mechanisms, operational transparency and user trust, leading to sustainable station management. The results are supposed to aid the electric vehicles using to make the battery swapping system more efficient, reliable and economical [10]. This application enhances the user experience and supports the overall goals of green mobility and sustainable energy transition.

2. LITERATURE REVIEW

Lately, there is a growing interest in the estimate and management of battery health which has greatly contributed to the improvement of the EV performance and reliability. Transformer architectures have been shown to possess great capabilities for RUL estimation of lithium-ion batteries, as they are able to efficiently model the temporal dependence and deterioration patterns in high-dimensional data [11]. This technique was quite accurate and robust to noise. However, it frequently has enormous computing requirements and requires big training datasets, which limits its usefulness for real-time applications. Also, in the study of ML-based PHM systems for Li-ion batteries [12] the significance of the data driven models for prediction of deterioration behaviour and operational safety assurance was highlighted. It was noted however that this review revealed that there was a great need for research in the area of integration of the RUL prediction models into the operational systems like BSS for a fair and efficient energy management.

A few studies have examined how user behavior is related to battery degradation to improve SOH estimation. For instance, He et al. simulated the effect of different driving and charging habits on the accuracy of SOH prediction in the actual EV traffic data [13]. Their conclusions highlighted the importance of incorporating the behavioral component in the degradation models and the methods they presented were not scalable on heterogeneous data sets. Additionally, Li et al. [14] discussed the feature selection technique for SOH estimation, and it is important to select the influential features from the charge–discharge profiles. These methods are based on features and improved the interpretability of the model and reduced the complexity of the model, but typically used fixed representations for features, which did not consider the dynamic nature of battery health during real-time operation. Similarly, the effect of temperature on the batteries' performance has been generally accepted as an important factor. Karlsen et al. [15] performed a survey of the temperature dependent issues in battery management systems and presented design guidelines for thermal-aware monitoring. The adaptation to temperature has not been well addressed for actual implementation in various conditions in a data-driven RUL estimate framework.

Besides health estimation, operational research for BSS management has focused on optimization of cost, efficiency and battery allocation strategies. Wu gave a thorough survey of the different modes of operation and decision moments of BSS, such as scheduling, inventory control and pricing models [16]. The study gave meaningful taxonomies, however, one of the significant drawbacks of the study was that the current pricing methods were not fair or transparent. In this context, hybrid optimisation frameworks are proposed to be more efficient for battery allocation. Madhanakkumar et al. suggested a hybrid approach for optimizing the battery swapping process which considers energy usage and service time [17]. These models work well for minimizing costs, but are generally unable to take user fairness in battery exchange with different deterioration levels into account. Yang et al. improved this research by forming an optimum battery allocation model based on the SOH and the SOC [18]. Their research revealed that their usage of resources had been higher, but failed to take into account the costs associated with the battery life of different users.

Furthermore, there has been a lot of interest in economic models to support battery swapping. Hu et al. have studied the ideal pricing techniques using the pay-per-swap and subscription approaches [19]. Their analysis showed that while subscription models could make revenue more predictable, if battery RUL differences are not considered, it could inadvertently create inequities among the users. Likewise, Liang and Zhang investigated battery swap pricing and charging strategies for electric taxis in China, considering the cost recovery and user satisfaction [20]. While these research gave some valuable inputs to the pricing design, most of them focused on static or fixed pricing mechanisms without dynamic adjustments based on battery health or RUL estimation.

To sum up, many studies have been done that resulted in remarkable achievements in predicting battery status, optimizing switching stations, and formulating pricing policies. But, existing systems often operate in isolation, either with regard to technical optimization or to economic justice, without combining them. The real-time data-driven systems dealing with both RUL estimate and equitable pricing at the same time have a large gap. This is why the present work proposes a novel perspective that considers battery performance assessment and equitable pricing, further enhancing user confidence and the effectiveness of the battery-swapping operations.

3. MATERIALS AND METHODS

The proposed system seeks to create a successful real-time platform for RUL estimation for improving fairness, reliability, and operating economy of EVs swapping stations. The Battery RUL Dataset from Kaggle is used for the battery degradation dynamics modelling. The data are metrics including cycle index, discharge time, voltage behavior, and charging characteristics. Data preprocessing, feature engineering and predictive modelling using multiple ML algorithms including RF [21] and Lasso, Gradient Boosting [22] and Kernel Ridge [23] and Decision Tree [24] and XGBoost are included in the workflow to learn linear and nonlinear dependency relationships that affect battery health. Ensemble learning methods are used to boost the predictive power and robustness: Stacking and Voting Regressors are included. LIME and SHAP enhance the interpretability of the model by providing an explanation of the role of important elements in the results of prediction. Lastly, the real-time prediction, visualization, and user engagement capabilities are achieved by the use of a web interface developed with Flask, which provides transparency and fairness for decision making in EV battery management.

“Fig.1 Proposed Architecture”

The decision making process for EV battery swapping based on RUL estimation is shown in fig.1. The RUL is computed when the battery data are collected from the EV. The system includes a comparison of the RUL of the EV battery to the evolving station battery [25]. If the criteria is equal or higher or above some threshold value, then swapping is allowed and the price is computed as per the same. In any other case, swaps are restricted. This ensures best utilization of batteries [26], fairness and effective management of energy resources.

a) Dataset Collection:

The Battery RUL data set is obtained from Kaggle open source repository and it comprises 15064 samples and nine features indicating the most crucial electrochemical and operational parameters of Li-ion battery (see Fig. 2). The features included in the dataset are cycle index, discharge time, voltage features and charging time. The goal variable is RUL. All features are continuous and numerical and thus are suitable for regression modelling. The general framework is helpful to design and evaluate the RUL estimate data-driven prognostic models in the electric vehicles' battery management systems in various operating conditions.

	Cycle_Index	Discharge Time (s)	Decrement 3.6-3.4V (s)	Max. Voltage Dischar. (V)	Min. Voltage Charg. (V)	Time at 4.15V (s)	Time constant current (s)	Charging time (s)	RUL
0	1.0	2595.30	1151.488500	3.670	3.211	5460.001	6755.01	10777.82	1112
1	2.0	7408.64	1172.512500	4.246	3.220	5508.992	6762.02	10500.35	1111
2	3.0	7393.76	1112.992000	4.249	3.224	5508.993	6762.02	10420.38	1110
3	4.0	7385.50	1080.320667	4.250	3.225	5502.016	6762.02	10322.81	1109
4	6.0	65022.75	29813.487000	4.290	3.398	5480.992	53213.54	56699.65	1107

Fig.2 Battery RUL Dataset

b) Data Pre-processing:

The quality of the data (data integrity) is checked in the data pre-processing stage and, if needed, data redundancies and anomalies are eliminated. No duplicated records were found and verified to avoid any bias in the statistical description of the data set. This stage ensures the training process is unbiased and accurate, preventing duplication of data that could lead to an over-optimistic estimation of the model's accuracy or prediction errors. The lack of duplication provides the quality and trustworthiness of the data and its suitability for analytical and predictive modeling tasks in the future.

c) Data Visualization:

Data visualization was employed to understand the distribution of data and relationship between the features. The distribution plots of the variable RUL were checked for normality and outlying data, to ensure a fair representation of the target. In addition, correlation heat maps were used to identify relationships between variables in order to analyse the significance of variables. This process will provide important insights into the structure of the data, help to make intelligent decisions regarding feature selection, and enhance the interpretability of subsequent ML modeling efforts.

d) Training and Testing:

The dataset was divided into training and testing sets to assess the model's ability to generalize. The data was split 80/20 so that a large percentage of the data could be utilized to learn, but also have a representative group of data to validate performance. The split is used to reduce overfitting, and also allows for an equitable assessment of predictive performance on new data . A proper partitioning guarantees the created model to provide good generalization, reliability and repeatability on real-world battery degrading scenarios.

e) Algorithms:

Random Forest Regression is an ensemble learning method for regression, which creates many decision trees and combines their output to get a more accurate and stable forecast. Each tree is trained on random selections of data and features . This helps to minimize overfitting and enhance generalization . The algorithm is stable and robust to noise because it takes the average of the predictions . It handles highly nonlinear interactions very well and is therefore very successful in modelling complex patterns in multivariate regression problems [27].

$$Gini = 1 - \sum_{i=1}^{C} (Pi)^2 \qquad (1)$$

Lasso Regression or Least Absolute Shrinkage and Selection Operator introduces a regularization term to the size of the regression coefficients. This leads to a low model complexity and in fact does feature selection by reducing the unnecessary coefficients to zero. The method is more interpretable and will not over-fit in high dimensional data sets. It balances out model accuracy and simplicity . Does an efficient analysis of correlated predictors. It performs well in generalisation tasks in predictive modelling.

Gradient Boosting An ensemble technique which is used to build a succession of weak learners, typically decision trees, with the aim of decreasing the prediction error. The next learner tries to eliminate the residuals of the previous models and the better he gets. The approach is able to successfully capture the nonlinear relationships and complicated feature interactions. It has an iterative optimization method that enhances the accuracy and robustness of the system, making it suitable for prediction tasks that require high precision and adaptation to different data distributions [28].

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x) \quad (2)$$

Kernel Ridge Regression Describes Kernel Ridge Regression, which uses kernel method and ridge regularization to map features and model the nonlinearity of the input variables and the target outputs. It maps data into higher dimensional space by the use of kernel function to allow linear regression to model the complex interactions. The ridge penalty can be used to avoid over-fitting, by restricting the magnitude of the coefficients, thus providing stability. This combination allows for fast processing of high-dimensional data and for the smooth and generalized processing of prediction in various operation environments.

A DT Regression is a recursive partitioning of the feature space into regions minimizing the variance within each partition. It implements decision making hierarchically, with branching structures. Each node is a condition based on a feature . This is a natural approach and allows for modelling of non-linear relationships. Although it is very sensitive to noise in isolation, its simplicity and versatility have made it a fundamental element for ensemble approaches and comparative evaluation of performance in regression analysis [29].

$$I\ (i) = 1 - \sum_{i=1}^{k} p_i^2 \quad (3)$$

XGBoost Regression (also known as Extreme Gradient Boosting) is an optimized ensemble method which is very efficient and effective in prediction. It adds to the traditional boosting with regularization, parallel computation and better tree building [30]. It is very effective in coping with missing data and large size data sets, with minimum bias and variation. Its strength, scalability and great learning power makes it appropriate to achieve accurate and reliable regression results in complex real world prediction scenarios.

$$\hat{y}_i = \sigma\left(\sum_{k=1}^{K} f_k(x_i)\right), f_k \in F \quad (4)$$

The Voting Regressor combines predictions from numerous base learners like RF, Gradient Boosting, and XGBoost to generate a well-balanced and precise prediction. It blends several models, typically with the help of simple averaging or weighted voting, which decreases the biases of single models and boosts stability. We show that this ensemble technique increases generalization and minimizes prediction variance by using the complimentary capabilities of each constituent algorithm to provide consistent and reliable regression performance across a variety of datasets.

$$\hat{y}\ = argmax_c\left(\sum_{i=1}^{n} II\ (\hat{y}_i = c)\right) \quad (5)$$

The multi-layered ensemble model, namely, Stacking Regressor, consists of several base models like RF, GB, XGBoost etc. and a meta-learner like Linear Regression. The basic models make initial predictions, followed by the use of these predictions as inputs to the meta-model to improve the final results. This hierarchical learning system learns both linear and non-linear correlations, thus enhancing accuracy. Good stacking mixes allows for modeling of variety and enhances the generalization and global prediction accuracy.

$$\hat{y} = g(Y_{base}) = g\big(f_1(x), f_2(x), \ldots, f_m(x)\big) \quad (6)$$

f) Integration of XAI & Flask:

To interpret the regression results with XAI methods, LIME and SHAP are applied to make the model more transparent. LIME provides instance-level explanations by identifying the most influential features to the predictions, and also allows for visualization of their positive or negative influence by bar and waterfall charts. Likewise, SHAP offers relevance scores for each feature within a single framework, based on Shapley values, enabling the determination of the global contribution of input variables towards the model's predictions in an interpretable way using visuals.

The integration is successful with the Flask framework—a lightweight web server to deploy and interact with the model. It can be used to enter data and make predictions as well as show the findings of interpretability. This integration ensures the ease of access, interpretability, and reliability of machine learning predictions for end users or decision makers.

4. EXPERIMENTAL RESULTS

MSE: A measure of error in statistical models is called the MSE. It is the average of the squares of the differences between the observed and expected values. The MSE is 0 when the model is correct. The more the model is wrong, the more its value increases. The MSE is also known as MSD.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \qquad (7)$$

RMSE: The root mean square error (RMSE) is a measure of the average difference between values predicted by a statistical model and the actual values. As a number, it's the standard deviation of the residual. The residuals are the distance between the data points and the regression line.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} ||y(i) - \hat{y}(i)||^2}{N}} \qquad (8)$$

MAE: Absolute mistake is the amount of mistake you have in your measurements. It is the difference between the measured and 'true' values. For example, if your weight is 89 lbs and the scale shows 90 lbs, then the absolute error of the scale is 90 lbs – 89 lbs = 1 lbs.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (9)$$

R2 Score: The sum squared regression is the sum of the squares of the residuals. The total sum of squares is the sum of the distance the data is away from the mean all squared.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \qquad (10)$$

Table.1 Performance Evaluation

ML Model	**MSE**	**RMSE**	**MAE**	**R^2-Score**	**SSE**
Random Forest	14.242	3.774	2.097	1.000	42,912.106
Lasso	54.550	7.386	4.649	0.999	42,912.106
Gradient Boosting	37.900	6.156	4.093	1.000	114,192.726
Kernel Ridge	204.812	14.311	7.258	0.998	617,097.237
Decision Tree	28.616	5.349	2.273	1.000	86,219.000
XGBoost	12.545	3.542	2.219	1.000	37,797.279

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Extension (Voting)	11.082	3.329	1.851	1.000	33,390.170
Extension (Stacking)	**9.236**	**3.039**	**1.619**	**1.000**	**27,826.566**

The performance evaluation of the regression models is shown in Table.1 which shows the lowest mistakes and the maximum prediction accuracy of the Stacking ensemble.

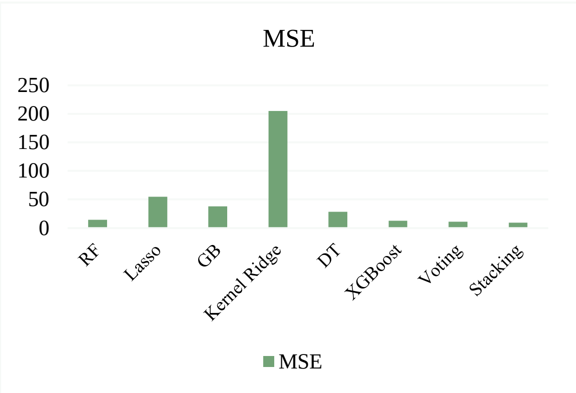

Fig.3 MSE Comparison Graph

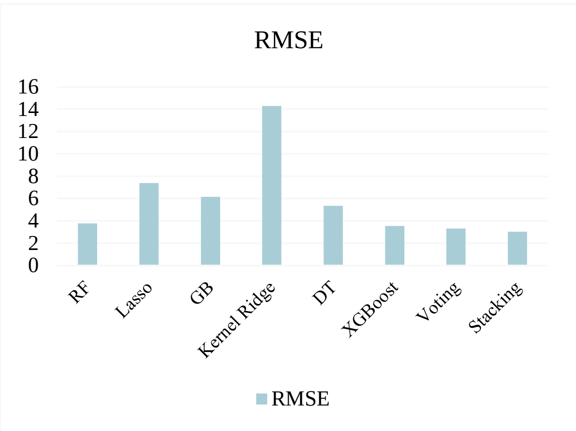

Fig.4 RMSE Comparison Graph

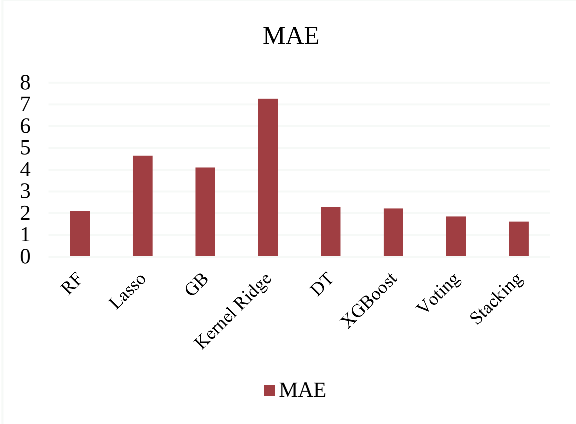

Fig.5 MAE Comparison Graph

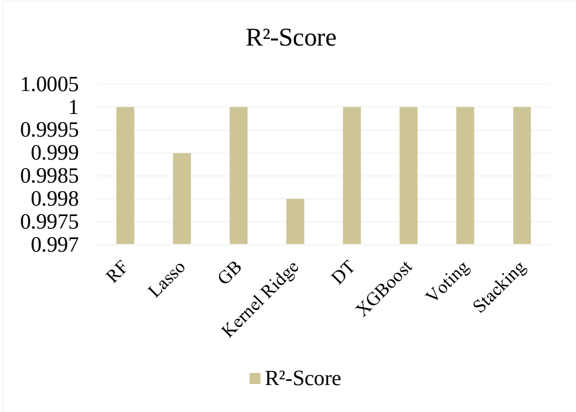

Fig.6 R2 Score Comparison Graph

The comparison graphs (fig.3 to 6) above shows the model performance metrics and it is clear that in all the tests the Stacking ensemble performs better with more accuracy and less error.

Fig.7 Enter Input Data

In fig.7 User gives the inputs in the suitable containers to forecast the final analysis.

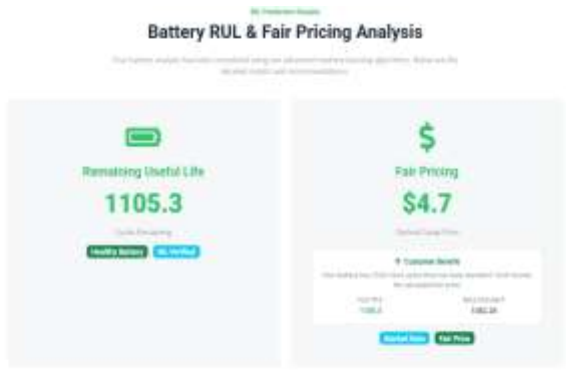

Fig.8 Predicted Results

The forecast shows that the battery is healthy with 1105.3 cycles left and suggest a fair swap price of $4.7 as shown in fig.8.

Fig.9 Enter Input Data

The interface of a battery RUL and fair pricing prediction is shown in Fig. 9 with an input box for the cycle index, discharge time, voltage metrics and a display of the prediction button in green for charging time.

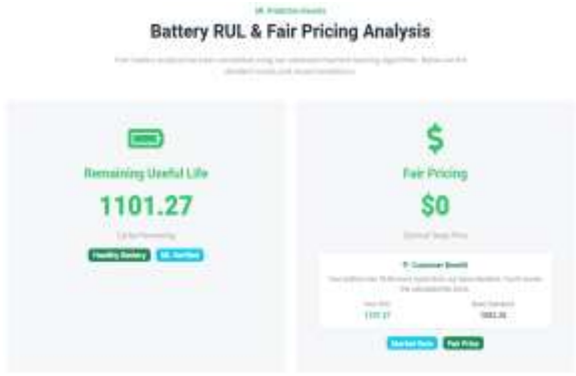

Fig.10 Predicted Results

The forecast indicates that the battery is healthy, with 1101.27 remaining cycles and a good swap price of $0.00 (see fig.10).

5. CONCLUSION

Last, the proposed real-time RUL estimation system effectively addresses the problem of fair and transparent battery pricing mechanism for EV battery swapping stations from a data-driven ML approach. The dataset from Kaggle is called Battery RUL and it contains cycle index, discharge duration, voltage and charge data. These are all crucial parameters for a battery. Several regression algorithms were trained and assessed on predicting the lifespan of a battery. The accuracy of deployed models for predicting the RUL based on the battery degradation indicators was very high, including RF, Lasso, GB, Kernel Ridge, DT and XGBoost. Among these, XGBoost performed the best with an RMSE of 3.50 proving its efficiency in the modelling of the non-linear connections in the dataset. For better performance, Stacking and Voting Regressors were added with RMSE of 3.039 and 3.329 respectively which showed better generalization and stability. Moreover, we applied XAI methods, including LIME and SHAP to assess feature contribution and improve the transparency of the model. A user friendly interface based on Flask also enables real-time prediction and interactive decision support. To conclude, the system offers a trustworthy, fair pricing and operational efficiency, and an interpretable and scalable framework for RUL estimate that is essential for the growth of the EV battery swapping ecosystem.

The proposed system has immense potential for improvement and scalability in future. For future work, DL models and the IoT sensors can be integrated to enhance real-time RUL prediction accuracy and flexibility under various battery types and environments. Blockchain technology can offer transparent data management and secured transaction records in battery swapping networks. Moreover, the system can be expanded with predictive maintenance and autonomous battery health management, providing greater operational efficiency. The large scale deployment and integration into smart grid systems will further promote sustainability and contribute to fair, efficient and intelligent energy management for next generation electric transportation systems.

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