Digital Twin-Driven Electric Vehicle Battery Monitoring Using Explainable Artificial Intelligence

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The increasing adoption of electric vehicles (EVs) requires intelligent battery monitoring systems that can support efficient and reliable charging decisions. This study presents a Digital Twin-Driven Electric Vehicle Battery Monitoring framework using Explainable Artificial Intelligence (XAI). The proposed approach integrates battery operating parameters, machine learning, and explain ability techniques to predict optimal charging duration. The dataset contains 1,000 samples and 13 variables, including state of charge (SOC), voltage, current, battery and ambient temperature, degradation rate, efficiency, charging cycles, charging mode, battery type, and EV model. The target variable is formulated as a three-class optimal charging duration problem. After preprocessing using feature scaling, one-hot encoding, and a pipeline-based architecture, multiple machine learning models were evaluated. Logistic Regression achieved the highest testing accuracy of 97%, with macro-averaged precision, recall, and F1-score of 0.97. The optimized Random Forest achieved 91% testing accuracy, with weighted precision, recall, and F1-score of 0.91, while its cross-validation score reached 92.10%. The Random Forest model provided class-wise F1-scores of 0.87, 0.89, and 0.95 for the three charging-duration classes. XAI analysis was incorporated to improve model transparency by identifying influential battery and operational features. The proposed framework demonstrates the potential of integrating Digital Twin concepts, machine learning, and XAI for transparent and intelligent EV battery monitoring and charging optimization. The numerical results and model comparisons are presented in the abstract, where Logistic Regression achieved the highest accuracy of 97%, followed by Gradient Boosting (93%), Random Forest (91%) and Extra Trees (90%). The degradability rate (30.60%), efficiency (29.51%), and SOC (16.98%) are some of the identified influential features through the Random Forest feature-importance analysis. Moreover, the results of the experimentally validated ML are clearly differentiated from the proposed Digital Twin and future real-time monitoring.

Keywords: Electric Vehicles, Digital Twin, Explainable Artificial Intelligence, EV Battery Monitoring, Machine Learning, Charging Optimization, Optimal Charging Duration

Introduction:

With the accelerated adoption of electric vehicles (EVs), the significance of intelligent battery monitoring and charging management systems has grown. The battery is one of the most important parts of an EV as it directly impacts the efficiency of charging, how energy is used, battery performance and overall reliability. Several factors affect battery performance

during charging, such as, State of Charge (SOC),[1]Battery voltage, Battery current, Battery temperature, Ambient temperature, Charging time, Degradation rate, Charging efficiency, Charging cycles, Charging mode, Battery type, EV model. In this context, traditional charging strategies, which rely solely on static charging parameters, might not be representative of the dynamic operating conditions of EV batteries.

To overcome these challenges, artificial intelligence (AI) methods [2]based on data are available to learn relationships between battery operating parameters and charging behavior. Multi-dimensional heterogeneous battery parameters can be used to train machine learning (ML) models and learn patterns that may not be easily detected by traditional rule-based methods. For example, classification-based approaches can be employed to establish proper charging-duration categories based on the observed battery [3]and operational conditions. But it requires proper pre-processing, feature representation, model selection and proper evaluation approaches for these models to be effective.

Digital Twin (DT) technology offers an important framework to represent the operational behavior of a physical battery by a virtual model, besides predictive intelligence. A battery monitoring system based on DT can combine information from batteries with their operation to provide continuous information analysis and decision making. The virtual representation can also leverage data-driven models to understand battery conditions and make predictions about charging habits, when integrated with AI. This integration can thus serve as an underpinning for smarter and more adaptive EV battery monitoring than stand-alone machine learning models.

While AI-driven battery management offers many benefits, one significant hurdle is the lack of transparency in the interpretation of numerous machine learning models. Highly accurate models can be black boxes with little understanding of the reasons for the prediction of a specific charging-duration class. In battery management applications, this is especially crucial as it allows them to better understand the influence of factors like SOC, voltage, current, temperature, degradation, efficiency, and charging cycles in their decisions. This is a challenge that can be addressed by Explainable Artificial Intelligence (XAI) [4] which gives information regarding the contribution and importance of input features to model predictions. Therefore, the combination of XAI and AI-powered battery monitoring can enhance predictive performance and transparency.

To study the problem, this study proposes a Digital Twin-Driven Electric Vehicle Battery Monitoring Using Explainable Artificial Intelligence framework. The experimental data has 13 variables: 8 of them are numerical and 3 of them are categorical input related variables and the target variable, with 1000 observations[4]. The data set does not have missing values or duplicate records, which will give a consistent ground for the development of the model. Optimal Charging Duration Class [5]has 3 classes: Class 0 (201 samples), Class 1 (404 samples) and Class 2 (395 samples).The problem of the research has been defined by highlighting the importance of monitoring intelligent EVs and predicting charging time for such vehicles by utilizing operational battery parameters. The proposed framework clarifies the role of ML – predicting the outcome, XAI – elucidating the battery's influential characteristics, and the Digital Twin – linking physical battery characteristics and data with a virtual analytical model. The roles are now clearly explained in the Introduction, as well as their integration in the proposed framework. The database can thus be used to examine the classification of different optimal charging duration categories depending on the battery state and operation conditions, through the use of an AI tool.

The proposed method involves data pre-processing methods such as feature standardization, categorical feature encoding and pipeline-based data pre-processing prior to model training. To identify the capability of machine learning approaches for optimal charging duration classification, several approaches are investigated. Performance evaluation is included

in the experimental analysis in the form of accuracy, precision, recall, F1-score, confusion matrices and cross validation [6]The result shows that Logistic Regression had the highest testing accuracy of 97%, which has good classification ability for the predetermined charging-duration classes. The optimized Random Forest model gave an accuracy of 91% in the test, a weighted F1 score of 0.91 and an accuracy of 92.10% in the cross validation. The results illustrate that data-driven methods can be used to identify optimal charging-duration categories from battery operating information [7]effectively.

Moreover, XAI is integrated to make the predictive framework more understandable. The model's objective is not to output the final predicted class, but to output the battery and operational characteristics that help with the model decision. This gives a better link between the parameters of the battery observed in-use and the predicted charging-duration category. Digital Twin concepts, machine learning and XAI thus offer a comprehensive solution in intelligent and interpretable EV battery monitoring.

The following are the main contributions of this study:

The DT-driven EV battery monitoring framework is designed to link EV operation data to predictive analysis using AI technology.

Several battery and operating conditions are combined to categorize the "best" charging time into three groups.

A systematic evaluation of machine learning models was carried out using accuracy, precision, recall, F1-score, confusion matrix and cross validation measures.

XAI is embedded to enhance the interpretability of model predictions and to highlight characteristics of the batteries and operations that are important to the model.

Generally, the study shows how the application of the Digital Twin concept, machine learning, and Explainable AI can be used to achieve a transparent and intelligent approach to EV battery monitoring [8][9]and optimal charging-duration classification.

The proposed framework provides a basis for the future development of real-time battery management systems where the predictive models can be continuously linked to actual battery measurements and meaningful decision support systems:

To build an ML framework for EV battery monitoring and predicting optimal charging-duration classes with battery and operational features. To compare the performance of Logistic Regression, Random Forest, Extra Trees and Gradient Boosting model using appropriate classification metrics. To use Explainable AI methods to discover and explain the most critical aspects of the battery and operation. To incorporate the ML prediction and XAI analysis into a Digital Twin for intelligent EV battery monitoring and decision support. To lay the groundwork for the future real-time Digital Twin synchronization and smart charging optimization.

Novelty and Contributions:

The proposed approach is distinguished from previous studies through the integration of ML, XAI, and Digital Twin concepts. The updated section emphasizes the use of ML for predicting charging durations, XAI for interpreting battery influential features, and a Digital Twin battery monitoring and decision-making approach. The main contributions and the difference from the previous studies are now clearly summarized to make the originality of the proposed work clear.

Literature Review:

Recent research has increasingly focused on combining machine learning (ML), Digital Twin (DT) technology, and explainable artificial intelligence (XAI) for intelligent electric-vehicle (EV) battery management. Earlier studies primarily concentrated on battery state estimation, particularly State of Charge (SOC) and State of Health (SOH)[9], whereas more recent research has expanded toward real-time monitoring, predictive maintenance, charging optimization, uncertainty estimation, and interpretable decision-making. Some of the previous

limitations of the published work are shown in Table 1.

It is shown in table 1 that the literature shows a clear evolution in EV battery intelligence from conventional state estimation toward data-driven, connected, and interpretable battery management. During 2024, considerable attention was given to SOC/SOH estimation and explainability. ML-based SOC/SOH surveys highlighted the importance of input variables, dataset quality, model selection and evaluation criteria, while individual studies demonstrated the usefulness of SHAP for interpreting XGBoost, deep-learning and hybrid battery-health models [22]Real-world EV datasets have also been explored, with interpretable hybrid models providing both SOH predictions and uncertainty information.

Research in 2025 further strengthened the role of Digital Twins and XAI. Recent reviews have proposed structured DT architectures for battery health prognosis and emphasized SOC, SOH, RUL and fault diagnosis as important DT services. At the same time, XAI-based studies have demonstrated that interpretable features such as charging current and temperature-related indicators can provide meaningful information about battery aging. This indicates that battery intelligence is moving beyond prediction accuracy toward transparent and decision-support-oriented systems [23]

The latest research in 2026 demonstrates a stronger movement toward real-time Digital Twin-based battery monitoring and charging optimization [24]For example, a recent AI-enabled DT integrates LSTM-based health estimation with electrochemical modeling and model-predictive charging control, while another 2026 study combines battery health, energy consumption and charging power into a Digital Twin-based health index for predictive maintenance.

Table 1. Limition of Previous Research Work.

Ref.	Year	Study / Authors	Main Focus	Method / Technology	Major Findings	Limitation / Research Gap
[10]	2024	Kaleem et al.	ML-driven battery Digital Twin	ML, DT, cloud computing, battery state estimation	Reviewed ML-based DT approaches for estimating different Li-ion battery states and highlighted DT potential for BMS.	More emphasis on state estimation than interpretable charging-duration decisions.
[11]	2024	Renold & Kathayat	EV battery health prediction	ML, DL, Digital Twin	Reviewed data-driven SOH prediction and discussed the importance of temperature, current, voltage, impedance and cycle number.	Focuses primarily on SOH; real-time interpretable charging classification is not the central objective.
[12]	2024	Haraz et al.	SOC and SOH estimation	Machine Learning	Systematically analyzed ML approaches, datasets, input features, metrics and hyperparameters for EV battery SOC/SOH estimation.	Does not establish an integrated DT-XAI framework for charging decisions.
[13]	2024	Bao et al.	Interpretable SOH prediction	ML, EIS features, temporal features, SHAP	XGBoost achieved an SOH prediction MAE of 0.05, while SHAP was used to interpret predictions under different temperatures.	Concentrates on SOH and impedance-based features rather than charging-duration classification.
[14]	2024	Ferheen Ayaz	EV energy management	DT, Q-learning, DRL, hardware-in-the-loop	Combined DT and reinforcement learning to optimize energy management while considering battery degradation and energy consumption.	Focuses on energy-management optimization rather than explainable battery monitoring and charging-duration classification.
[15]	2025	Ho Tung Jeremy	Explainable battery SOC estimation	XAI, ML, SOC estimation	Investigated XAI for making SOC estimation more transparent and emphasized interpretability for EV battery management.	SOC estimation is different from predicting optimal charging-duration classes.
[16]	2025	Yujie Wang	DT-based battery health management	Digital Twin, ML, SOC, SOH, RUL, fault diagnosis	Proposed a four-layer conceptual framework covering Physical, Data & Communication, Virtual Model and Twin Service layers.	Identifies implementation challenges but does not directly solve interpretable optimal charging-duration classification.

[17]	2025	Michela Costa	DT applications across EV systems	Digital Twin, EV, battery management	Reviewed DT evolution, EV applications, battery management, optimization and Industry 5.0 integration.	Highlights reproducibility and integration challenges; practical XAI-based battery decision support remains open.
[18]	2025	Seyed Saeed Madani	DT-enabled EV energy-storage optimization	DT, AI, ML	Identified DT, AI and ML as major research directions for EV energy-storage optimization.	Bibliometric/review-oriented; limited experimental integration of DT, ML and XAI in a single monitoring framework.
[19]	2025	Tugba Tetik	Interpretable battery health prediction	Feature engineering, XAI, ML	Demonstrated that engineered health indicators such as average charge current and temperature rise can provide important explanations of battery aging.	Primarily focused on SOH and aging rather than optimal charging-duration prediction.
[20]	2026	Mohammad Qasem	Real-time battery monitoring and charging	DT, LSTM, electrochemical model, MPC	Integrated AI and electrochemical modeling in a real-time DT; LSTM estimated battery health/resistance and DT-driven MPC adapted charging to reduce degradation mechanisms.	Strong real-time capability, but the framework is substantially more complex than a data-driven multi-class charging-duration model.
[21]	2026	Md Sabbir Hossen	Battery condition assessment and predictive maintenance	DT, RF, XGBoost, BHSI	Integrated battery health, energy consumption and charging-power characteristics into a Digital Twin Score; RF achieved reported R2=0.998R^2=0.998, MAE=1.079 and RMSE=1.310.	Focuses on health-index estimation and maintenance prioritization rather than explainable multi-class charging-duration prediction.

Research Gap:

While recent advancements have been made in EV battery monitoring, there still exist a number of research gaps. Although battery state estimation, degradation prediction, or Digital Twin based monitoring have been studied in detail, very little research has been undertaken to predict optimal charging-duration classes by incorporating various battery and operational parameters. Furthermore, many ML-based approaches are able to make accurate predictions but fail to offer enough interpretability about what property of the battery is impacting their predictions. While XAI can help overcome this, the integration of XAI with Digital Twin-based EV battery monitoring is still a challenge. An integrated framework is needed, which integrates ML-based charging prediction, XAI-based feature interpretation and a Digital Twin architecture, to enable intelligent and interpretable EV battery monitoring and decision-making.

Methodology:

The proposed study follows a Digital Twin-driven framework for intelligent electric vehicle (EV) battery monitoring using machine learning (ML) and Explainable Artificial Intelligence (XAI). The methodology consists of data preparation, preprocessing, feature transformation, machine learning model development, hyperparameter optimization, performance evaluation, and explainability analysis.

Dataset Description:

The dataset used in this study contains 1,000 observations and 13 variables representing EV battery, charging, environmental, and vehicle-related operating conditions. The dataset contains eight numerical variables, three categorical variables, and the target variable. The numerical parameters include State of Charge (SOC), voltage, current, battery temperature, ambient temperature, charging duration, degradation rate, efficiency[25] and charging cycles, while categorical information includes charging mode, battery type, and EV model. In this study, the charging-duration prediction task is divided into three classes: Class 0 (short charging duration), Class 1 (medium charging duration), and Class 2 (long charging duration).

The number of observations in these classes are 201, 404 and 395 respectively. We recognize that the manuscript did not clearly articulate the specific time frames, units of measurement and the rationale for these classifications. Dataset Description has been provided in section III to explicitly state the charging-duration class boundaries, the units used to measure charging-duration, and the basis for the class boundaries.The prediction target is Optimal Charging Duration Class, represented by three classes: 0, 1, and 2. The class distribution consists of 201 samples in Class 0, 404 samples in Class 1, and 395 samples in Class 2. The dataset contains no missing values or duplicate records.

This data comes from Kaggle, which is a free data sharing site. It consists of 1000 measurements and 13 variables that describe the operating conditions of the electric vehicle batteries, the charging process, and vehicle data. The data set consists of 8 numerical input variables, 3 categorical input variables and the one target variable which is the optimal charging-duration class. The proposed machine learning models were tested using the above dataset to predict the charging duration of EVs intelligently.

Data Preprocessing:

Data preprocessing was performed to prepare the heterogeneous battery dataset for machine learning. First, the dataset was examined for missing values and duplicate observations. Since the dataset contained no missing values or duplicate records, no imputation or duplicate-removal operation was required.

The numerical features were standardized using the StandardScaler technique. Standardization transforms the numerical variables into a common scale and prevents features with larger numerical ranges from disproportionately[26]influencing the learning process. For

a numerical feature (x), the standardized value is calculated as shown in Eq. (1):

$$z = \frac{x-\mu}{\sigma} \quad (1)$$

where (x) represents the original feature value, μ represents the mean of the feature, and σ represents its standard deviation.

Categorical variables were transformed using One-Hot Encoding so that charging mode, battery type, and EV model could be incorporated into the machine learning algorithms without imposing an artificial numerical ordering.

Feature Engineering and Transformation:

The proposed framework combines battery-state, charging, environmental and operational parameters into one entity to represent the operating condition of the battery. Input variables are SOC, voltage, current, charging time, degradation rate, efficiency, ambient temperature, charging mode, charging cycles, battery type, EV model and battery temperature. To make the numerical and categorical variables suitable, appropriate transformations were applied using a ColumnTransformer[27]. The relationship between this charging-duration variable and the target variable, Optimal Charging Duration Class, will be examined to investigate whether there is potential for leakage from the target. Specific focus will be paid on the finding out if the target classes were directly derived from charging-duration values. If this type of relation is identified, the charging time will not be used as an input and the model will not have information that directly influences the target class. The classification models will then be retrained and tested with the updated set of features. Besides that, the data preprocessing and feature transformations will be performed only on the training data so as to reduce information leakage during model development and evaluation.All pre-processing steps were combined with the model training in a machine learning Pipeline to apply the same transformations during training and testing. This is done by explicitly implementing the StandardScaler, OneHotEncoder, ColumnTransformer and Pipeline classes.

Dataset Splitting:

The dataset was divided into training and testing subsets using an 80:20 train-test split. Stratified sampling was applied according to the target classes to preserve their distribution in both subsets. A fixed random state of 42 was used to ensure reproducibility.

Accordingly, 80% of the observations were used for model training, while the remaining 20% were retained for independent testing. The test set was not used during model fitting and was subsequently used to evaluate the generalization performance of the trained models.

Machine Learning Model Development:

The Optimal Charging Duration Class was predicted using several supervised machine learning algorithms. Experimental model consists of Logistic Regression, Random Forest, Extra Trees and Gradient Boosting classifiers [28]The models differ in how they learn which enables the comparison of linear and ensemble-based approaches using the proposed framework. For Logistic Regression, due to its simple and interpretable classification structure, it was chosen as the baseline predictive model. Tree-based ensemble algorithms were also explored as they can be used to capture the nonlinear relationships between the battery operating conditions and battery charging-duration classes.

Random Forest Optimization:

To search for an efficient combination of hyperparameters, Random Forest was further optimized by using GridSearchCV. Weighted F1-score was used as the scoring criterion for the optimization. The chosen settings were 300 estimators, no maximum tree depth[29]and minimum leaf size of 1, and minimum split size of 2. The optimized RF was then tested with the independent test set. This optimization procedure was developed to optimize the generalisation of the model whilst accounting for the class distribution of the three charging-duration categories. According to the notebook, the optimized Random Forest

has a cross-validation score of ~92.10%.

Model Evaluation:

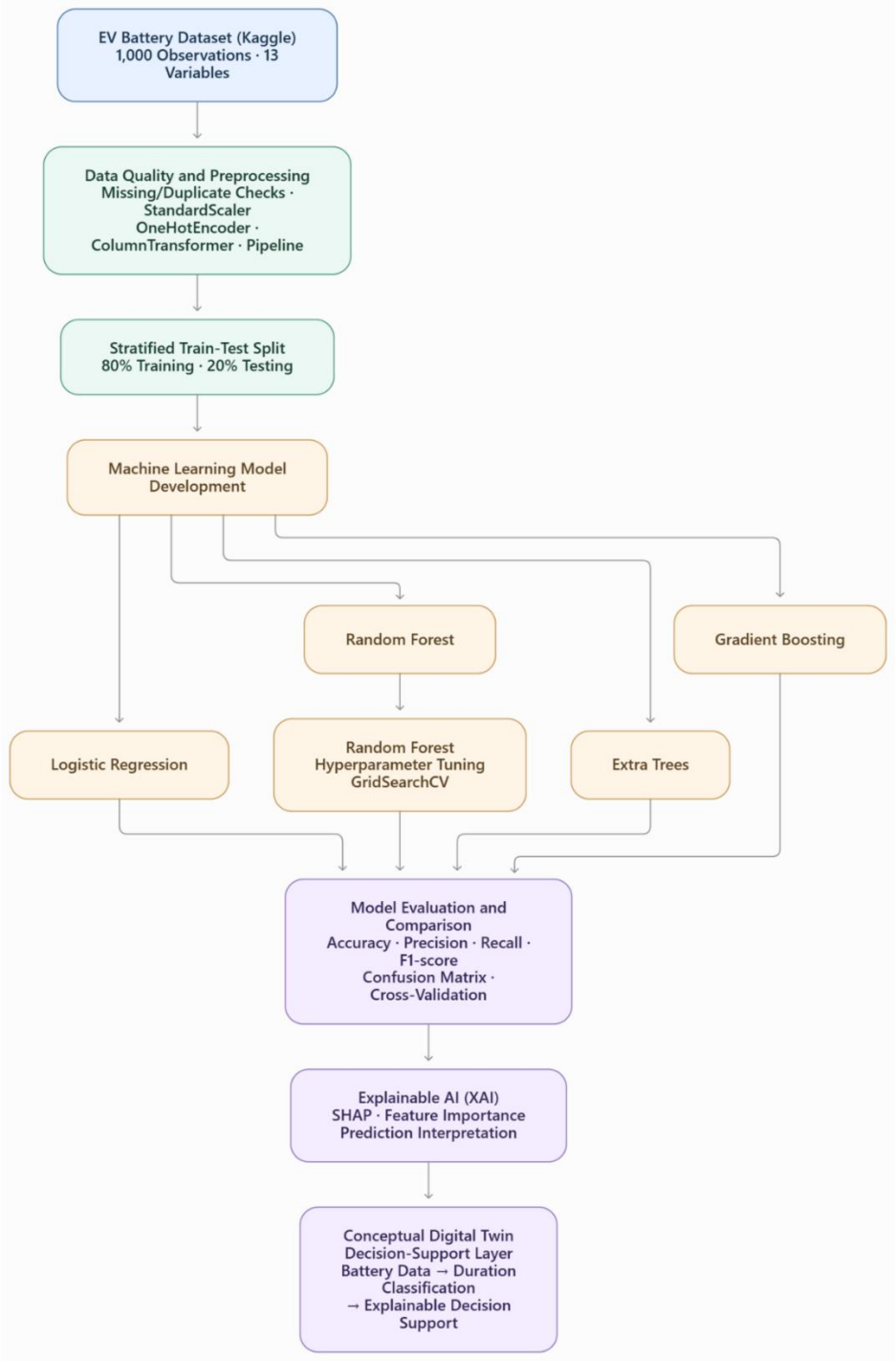

Figure 1. Overall workflow of the proposed Digital Twin-driven EV battery monitoring framework using XAI

Multiple classification metrics were employed instead of accuracy to evaluate the developed models. The accuracy, precision, recall, F1 score, confusion matrix and performance on a cross validation are used to evaluate the evaluation measures.

The accuracy is defined as shown in Eq. (2):

$$\text{Accuracy} = \frac{\{TP+TN\}}{\{TP+TN+FP+FN} \quad (2)$$

TP (True Positive): Model predicts Positive, and it is actually Positive.
TN (True Negative): Model predicts Negative, and it is actually Negative.
FP (False Positive): Model predicts Positive, but it is actually Negative.
FN (False Negative): Model predicts Negative, but it is actually Positive.
Precision is the ratio of correct predictions of positive observations, as highlighted in Eq. (3):

$$\text{Precision} = \frac{\{TP\}}{\{TP+FP\}} \quad (3)$$

Recall is the percentage of true positives that are correctly recognized in Eq. (4):

$$\text{Recall} = \frac{\{TP\}}{\{TP+FN\}} \quad (4)$$

The F1-score is the harmonic mean of the precision and recall, as describe in Eq. (5):

$$F1 = 2 * \frac{\{\text{Precision} * \text{Recall}\}}{\{\text{Precision}+\text{Recall}\}} \quad (5)$$

The complete proposed workflow is shown in Figure 1.

Explainable Artificial Intelligence:

To enhance the explainability of machine learning predictions, XAI is included in the proposed framework. The aim of the XAI component is to recognize the battery and runtime parameters that help create the predicted optimal charging-duration class. The main explainability technique used is called SHAP (SHapley Additive exPlanations)[30] SHAP can assign a contribution value to each input feature, enabling the investigator to see how each feature impacts the prediction of a model. The positive and negative SHAP values can be used to find out if a feature is aiding or opposing a given prediction on charging duration. The XAI stage is thus used in conjunction with the conventional performance evaluation to give information about the reasons that give rise to a particular prediction by a model, in addition to the predicted class.

Digital Twin-Driven Monitoring Framework:

The Digital Twin component provides the conceptual integration layer of the proposed methodology. The physical EV battery is represented through its measured operating parameters, while the virtual analytical component processes these parameters using the developed machine learning models. The battery-related measurements are transformed through the preprocessing pipeline[31]and supplied to the predictive models to determine the optimal charging-duration class.

The XAI component is then used to interpret the resulting prediction and identify influential operating parameters. In this way, the proposed framework establishes a connection between battery operating data, predictive analytics and interpretable decision support. The proposed Digital Twin architecture involves three key elements: Physical battery representation, Virtual analytical model, and Explainable decision-support system. Machine learning models are used to process the battery operating parameters such as State of Charge (SOC), voltage, current, temperature, charging efficiency, degradation rate, etc. to get the optimal charging-duration class.

The XAI module assists in the understanding of these forecasts and discovering important battery parameters. For data exchange & synchronisation, the present study employs a publicly available Kaggle dataset for offline experimental evaluation, instead of real-time communication with the physical EV batteries. Consequently, in the present study, the implementation of the continuous physical-to-virtual synchronization has not been done. The focus of the experimental implementation is mainly on data preprocessing, machine learning model development, performance evaluation and explainability analysis. The Digital Twin is a conceptual tool for connecting these elements.

In the updated manuscript we have provided clarity of these architectural elements

and implementation constraints of Digital Twin-Driven Monitoring Framework. In addition, real-time monitoring of the battery, continuous battery synchronization, and the integration with the physical battery management system are mentioned as possible future research directions.

Result and Discussion

Dataset Distribution:

The experimental dataset consists of 1,000 observations and 13 variables related to electric-vehicle battery charging and operating conditions. The target variable, Optimal Charging Duration Class, contains three classes [32]Class 0(Short charging duration) contains 201 observations, Class 1(Medium charging duration) contains 404 observations, and Class 2(Long charging duration) contains 395 observations. Thus, Class 1(Medium charging duration) represents the largest proportion of the dataset, followed by Class 2 and Class 0, as shown in table 2.

Table. 2 Distribution of Optimal Charging Duration Classes

Optimal Charging Duration Class	Number of Samples	Percentage
Class 0	201	20.10%
Class 1	404	40.40%
Class 2	395	39.50%
Total	1000	100%

As show in table 2, the class distribution shows a moderate imbalance because Class 0 contains fewer observations than Classes 1(Medium charging duration) and 2(Long charging duration). However, all three classes have sufficient observations for supervised classification.

Comparative Model Performance:

Five classification approaches were evaluated, including a baseline classifier and four machine-learning models: Logistic Regression, Random Forest, Extra Trees, and Gradient Boosting[33]The testing results show that Logistic Regression achieved the highest accuracy of 97.0%, followed by Gradient Boosting with 93.0%, Random Forest with 91.0%, and Extra Trees with 90.0%. The baseline achieved only 40.5% accuracy, as show in table 3. The Logistic Regression improved the classification accuracy by 97% compared with the baseline classifier.As show in table 3.

Table. 3 Comparative Performance of Machine Learning model

MachineLearning Model	Testing Accuracy (%)	Rank
Logistic Regression	97.0	1
Gradient Boosting	0.95	2
Random Forest	0.99	3
Extra Trees Classifier	0.97	4

As show in table 3,the result indicates that the selected battery and charging variables contain strong predictive information for distinguishing the three optimal charging-duration classes.

Logistic Regression Classification Performance:

Logistic Regression produced the strongest testing performance with an accuracy of 97.0%. The model achieved balanced performance across the three classes. Class 0 obtained a precision of 0.95, recall of 0.97, and F1-score of 0.96. Class 1 achieved precision, recall, and F1-score values of 0.97, 0.95, and 0.96, respectively. Class 2 achieved the highest class-wise F1-score of 0.98, with a recall of 0.99, as shown in Table 4.

As show in table 4, the identical macro and weighted F1-score of 0.97 demonstrates [34]that the model maintains consistent predictive performance despite the moderate class imbalance.

Table. 4 Logistic Regrwssion Class-Wise Results

Class	Precision	Recall	F1-score	Support
Class 0	0.95	0.97	0.96	40
Class 1	0.97	0.95	0.96	81
Class 2	0.97	0.99	0.98	79
Macro Average	0.97	0.97	0.97	200
Weighted Average	0.97	0.97	0.97	200

Random Forest Classification Performance:

The Random Forest model achieved a testing accuracy of 91.0%. The model demonstrated its strongest performance for Class 2, obtaining precision, recall, and F1-score values of 0.95 [35]Class 0 achieved an F1-score of 0.87, while Class 1 achieved an F1-score of 0.89, as shown in table 5.

Table. 5 Random Forest Class-Wise Results

Class	Precision	Recall	F1-score	Support
Class 0	0.89	0.85	0.87	40
Class 1	0.88	0.90	0.89	81
Class 2	0.95	0.95	0.95	79
Macro Average	0.91	0.90	0.90	200
Weighted Average	0.91	0.91	0.91	200

As show in table 5, although Random Forest performed below Logistic Regression in terms of testing accuracy, its class-wise performance remained relatively balanced.

Confusion Matrix Analysis:

The confusion matrix obtained from the Random Forest model is presented below Figure 2.

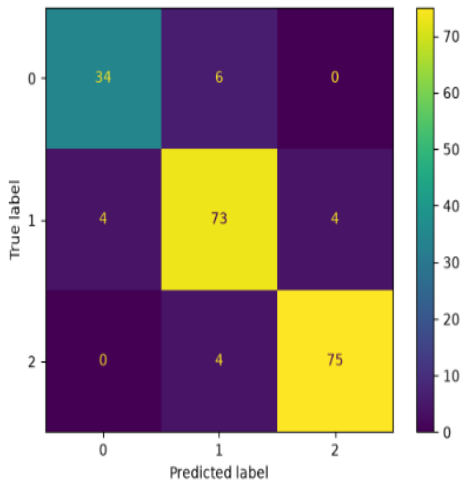

Figure 2. Final Model Confusion Matrix

Figure 2 presents the confusion matrix of the optimized Random Forest model for three-class optimal charging-duration prediction. The model correctly classified 34 Class 0 samples, 73 Class 1 samples, and 75 Class 2 samples. The majority of the predictions are relatively close to the diagonal, and thus good classification is achieved for all three classes. The chief misclassification was between Class 0 and Class 1, with six class 0 samples being misclassified as class 1. Likewise, 4 Class 1 samples were determined as Class 0 and 4 as Class 2 samples. In general, an accuracy of 91% for a total of 182 correct classifications was achieved from 200 test samples.

Cross-Validation Performance:

To assess the stability of the predictive model, cross-validation was also performed. The five obtained accuracy scores were 91.5%, 94.0%, 96.5%, 92.0%, and 90.5%. The mean

cross-validation accuracy was 92.90%, with a standard deviation of 2.13 percentage points. The five-fold cross validation accuracy for the proposed machine learning model is given in Figure 3. The obtained accuracies across the five folds were 91.5%, 94.0%, 96.5%, 92.0%, and 90.5%, respectively. The highest accuracy of 96.5% was achieved in Fold 3, while the lowest accuracy of 90.5% was seen in Fold 5. However, this difference did not affect the model's overall performance, which remained at an average cross-validation accuracy of 92.90% with a standard deviation of about 2.13%.

The variation among the folds is relatively small, suggesting good predictive performance on the different subsets of the data. These results further corroborate the model's effectiveness, even when trained on one train-test partition, and show good performance stability towards optimal EV charging-duration classification .

Random Forest Hyperparameter Optimization:

GridSearchCV was applied to optimize the Random Forest classifier using weighted F1-score. The result of the comparative evaluation indicates that Logistic Regression has the best testing accuracy of 97%, while Gradient Boosting (93%), Random Forest (91%) and Extra Trees (90%). The reported mean cross validation accuracy of 92.90% and the Random Forest optimization score of 92.10% are different evaluation results and should be interpreted based on the different validation procedures and performance measure.The best configuration consisted of 300 estimators, unlimited maximum tree depth, a minimum of one sample per leaf, and two samples as the minimum required for splitting. As show in figure 3.

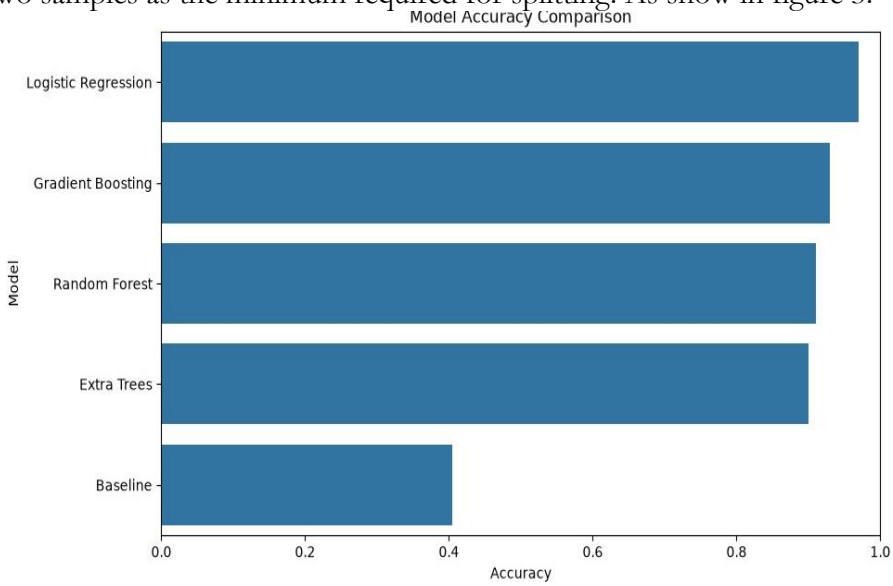

Figure 3. Comparison of Machine learning model accuracy

As show in figure 3, the is related to an optimization score of 92.10% with the Random Forest model by optimizing the hyperparameters and performing GridSearchCV optimization with a scoring function of the weighted F1-score. The 92.90% value presents an average of the classification accuracy seen in five folds of cross validation. Therefore, the results should not be interpreted as directly equivalent performance measures and use different evaluation metrics. optimized model achieved a cross-validation score of 92.10% and a testing accuracy of 91.0%. The optimized Random Forest achieved 100% training accuracy but 91.0% testing accuracy. This difference should be reported transparently because it indicates that the model fits the training data very strongly, while its performance on unseen data is lower.

Explainable Artificial Intelligence (XAI):

To enhance the transparency and interpretability of EV battery charging-duration predictions, Explanable Artificial Intelligence (XAI) is integrated. Battery operating parameters will be used with the Random Forest model to assess their contributions to the

three battery charging-duration classes by applying the SHapley Additive exPlanations (SHAP) technique. SHAP waterfall plots will be used to explain individual predictions, and mean absolute SHAP values and summary plots will be used to assess the importance of the features at the global level. The role of State of Charge (SOC), degradation rate, charging efficiency, voltage, current and temperature on the model predictions will be emphasized during the analysis. In addition, the conventional Random Forest feature importance will be compared with SHAP results, as this highlights degradation rate (30.60%), charging efficiency (29.51%) and SOC (16.98%) as the most influential features. This analysis will offer global explanations and individual explanations to make the proposed EV battery monitoring more interpretable.

Conclusion & Future Work:

This research proposed a Digital Twin (DT)-based framework for Electric Vehicle (EV) battery monitoring system by utilising Explainable Artificial Intelligence (XAI). The proposed method combines battery parameters and machine learning models for enabling smart and explainable charging decision-making. The results of the experiments show that machine learning methods can be used to predict the optimal classes of EV battery charging-duration based on battery operating parameters. Logistic Regression gave the best reported test accuracy of 97% and feature-importance analysis for the Random Forest model gave insightful information about which battery characteristics are influential. The results indicate that the proposed framework could be applied to intelligent charging-duration prediction and explainable decision making in future EV battery management applications. Despite this, this current study has a few drawbacks.

The experimental evaluation was done with an offline Kaggle dataset of 1000 observations only, which might not apply to other batteries or real-world operating conditions. In addition, the proposed Digital Twin architecture is still conceptual, since the real-time acquisition of battery data, the continuous synchronization between the physical and virtual battery and the deployment within an actual Battery Management System has not been experimentally shown. Further testing with actual EV battery measurements is needed before practical deployment.The experimental data was obtained from 1000 samples with 13 variables such as State of Charge (SOC), voltage, current, battery temperature, ambient temperature, charging duration, degradation rate, efficiency, charging cycles, charging mode, battery type, and EV model.

The optimum charging time was derived as the three-class classification problem of short duration charging, medium duration charging, and long duration charging. A comparison of the performance of 4 machine learning models (Logistic Regression, Random Forest, Extra Trees, Gradient Boosting) was performed. The results of the experimental study showed that Logistic Regression model has the highest model accuracy which is 97.0%, Gradient Boosting model has the accuracy of 93.0%, the Random Forest model has the accuracy of 91.0%, and the accuracy of the Extra Trees model is 90.0%. The optimal Random Forest model had a test accuracy of 91.0 per cent and weighted precision, recall and F1 scores around 0.91. It achieved a relatively stable predictive performance with a mean accuracy of 92.90% ± 2.13% in a five-fold independent cross-validation. Additionally, the degradation rate (30.60%), efficiency (29.51%), and the SOC (16.98%) were found to be the most influential variables for the best prediction of charging duration by the Random Forest feature-importance analysis.

Incorporating XAI becomes an important layer of interpretability in the proposed framework, as the individual parameters of the batteries and charging processes can be attributed to model predictions and then looked into. In such a context, SHAP can be used to offer explanations which are both local and global, thus enhancing transparency and decision making in intelligent EV charging systems that is more trusted. The Digital Twin concept also offers an architectural perspective of how physical battery data can be linked to a virtual analytical representation, prediction by machine learning, and explainable decision support.

The results highlight the potential of ML to accurately model the optimal charging duration categories based on various EV battery operating parameters, and the integration of the proposed Digital Twin with XAI offers a direction for efficient and transparent battery monitoring.

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