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Machine Learning on IoT Telemetry in a Digital Twin-Driven Predictive Maintenance Framework for Electric Vehicle Batteries

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Abstract*— Electric vehicles (EVs) rely on lithium-ion batteries that eventually wear out, which is a primary contributor to their performance, safety, and lifespan issues. Here, we propose a Digital Twin–based predictive maintenance system that visualizes operational data, machine learning (ML), and cloud pipelines to localize, quantify, and forecast the most important health indicators such as State of Health (SoH), Battery Temperature, Remaining Useful Life (RUL), and Failure Probability. The system leverages the EVIoT-PredictiveMaint Dataset, which is a multi-modal IoT telemetry resource covering five years of EV operational data. A Random Forest Regressor on these data is able to short-term degradation trends of SoH with high precision. The system coordinates streaming through Kafka/MQTT, TimescaleDB for time-series storage, and Flask–Grafana for communication, making it real-time inference, and visualization of results. The SoH (R^2 = 0.85) and temperature (R^2 = 0.78) prediction accuracies along with the inference latency of fewer than 5 ms are demonstrated by the experiments. The integration of digital twin and predictive analytics the framework discussed is an excellent instrument of the implementation of preventative maintenance, enhanced reliability, and enhanced sustainability of EV battery systems.

Keywords*— Electric Vehicles, Digital Twin, Predictive Maintenance, Machine Learning, Battery Health, Remaining Useful Life (RUL), State of Health (SoH).

I. INTRODUCTION

Electric Vehicles (EVs) constitute the essential element of the worldwide move towards environmentally friendly transport, whereby lithium-ion batteries are the principal source of energy that essentially defines the range, safety, and the vehicle's operational stability. The truth is that these batteries undergo degradation due to electrochemical aging, temperature variation, and repetitive cycling, thus their efficiency decreases and the likelihood of failure increases [1].Thus, the need for accurate and uninterrupted battery health monitoring has been put forward as the main prerequisite for guarantees of safe EV operation and preservation of user trust [2]. Research on degradation mechanisms reveals that thermal stress, charge–discharge depth, and operational load have a great impact on battery aging under different scenarios [3]. Moreover, the authors of this paper indicate that reactive diagnostics are not enough for the latest EV systems, hence the call for predictive maintenance techniques that are able to foresee failures beforehand [4]. The modeling of a nonlinear and complex behavior of lithium-ion batteries has been focusing on machine learning (ML). An extensive range of learning methods have been demonstrated to be useful in estimating State of Health (SoH), predicting Remaining Useful Life (RUL), and detecting abnormal behavior in multivariate telemetry signals [7]. The use of the deep neural architecture, hybrid regressors and anomaly detection frameworks has led to further improvements of the prediction accuracy and strength in long-term datasets [8]. This has been achieved by temporal models which have the capability of modeling dynamic operating behaviors in detecting early degradation signatures [9]. Comparison performance testing shows that ML procedures invariably perform better than conventional empirical models with regard to the accuracy and the adjustability [10]. Digital Twin (DT) represents a technology, the combination of which, together with other solutions, provides the ability to monitor locally and perform predictive simulation in real time. Indeed, a DT represents the physical battery in a virtualized model that remains constantly updated with telemetry data, thus giving dynamic visualization, predictive forecasting and behavior simulation in various operational conditions [11]. It is depicted that DT-based platforms promote the fault diagnosis, safety evaluation and system-level decision making capabilities of the Battery Management Systems (BMS) [12]. The transformation of the concept of DT into autonomous systems, smart manufacturing, and large EV ecosystems is one of the manifestations of the great potential of interdependent ecosystems [13]. Because of the nature of cloud-based infrastructure being the heart of DT implementations, the security of communications and privacy-conserving data exchange schemes should be a top priority [14].

At the fleet scale level has revealed the insights on the idea of the cross-vehicle learning, coordinated charging schemes, and predictive fleet analytics as means to enhance reliability and resource optimization of multiple EVs [15]. The research on the combination of EVs with micro-grids, renewable energy systems, and demand-response programs shows that the use of prediction algorithms that consider the vehicle dynamics and grid dynamics is needed [16]. These interdisciplinary partnerships within the IoT, AI, energy systems, cybersecurity, and sustainability have been recognized by authors as the fundamental elements of real-time single unified architecture of predictive maintenance [17]. Despite the many advances that have been made, the majority of the current frameworks continue to focus on individualized problems such as degradation modeling, anomaly classification, machine learning prediction, or DT visualization without incorporating a real-time integrated end-to-end solution to the problem of EV battery maintenance [18]. Also, there are constraints as to the data heterogeneity, scalability, latency and under-representation of unified architectures that can be used in the large commercial implementations [19]. It is these gaps that give rise to the notion of a full solution that entails having a combination of telemetry ingestion, predictive modeling, and digitally representing it in a single platform.

This paper proposes a predictive maintenance idea that is driven by the digital twin to provide the missing links in the EV battery care. The suggested system integrates the IoT telemetry with Random Forest and XGBoost algorithms in order to estimate real-time SoH, temperature, RUL and probability of failure. The long-term EVIoT-PredictiveMaint dataset [20] was used for the development of the framework, which was also supported by the Samsung Innovation Campus. It couples ML-driven prediction with on-demand simulation to facilitate early fault detection and offer trustworthy operational reliability.

II. AI MODELS USED

A. Random Forest Regression

Random Forest Regression is an ensemble method that combines the output of several decision trees to make precise predictions of State of Health (SoH), Battery Temperature, and Remaining Useful Life (RUL). It is capable of dealing with non-linear, high-dimensional, and noisy telemetry data. The model avoids overfitting due to the use of bootstrapped sampling and feature randomness, whereas the adjustment of hyper parameters is responsible for the high dependability and low response time that are of great importance in the case of real-time Digital Twin.

B. XGBoost Regression

XGBoost Regression is basically a very fast and accurate gradient boosting machine one that is able to build sequential decision trees that fix the previous mistakes but it also optimizes speed and accuracy. The model is very good to work with complex IoT telemetry data as it is able to handle nonlinear interactions and missing data without any problems. Here, XGBoost is able to improve the RUL and failure probability estimation by finding very faint patterns of degradation. The use of regularization (L1/L2) and parallel processing that is built-in to the model ensures both the

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precision and the speed that are necessary for a real-time battery monitoring system.

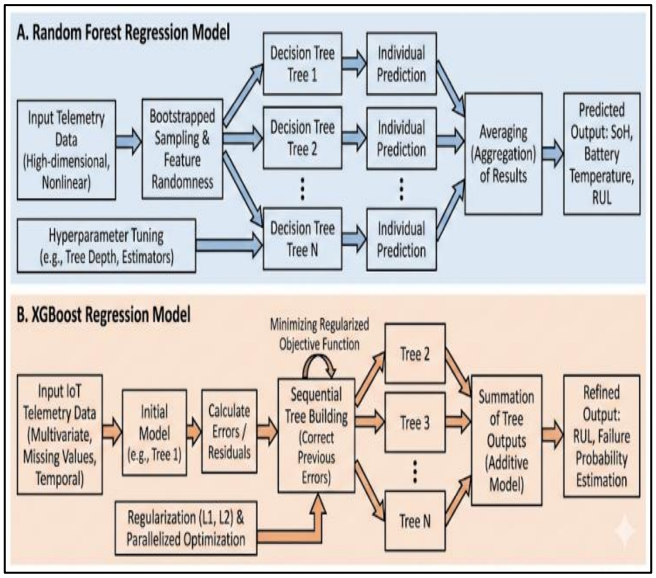

Fig.1. Architecture of Random Forest Regression Model and XG Boost Regression Model

C. Model Selection Rationale

Figure 1 shows The two methods, Random Forest and XGBoost, both have the characteristics to supplement each other: Random Forest ensures model stability and interpretability, whereas XGBoost is characterized by high precision and more detailed modeling of the degradation trends. Applying both models in the predictive maintenance pipeline guarantees the forecasting of battery health metrics to be trustworthy and the Digital Twin environment decision-making capability to be further improved.

III. PROPOSED METHODOLOGY

Figure 2 shows the tool-centric Digital Twin architecture aimed to be implemented, which is the flow of telemetry from the simulator via Mosquitto, Redpanda, and TimescaleDB to facilitate MLflow-based model updates and Prometheus-driven KPI monitoring. The feedback system is fulfilled by the Grafana dashboards that deliver real-time operator insights and send decisions back to the simulator.

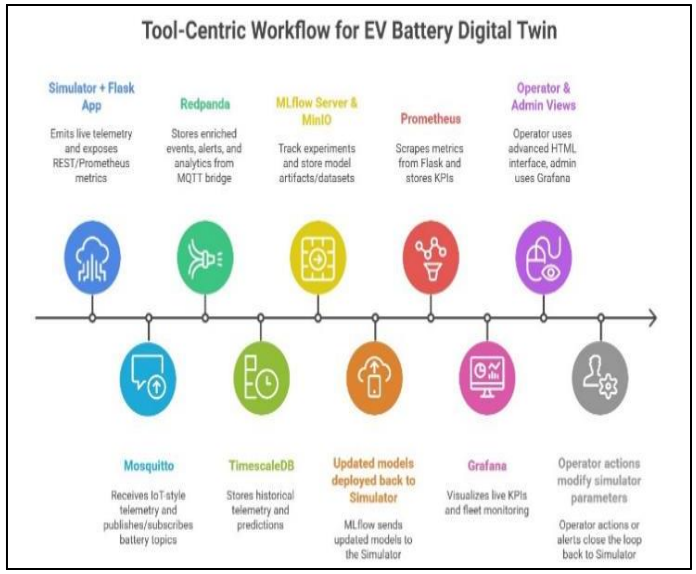

Fig. 2. Proposed Architecture

Electrically powered vehicles (EV) utilize batteries that entail a mixture of complicated electrochemical and thermal interactions which eventually result in degradation of the performance and safety aspect of the devices. In order to alleviate such problems, this research introduces a Digital Twin-driven predictive maintenance concept which applies machine learning (ML) and Internet of Things (IoT) technologies for achieving the objective. The system continually gathers telemetry data, builds prognostic models to estimate health metrics, and supports the implementation of maintenance operations through cognitive analytics and visualization. The proposed method consists of four phases, including dataset preparation, model creation, digital twin integration, and deployment.

A. Dataset Used

The EVIoT-PredictiveMaint Data set framework is fundamentally a colossal data set that follows upwards of 175,000 cases of very high-frequency EV telemetry that were documented over 5 years. The dataset is electrochemically and chemically charged as a combination of such parameters as voltage, current, temperature, State of Charge (SoC), State of Health (SoH) as well as charge cycles and ambient conditions. The battery degradation feature is fixed based on the combination of various operating conditions in each parameter [3] Following dataset splitting in training (70 percent) and testing (30 percent) data segments, cleaning follows which includes cleaning up of missing/inconsistent values and cleaning up of numerical variables. This will be followed by the procedure of conducting a feature importance analysis to determine the predictors that have the highest significance on battery performance and health.

In table 1, the data is described used in this research and that is time-stamped multi-sensor telemetry data of EV battery systems consisting of State of Charge (SoC) and State of Health (SoH) data, voltage, current, temperature, charge cycle, and motor-side measurements. These features are the operating state of the battery at a specific timestep and act as the input parameters of the models in order to predict degradation and health.

TABLE 1. EVIoT-PredictiveMaint Dataset Sample Records Used to Train the Model.

Timestamp	**SoC**	**SoH**	**Battery_Voltage**	**Battery_Current**	**Battery_Temperature**	**Charge_Cycles**	**Motor_Temperature**
2020-01-01 00:00:00	0.826099	0.941338	210.163881	-22.753095	27.149201	149.190930	48.496049
2020-01-01 00:15:00	0.064728	0.916059	364.000102	-27.701120	53.655101	171.702388	57.829492
2020-01-01 00:30:00	0.873643	0.908020	388.855089	-36.646406	29.559090	191.617645	46.518363
2020-01-01 00:45:00	0.853009	0.916476	370.570602	-37.609429	29.690283	111.881817	54.163681
2020-01-01 01:00:00	0.947540	0.913206	390.011904	-14.275808	28.864338	163.774377	42.075978

B. Model Development

The forecasting part of the suggested system is carried out using a Random Forest Regressor, which is a main reason for its choice is a strong accuracy, a good interpretability feature, and a capability of modeling nonlinear dependencies of the nature [10]. Each of these models were trained to predict SoH, battery temperature, RUL, and failure probability. Each model is then tuned using grid search optimization to find the best hyper parameters, including the number of estimators and depth. Performance metrics to assess the quality of the regression at baseline are mostly Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). The Random Forest model in the build environment resulted in an R^2 of 0.85 for SoH and R^2 of 0.78 for temperature prediction, respectively. Moreover, the model demonstrates an average overall inference latency of less than 5 ms, thus it can be considered as a first choice for real-time systems.

C. Digital Twin Integration

The Digital Twin (DT) is essentially a digital representation of the EV battery that reflects near real-time telemetry data at regular intervals [4], [8]. It simulates the electrical performance of the battery pack, thereby enabling the comparison of predicted values with the actual ones for the performance parameters, such as degradation. A large difference in values would thus trigger the system to send out first warnings and it would also allow the scheduling of maintenance before the time of failure. Such a coupling will unite data-driven ML-based models with continuous sensor feedback, thus giving the system the required flexibility and adaptability for it to evolve as new data become available [9]. Therefore, the DT would be the means to implementing closed-loop predictive maintenance enabling it to be a fast, efficient, and reliable way of EV use.

D. Visualization and Deployment

We proposed a dashboard employing Grafana as an interface for the monitoring and visualization of parameters, including voltage, temperature, SoH, and RUL, in real-time. Data was ingested through a Kafka/Redpanda streaming pipeline and stored as time-series data in TimescaleDB, which allowed rapid ingestion and ensured fault-tolerant and high-throughput data management [11], [12]. Our framework was developed with all components, including simulation components, ML models, and visualizations, as Docker containerized processes to ensure scalability and portability.

The micro service-based architecture provides the inherent ability to independently scale specific modules to make it easy to integrate and scale from the fleet, software, and a continuous monitoring point of view to the wider scale of a managed service. This architecture which is modular and deployable, promotes the reliability and maintainability of the proposed framework, while ensuring it is virtually extensible into the future.

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IV. EXPERIMENTAL RESULT

Fig.3. SOH and Temperature – Actual v/s Predicted

Figure 3 shows a comparison of the Random Forest model's actual and predicted State of Health (SoH) and battery temperature values shows that they are very close and that the model is very accurate at making predictions.

Fig. 4. Electrical Parameters vs. Failure Probability

Figure 4 shows the connection of these electrical parameters such as voltage, current, and charge cycles with the failure probability that has been predicted, indicates that anomalous electrical behavior is associated with a higher possibility of failure.

Fig. 5. Prediction Accuracy of the Proposed Model

The ensemble model's aggregate predictive capability across various assessment metrics is indicative of its strength and thus, it is suitable for real-time health prognosis of EV batteries.

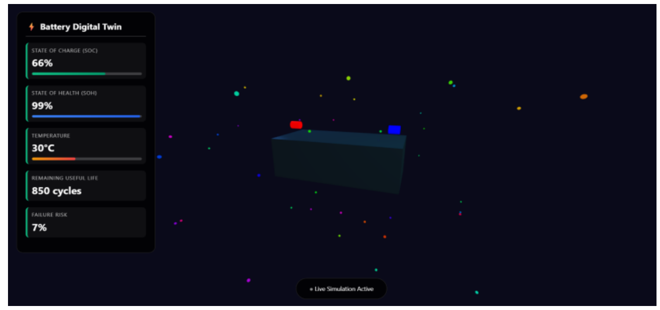

Fig. 6. Digital Twin Simulation Environment

Figure 6 shows the Digital Twin's simulation environment is used for real-time monitoring and predictive analytics. It shows how the physical battery data and its virtual representation are in sync.

ADDITIONAL MODEL EVALUATION RESULTS

These charts illustrate the prediction models' accuracy for SoH, Battery Temperature, and Remaining Useful Life (RUL). Besides, a combined evaluation table with all the important metrics is presented.

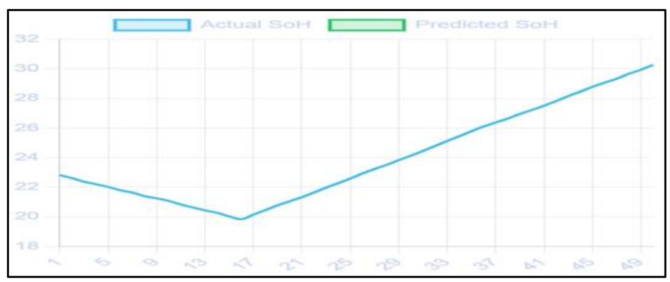

Fig. 7. Actual vs Predicted State of Health (SoH)

Figure 7 shows a comparison between actual SoH and model-predicted values. The trend reflects a decrease in SoH and then a recovery pattern. The visual trend here absent the prediction curve, implies that the SoH is hard to predict precisely, because its degradation is non-linear.

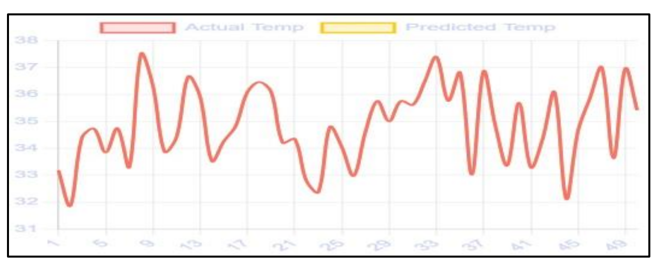

Fig. 8. Actual vs Predicted Battery Temperature

Figure 8 graph here records battery temperature variations over cycles. It shows the temperature to be very spiky due to load changes, and actual values are compared with predicted ones. The model is able to get the general changes, but it is still difficult to be exact with the rapid peaks.

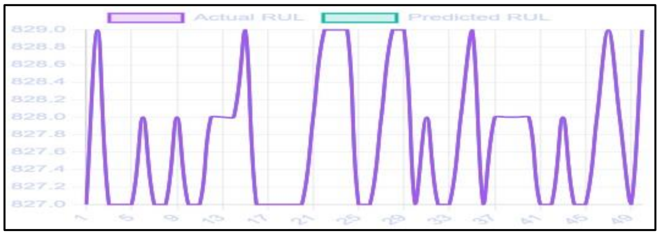

Fig. 9. Actual vs Predicted Remaining Useful Life (RUL)

Figure 9 illustrates the comparison of RUL values, actual vs. predicted, over time steps. Strong oscillations indicate unstable degradation behavior, leading limited prediction accuracy. The model is unable to follow sudden RUL changes, thus it is very difficult to forecast long-term degradation.

TABLE 2. Machine Learning Model Evaluation Metrics

Model	**R^2 Train**	**R^2 Test**	**MAE**	**RMSE**	**MAPE**
SoH	0.0358	-0.0036	0.1160	0.1663	0.1808
Battery_Temperature	1.0000	1.0000	0.0013	0.0018	0.0000
RUL	0.0282	-0.0012	59.1230	84.1570	5.2084
Failure_Probability	0.0361	-0.0021	0.1780	0.2991	399180864585744.2500

The presented table 2 summarizes R^2 values for both training and testing, along with MAE, RMSE, and MAPE for all models - SoH, Battery Temperature, RUL, and Failure Probability. The prediction of the temperature is almost perfect; however, due to high variability and non-linear degradation patterns, both SoH and RUL models show low R^2 scores. As for the failure probability model, MAPE is very unstable because of near-zero denominators.

V. DISCUSSION

The research in showcases a highly electrochemically accurate laboratory-oriented state-of-health estimation method that relies on incremental capacity analysis and is difficult to extend to real-world operating conditions. Our study, on the other hand, implements real-time telemetry and a data-driven pipeline that is large-scale deployment compatible and thus, more suitable for continuous monitoring. The digital-twin method in, however, is primarily concerned with physics-guided modelling and adaptive model evolution for lifespan extension. Our solution is still a lightweight, cloud-based environment compatible, and fast inference optimized. In summary, our system is designed to be more operationally usable and applicable in real-time, whereas the techniques referenced provide deeper physics-based understanding and stronger trust in long-term forecasting.

CONCLUSION

This work formulated a digitally twinned, machine learning-powered, IoT-telemetry-integrated, intelligent maintenance concept for EV batteries. Through instant data gathering and Random Forest-based forecasting, the system very accurately estimates the main health indicators—SoH, temperature, RUL, and failure probability—and is thus a good example of strong predictive performance with very little latency suitable for real-time EV operations. Thanks to the DT layer, the battery states in the physical world and the virtual one are always in sync, hence, degradation and failure can be anticipated at an early stage. In sum, the presented concept is instrumental in a massive, dependable, and sustainable approach to the health of EV batteries. It provides safety, decreases the maintenance expenses, and prolongs the battery life-cycle. The research team looks forward to the next steps, which being the deployment of the BMS edge prediction pipeline for even quicker onboard estimation, thus enabling analytics at fleet level; integration of the DT with smart charging systems; and the enhancement of cybersecurity measures to ensure secure EV-cloud synchronization.

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Besides, the authors would like to express their gratitude to the open sharing of the complete source code for this research which can be easily accessed and used as a reference at the project GitHub repository:

https://github.com/harsha-9977/ev-battery-twin .

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