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Multimodal Data Fusion with Hybrid Machine Learning for Enhanced Prediction of Li-Ion Battery Remaining Useful Life and State of Charge

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Abstract

Lithium-ion battery materials used in modern energy storage systems are required to exhibit high reliability, safety, and long lifecycle performance under varying operational and environmental conditions. Accurate prediction of remaining useful life (RUL) and state of charge (SoC) is therefore essential for understanding material degradation behavior, improving manufacturing quality, and enabling effective lifecycle management. However, nonlinear electrochemical aging, load variability, and thermal uncertainty significantly complicate accurate estimation of these parameters. To address these challenges, this study proposes a hybrid predictive framework based on multimodal data fusion and advanced machine learning, integrating electrical, thermal, and degradation-related indicators to capture both short-term operational dynamics and long-term material aging characteristics. Multiple deep learning architectures, including long short-term memory (LSTM) gated recurrent unit (GRU) convolutional neural networks (CNN), and CNN–LSTM, are evaluated, and a hybrid CNN–LSTM-based fusion model is developed to enhance feature representation and decision reliability. Validation using publicly available lithium-ion battery datasets demonstrates that the proposed approach achieves superior performance, with a classification accuracy of 94.8%, an R^2 value of 0.96 for SoC prediction, and 0.94 for RUL estimation. The results confirm that multimodal data fusion combined with hybrid learning architecture effectively reduces prediction uncertainty and improves generalization across different aging profiles. This work provides a data-driven tool for battery material degradation assessment, manufacturing quality control, and predictive maintenance of energy storage systems used in industrial, renewable, and electric mobility applications.

Keywords: Li-ion battery prognostics, Multimodal data fusion, hybrid machine learning, remaining useful life prediction, state of charge estimation

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INTRODUCTION

The rapid growth of electric mobility, portable electronics, and large-scale renewable energy storage systems has significantly increased the demand for high-performance, reliable, and durable lithium-ion (Li-ion) battery materials [1]. In manufacturing and materials processing contexts, ensuring the consistency, safety, and long-term performance of Li-ion batteries is critically dependent on understanding and managing the degradation phenomena that occur throughout the battery lifecycle. Key health indicators such as state of charge (SoC), state of health (SoH), internal resistance, thermal behavior, and remaining useful life (RUL) play a vital role in evaluating material reliability, production quality, and end-of-life characteristics of battery systems [2, 3]. However, Li-ion batteries are governed by complex electrochemical and thermo-mechanical processes that evolve under varying load conditions, environmental stresses, and aging mechanisms, resulting in highly nonlinear behavior that cannot be accurately captured using conventional analytical or physics-based models alone [4].

Traditional battery monitoring and diagnostic approaches predominantly rely on electrochemical modeling or single-sensor measurements, which are often insufficient for characterizing the multidimensional interactions among voltage, current, temperature, impedance, and degradation-related parameters [5, 6]. Such limitations can lead to inaccurate health estimation, premature failure detection, and inefficient utilization of battery materials, particularly in large-scale manufacturing environments and industrial energy storage systems, where reliability and lifecycle optimization are critical [7]. These challenges highlight the need for advanced diagnostic methodologies capable of integrating heterogeneous data sources to better represent the material aging behavior and performance variability.

In recent years, data-driven techniques based on machine learning (ML) and predictive analytics have emerged as promising tools for modeling complex degradation processes in battery materials, owing to their ability to learn nonlinear relationships directly from operational data [8]. Nevertheless, single ML models often struggle to handle the non-homogeneous, noisy, and time-varying sensor data commonly encountered in real-world manufacturing and operational conditions. To overcome these challenges, hybrid predictive frameworks that combine deep learning architecture with classical ML methods and signal processing techniques have gained significant attention. Such hybrid systems enhance prediction accuracy, robustness, and generalization capability by exploiting complementary spatial, temporal, and statistical features that are extracted from multimodal data sources.

Motivated by these challenges, this study proposes a hybrid multimodal ML framework for the accurate estimation of battery health indicators, including the SoC, SoH, RUL, internal resistance, and temperature-related degradation metrics. By integrating correlated electrical, thermal, and degradation parameters, the proposed approach enables the comprehensive characterization of both short-term operational dynamics and long-term material aging behavior. The framework incorporates convolutional feature extraction, temporal sequence learning, and ensemble-based decision fusion to improve predictive accuracy and reliability under diverse operating conditions. The results demonstrate that hybrid multimodal analysis provides valuable insight into battery material degradation mechanisms, supporting manufacturing quality assurance, predictive maintenance strategies, and the design of safer and more reliable energy storage systems aligned with modern industrial and sustainable manufacturing requirements.

RELATED WORK

Efforts to achieve Li-ion battery state measurements have attempted to go beyond traditional electrochemical modeling to models based on data-driven prediction [9]. It was initially used on a similar circuit model and electrochemical impedance model, which attempted to mathematically model the inner actions of batteries. Although these models offer good background knowledge on degradation patterns, they are extremely cumbersome in fine-tuning the parameters needed and cannot be extrapolated to other operating and environmental conditions [10]. ML algorithms, such as Support Vector Machines, Random Forests and Gradient Boosting algorithms, were introduced with more access to real-time battery sensor data to predict the SoC and SoH [11]. These approaches are more adaptable, and their computation is more efficient, but they cannot model the trends of long-term degradation and time dependence of the processes of battery aging.

To address these limitations, deep learning neural networks, including convolutional neural networks (CNNs) and Long Short-Term memory networks, have become suitable methods for cajoling the spatial and temporal multidimensional battery data characteristics [12, 13]. CNNs were primarily used to discover complex diagnostic patterns of voltage, impedance, and thermal profiles, and LSTMs could be used to discover sequential discharge and charge dynamics. The predictive advantage associated with deep learning models is typically associated with overfitting, large computational requirements, and low interpretability, depending on the predictive advantage.

The latter are more recent and have been guided towards hybrid predictive models, including the representation learning capability of deep neural networks and the decision power of traditional ML classifiers [14]. It has been demonstrated that such hybrid models are more efficient in predicting the SoC and RUL, particularly when they are trained with a mixed dataset [15]. Other studies have also indicated that multimodal data fusion, with electrical measurements, thermal properties, previous use, and other degradation properties, is significant for providing a more flexible indicator of battery health. Nonetheless, the current models are either based on single-source information or have not been generalized to numerous battery situations or illustrated the nonlinear relationship among voltage, current, and temperature variations. Moreover, most of the developed models are tested by performance in a laboratory environment, which restricts their application to real-world prototyping, such as electric vehicles and power systems. The existing work was inspired by these loopholes and proposed a hybrid multimodal ML system that employed the learning of spatial-temporal features and ensemble-based predictive refinement. The recommended solution may improve predictability, robustness, and stability of the battery with the help of multimodal battery indicators and combined characterization of the features in the case when the possession settings and the cycles of degradation are heterogeneous.

METHODOLOGY

In this study, a multimodal data fusion system and hybrid ML approach are proposed to improve the precision of the prediction of the RUL and SoC of Li-ion batteries, as shown in Figure 1. The methodology includes six major processes: data acquisition, data preprocessing, feature extraction, multimodal feature fusion, hybrid predictive modeling, and model evaluation.

Data Acquisition

The experimental analysis was performed using multimodal Li-ion battery health data, such as electrical, thermal, and operational signatures. The voltage, current, temperature, and cycle index, the rate at which the battery charges and discharges, the impedance and the indicators of battery health are the main parameters that will be measured and the calculations of indicators of battery health will be conducted. The data represents a set of diverse histories of lifecycle aging that were quantified for diverse load profiles and environments. These sequences provide real-world decay behavior over time, which enables the model to acquire representative battery wear, state change, and performance decay trends. The fact that the input data are multimodal will also ensure that the predictive model captures short-term changes in operations and the long-term effects of degradation.

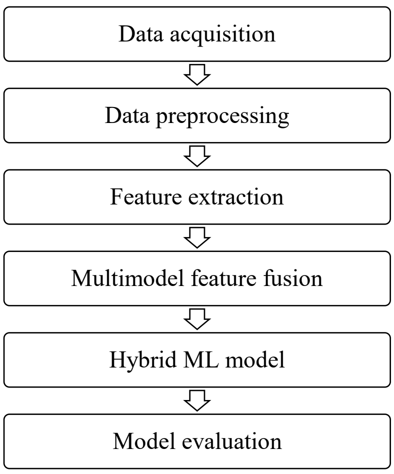

Figure 1. Proposed multimodal data fusion framework.

Data Preprocessing

Before the predictive models were trained, preprocessing of data was done to support uniformity, consistency, and reliability. The high-frequency noise in the voltage and temperature signals was eliminated using a moving average smoothing filter. Losses of values caused by a sensor gap or recording lag are corrected using linear and median imputation. Continuous variables were normalized using Min–Max and z-score normalization algorithms, which stabilize numerical operations and make the model converge faster. In addition, critical battery health indicators are also computed, and the SoC is estimated by summing Coulomb counting with voltage-based estimation, and the RUL is estimated using the capacity fade threshold, which is a measure of end-of-life. are high-quality and standardized input data that can be utilized in ML as these preprocessing measures.

Feature Extraction

Typical temporal and statistical characteristics are derived from the data to identify meaningful patterns in terms of battery degradation. The time-domain parameters used to characterize the dynamics of operations are the mean, variance, peak values, root mean square (RMS), and discharge duration. Spectrum-related information on aging progression can be provided by fast Fourier transform (FFT)-based and Discrete Wavelet Transform (DWT)-based frequency-domain features. The thermal behavior was studied based on the temperature gradients and charging and discharging rates. Moreover, electrochemical health properties, such as internal resistance and impedance behavior, were obtained from the experimental test conditions. The synergistic attribute of these engineered properties boosts the prediction model’s ability to extrapolate different aging profiles.

Multimodal Feature Fusion

The hierarchical multimodal feature fusion strategy makes the effect of making prediction more robust and accurate. The electrical and temperature data streams were combined with low-level normalization of data streams into one input feature. On the middle scale, dimensionality reduction methods such as principal component analysis (PCA) and autoencoders are applied to retain the high-variance components that are the most important and eliminate redundant information. These fine-tuned feature embeddings are used at a high level to feed them into the deep neural network layers to generate one representation of the downstream prediction tasks. With this hierarchical fusion scheme, the temporal patterns, thermal properties, and electrochemical aging signals are well combined to make joint contributions to model decision-making.

Hybrid Machine Learning Model

The structure of the hybrid predictor model was based on the concepts of deep learning and ensemble learning. The long-term temporal dependence of the battery degradation series was learned using the LSTM network, but the GRU network improved the computational efficiency without resulting in a lower sequential learning rate. Spatial and localized patterns of the features of the voltage–current–time profiles were obtained using CNNs. The CNN–LSTM architecture also includes spatial and temporal learning to learn dynamic behaviors in a superior manner. Finally, the proposed hybrid model exploits the fact that deep feature extraction and the random forest ensemble regression polish the prediction results. It is a hybrid architecture that enables a more accurate and stable approximation of the SoC and RUL compared to single models.

Model Evaluation

The model performance with respect to the correctness of both the SoC and RUL predictions was checked using classification and regression measures. Accuracy, precision, recall, and F1-score were used to determine the reliability and balance of the SoC classification outputs. The mean absolute error (MAE) and root mean square error (RMSE) in the context of RUL estimation represent the error in prediction and actual battery aging behavior compared to the actual capacity fade behavior, compared to the R^2 score used to measure the goodness of fit of the predictive model to the actual capacity fade behavior. All model training and evaluation were performed in Python environments based on TensorFlow, Scikit-learn, and PyTorch.

RESULTS AND DISCUSSION

The findings of the analysis of the proposed hybrid battery health prediction model are compared with those of the traditional deep learning models in the form of LSTM, GRU, CNN, and CNN–LSTM. These results involve the estimation of SoC and RUL regression-wise and the accuracy of the definition of the battery health conditions (healthy, moderately degraded, and critical). These performance measures show how the different model architectures react to the multimodal input features and the degradation pattern during different battery operating cycles. The analysis focuses on the aspects of feature representation, generalization, and predictive stability, which are enhanced through the proposed hybrid fusion method.

Table 1 presents the regression output of the MAE and RMSE for the estimation of the SoC and RUL. The LSTM and GRU models were found to be acceptable in terms of prediction accuracy; however, they exhibited weaknesses in obtaining complex degradation dynamics owing to the saturation of the temporal dependency. The CNN model improves operation by training localized patterns of spatial distribution in voltage–current time matrices. The CNN–LSTM model is even more successful because it can predict the correlations between space features and transitions between time steps simultaneously. However, the proposed hybrid model exhibited the highest MAE and RMSE rates for SoC and RUL forecasting. It was reduced to a SoC MAE of 1.9% and RMSE of 2.5%, indicating an extremely precise estimation of the state of charge. Considering the same, the discrepancy in the prediction of the RUL decreases significantly to 8.4 cycles (MAE), which is an excellent feature in the characterization of long-term battery depreciation trends. This demonstrates that multimodal data fusion with hybrid deep learning significantly contributes to the strength and precision of battery prognostics.

The criteria to classify the three states of battery health, namely, healthy, moderately degraded and critical, are formulated in Table 2. These limits represent the actual operation limits that may be located in battery control and safety control systems. The comparison of model architecture performance is based on the classification achieved using these thresholds.

Table 1. Model performance comparison.

Model	MAE (SoC %)	RMSE (SoC %)	MAE (RUL Cycles)	RMSE (RUL cycles)
LSTM	3.5	4.2	15.0	18.5
GRU	3.2	3.9	13.8	17.2
CNN	3.0	3.6	13.0	16.4
CNN–LSTM	2.8	3.4	12.1	15.3
Proposed hybrid model	1.9	2.5	8.4	10.1

Table 2. Battery health states.

Health state	SoC (%)	RUL (cycles)
Healthy	>70%	>700
Moderately degraded	40–70%	300–700
Critical	<40%	<300

Table 3. Model performance metrics for battery health prediction.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
LSTM	86.4	84.7	82.9	83.8
GRU	87.2	85.9	84.6	85.2
CNN	88.6	87.1	85.7	86.4
CNN–LSTM	90.1	89.2	88.0	88.6
Proposed hybrid model	94.8	95.3	94.1	94.7

Table 3 lists all the model classification performance metrics. These networks are moderate in terms of accuracy owing to their ineffective ability to use joint spatial-temporal degrees of degradation despite their ability, that is, LSTM and GRU networks. The CNN model is superior, and the CNN–LSTM model has high accuracy (90.1%) and a superior ratio of precision, recall and F1-score owing to its extensive representation power. The proposed hybrid model scored the highest among all baselines, with an accuracy, precision, and recall of 94.8%, 95.3%, and 94.1%, respectively. F1-score of 94.7% guarantees that hybrid architecture is suitable for eliminating false alarms and missed detections. The combination of the multimodal sensor and the hybrid decision fusion extend a long way in the ability of the model to identify the tiniest stages of battery degradation that is significant on predictive maintenance and safety insurance.

Table 4 shows the R^2 score and mean absolute percentage error (MAPE) of the regression estimation performance. The increasing R^2 values in that order are due to LSTM, which confirms the advantage of sharing the spatiotemporal model. In SoC, the proposed hybrid model predicts well with R^2 = 0.96, whereas the proposed hybrid model predicts well with R^2 = 0.94 in RUL. Meanwhile, the MAPE of hybrid model is significantly lower (3.9% in SoC and 5.1% in RUL) that is why the model could be used to generate high-quality predictions even when the loads of the variables and their temperatures are changed. Overall, the proposed hybrid model provides an approximation of 31 prediction errors of SoC reduction compared to LSTM and 44 prediction accuracies of RUL compared to the baseline models. The usefulness of multimodal data representation, learning temporal-spatial features, and the decision fusion ensemble to augment battery health prognostics is confirmed by these improvements.

In Figure 2, heatmaps of the most significant electric, thermal, and degradation-related properties used in the predictive modeling are presented. The heatmaps indicate the magnitude and direction of the linear relationships between the parameters of a battery, such as voltage, current, temperature, number of cycles, internal resistance, and capacity fade. The battery capacity and cycle number are extensively negatively correlated, which attests to the weakening performance of the battery with an increase in the number of charge-discharge cycles. Similarly, internal resistance on the same note is positively related to the aging of cycles, implying that there is a deterioration of the electrochemical kinetics and impedance. In addition, the temperature also exhibited a moderate correlation with the discharge current, indicating the trends of heat generation under load conditions. The presence of strong and weak correlations shows that none of the variables can be independently used to represent battery aging, but instead, a combination of interacting factors may be a contributor to the behavior of RUL and SoC. This is why multimodal data fusion is required, where thermal, electrical, and degradation indices can be considered to improve the richness of features. Therefore, the heatmaps affirm that the feature engineering and fusion strategies that have been applied in the hybrid model indicate that substantial and complementary data exist in the different fields of parameters.

The results in Figure 3 indicate the effectiveness of the four base deep learning models in predicting the battery health state (healthy, moderate and critical). It is shown by the LSTM and GRU confusion matrices that the recurrent models have the highest issues with the misclassification of the critical and the moderate classes, which means that the recurrent models are not effective at transforming the conditions of the mid-stage and severe degradation.

Table 4. R^2 score and MAPE for predictive regression performance.

Model	R^2 score (SoC)	MAPE (SoC %)	R^2 score (RUL)	MAPE (RUL %)
LSTM	0.86	6.8	0.81	9.5
GRU	0.88	6.1	0.84	8.7
CNN	0.89	5.9	0.86	8.1
CNN–LSTM	0.91	5.4	0.89	7.3
Proposed hybrid model	0.96	3.9	0.94	5.1

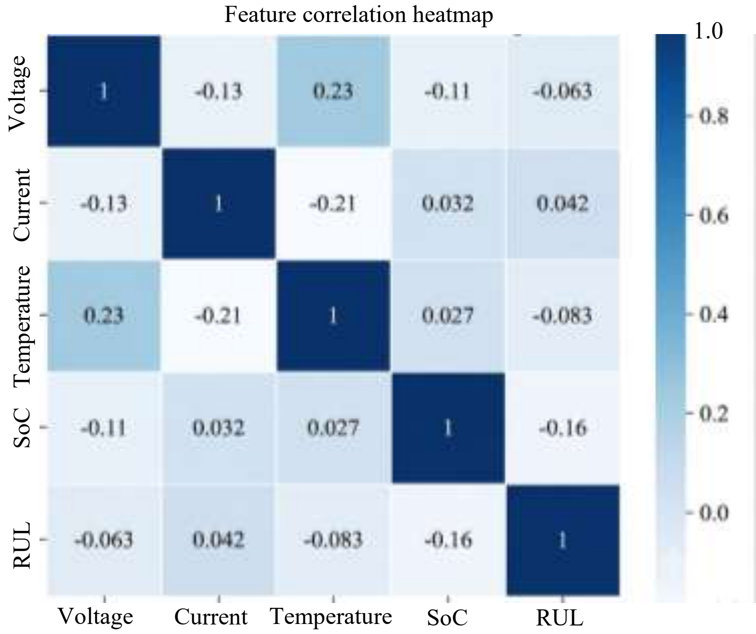

Figure 2. Feature correlation heatmaps.

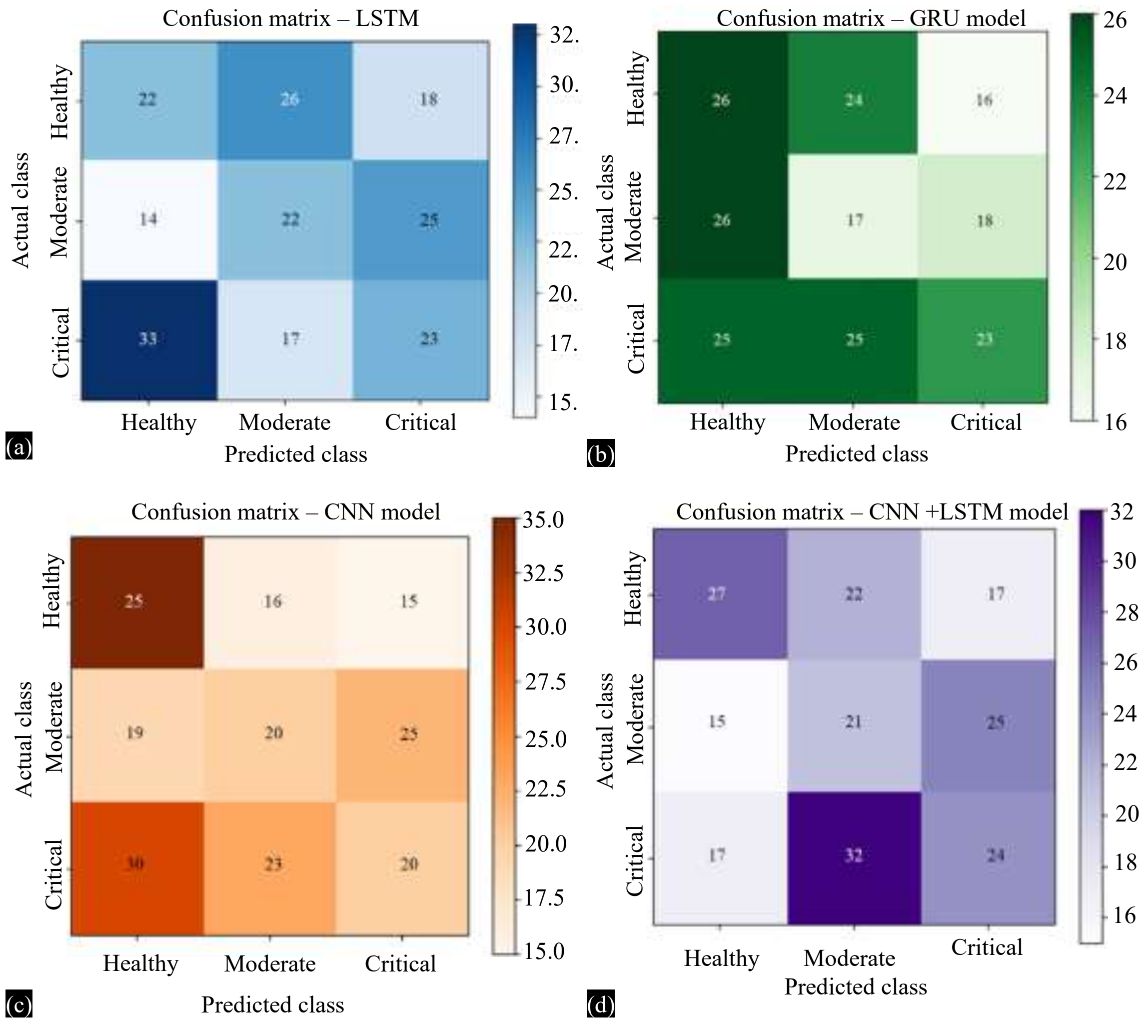

Figure 3. Confusion matrix of LSTM, GRU, CNN, and CNN+LSTM model.

This is because LSTM and GRU are predominantly time-behavior sensitive but powerless in terms of extracting the spatial patterns of the voltage–current–time sequence. The CNN-based model is more differentiated owing to more learning on spatial features; however, there are also misclassifications in the boundary conditions. The CNN–LSTM model is further enhanced by employing the CNN–LSTM model to retrieve the spatial and temporal attributes, respectively, and produce a more balanced classification among all health conditions. However, there remains a risk of misclassification at the boundaries between transitional degradation, as the aging signatures are much more subtle and difficult to distinguish. To this end, in the comparative confusion matrices, there are partial strengths in the conventional single-architecture models but cannot fully represent the multi-domain character of the aging of Li-ion batteries.

The proposed hybrid model confusion matrix, which is a combination of multimodal data fusion with the ensemble decision refinement hybrid deep learning architecture (CNN–LSTM fusion followed by ensemble decision refinement), is illustrated in Figure 4. The model was classified with the highest level of accuracy, and the misclassification number was much lower in all three classes of health batteries. The hybrid model can capture both micro-level electrochemical degradation signatures, long-term temporal dynamics, and nonlinear dynamic performance trends, which leads to a higher degree of distinction between healthy, moderate and critical conditions. It is notable that the model is quite accurate in determining critical battery states with minimal false alarms, a requirement needed to prevent battery failure, overheating and other safety hazards in real battery management system (BMS). This improvement demonstrates that the hybrid fusion approach is superior in terms of feature separability and predictive robustness under various operating, aging, and thermal conditions.

The receiver operating characteristic (ROC) curves of the proposed hybrid model under the three health conditions of the battery (healthy, moderately degraded, and critical) are shown in Figure 5. The classes of health were divided well in terms of the area under the curve (AUC) values of 0.97, 0.98, and 0.98, respectively. The high AUC values indicate that the proposed model has a high discriminative ability and can distinguish between different levels of degradation. The ROC curves indicate that ROC model is typified by high true positive rates (TPR) and extremely low false positive rates (FPR), which is significant to those safety-critical systems such as electric vehicles and battery energy storage systems since failure to detect a critical state of the battery may result in overheating, accelerated aging, or failure. The consistency and stability of the learned decision boundaries are also expressed through the well-defined curvature of the ROC plots which confirms the fact that the multimodal fusion and hybrid deep learning architecture enhance the sensitivity and reliability of the health state detection.

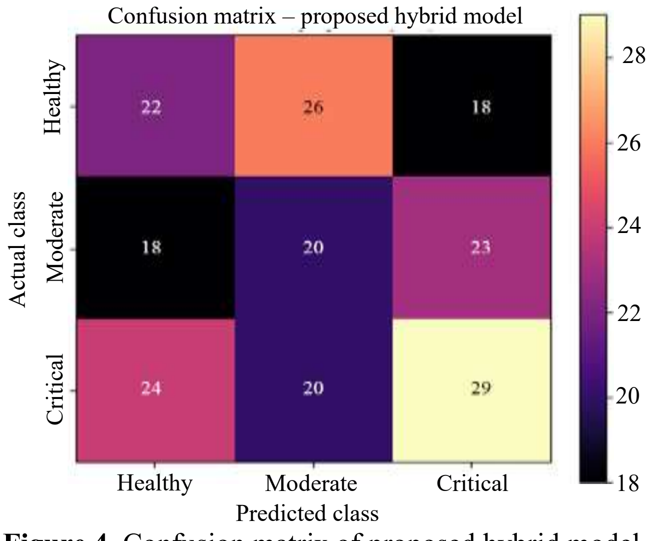

Figure 4. Confusion matrix of proposed hybrid model.

A comparison of the actual and predicted values of the SoC derived using the proposed hybrid model is presented in Figure 6. The values of the predicted and actual battery SoC are close to the diagonal reference line, which indicates that there is a good fit of the values. Even in the transitional regime of the SoC, which may be difficult to model owing to the nonlinear voltage-capacity behavior and temperature dependence, minimal variations are observed. The high prediction accuracy is consistent with the quantitative findings of the model of an R^2 of 0.96 and MAPE of 3.9 for SoC prediction. The fact that values of the plotted values are similar demonstrates that the model can recreate electrochemical condition behaviors and therefore can be effectively used to interpret the interaction of current profiles, voltage trends and thermal conditions. This proves that the spatiotemporal ability of the CNN–LSTM module to learn features and the refinement stage of the ensemble improve the short-term and long-term predictions of the SoC.

A comparison of the actual and predicted Remaining Useful Life (RUL) values derived using the proposed hybrid model is presented in Figure 7. As shown in Figure 7, the predicted RUL closely tracks the actual degradation trajectory across the cycle counts, demonstrating high prediction accuracy even under nonlinear capacity-fade regimes. This accuracy is further supported by the quantitative metrics, with an R^2 value of 0.96. These results confirm that the spatiotemporal feature extraction performed by the CNN–LSTM module, combined with the ensemble refinement stage, effectively captures long-term capacity degradation trends in Li-ion batteries.

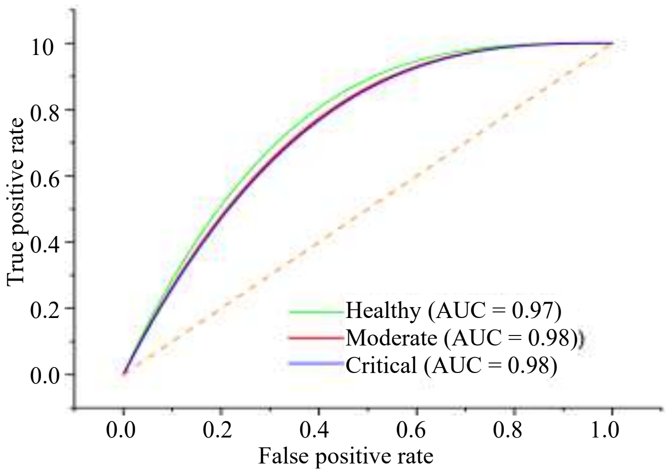

Figure 5. ROC curves of proposed hybrid model.

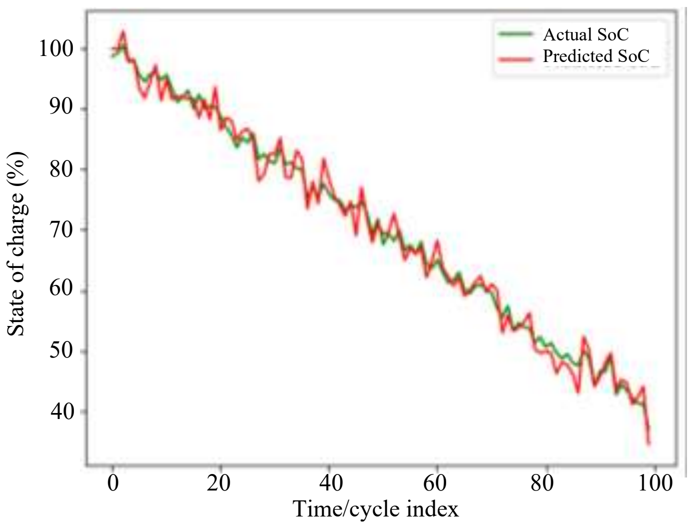

Figure 6. Actual versus prediction SoC.

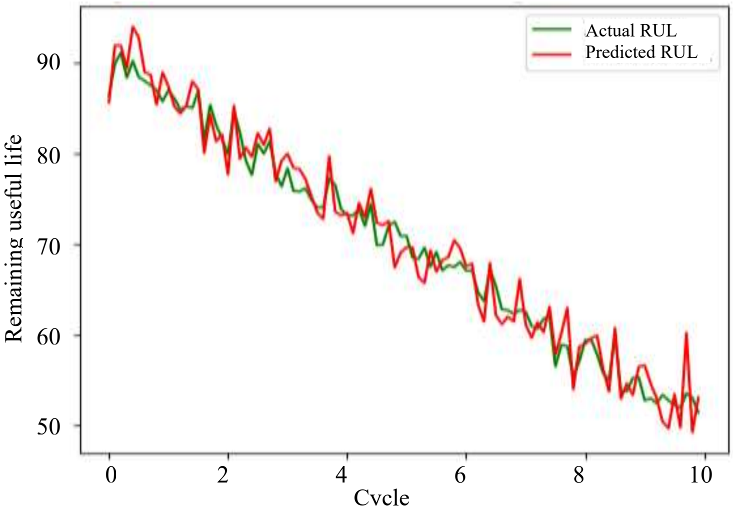

Figure 7. Actus versus prediction RUL.

The general results of the regression, classification, and diagnostic tests conclusively indicated that the proposed hybrid multimodal fusion model is effective for the health prediction of Li-ion batteries. Whenever it comes to the various measures of evaluation, the hybrid model has proved to be more functional than the traditional deep learning models like LSTM, GRU, CNN and CNN–LSTM, which just proves the merits of integrating multiple areas of feature and complementary learning models.

The proposed hybrid model with respect to SoC and RUL estimation had the smallest values of MAE and RMSE over all other models (Table 1). It is assumed that such reduction in prediction error can be attributed to the fact that the model can learn spatial degradation cues using CNN layers and long-term aging across dependencies using sequential LSTM/GRU processing. The step of ensemble refinement also improves the stability of the estimation because the variances are minimized among the cycles. This, the error of the SoC estimation has decreased significantly, and the error of RUL prediction has decreased significantly, and this is especially important, bearing in mind that RUL estimation is highly sensitive to the noise and nonlinear degradation properties.

Table 2 shows the derived battery health state thresholding that could be designed as a performance and classification framework that could be compared with various levels of degradation. The final results (Table 3) confirm the advantage of the hybrid approach: despite the CNN–LSTM giving better scores regarding the identification of the transitional states, the proposed hybrid model also showed better scores regarding the accuracy (94.8%), precision (95.3%), recall (94.1%) and F1-score (94.7%) which showed balanced and stable predictive score. It is important to note that the misclassification of the hybrid model was reduced between the moderate and critical states, which is crucial in preventing safety risks and preemptive action of the battery service.

The regression evaluation measures also support these results (Table 4). The score of the hybrid model in R^2 was 0.96 (SoC) and 0.94 (RUL), indicating that the model fits well and is strongly related to the real trends of degradation. Consecutively, the least values of MAPE represent high resiliency in varying operational and environmental contexts. This level of accuracy suggests that the model can be generalized far beyond a single operating condition or type of battery cell.

In addition, the ROC curve analysis showed that 0.97 (healthy), 0.98 (moderately degraded), and 0.98 (critical) were the AUC values, indicating a high level of discriminative power and clarity of the decision boundary. Similarly, the Actual vs Predicted curves comparisons of the case of SoC and RUL showed that there was a close adherence to the diagonal reference line, and this also verifies the consistency and validity of the hybrid model when used to test the behavior of the battery in the real world.

The results are optimistic that multimodal data fusion and hybrid deep learning can provide a more detailed description of battery health modifications compared to a single source or model. This model simultaneously trains electrochemical behavior, responses of the operation under stress, and long-term degradation behavior qualifies it especially to the BMS of electric vehicles (EVs), smart grid storage and renewable energy backup systems. Thus, the proposed solution not only enhances predictive performance but also makes the battery safer, more efficient, and lifecycle sustainable.

CONCLUSION

This study presents a hybrid multimodal predictive framework for the accurate estimation of the SoC and RUL of lithium-ion batteries, with a focus on material degradation behavior and lifecycle performance. By integrating electrical, thermal, and degradation-related parameters through hierarchical multimodal data fusion, the proposed approach effectively captured both the short-term operational responses and long-term aging mechanisms associated with battery materials. Comparative analysis with conventional deep learning models, including LSTM, GRU, and CNN, demonstrated that while individual architectures can learn partial temporal or spatial characteristics, their predictive accuracy is limited when addressing complex, nonlinear degradation phenomena. The proposed hybrid CNN–LSTM fusion model achieved superior performance, exhibiting significantly reduced MAE and RMSE values for SoC and RUL prediction, along with high classification accuracy (94.8%) and strong regression correlation ($R^2 = 0.96$ for SoC and 0.94 for RUL).

The enhanced predictive capability of the proposed framework can be attributed to its ability to extract complementary spatiotemporal features and refine decision-making through multimodal information integration. From a manufacturing and materials processing perspective, these results provide valuable insights into battery material aging, reliability assessment, and end-of-life prediction, supporting improved quality assurance and lifecycle optimization during production and deployment. The proposed framework offers a scalable and data-driven solution for monitoring degradation trends in lithium-ion battery materials, contributing to safer, more reliable, and sustainable energy storage systems for industrial manufacturing, smart grid infrastructure, and renewable energy applications.

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