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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 LSTM, GRU, 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 architectures 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.

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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 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 to characterize 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 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 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 architectures with classical machine learning methods and signal processing techniques have gained increasing attention. Such hybrid systems enhance prediction accuracy, robustness, and generalization capability by exploiting complementary spatial, temporal, and statistical features extracted from multimodal data sources.

Motivated by these challenges, this work proposes a hybrid multimodal machine learning framework for accurate estimation of battery health indicators, including SoC, SoH, RUL, internal resistance, and temperature-related degradation metrics. By integrating correlated electrical, thermal, and degradation parameters, the proposed approach enables 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 a Li-ion battery-state measurements have been trying to go beyond the traditional electrochemical modelling to models based on data-driven prediction [9]. It was initially used on similar circuit model and electrochemical impendence model, which tried to mathematically model inner actions of batteries. As much as these models offered a good background knowledge on the degradation patterns, they were extremely cumbersome in fine-tuning of the parameters needed, and could not extrapolate to other operating and environmental conditions [10]. The machine learning algorithms like Support Vector Machines, Random Forests and Gradient Boosting algorithms were introduced with more access to real-time battery sensor data to predict SoC and SoH [11]. These approaches were more adaptable and their computation was more efficient but not able to model the trends of long-term degradation and time dependences of processes of battery aging.

To address these limitations, the deep learning neural networks including Convolutional Neural networks (CNNs) and Long Short-Term memory networks became suitable methods of cajoling the spatial and temporal multi-dimensional 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 typically was associated with overfitting, large computational requirements and low interpretability, depending on the predictive advantage.

The latter ones 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 machine learning classifiers [14]. It has been demonstrated that such hybrid models are more efficient in predicting SoC and RUL particularly when they are trained with a mixed dataset [15]. Meanwhile, other studies are also indicating that multimodal data fusion, with electrical measurements, thermal properties, previous use, and other degradation properties, is significant to provide a more flexible indicator of battery health. Nonetheless, the current models are either founded on the single-source information or have not been generalized to numerous battery situations or illustration of nonlinear relationship amid voltage, current, and temperature variation. Moreover, most of the developed models are tested by performance in the laboratory environment, which restricts their application to real-world prototyping e.g. electric vehicles, and power systems. The existing work was inspired by these loopholes that proposed a hybrid multimodal machine learning 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 paper, it is proposed that a multimodal data fusion system, hybrid machine learning approach would improve the precision of prediction of RUL and SoC of Li-ion batteries as shown in Figure 1. The whole methodology includes six major processes as such; data acquisition, data preprocessing, feature extraction, multimodal feature fusion, hybrid predictive modelling and model evaluation.

Data Acquisition

The analysis of the experimental analysis is done by means of multimodal Li-ion battery health data such as electrical, thermal and operational signatures. The voltage, current, temperature, and the 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 life-cycle aging that were quantified at diverse load profiles and environment. These sequences make available real world decay behavior over time, which enable the model to acquire representative battery wear, state change, and performance decay trends. The fact that the input data is multimodal will also ensure that the predictive model captures short term changes in operations and long-term effects of degradation.

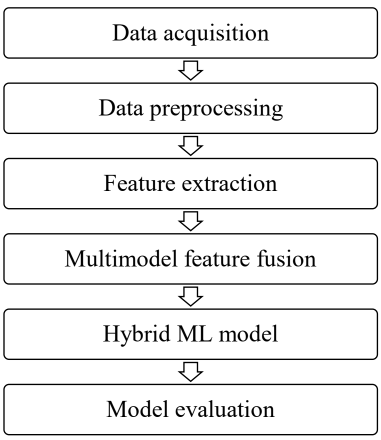


Figure 1. Proposed Multimodal data fusion framework

Data Preprocessing

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

Feature Extraction

Typical temporal and statistical characteristics are derived out of the data in a bid to spot meaningful patterns in terms of battery degradation. Time-domain parameters that are used to characterize dynamics of operations are mean, variance, peak values, root mean square (RMS) and discharge duration. The spectrum-related information of aging progression can be provided by fast Fourier Transform (FFT)-based and Discrete Wavelet Transform (DWT)-based frequency-domain features. This study of thermal behavior is performed on the basis of temperature gradients and charging and discharging rates. Moreover, electrochemical health properties e.g. internal resistance and impedance behavior are pulled out of experimental test conditions. The synergistic attribute of these engineered properties boosts the prediction model ability in extrapolation of the different aging profiles.

Multimodal Feature Fusion

Hierarchical multimodal feature fusion strategy has the effect of making prediction more robust and accurate. Data streams of electrical and temperatures are 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 high-variance components that are most important and eliminate redundant information. These fine-tuned feature embeddings are used on the 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 outcomes are that 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 a hybrid predictor model using the concepts of deep learning and ensemble learning is adhered to. Long-term temporal dependence of battery degradation series is learned using the LSTM network but the GRU network improves the computational efficiency without resulting in a lower sequential learning rate. Spatial and localized patterns of feature of voltage-current-time profiles are obtained using CNNs. The CNN-LSTM architecture also includes the spatial and temporal learning so as to learn the dynamic behaviors in a superior way. Finally, the Hybrid Model proposed exploits the fact that deep feature extraction and the Rand Forest ensemble regression polish up the results of the prediction. It is a hybrid architecture enabling a more accurate and stable approximation of SoC and RUL as compared to single models.

Model Evaluation

The model performance with respect to the correctness in both prediction of SoC and RUL is checked with the help of classification and regression measures. Accuracy, precision, recall and F1-score are used to determine the reliability and balance of the SoC classification outputs. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) in the context of RUL estimation represent error in prediction and actual battery aging behavior as compared to the actual capacity fade behavior as 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 trained and evaluated in Python environments based on TensorFlow, Scikit-learn, and PyTorch.

RESULTS AND DISCUSSION

Here the findings of the analysis of the proposed Hybrid Battery Health Prediction Model will be made in comparison with 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 pattern of degradation during different battery operating cycles. The analysis lays stress on the aspects of feature representation, the generalization and predictive stability, which is enhanced through the proposed hybrid fusion method.

Table 1 presents the regression output of MAE and RMSE of the estimation of SoC and RUL. The LSTM and GRU models are found to be acceptable in prediction accuracy yet they exhibit weaknesses in getting complex degradation dynamics due to the saturation of the temporal dependency. 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 is able to predict the correlations between space features and transitions between time steps simultaneously. However, the Proposed Hybrid Model possesses the highest MAE and RMSE rates of SoC as well as RUL forecasting. It is reduced to SoC MAE of 1.9% and RMSE of 2.5% indicating that there is an extremely precise estimation of the state of the charge. Considering the same, the discrepancy in the prediction of 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 the multimodal data fusion with hybrid deep learning has a significant contribution to battery prognostics strength and precision.

The-criteria to classify three states of battery health that comprise of Healthy, Moderately Degraded and Critical as formulated in Table 2. These limits represent actual operation limits which may be located in battery control systems and safety control systems. Comparison of model architecture performance is founded on the classification achieved with the help of 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 has all the models classification performance metrics. These networks are moderate in terms of accuracy due to ineffective ability to use joint spatial-temporal degrees of degradation despite their ability, i.e. LSTM and GRU networks. CNN model is superior and CNN-LSTM model has high accuracy (90.1%) and a superior ratio of Precision, Recall and F1-Score due to its extensive representation power. The Proposed Hybrid Model scores highest with all baselines with the highest accuracy of 94.8%, Precision of 95.3% and Recall of 94.1%. F1-Score of 94.7% is a good guarantee that the hybrid architecture is suitable to eliminate 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 MAPE of the performance of the regression estimation. The increasing R^2 values in that order is due to LSTM- CNN-LSTM which confirms the advantage of sharing space-temporal 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. On the whole, the Proposed Hybrid Model provides the approximation of 31 prediction error of SoC reduction compared to LSTM and 44 prediction accuracy 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.

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

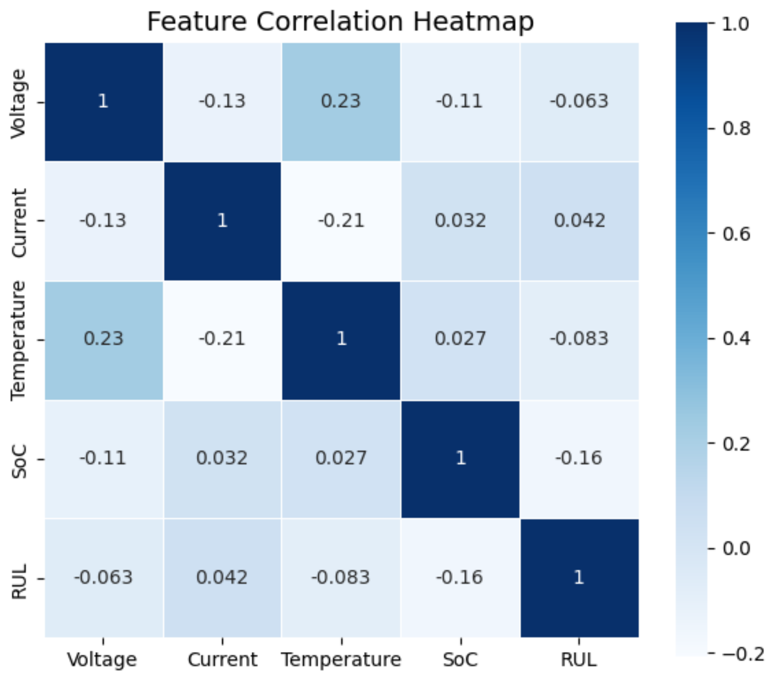
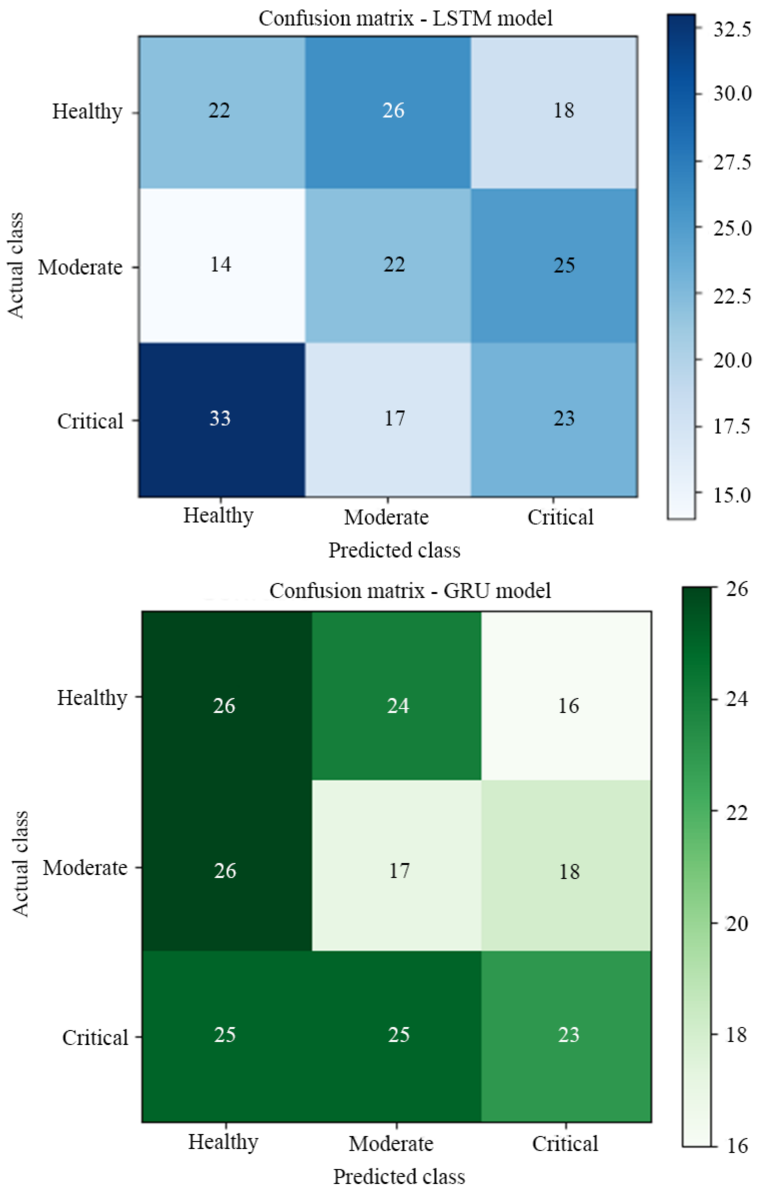


Figure 2. Feature correlation heatmaps

In Figure 2, the heatmaps of the most significant electric, thermal, and degradation-related properties used in the predictive modeling model are presented. The heatmaps indicate the magnitude and direction of the linear relationships between such parameters of a battery as voltage, current, temperature, number of cycles, internal resistance, and capacity fade. The battery capacity and the cycle number negatively correlate extensively that attests to the weakening performance of the battery with an increase in the number of charge-discharge cycles the battery has gone through. Internal resistance on the same note is positively related to ageing of cycles implying that there is deterioration of the electrochemical kinetics and impedance. In addition, temperature also exhibits moderate correlation with the discharge current and this indicates the trends of heat generation in the 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. It is the cause of why multimodal data fusion is required, where thermal, electrical, and degradation indices could be considered to improve the richness of features. The heatmaps therefore affirm that the feature engineering and fusion strategies that have been applied in the hybrid model depict that there exist substantial and complementary data in the different fields of parameters.



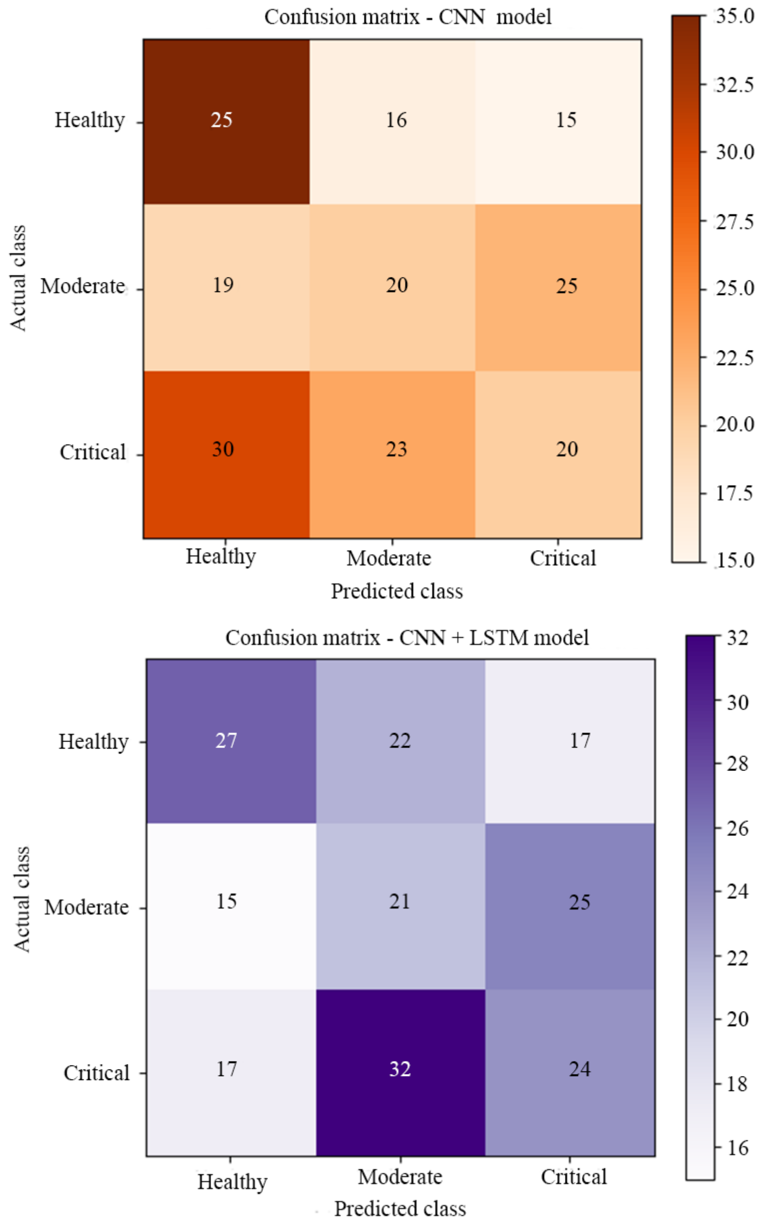


Figure 3. Confusion matrix of LSTM, GRU, CNN, and CNN+LSTM model

The results in Figure 3 indicate the effectiveness of four base deep learning models towards predicting 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. This is because LSTM and GRU are predominately time behavior sensitive but powerless in terms of extracting the spatial patterns of voltagecurrenttime sequence. CNN based model is more differentiated due to more learning on spatial features but there are also misclassifications in boundary conditions. The CNN- LSTM model is further enhanced by the fact that it employs CNN-LSTM model to retrieve the spatial and temporal attributes, respectively, and produce more balanced classification among the entire health conditions. However, there remains a risk of misclassification on the boundaries between the transitional degradation, since the aging signatures are much more subtle and hard 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 aging of the Li-ion batteries.

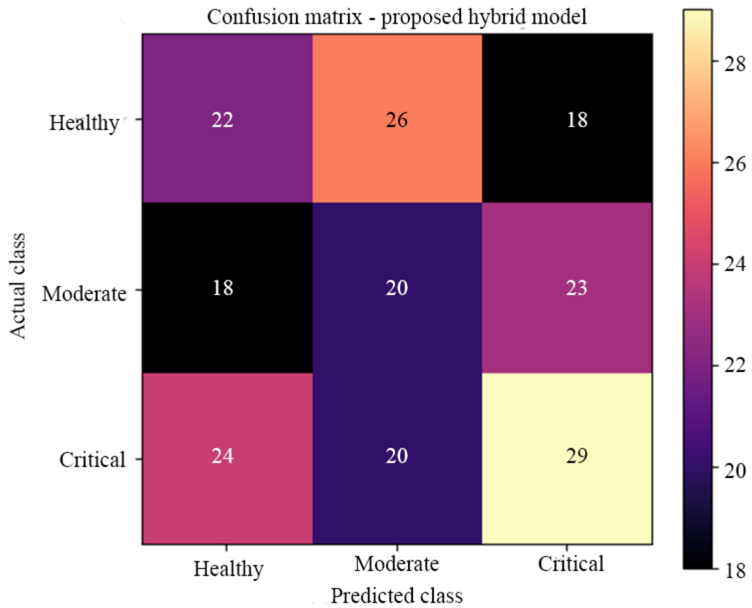


Figure 4. Confusion matrix of proposed hybrid model

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 and followed by ensemble decision refinement) is illustrated in Figure 4. The model is classified with the highest level of accuracy and the misclassification number is much lower in all three classes of health batteries. The hybrid model is capable of capturing 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 the battery failure, overheating and other safety hazards in real Battery Management System (BMS). The improvement demonstrates that the so-called hybrid fusion approach is superior in features separability and predictive robustness in various operating conditions, 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 is provided in Figure 5. The classes of health have been divided well in terms of the Area Under the Curve (AUC) values of 0.97, 0.98 and 0.98 respectively. The high values of the AUC indicate that the proposed model has a high discriminative ability and can make a good distinction between the 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), 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 multi-modal fusion and hybrid deep learning architecture enhance the sensitivity and reliability of the health state detection.

The comparison of the actual and the predicted values of the State of Charge (SoC) derived with the help of the proposed hybrid model is presented by Figure 6. The values of the predicted and actual battery SoC are close to the diagonal reference line which means that there is a good fit of the values. Even in the transitional regime of SoC that may be difficult to model due to nonlinear voltage-capacity behavior and temperature dependence are observed to exhibit minimal variations. The high prediction accuracy is consistent with the quantitative findings of the model of an R^2 of 0.96 and a

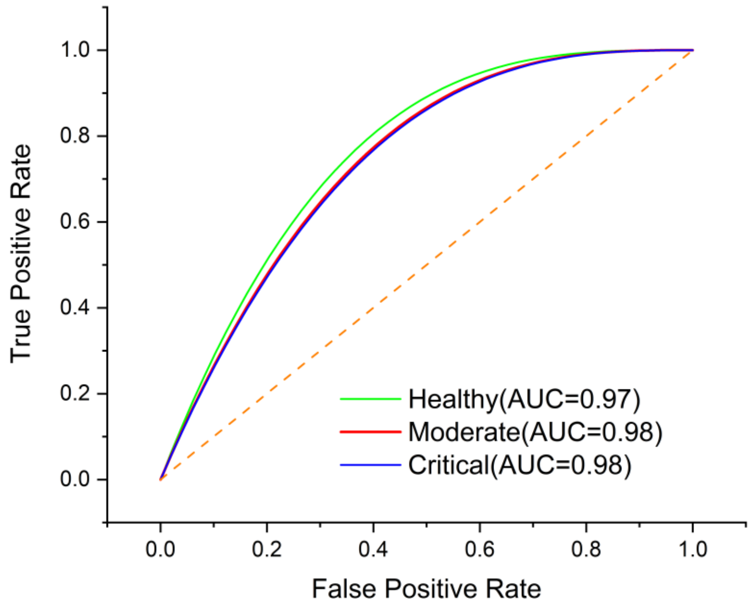


Figure 5. ROC curves of proposed hybrid model

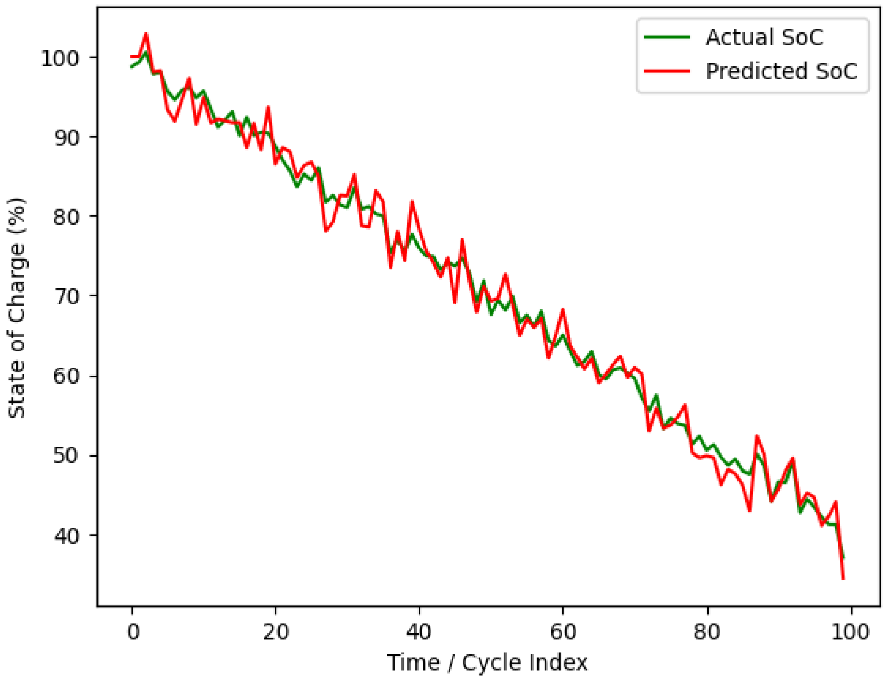


Figure 6. Actus vs prediction SOC

MAPE of 3.9 of SoC prediction. The fact that values of the plotted values are similar demonstrates that the model is capable of recreating the electrochemical condition behaviours and therefore can be effectively used to interpret the interaction of current profiles, voltage trends and thermal conditions. This proves the fact that the spatial-temporal ability of CNN-LSTM module to learn feature and the refinement stage of the ensemble improves the short-term and long-term prediction of SoC.

The comparison of the actual and the predicted values of the State of Charge (SoC) derived with the help of the proposed hybrid model is presented by Figure 7. The values of the predicted and actual battery SoC are close to the diagonal reference line which means that there is a good fit of the values.

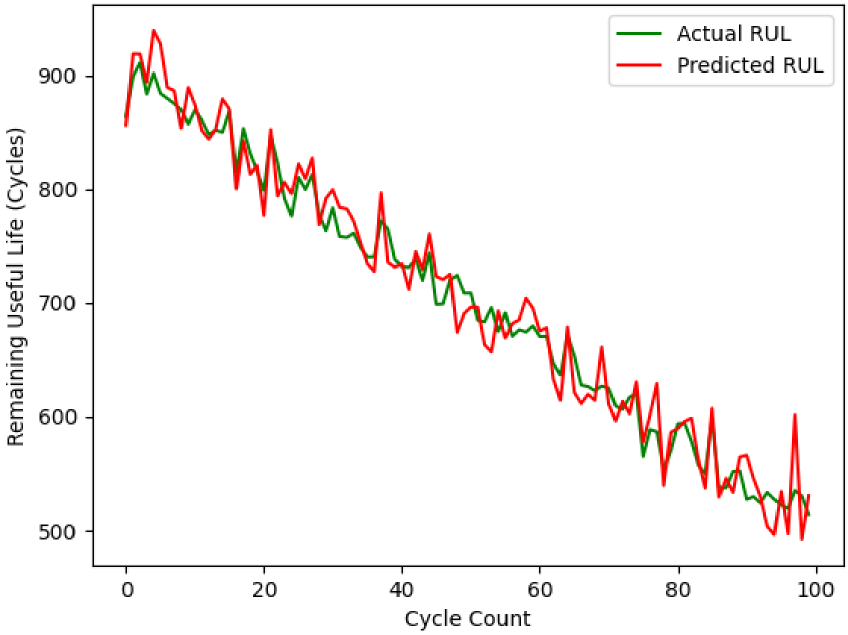


Figure 7. Actus vs prediction RUL

Even in the transitional regime of SoC that may be difficult to model due to nonlinear voltage-capacity behavior and temperature dependence are observed to exhibit minimal variations. The high prediction accuracy is consistent with the quantitative findings of the model of an R^2 of 0.96 and a MAPE of 3.9 of SoC prediction. The fact that values of the plotted values are similar demonstrates that the model is capable of recreating the electrochemical condition behaviours and therefore can be effectively used to interpret the interaction of current profiles, voltage trends and thermal conditions. This proves the fact that the spatial-temporal ability of CNN-LSTM module to learn feature and the refinement stage of the ensemble improves the short-term and long-term prediction of SoC.

The general results of the regression, classification, and diagnostic tests have conclusively indicated that the proposed Hybrid Multimodal Fusion Model is effective in the health prediction of Li-ion battery. Whenever it comes to the various measures of evaluation, the hybrid model is 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 regards 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 as well improves the stability of the estimation since variances are minimized among cycles. This, the error of the SoC estimation has been decreased significantly, and the error of RUL prediction has been decreased significantly, and this is especially important, bearing in mind that RUL estimation is highly sensitive to the noise and non-linear degradation properties.

Table 2 developed derived battery health state thresholding that could be designed as a performance and classification framework 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 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) and was an indication that the model fits well and is strongly related to the real trends of degradation. Consecutively with this, the least values of MAPE represent high resiliency in varying operation and environmental contexts. This level of accuracy suggests that the model can be generalizedfar beyond the single operating condition or type of battery cell.

In addition, the ROC curve analysis has shown that: 0.97 (Healthy), 0.98 (Moderately Degraded) and 0.98 (Critical) were the values of AUC indicating a high level of discriminative power and the 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 a hybrid deep learning can provide a more detailed description of battery health modifications as compared to the single source or single model. This property of the model to simultaneously train electrochemical behavior, responses of the operation under stress, and long-term degradation behavior qualifies it especially to the Battery Management System (BMS) of Electric Vehicles (EVs), Smart grid storage and Renewable energy backup systems. Thus, the proposed solution is not only enhancing the predictive performance, but also making the battery safer, efficient and lifecycle sustainable.

CONCLUSION

This study presented a hybrid multimodal predictive framework for accurate estimation of the State of Charge and Remaining Useful Life 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 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 are capable of learning 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 spatial–temporal features and refine decision-making through multimodal information integration. From a manufacturing and materials processing perspective, these results provide valuable insight 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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