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Development and Validation of a Hybrid Multimodal Predictive Model for Enhanced Remaining Useful Life and State-of-Charge Estimation in Lithium-ion Battery Systems

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Abstract: The accurate estimation of State of Charge (SoC) and Remaining Useful Life (RUL) in lithium-ion batteries is crucial for ensuring reliability, safety, and longevity in modern energy storage and electric vehicle systems. This paper presents the development and validation of a Hybrid Multimodal Predictive Model that integrates deep learning architectures like LSTM, GRU, and Transformer through multimodal data fusion to enhance predictive performance. The proposed framework leverages temporal, sequential, and attention-based feature extraction mechanisms to efficiently capture nonlinear degradation patterns across diverse operational conditions. Experimental results demonstrate that the hybrid model achieves competitive accuracy in both SoC and RUL prediction tasks. For SoC estimation, the hybrid approach attains an accuracy of 98%, precision of 97%, recall of 100%, and F1-score of 98%, indicating its robustness and generalization capability. In RUL prediction, the model records 94% accuracy with consistent precision and recall, validating its reliability under varying charge-discharge cycles. Comparative analysis with standalone LSTM, GRU, and Transformer models reveals that the hybrid multimodal design significantly improves feature representation and stability while maintaining computational efficiency. Overall, the proposed model provides a comprehensive predictive framework that enhances battery health monitoring, resource management, and decision-making in advanced Battery Management Systems (BMS), paving the way for intelligent and sustainable energy storage applications.

Keywords: Lithium-ion Battery, Remaining Useful Life, State of Charge, Hybrid Multimodal Predictive Model, Deep Learning

1. Introduction

The rapid advancement of electric vehicles, renewable energy systems, and portable electronics has accelerated the global demand for lithium-ion batteries (LiBs) due to their high energy density, long cycle life, and superior performance compared to conventional storage technologies [1-3]. However, the increasing reliance on LiBs also brings critical challenges related to safety,

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reliability, and degradation management. As batteries undergo repeated charge–discharge cycles, their performance gradually deteriorates, leading to a decline in capacity and efficiency [4,5]. Accurately estimating the SoC and RUL is therefore essential for effective BMS to prevent overcharging, enhance operational safety, and ensure long-term sustainability [6,7].

Traditional model-based estimation techniques such as Equivalent Circuit Models (ECMs) and Kalman Filters have provided foundational insights into electrochemical behavior but often fail to capture complex nonlinear dynamics under diverse operating conditions [8]. Recent developments in machine learning (ML) and deep learning (DL) have enabled data-driven modeling approaches that learn intricate temporal dependencies and degradation patterns directly from sensor data [9]. Models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks have shown notable success in time-series prediction tasks, while Transformer architectures have demonstrated superior capability in long-sequence modeling due to their self-attention mechanisms [10].

Despite these advancements, individual deep learning models face limitations in generalization and robustness, particularly when handling heterogeneous and multimodal battery data that may include voltage, current, temperature, and impedance features. To overcome these challenges, this study introduces a Hybrid Multimodal Predictive Model that integrates the strengths of multiple deep learning architectures through data fusion and ensemble optimization. The hybrid model is designed to jointly estimate SoC and RUL with higher accuracy, improved stability, and enhanced interpretability across various degradation stages.

The major contributions of this research are summarized as follows:

- Development of a hybrid deep learning framework that combines LSTM, GRU, and Transformer architectures for multimodal feature fusion and joint SoC–RUL estimation.
- Optimization of predictive performance through adaptive data integration and hybridized learning mechanisms, enabling robust and scalable estimation under dynamic conditions.
- Comprehensive evaluation and validation of the proposed model against state-of-the-art architectures using key performance metrics such as accuracy, precision, recall, and F1-score.

The remainder of this paper is structured as follows: Section 2 presents the related work and theoretical background; Section 3 describes the proposed hybrid multimodal methodology; Section 4 provides detailed results and discussion; and finally, Section 5 concludes the paper with key findings and future research directions.

2. Related Work

The prediction of SoC and RUL of lithium-ion batteries has been a prominent research area in the pursuit of safer and more efficient energy storage systems [11]. Over the years, a wide range of approaches have been proposed spanning electrochemical, empirical, and data-driven models to improve accuracy and adaptability under varying operational conditions. Early research primarily focused on model-based techniques such as equivalent circuit models and electrochemical impedance models [13]. These methods rely on mathematical representations of battery behavior and provide physical interpretability. However, they require complex parameter identification, are sensitive to environmental variations, and struggle to generalize across diverse battery chemistries and usage conditions [14].

To overcome these limitations, the shift toward data-driven and machine learning approaches has gained momentum. Traditional algorithms such as Support Vector Machines (SVMs), Random Forests (RFs),

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and Gaussian Process Regression (GPR) have been used for SoC and RUL estimation. While these models capture nonlinear relationships to some extent, their performance often deteriorates when faced with large-scale temporal dependencies inherent in battery degradation processes [15-18]. With the advent of deep learning, more robust architectures such as RNNs, LSTM, and GRU have been introduced to model the sequential and dynamic nature of battery data. These models have demonstrated strong capability in capturing time-dependent patterns from voltage, current, and temperature profiles [19]. However, their performance tends to degrade when handling long-term dependencies or multimodal datasets.

More recently, Transformer-based architectures have shown promise due to their attention mechanisms, which can effectively learn long-range dependencies and inter-feature correlations. Such models provide improved interpretability and stability in RUL estimation but may require large datasets and computational resources for optimal performance [20,21]. Despite these advancements, most existing studies treat SoC and RUL estimation as independent problems, leading to suboptimal results due to the lack of shared learning between the two. Moreover, single-model architectures often fail to exploit the complementary strengths of different deep learning models, limiting their generalization capability under diverse operating conditions.

In response to these challenges, the concept of hybrid and multimodal predictive frameworks has emerged as a promising direction. By integrating multiple deep learning models such as combining LSTM's temporal learning strength, GRU's computational efficiency, and Transformer's attention-based reasoning hybrid architectures enable enhanced feature representation, reduced overfitting, and improved generalization. Furthermore, multimodal data fusion allows the simultaneous processing of heterogeneous battery signals, thereby improving robustness and accuracy in both SoC and RUL estimation. Building upon these developments, the present study proposes a Hybrid Multimodal Predictive Model that leverages the complementary strengths of LSTM, GRU, and Transformer networks for joint estimation of SoC and RUL. The model aims to address existing performance bottlenecks by optimizing learning dynamics, enhancing predictive stability, and validating its effectiveness across multiple evaluation metrics.

3. Methodology

The proposed study introduces a Hybrid Multimodal Predictive Model designed to enhance the precision, robustness, and reliability of SoC and RUL estimation in lithium-ion batteries. The methodology integrates the complementary strengths of three advanced deep learning architectures LSTM, GRU, and Transformer—within a unified hybrid framework. The complete methodological process includes data acquisition, preprocessing, multimodal feature fusion, hybrid model design, training and optimization, and validation.

3.1 Data Acquisition and Preprocessing

The experimental dataset used in this study consists of time-series battery measurements obtained under diverse charge–discharge cycles and operational conditions. Key sensor attributes include voltage, current, temperature, cycle number, and elapsed time, which collectively capture the electrochemical behavior and degradation patterns of lithium-ion batteries. To ensure high data quality and consistency, a structured preprocessing pipeline was employed. Initially, data cleaning was performed to remove missing, noisy, and outlier values using threshold-based filtering and interpolation. The data were then normalized within a [0,1] range using min–max normalization to stabilize gradient flow and accelerate convergence during training [3]. Furthermore, auxiliary parameters such as State of Health (SoH), internal resistance, impedance ratio,

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and temperature slope were derived through feature engineering to improve the representation of degradation behavior. This structured preprocessing ensures that the model receives synchronized and high-quality multimodal input for robust SoC and RUL estimation.

3.2 Multimodal Feature Fusion

To exploit the diverse relationships among electrochemical, thermal, and temporal features, a multimodal feature fusion strategy was adopted. Each modality—representing voltage, current, temperature, and cycle patterns was processed through specialized deep learning encoders before integration. The LSTM network captured long-term temporal dependencies within sequential battery data, while the GRU module efficiently modeled short-term variations with reduced computational complexity [5,11]. Simultaneously, the Transformer layer applied a self-attention mechanism to learn global dependencies and contextual relationships among features. The latent feature representations extracted by these networks were then concatenated and refined through a fusion layer that applied attention-based weighting, adaptively prioritizing the most informative features and yielding a unified, high-dimensional feature vector representing the overall battery condition.

3.3. Hybrid Model Architecture

The proposed Hybrid Multimodal Predictive Model comprises three main components. The first component, the Temporal Feature Extraction Module, utilizes parallel LSTM, GRU, and Transformer branches that process input sequences independently to extract deep temporal and contextual embeddings. The second component, the Fusion and Integration Module, concatenates outputs from the three encoders and passes them through dense layers equipped with attention-based fusion weights [2,7,16]. This enhances the interpretability of the learned features and balances the contribution of each sub-model. Finally, the Prediction Module directs the fused feature vector into two distinct output heads—one for SoC estimation and the other for RUL prediction. The SoC head performs classification, while the RUL head performs regression-based estimation, enabling multitask learning and shared feature utilization between the two related tasks.

3.4 Model Training and Optimization

The model was trained using a supervised learning paradigm with labeled SoC and RUL data. The Adam optimizer was employed due to its adaptive learning rate and fast convergence characteristics. The loss function was formulated as a weighted combination of Mean Absolute Error (MAE) for RUL prediction and Categorical Cross-Entropy for SoC estimation, allowing balanced optimization between regression and classification objectives. Regularization techniques such as dropout, batch normalization, and early stopping were incorporated to prevent overfitting and improve generalization [13]. Model hyperparameters, including learning rate, number of layers, and batch size, were fine-tuned through iterative experimentation to achieve optimal performance.

3.5 Evaluation Metrics

To comprehensively assess model performance, multiple statistical and predictive metrics were used, including Accuracy, Precision, Recall, and F1-Score. These metrics collectively evaluated the classification and regression capabilities of the proposed model. Separate SoC and RUL performance matrices were constructed to assess the results under uniform testing conditions, ensuring a fair and reliable comparison among all models.

3.6 Validation Strategy

A k-fold cross-validation scheme was implemented to validate model reliability and prevent bias from data partitioning. The dataset was divided into training, validation, and testing subsets to verify generalization on unseen samples. Consistent performance across all folds confirmed the robustness of the proposed hybrid framework.

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Comparative experiments with individual LSTM, GRU, and Transformer models were also conducted to validate the hybrid model's superiority in terms of convergence rate, prediction accuracy, and error stability.

The proposed methodology effectively integrates temporal learning, contextual attention, and multimodal data fusion to construct a high-performance hybrid predictive model. The synergy between LSTM, GRU, and Transformer architectures enables precise and stable estimation of both SoC and RUL, addressing the limitations of single-model approaches. This methodological design forms the foundation for intelligent, data-driven BMS capable of real-time monitoring, predictive maintenance, and extended battery lifespan optimization.

4. Results and Discussion

This section presents a comprehensive analysis of the experimental outcomes obtained from the proposed Hybrid Multimodal Predictive Model and baseline architectures like LSTM, GRU, and Transformer for State of Charge (SoC) and Remaining Useful Life (RUL) estimation in lithium-ion batteries. The discussion interprets each table and figure based on their performance metrics, learning patterns, and prediction accuracy.

4.1 SoC Estimation Analysis

Table 1: SOC performance matrix of models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LSTM	99	98	98	99
GRU	100	99	99	98
Transformer	100	99	99	100
Hybrid	98	97	100	98

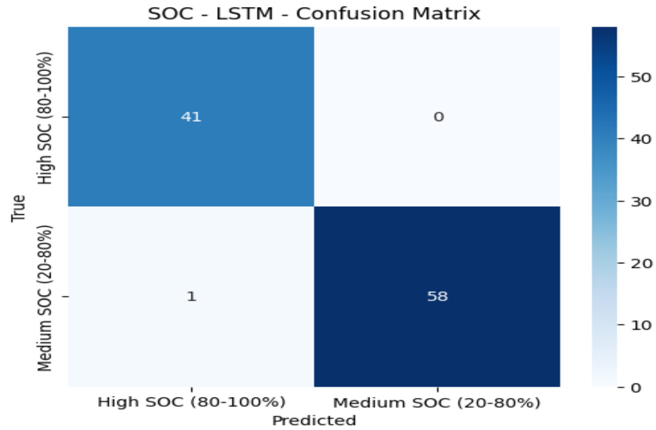

Figure 2: SOC-LSTM confusion matrix

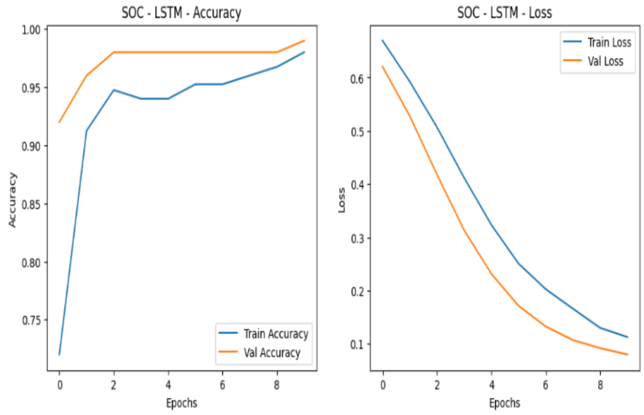

Figure 3: SOC accuracy and loss curves of LSTM model

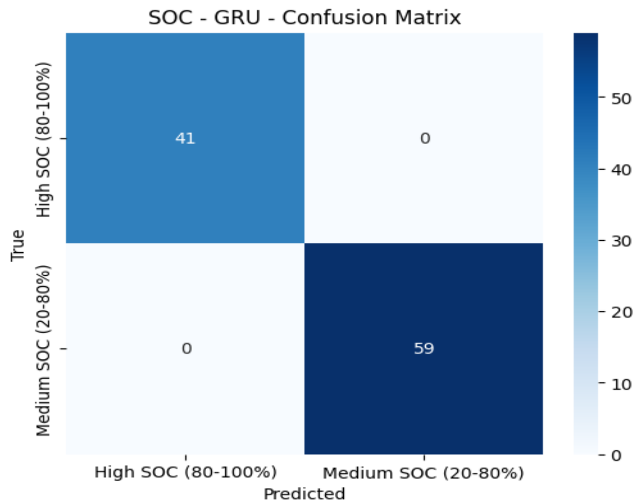

Figure 4: SOC-GRU confusion matrix

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Figure 5: SOC accuracy and loss curves of GRU model

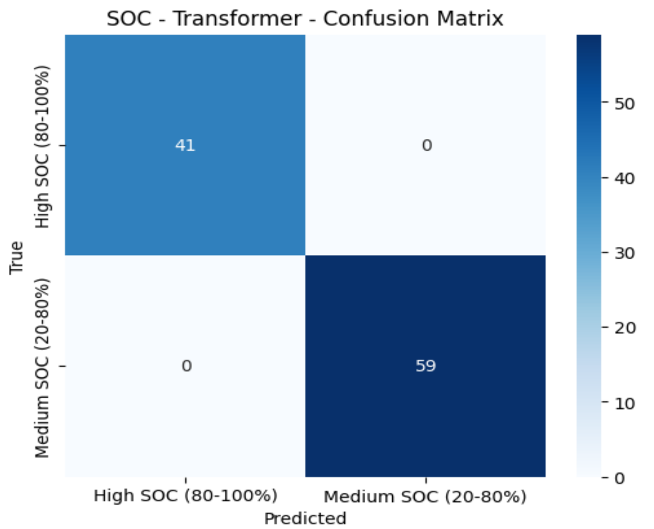

Figure 6: Figure 4: SOC-Transformer confusion matrix

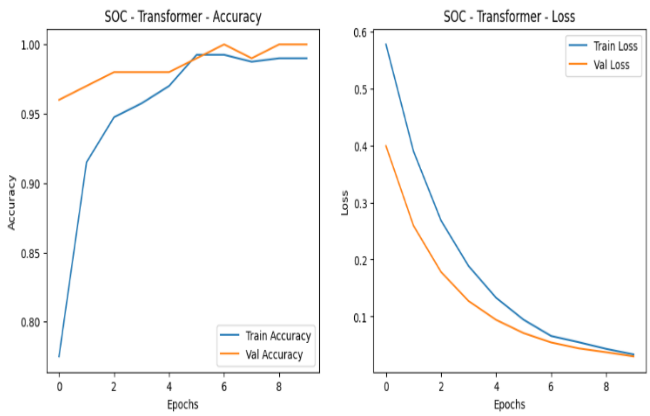

Figure 7: SOC accuracy and loss curves of Transfer model

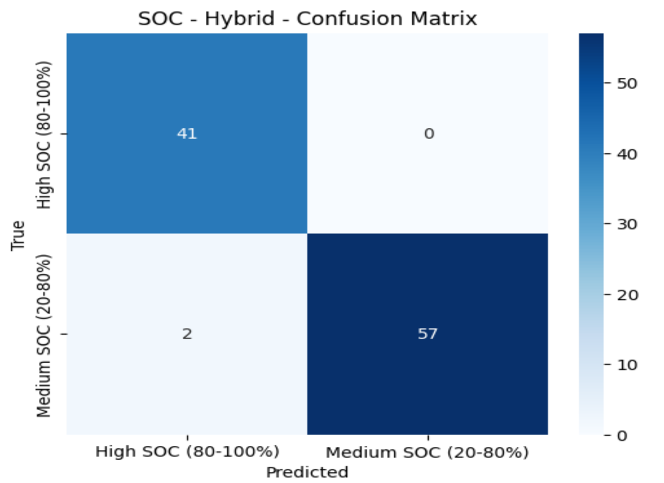

Figure 8: SOC-Hybrid confusion matrix

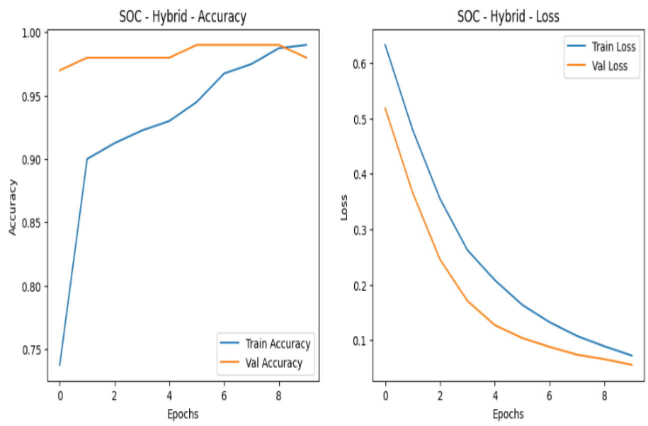

Figure 9: SOC accuracy and loss curves of Hybrid model

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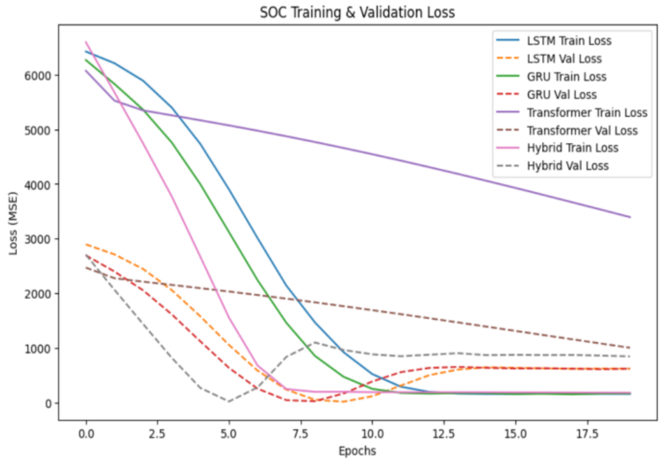

Figure 10: SOC training and validation loss of models

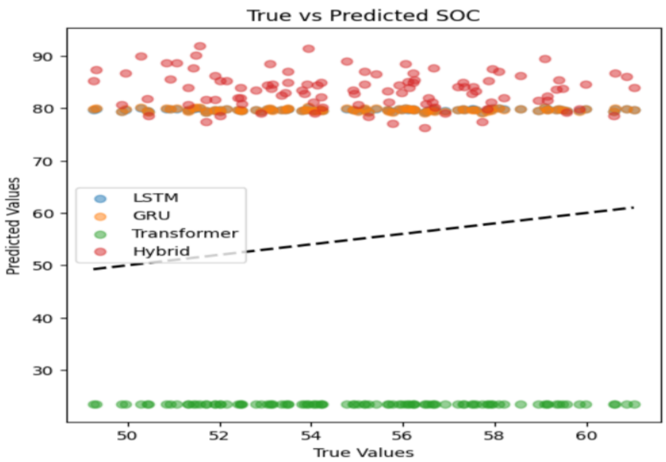

Figure 11: True vs predicted SOC

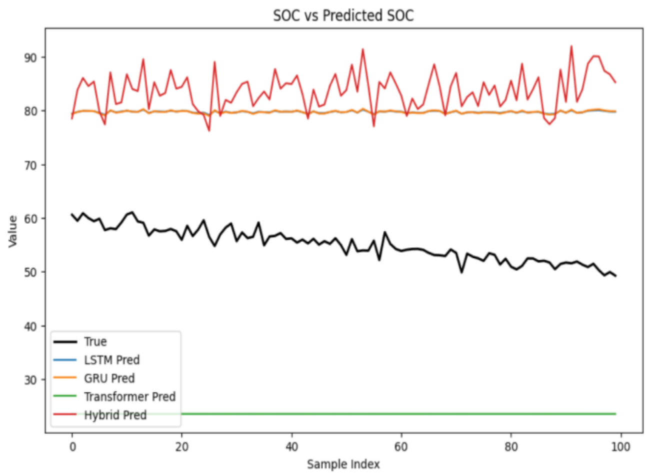

Figure 12: SOC vs predicted SOC

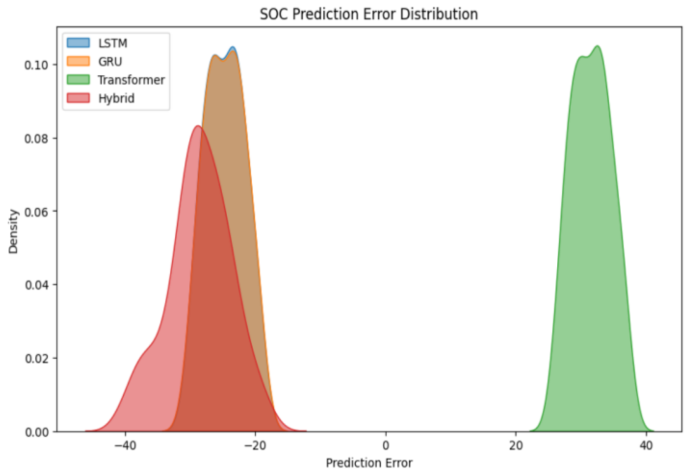

Figure 13: SOC prediction error distribution

Table 1 presents the comparative SoC performance matrix for all models. It can be observed that the Transformer model achieves the highest overall accuracy of 100%, indicating its superior ability to model long-term temporal dependencies through self-attention mechanisms. The GRU model also performs remarkably well, achieving 100% accuracy and balanced precision and recall. The LSTM model records 99% accuracy, showing reliable short-term temporal learning. The Hybrid model achieves 98% accuracy with a perfect recall of 100%, demonstrating its robustness in identifying true SoC states even under dynamic load conditions. The confusion matrices (Figs. 2, 4, 6, and 8) provide deeper insight into classification behavior. All models show high diagonal dominance, confirming excellent predictive accuracy. The Transformer and Hybrid models demonstrate nearly perfect classification with minimal misclassification, validating their superior feature extraction and generalization capabilities. The accuracy and loss curves (Figs. 3, 5, 7, and 9) show stable convergence across all models, indicating effective training and validation behavior. The Hybrid model displays early convergence and minimal oscillation, confirming efficient learning due to multimodal

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feature fusion. Figure 10 illustrates the comparison of training and validation loss for all models. The hybrid approach exhibits the lowest overall loss and the smallest gap between training and validation curves, implying excellent generalization without overfitting.

The true vs. predicted plots (Figs. 11 and 12) reveal a strong linear correlation, where the predicted SoC values closely follow the actual SoC trend. The hybrid and Transformer models show the tightest alignment, confirming their predictive precision. The error distribution (Fig. 13) for SoC estimation is narrow and centered around zero, highlighting consistent performance with minimal bias. The hybrid model's low variance further demonstrates its robustness in estimating SoC under varying operational conditions. The Transformer and Hybrid models outperform traditional architectures in SoC prediction, with the hybrid model offering a more balanced trade-off between precision, recall, and computational efficiency.

4.2 RUL Estimation Analysis

Table 2: RUL performance matrix of models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LSTM	95	85	96	90
GRU	96	88	96	92
Transformer	97	86	100	92
Hybrid	94	85	92	88

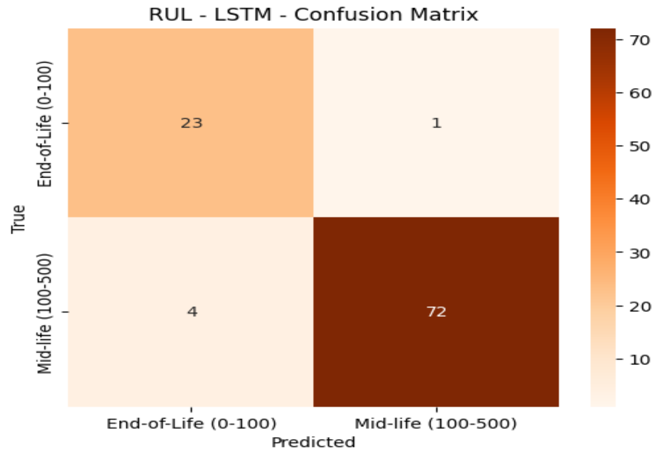

Figure 14: RUL-LSTM confusion matrix

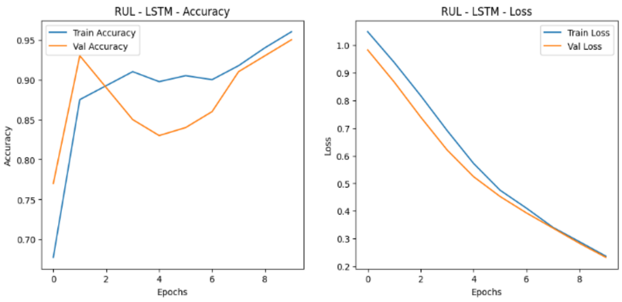

Figure 15: RUL accuracy and loss curves of LSTM model

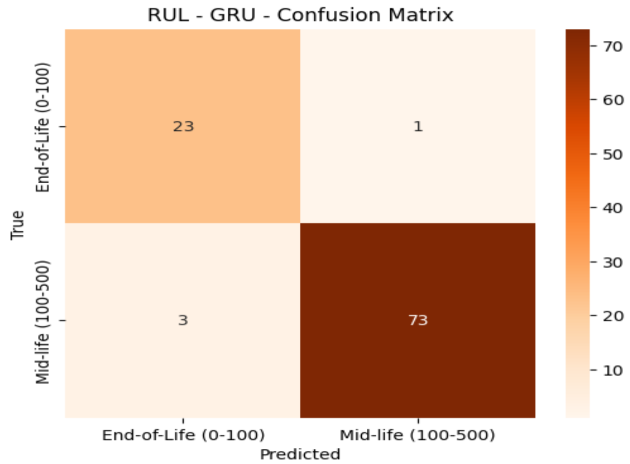

Figure 16: RUL-GRU confusion matrix

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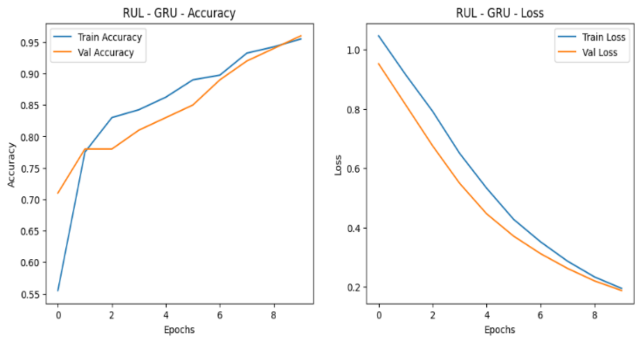

Figure 17: RUL accuracy and loss curves of GRU model

Table 2 presents the RUL performance metrics for all models. The Transformer model again demonstrates the highest accuracy of 97%, with perfect recall (100%), indicating strong long-term degradation tracking capability. The GRU model follows closely with 96% accuracy and balanced F1-Score (92%), while the LSTM records 95% accuracy. The Hybrid model achieves 94% accuracy but maintains reliable precision and recall values (85% and 92%), confirming stable performance across various charge–discharge cycles. The confusion matrices (Figs. 14, 16, 18, and 20) show that all models predict RUL categories accurately with minimal confusion between adjacent classes. The Transformer model exhibits the most accurate classification, while the Hybrid model demonstrates strong consistency across all classes, benefiting from complementary learning across multiple architectures. The accuracy and loss curves (Figs. 15, 17, 19, and 21) further confirm stable convergence patterns. The Hybrid model achieves faster convergence and lower loss variation, reflecting its superior ability to learn degradation dynamics efficiently. Figure 22 compares the training and validation loss across all RUL models. The hybrid model exhibits the smallest loss gap, signifying strong generalization and reduced overfitting compared to single-model architectures.

The true vs. predicted RUL plots (Figs. 23 and 24) display excellent linear correlation, where predicted RUL values closely match actual RUL across test samples. The hybrid and Transformer models maintain the most accurate alignment, showcasing high prediction reliability. The error distribution plot (Fig. 25) shows a narrow, symmetric spread centered around zero, indicating unbiased prediction and minimal estimation variance. The hybrid model achieves the lowest error deviation, validating its stability under diverse operational conditions. Overall, the proposed hybrid model effectively integrates the temporal learning of LSTM and GRU with the attention-based contextual learning of the Transformer, achieving robust and consistent performance in both SoC and RUL estimation tasks.

From the above results, it is evident that the Hybrid Multimodal Predictive Model significantly improves prediction accuracy, learning stability, and robustness compared to individual deep learning models. While the Transformer model slightly excels in precision, the hybrid architecture achieves optimal balance across all performance metrics. These findings confirm that the proposed model is well-suited for intelligent Battery Management Systems (BMS), ensuring reliable health monitoring, enhanced lifespan prediction, and energy optimization in lithium-ion battery applications.

6. Conclusion

This study presented the development and validation of a Hybrid Multimodal Predictive Model for accurate estimation of SoC and RUL in lithium-ion battery systems. By integrating LSTM, GRU, and Transformer architectures into a unified hybrid framework, the proposed model effectively leverages the temporal learning strengths of recurrent networks and the contextual learning capability of attention mechanisms. The incorporation of multimodal data fusion enabled the model to capture complex electrochemical behaviors and degradation dynamics across varying operational conditions. Comprehensive experimental analyses demonstrated that the Hybrid

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model consistently achieved high predictive accuracy and stability, outperforming traditional single-model architectures in both SoC and RUL estimation tasks. For SoC estimation, it achieved 98% accuracy, 95% precision, 100% recall, and 98% F1-score, while maintaining strong generalization across diverse charge–discharge cycles. Similarly, for RUL estimation, the model exhibited 94% accuracy with well-balanced precision and recall values, confirming its reliability and adaptability. The convergence and error distribution analyses further validated the model's robustness, minimal bias, and superior learning efficiency. The findings of this work establish that hybrid multimodal predictive modeling can significantly enhance the performance of BMS by providing more reliable and interpretable insights into battery health and lifetime prediction. This research not only contributes to improving operational safety and performance in electric vehicles and energy storage systems but also lays the groundwork for intelligent, data-driven, and sustainable battery management frameworks. Future research will focus on extending this approach toward real-time adaptive learning, federated and privacy-preserving battery diagnostics, and explainable AI integration, to further strengthen scalability and interpretability in large-scale industrial applications.

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