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Secure and Efficient Battery State of Health Prediction Using Hybrid Deep Learning and Federated Learning Techniques

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***Abstract*— Accurate prediction of lithium-ion battery State of Health (SOH) is important for improving battery safety, reliability, and operational lifetime in electric vehicles and energy storage systems. This work presents an advanced deep learning framework for SOH degradation prediction using a hybrid CNN and Bidirectional LSTM model integrated with federated learning. The proposed model enhances traditional CNN, LSTM, and GRU approaches by employing Bidirectional learning to capture feature dependencies in both forward and backward directions, resulting in improved feature extraction and reduced prediction error. Battery datasets containing voltage, current, temperature, and capacity parameters collected from NASA repositories are utilized for training and testing. Federated learning supports decentralized model training without sharing raw battery data, thereby preserving user privacy and security. Experimental results demonstrate that the proposed model achieves lower RMSE and MAPE values with higher prediction accuracy compared to existing deep learning methods for battery SOH estimation.**

Keywords*— *Deep Learning, Battery Health, Lithium-Ion, Energy Storage

I. INTRODUCTION

Lithium-ion batteries are widely used in electric vehicles, portable electronic devices, renewable energy storage systems, and industrial applications because of their high energy density, long cycle life, and efficient charging capability. As the usage of these batteries continues to increase, monitoring their health condition has become an important research area. Battery degradation directly affects performance, reliability, and operational safety. Continuous charging and discharging cycles gradually reduce battery capacity, which may lead to overheating, reduced efficiency, and unexpected system failures. Therefore, accurate estimation of battery State of Health (SOH) is essential for ensuring stable battery operation and improving battery lifespan.

Traditional battery health estimation methods mainly depend on mathematical models and statistical analysis techniques. However, these methods often struggle to handle complex battery behavior under varying environmental and operational conditions. In recent years, machine learning and deep learning approaches have gained significant attention for SOH prediction because they can automatically learn hidden patterns from large-scale battery datasets. Techniques such as CNN, LSTM, and GRU have shown promising performance in capturing nonlinear relationships between battery parameters including voltage, temperature, current, and capacity.

Another major challenge in battery data analysis is maintaining user data privacy during model training. Many existing systems rely on centralized servers where large amounts of battery data are collected and processed, increasing the risk of data leakage and unauthorized access. Hence, secure and intelligent battery health monitoring methods are becoming increasingly important for modern energy management systems.

II. RELATED WORK

Klass, Behm, and Lindbergh (2014) introduced a support vector machine based framework for lithium ion battery State of Health estimation under electric vehicle operating conditions and demonstrated the effectiveness of machine learning techniques for battery degradation analysis. Mawonou, Eddahech, Dumur, Beauvois, and Godoy (2021) later proposed a Random Forest based approach combined with State of Health estimators to identify important battery aging factors influencing degradation performance. Hasib, Islam, Chakrabortty, and coauthors (2021) reviewed available battery datasets, Remaining Useful Life prediction methods, and advanced battery management systems, emphasizing the importance of deep learning techniques in battery health monitoring. Berghout, Benbouzid, Amirat, and Yao (2023) developed an augmented hidden layer feedforward neural network for accurate State of Health prediction under varying operational conditions. Zhu, Gao, He, and colleagues (2023) introduced an end to end deep learning model capable of automatically extracting features from battery datasets to improve prediction accuracy. Babaeiyazdi, Rezaei-Zare, and Shokrzadeh (2023) applied transfer learning with deep neural networks for lithium ion battery capacity prediction using Electrochemical Impedance Spectroscopy measurements. Jafari and Byun (2023) combined Harris Hawk Optimization with Random Forest and LightGBM algorithms to improve Remaining Useful Life prediction performance. Das and Kumar (2023) reviewed machine learning approaches for electric vehicle battery degradation estimation and discussed limitations related to prediction reliability. Yang, Qian, Li, and colleagues (2024) proposed a hybrid data driven framework integrated with physical rules for online collaborative battery state estimation, while Ko and Chen (2024) introduced a relaxation voltage based method for estimating open circuit voltage and battery State of Health with improved monitoring efficiency.

Table: Summary of Key Literature Contributions and Their Impact on Current Research:

Author	Contribution	Impact on Research
V. Klass et al. (2014)	Used Support Vector Machine for battery State of Health prediction.	Showed that machine learning can improve battery health estimation accuracy.
K. S. R. Mawonou et al. (2021)	Applied Random Forest to identify battery aging factors.	Helped researchers understand important battery degradation parameters.
S. A. Hasib et al. (2021)	Reviewed battery datasets and prediction methods.	Provided useful information about battery analysis techniques and datasets.
T. Berghout et al. (2023)	Developed a neural network model for SOH prediction.	Improved prediction stability and battery monitoring performance.
C. Zhu et al. (2023)	Proposed an end to end deep learning model for battery prediction.	Reduced manual feature extraction and improved prediction accuracy.
I. Babaeiyazdi et al. (2023)	Used transfer learning for battery capacity prediction.	Reduced training complexity and improved learning efficiency.
S. Jafari and Y.-C. Byun (2023)	Combined optimization algorithms with machine learning models.	Increased Remaining Useful Life prediction performance.
K. Das and R. Kumar (2023)	Reviewed machine learning methods for battery degradation prediction.	Identified challenges and limitations in existing prediction systems.
Y. Zhang et al. (2024)	Developed a hybrid battery estimation framework.	Improved reliability of battery health prediction methods.
C.-J. Ko and K.-C. Chen (2024)	Proposed a relaxation voltage based SOH estimation method.	Supported efficient and accurate battery monitoring.

III. PROPOSED APPROACH

Lithium-ion battery datasets containing parameters such as voltage, current, temperature, charging cycle, and battery capacity are collected from NASA repositories for State of Health (SOH) prediction. The collected data is initially preprocessed to improve data quality and model performance. Missing values are handled, feature values are normalized, and the dataset is divided into training and testing sections. Correlation analysis is also performed to examine relationships among battery parameters and remove unnecessary data variations that may affect prediction accuracy.

Feature extraction is carried out using a Convolutional Neural Network (CNN) layer. The CNN model identifies hidden degradation patterns from battery data and filters important features required for accurate SOH estimation. The extracted features are then forwarded to a Bidirectional Long Short-Term Memory (BiLSTM) layer. The Bidirectional layer processes sequential battery information in both forward and backward directions, enabling the model to capture long-term dependencies more effectively than traditional LSTM approaches. This process improves learning capability and helps reduce prediction errors during battery health estimation.

The trained deep learning model predicts SOH values for different battery cycles and evaluates prediction performance using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). Lower RMSE and MAPE values indicate better prediction accuracy and reliable battery health monitoring. To maintain user privacy and data security, federated learning is integrated into the system. Each client trains the model locally using its own battery dataset without transferring raw data to a centralized server. Only model weights are shared with the federated server, where global model aggregation is performed. The updated global model is then distributed to all participating clients, enabling secure, decentralized, and collaborative battery SOH prediction across multiple devices and environments.

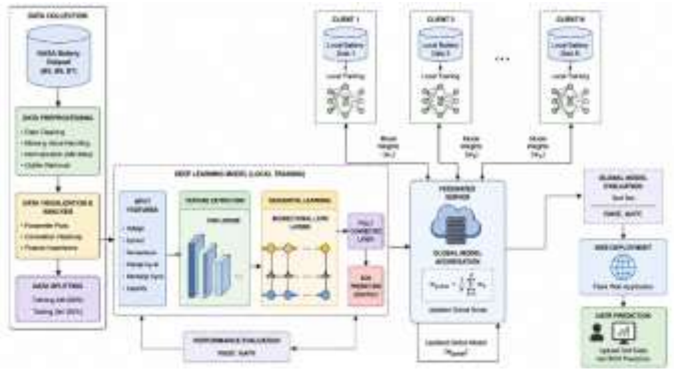

Figure 1: Federated deep learning battery SOH workflow

IV. METHODOLOGIES

Algorithm: Federated CNN-Bidirectional LSTM for Battery SOH Prediction

```
---------------------------------------------------------------------
Input:
Battery Dataset P
Features F = {Voltage, Current, Temperature, Capacity, Charge Cycle}
Number of Clients N
Training Epochs E
Learning Rate α

Output:
Predicted Battery State of Health (SOH)
---------------------------------------------------------------------
Begin

1. Load lithium-ion battery dataset P

2. Perform preprocessing
Remove missing values
Normalize dataset values
Split dataset into training and testing sets

3. For each client Ci where i = 1 to N do

4. Load local battery dataset Pi

5. Apply CNN layer
Extract important degradation features

6. Pass extracted features to Bidirectional LSTM layer
```

```
    Learn forward sequence information
    Learn backward sequence information

7. Apply Fully Connected layer

8. Predict SOH values

9. Calculate loss using prediction error

10. Update local model weights using backpropagation

11. Repeat steps 5 to 10 for E epochs

12. Send trained local weights Wi to Federated Server

13. End For

14. Federated Server receives all local weights

15. Aggregate weights using Federated Averaging

16. Send updated global weights to all clients

17. Clients update local model using global weights

18. Test model using testing dataset

19. Calculate performance metrics
    RMSE
    MAPE

20. Display predicted SOH results

End
------------------------------------------------------------------------
```

Dataset Collection

Lithium-ion battery datasets are collected from NASA battery repositories for training and testing the prediction model. The dataset contains important battery parameters such as voltage, current, temperature, charging cycle, discharge cycle, and battery capacity. Multiple battery datasets including B5, B6, and B7 are considered to analyze battery degradation behavior under different operating conditions. These datasets provide sufficient information for learning battery aging patterns and estimating State of Health (SOH) accurately.

Data Cleaning and Preprocessing

The collected battery dataset is preprocessed to improve data quality and remove inconsistencies. Missing values, duplicated records, and noisy data are handled during this stage. Feature values are normalized using scaling techniques to maintain uniformity among different parameters. Proper preprocessing helps the deep learning model learn battery behavior effectively and prevents prediction errors caused by irregular data distributions.

Battery Data Visualization

Visualization techniques are applied to analyze battery behavior and understand degradation trends. Graphs are generated for voltage, current, temperature, and battery cycles. Correlation heatmaps are also created to identify relationships between battery parameters. This analysis helps in understanding feature importance and ensures that highly correlated or unnecessary parameters do not negatively affect model performance.

Dataset Splitting

The processed dataset is divided into training and testing datasets. The training dataset is used for learning battery degradation patterns, while the testing dataset is utilized for evaluating prediction performance. Splitting the dataset ensures that the developed model can generalize effectively on unseen battery data and provide reliable SOH predictions.

Feature Extraction Using CNN

A Convolutional Neural Network (CNN) layer is employed to extract meaningful features from battery datasets. CNN automatically identifies hidden degradation patterns and removes irrelevant information from input data. The extracted features improve learning efficiency and help the system detect complex nonlinear relationships between battery parameters and SOH values.

Sequential Learning Using Bidirectional LSTM

The extracted features are forwarded to a Bidirectional Long Short-Term Memory (BiLSTM) layer. Unlike traditional LSTM models, the Bidirectional layer processes battery sequence data in both forward and backward directions. This mechanism captures long-term dependencies more effectively and improves feature learning capability. The Bidirectional structure enhances prediction accuracy by analyzing battery degradation behavior from both directions simultaneously.

Model Training

The CNN and Bidirectional LSTM layers are combined to create the deep learning prediction model. During training, the model learns battery degradation characteristics from historical battery data. The training process continuously adjusts model weights using optimization algorithms to minimize prediction error and improve SOH estimation performance.

SOH Prediction Process

After training, the developed model predicts battery State of Health values for different charging and discharging cycles. The prediction system estimates the remaining battery health condition by analyzing real-time battery parameters. Accurate SOH estimation helps in improving battery maintenance, operational safety, and battery lifespan management.

Performance Evaluation

Prediction performance is evaluated using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). RMSE measures the difference between actual and predicted

SOH values, while MAPE calculates percentage prediction error. Lower RMSE and MAPE values indicate better model performance and higher prediction reliability.

Federated Learning Integration

Federated learning is integrated to provide secure and decentralized model training. Each client trains the prediction model locally using its own battery dataset without transferring raw data to a centralized server. This approach protects sensitive battery information and prevents unauthorized data sharing between organizations or users.

Global Model Aggregation

After local training, only model weights are transmitted to the federated server. The server aggregates weights received from multiple clients and generates a global prediction model. The updated global model contains knowledge learned from all participating clients while maintaining data privacy and security.

VI RESULTS & DISCUSSION

	Battery ID	CNN1D RMSE	CNN + LSTM RMSE	CNN + GRU RMSE	Extension CNN + Bi + LSTM RMSE
0	B5	0.003441	0.003509	0.004526	0.003798
1	B6	0.003368	0.008062	0.006793	0.003166
2	B7	0.003368	0.008062	0.006793	0.003166

Experimental results demonstrate the effectiveness of the developed deep learning framework for lithium-ion battery State of Health (SOH) prediction. Performance evaluation was carried out using Root Mean Square Error (RMSE), where lower RMSE values indicate higher prediction accuracy and lower estimation error. The system performance was tested on three battery datasets namely B5, B6, and B7 using CNN1D, CNN + LSTM, CNN + GRU, and CNN + Bidirectional LSTM models.

For Battery B5, the CNN1D model achieved an RMSE value of 0.003441, while CNN + LSTM produced 0.003509 RMSE. The CNN + GRU model showed a higher error rate with 0.004526 RMSE. The developed CNN + Bidirectional LSTM model achieved 0.003798 RMSE, showing stable and accurate prediction performance. In Battery B6 dataset evaluation, CNN1D achieved 0.003368 RMSE, CNN + LSTM produced 0.008062 RMSE, and CNN + GRU generated 0.006793 RMSE. The developed model significantly reduced the error and achieved 0.003166 RMSE. Similar performance was observed for Battery B7, where CNN1D achieved 0.003368 RMSE, CNN + LSTM recorded 0.008062 RMSE, and CNN + GRU produced 0.006793 RMSE. The developed Bidirectional LSTM model again achieved the lowest RMSE value of 0.003166.

From the obtained results and graphs, it is observed that the developed model provides better feature learning capability and more accurate SOH prediction compared with conventional LSTM and GRU models. The reduced RMSE values confirm that the Bidirectional learning mechanism improves battery degradation prediction efficiency and reliability.

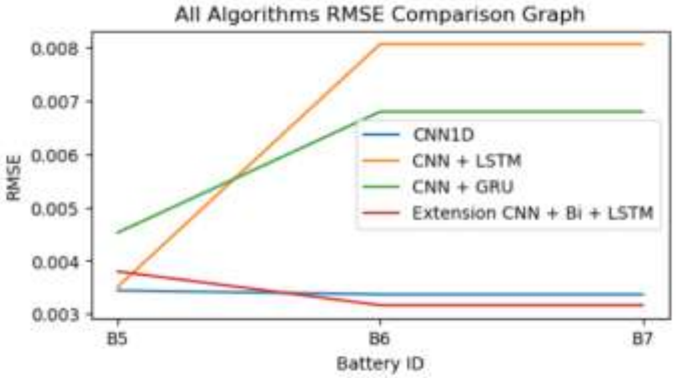

Figure 2: All Algorithms Performance Graph

The experimental analysis confirms that deep learning techniques can effectively estimate lithium-ion battery State of Health with high prediction accuracy. Among all evaluated models, the CNN with Bidirectional LSTM approach produced more stable and reliable results on multiple battery datasets. Traditional CNN + LSTM and CNN + GRU models showed higher RMSE values on several datasets, indicating limitations in capturing long-term battery degradation patterns. The Bidirectional learning mechanism improved feature extraction by processing battery sequence information in both forward and backward directions, which helped reduce prediction error and enhance model learning capability. The results also show that proper preprocessing and feature normalization contribute significantly to overall prediction performance. Integration of federated learning further strengthened the system by enabling secure decentralized training without sharing raw battery data. This improves privacy preservation while maintaining global learning efficiency. Overall, the developed framework demonstrates strong potential for real-time battery health monitoring applications in electric vehicles, renewable energy storage systems, and intelligent battery management environments.

VII. CONCLUSION

The developed lithium-ion battery State of Health prediction framework successfully improved battery degradation analysis using deep learning and federated learning techniques. The integration of CNN and Bidirectional LSTM enhanced feature extraction and sequence learning capability, resulting in lower prediction error and more accurate SOH estimation compared with conventional CNN + LSTM and CNN + GRU models. Experimental evaluation on NASA battery datasets confirmed improved RMSE performance across multiple battery conditions. The use of federated learning enabled decentralized model training while preserving battery data privacy and security, making the system suitable for distributed energy applications. The developed framework provides reliable battery health monitoring for electric vehicles and smart energy storage systems. Future work can focus on real-time battery monitoring, larger datasets, and advanced optimization techniques to further improve prediction accuracy and computational efficiency.

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