ISSN 2319-5991 www.ijerst.com

Peer Reviewed, Referred & Indexed Journal

Research Paper

Privacy-Preserving Federated Learning Framework for Lithium-Ion Battery SOH Prediction Using Hybrid CNN-BiLSTM Models

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Abstract: Lithium-ion batteries are widely used in electric vehicles and portable electronic devices, where accurate State of Health (SOH) prediction is essential for ensuring safety, reliability, and efficient energy management. This paper proposes a deep learning-based framework for SOH estimation using hybrid architectures including CNN1D, CNN-LSTM, CNN-GRU, and an enhanced Bidirectional LSTM-CNN model to effectively capture nonlinear degradation patterns from battery data. The system utilizes NASA battery datasets (B5, B6, and B7) and applies preprocessing techniques such as normalization and Pearson correlation for feature optimization.To address data privacy concerns and improve model generalization, a federated learning approach is integrated, enabling decentralized training across multiple clients without sharing raw data. Experimental results demonstrate that CNN1D performs effectively for certain datasets, while the proposed Bidirectional LSTM-CNN model achieves superior performance with lower RMSE and MAPE values. The proposed framework enhances prediction accuracy, preserves data privacy, and provides a scalable solution for real-world battery management systems, supporting improved battery lifespan and operational safety.

Index terms - — *Lithium-Ion Battery, State of Health (SOH), Deep Learning, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Bidirectional LSTM, Federated Learning, Battery Degradation Prediction, Energy Storage Systems*

1. INTRODUCTION

Lithium-ion batteries have become a fundamental component in modern energy storage systems, powering applications such as electric vehicles, portable electronics, and renewable energy solutions. Their high energy density, long lifecycle, and efficiency make them the preferred choice over conventional batteries. However, over repeated charge and discharge cycles, lithium-ion batteries undergo degradation, leading to reduced capacity and performance. This degradation directly affects system reliability and can pose safety risks if not properly monitored. Therefore, accurate estimation of the State of Health (SOH), which indicates the remaining usable capacity of a battery, is crucial for ensuring safe operation, optimizing battery usage, and extending battery lifespan.

Traditional SOH estimation techniques, including model-based methods such as Electrochemical Impedance Spectroscopy, Coulomb Counting, and Kalman Filtering, require precise modeling and domain expertise, making them less adaptable to real-world dynamic conditions. Data-driven approaches using machine learning improve flexibility but often struggle to capture complex nonlinear degradation patterns. To overcome these limitations, this paper proposes a hybrid deep learning framework combining CNN, LSTM, GRU, and Bidirectional LSTM architectures to effectively learn spatial and temporal dependencies from battery datasets. Furthermore, a federated learning approach is integrated to enable decentralized model training while preserving data privacy. This combination enhances prediction accuracy, scalability, and robustness, making it suitable for real-world battery management systems.

2. LITERATURE SURVEY

a) Recent Progress of Deep Learning Methods for Health Monitoring of Lithium-Ion Batteries*:*

The widespread use of lithium-ion batteries (LIBs) as the main energy storage solution has accelerated the electrification of transportation in recent years. Battery management systems (BMS) are becoming essential elements in this environment due to the urgent necessity to guarantee the safe and effective functioning of these LIBs. State and temperature monitoring stand out as crucial for intelligent LIB management among the several BMS services. The precise forecast of the state of health (SOH) and the assessment of remaining usable life (RUL) are the two fundamental components of LIB health management that are the topic of this paper. In addition to extending the life of LIBs, accurate SOH forecasts provide priceless information for maximizing battery utilization. Furthermore, as the demand for electric cars continues to rise, precise RUL calculation is crucial for effective battery management and condition estimation. The article emphasizes how machine learning (ML) methods may improve LIB state predictions while lowering computing cost. The review attempts to clarify prospective future directions for utilizing ML in the context of LIBs by exploring the present status of research in this area. Notably, it highlights how important sophisticated RUL prediction methods are becoming and how they might help solve the problems brought on by the growing demand for electric cars. This thorough analysis highlights the creation of machine-learning applications designed especially for rechargeable LIBs while identifying current issues and offering a methodical approach to address them. Artificial intelligence (AI) technologies play a crucial role in this effort, as researchers want to accelerate battery performance improvements and get beyond current LIB restrictions. By using a symmetrical approach, ML balances battery management and makes a substantial contribution to the long-term advancement of transportation electrification. This paper offers a succinct summary of the literature, providing insights into the present situation, potential future developments, and difficulties associated with applying machine learning techniques for lithium-ion battery health monitoring.

b) Deep learning to estimate lithium-ion battery state of health without additional degradation experiment

A crucial factor that assesses the degree of battery deterioration is the state of health. However, it necessitates estimate rather than direct measurement. Although accurate state of health assessment has advanced significantly, the development of state of health estimation techniques is hampered by the time-consuming and resource-intensive degrading tests required to produce target battery labels. In this paper, we develop a deep learning system that allows battery state of health prediction without target battery labels. To generate precise estimate, this approach combines a swarm of deep neural networks with domain adaptability. We produce 71,588 samples for cross-validation using 65 commercial batteries from five different manufacturers. According to the validation findings, the suggested framework may guarantee absolute errors of less than 3% for 89.4% of samples (less than 5% for 98.9% of samples), with a maximum absolute error of less than 8.87% when target labels are not present. This paper illustrates the potential for quick creation of battery management algorithms for new-generation batteries using just historical experimental data, as well as the strength of deep learning in preventing deterioration studies.

c) Lithium-Ion Battery State of Health Estimation with Multi-Feature Collaborative Analysis and Deep Learning Method*:*

For battery management systems (BMS) to be reliable and safe, the battery state of health (SOH) must be accurately estimated. Because they frequently take into account data from single-source characteristics, the generality of current SOH estimate techniques is restricted. Thus, this study proposes a unique way to combine deep learning-based techniques with multi-feature collaborative analysis. Initially, differential thermal voltammetry (DTV) analysis, singular value decomposition (SVD), incremental capacity analysis (ICA), and terminal voltage characteristic (TVC) analysis are used to acquire a number of battery deterioration parameters. Based on the findings of a Pearson correlation analysis, the characteristics that are most closely associated with SOH are chosen as inputs for the deep learning model. By creating a deep learning framework supported by a long short-term memory (LSTM) neural network (NN) that incorporates multi-source characteristics as an input, the SOH estimation is accomplished. NASA and Oxford Battery Degradation datasets are used to validate a proposed approach. With a maximum root mean square error (RMSE) of less than 1%, the findings show that the proposed model offers excellent SOH estimate accuracy and generality. The suggested approach, which is based on a cloud computing platform, has the potential to improve battery full lifecycle management by offering a real-time battery health forecast.

d) State of health estimation for lithium-ion batteries based on hybrid attention and deep learning

For electric cars to operate dependably and safely, an accurate assessment of the condition of lithium-ion batteries is essential. A hybrid attention and deep learning approach for predicting the state of health of lithium-ion batteries is presented in this work. The charging data is used to construct the temperature difference curves, which are then smoothed using the Kalman filter. The link between temperature and aging is then described by extracting the health characteristics associated with capacity decline from the differential temperature curves. The battery's condition is then predicted using a hybrid attention and deep learning model that combines the advantages of convolutional neural networks, gated recurrent unit recurrent neural networks, and attention mechanisms. By contrasting the suggested strategy with eleven popular approaches, its higher prediction performance is confirmed. Without extracting strongly associated health characteristics, all estimation errors may be kept under 1.3%, demonstrating the established state of health estimation method's potential accuracy and dependability. Furthermore, the outcomes confirm that the suggested approach is capable of achieving satisfactory resilience to battery inconsistencies.

e) Battery health management using physics-informed machine learning: Online degradation modeling and remaining useful life prediction*:*

Over the past 10 years, lithium-ion batteries have been widely employed to power unmanned aerial aircraft, electric cars, and portable devices. Lithium-ion batteries lose capacity as they age. Therefore, the dependability, security, and effectiveness of systems powered by lithium-ion batteries depend on precise remaining usable life (RUL) prediction. However, internal aging processes and operating parameters (such as cycle duration, ambient temperature, and loading factors) influence battery aging, which is a complicated electrochemical process. In order to simulate the deterioration trend and forecast the RUL of lithium-ion batteries while taking battery health and operating circumstances into consideration, a physics-informed machine learning approach is presented in this study. A physics-based calendar and cycle aging (CCA) model is combined with an LSTM layer in the suggested physics-informed long short-term memory (PI-LSTM) model. The CCA model combines five operational stress factor models to quantify the aging effect of lithium-ion batteries. The PI-LSTM learns the link between the online monitoring data of various cycles (such as voltage, current, and cell temperature) and the deterioration trend identified by the CCA model using an LSTM layer. Following the PI-LSTM model's estimation of a battery's degradation pattern, another LSTM model is used to forecast the battery's future deterioration and remaining usable life (RUL) by learning the degradation trend indicated by the PI-LSTM model. The suggested approach was shown using monitoring data from eleven Lithium-ion batteries under various operating situations. According to experimental data, the suggested approach can estimate the RUL of lithium-ion batteries under various operating situations and properly describe their degrading behavior.

3. METHODOLOGY

i) Proposed Work:

The proposed system presents a hybrid deep learning-based framework for accurate prediction of the State of Health (SOH) of lithium-ion batteries using historical degradation data. The system utilizes NASA battery datasets (B5, B6, and B7), which include parameters such as voltage, current, temperature, and capacity. Initially, the dataset undergoes preprocessing steps including data cleaning, normalization, and Pearson correlation-based feature selection to remove redundancy and improve data quality. Multiple deep learning models—CNN1D, CNN combined with LSTM, CNN combined with GRU, and an enhanced Bidirectional LSTM-CNN architecture—are implemented to capture both spatial and temporal dependencies in battery degradation patterns. These models are trained and evaluated using performance metrics such as RMSE and MAPE to identify the most accurate approach.

To enhance privacy and scalability, the proposed system integrates a federated learning framework where multiple clients train models locally on their respective datasets without sharing raw data. Instead, only model weights are communicated to a central server, where global aggregation is performed to build an improved generalized model. The inclusion of Bidirectional LSTM further strengthens the system by learning from both forward and backward temporal sequences, improving feature extraction and prediction accuracy. This combination of hybrid deep learning models and federated learning ensures high accuracy, robustness, and data privacy, making the system suitable for real-world battery management applications.

ii) System Architecture:

The proposed system architecture is divided into three major stages: dataset preprocessing, centralized learning, and decentralized (federated) learning. In the first stage, raw battery data is collected and cleaned to remove inconsistencies and noise. The State of Health (SOH) and capacity values are computed from the dataset, followed by normalization to scale features into a uniform range. The processed data is then split into training and testing sets. Additionally, for federated learning, the dataset is segmented into multiple client partitions, enabling each client to train on its local data independently. This preprocessing stage ensures high-quality input data and prepares the system for efficient deep learning model training.

In the second stage, centralized learning is performed using multiple deep learning models such as 1D CNN, CNN+LSTM, and CNN+GRU. These models are trained for a fixed number of epochs to learn spatial and temporal features of battery degradation, followed by evaluation using performance metrics like RMSE and MAPE. The third stage introduces decentralized learning using a federated approach, where the dataset is distributed among multiple clients. Each client trains a local deep learning model, and only the learned model weights are sent to a central server. The server aggregates these weights to form a global model, which is then redistributed to clients for further training. This iterative process improves model generalization while preserving data privacy, resulting in an accurate, scalable, and secure SOH prediction system.

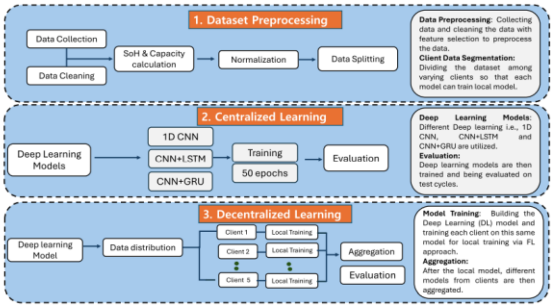


Fig1 Proposed system

iii) Modules:

1. Data Preprocessing Module:

This module handles collection, cleaning, and preparation of battery datasets. It removes missing or noisy data, computes SOH and capacity values, and applies normalization and Pearson correlation to select relevant features, ensuring high-quality input for model training.

2. Dataset Exploration and Visualization Module:

This module analyzes battery parameters such as voltage, current, temperature, and capacity. It generates graphs and statistical summaries to understand degradation trends and identify patterns before training deep learning models.

3. Data Splitting Module:

This module divides the processed dataset into training and testing sets. It also supports client-wise data segmentation for federated learning, ensuring balanced and unbiased model evaluation.

4. Model Training Module:

This module implements deep learning models including CNN1D, CNN+LSTM, CNN+GRU, and Bidirectional LSTM-CNN. These models learn spatial and temporal features from battery data to accurately predict SOH.

5. Federated Learning Module:

This module enables decentralized training where multiple clients train models locally using their data. Model weights are shared with a central server for aggregation, ensuring privacy-preserving collaborative learning.

6. Evaluation Module:

This module evaluates model performance using metrics such as RMSE and MAPE. It compares predicted and actual SOH values to determine the most accurate model.

7. SOH Prediction Module:

This module allows users to input new battery data and obtain predicted SOH values. It provides visual outputs such as graphs and tables for easy interpretation of results.

8. Web Interface Module (Flask):

This module provides a user-friendly interface for uploading data, selecting models, and viewing predictions. It ensures smooth interaction between users and the backend system.

iv) Algorithms:

1. CNN1D (Convolutional Neural Network - 1D): CNN1D is used to process sequential battery data such as voltage, current, and temperature over time. It applies one-dimensional convolutional filters to extract important temporal features related to battery degradation. The model efficiently captures local patterns in the data, enabling accurate SOH prediction with lower computational complexity. It serves as a strong baseline model and is also suitable for federated learning due to its lightweight structure.

2. CNN + LSTM (Convolutional Neural Network with Long Short-Term Memory): This hybrid model combines CNN for feature extraction and LSTM for learning long-term dependencies in battery data. The CNN layers identify spatial patterns, while LSTM units capture temporal relationships across charge-discharge cycles. This combination improves prediction accuracy by considering both short-term variations and long-term degradation trends in lithium-ion batteries.

3. CNN + GRU (Convolutional Neural Network with Gated Recurrent Unit):
CNN + GRU integrates convolutional layers with GRU, a simplified recurrent architecture that requires fewer parameters than LSTM. It effectively captures sequential dependencies while reducing training time and computational cost. The GRU gating mechanism helps retain relevant historical information, making it suitable for efficient and stable SOH prediction.

4. CNN + Bidirectional LSTM (Proposed Model):
The proposed model enhances prediction performance by combining CNN with Bidirectional LSTM. While CNN extracts spatial features, the Bidirectional LSTM processes the sequence in both forward and backward directions, capturing complete temporal information. This improves feature representation, reduces prediction errors, and provides more accurate and reliable SOH estimation compared to other models.

4. EXPERIMENTAL RESULTS

The proposed system was evaluated using NASA lithium-ion battery datasets (B5, B6, and B7), which include parameters such as voltage, current, temperature, and capacity. The dataset was preprocessed using normalization and feature selection techniques before training multiple deep learning models, including CNN1D, CNN+LSTM, CNN+GRU, and the proposed CNN + Bidirectional LSTM. The performance of each model was assessed using standard evaluation metrics such as Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). Experimental analysis shows that the CNN1D model achieved strong performance for battery B5 with RMSE of 0.003441 and MAPE of 0.019433, demonstrating its effectiveness in capturing local temporal patterns.

For batteries B6 and B7, the proposed CNN + Bidirectional LSTM model outperformed all other models, achieving the lowest RMSE of 0.003166 and MAPE of 0.011139, indicating superior capability in capturing complex temporal dependencies. The federated learning approach further enhanced model generalization by enabling decentralized training across multiple clients without sharing raw data. Comparative results show that hybrid models combining CNN with recurrent layers significantly improve prediction accuracy over standalone models. Overall, the experimental results validate that the proposed system provides accurate, robust, and privacy-preserving SOH prediction suitable for real-world battery management applications.

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Compare the number of true positives and negatives to get the reliability of the test. Following mathematical:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

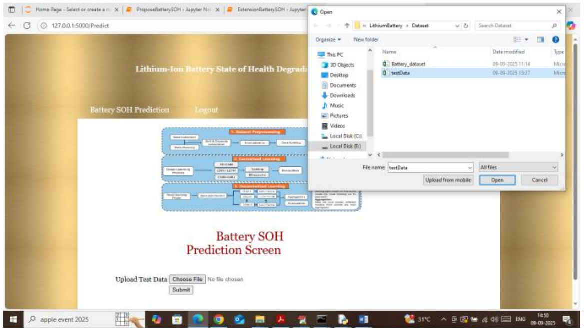
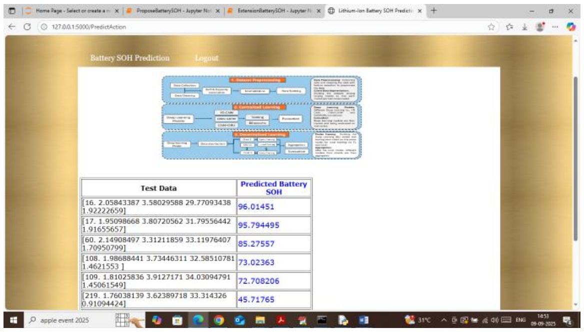


Fig: **results**



Test Data	Predicted Battery SOH
[16. 2.05843387 3.58029588 29.77093438 1.92222659]	96.01451
[17. 1.95098668 3.80720562 31.79556442 1.91655657]	95.794495
[60. 2.14908497 3.31211859 33.11976407 1.70950799]	85.27557
[108. 1.98688441 3.73446311 32.58510781 1.4621553]	73.02363
[109. 1.81025836 3.9127171 34.03094791 1.45061549]	72.708206
[219. 1.76038139 3.62389718 33.314326 0.91094424]	45.71765

Fig: Accuracy Comparison Graph

5. CONCLUSION

This paper presents a hybrid deep learning-based framework for accurate prediction of the State of Health (SOH) of lithium-ion batteries using NASA battery datasets. Multiple models, including CNN1D, CNN+LSTM, CNN+GRU, and the proposed CNN with Bidirectional LSTM, were implemented to capture both spatial and temporal degradation patterns. Experimental results demonstrate that the Bidirectional LSTM-based model achieves superior accuracy with lower RMSE and MAPE, while CNN1D performs effectively for specific datasets. These findings confirm that combining convolutional and recurrent architectures significantly improves SOH prediction performance.

Furthermore, the integration of federated learning enables decentralized model training while preserving data privacy, making the system scalable and suitable for real-world applications. By allowing multiple clients to collaboratively train models without sharing raw data, the approach enhances generalization and robustness. Overall, the proposed framework provides a reliable, efficient, and privacy-preserving solution for battery health monitoring, contributing to improved safety, extended battery lifespan, and optimized energy management in modern applications.

6. FUTURE SCOPE

The proposed system can be further enhanced by integrating real-time battery monitoring using IoT sensors, enabling continuous data collection and live SOH prediction for practical applications such as electric vehicles and smart grids. Advanced deep learning architectures such as Transformer-based models and attention mechanisms can be explored to improve the modeling of long-term dependencies and further enhance prediction accuracy. Additionally, incorporating Remaining Useful Life (RUL) prediction along with SOH estimation would provide a more comprehensive battery health management solution.

Future work can also focus on optimizing the model for edge devices to enable deployment in resource-constrained environments, reducing latency and improving real-time decision-making. Expanding the federated learning framework to include more diverse and large-scale datasets can improve model generalization across different battery types and operating conditions. Furthermore, integrating explainable AI techniques can help interpret model predictions, increasing transparency and trust in battery management systems.

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