Remaining Useful Life Assessment For Lithium-Ion Batteries Using Cnn-Lstm Hybrid Method

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Abstract -This project proposes a novel approach to assess the Remaining Useful Life (RUL) of lithium-ion batteries by employing a hybrid model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The CNN extracts spatial features from battery data, while the LSTM captures temporal dependencies, leading to more accurate RUL predictions. This method aims to improve predictive maintenance and battery management by providing precise estimates of battery health and longevity.

The objective is to enhance predictive maintenance strategies and improve battery management systems by accurately forecasting battery degradation. By utilizing CNN for feature extraction and LSTM for sequence prediction, the proposed method aims to capture both spatial and temporal patterns in battery performance data.

Key Words: Lithium-ion batteries, Remaining Useful Life, CNN-LSTM hybrid, Predictive maintenance.

1.INTRODUCTION

As lithium-ion batteries become increasingly integral to modern technology, from powering electric vehicles to enabling portable electronics, accurate prediction of their Remaining Useful Life (RUL) has become a pressing challenge. Effective RUL assessment is vital for optimizing battery performance, ensuring safety, and reducing operational costs. Traditional methods often fall short in capturing the complex degradation patterns of batteries, necessitating more sophisticated approaches. This research addresses this gap by proposing a hybrid model that combines Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks. The CNN is adept at extracting relevant features from the raw battery data, such as voltage and current profiles, which are crucial for understanding battery health. Meanwhile, the LSTM network excels at modelling temporal dependencies, allowing for accurate prediction of future battery performance based on historical data.

By integrating these two powerful techniques, this study aims to provide a robust framework for RUL estimation, improving the accuracy of predictive maintenance strategies and enabling more effective battery management. The proposed approach not only advances the state of the art in battery health monitoring but also offers practical benefits for extending battery life and enhancing the reliability of battery-dependent systems.

1.1 Aim

The aim of this research is to develop a robust method for predicting the Remaining Useful Life (RUL) of lithium-ion batteries by integrating Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks. This hybrid approach seeks to enhance the accuracy of RUL predictions by leveraging CNN for feature extraction and LSTM for capturing temporal dependencies in battery performance data. The goal is to improve predictive maintenance and battery management strategies, ultimately extending battery lifespan and optimizing operational efficiency.

1.2 Objective

- Develop a hybrid CNN-LSTM model for accurate prediction of the Remaining Useful Life (RUL) of lithium-ion batteries by integrating spatial feature extraction and temporal sequence analysis.
- Enhance predictive maintenance strategies by improving the precision of RUL estimates to optimize battery management and prevent premature failures.
- Analyze and validate model performance through comprehensive testing on real-world battery datasets to ensure reliability and effectiveness in diverse operational conditions.
- Provide actionable insights for extending battery lifespan and improving operational efficiency by accurately forecasting battery degradation patterns.

2. LITERATURE SURVEY

2.1 Existing System

In existing, the prediction of a Lithium-ion battery's lifetime is crucial for maintaining safety and reliability. In addition, it is utilized as an early warning system to prevent the battery's failure. Recent advance in Machine Learning (ML) is an enabler for new data-driven estimation approaches. In this paper, we suggest a combined approach, referred to as the CNN-LSTM-DNN, which combines Convolutional Neural Network (CNN), Long Short Term Memory (LSTM), and Deep Neural Networks (DNN), for determining the battery's remaining operational lifespan and enhancing prediction accuracy while maintaining acceptable execution time.

2.1.1 Disadvantages of Existing System

- In this case two datasets are used and low results occurred for one datasets.
- Time consumption is high.
- Theoretical limits.
- Ineffective at capturing complex, nonlinear relationships in battery data.
- Extensive manual feature extraction required.
- Poor handling of temporal dependencies in battery degradation data.

2.2 Proposed System

In this approach, a CALCE dataset was provided as input. The data entries has sourced from the dataset storehouse. We are required to take the four batteries such as CS2_33, CS2_34, CS2_36 and CS2_37. Next, we need to implement the data preprocessing step. In this step, we need to address missing values to prevent incorrect predictions, and to drop the unwanted columns because it is not required for our process. Subsequently, we need to split a dataset into test and train. The data is splitting relies on ratio. In train, majority of the data's will be there. In test, smaller portion of the data's will be there. Training portion is utilized to evaluate the model and testing portion is intended to predicting the model.

2.2.1 Advantages of Proposed System

- **Enhanced Accuracy**: The hybrid CNN-LSTM model improves prediction precision by combining CNN's ability to extract spatial features with LSTM's capability to analyze temporal dependencies, leading to more accurate Remaining Useful Life (RUL) estimates.

- **Improved Predictive Maintenance**: By providing reliable RUL forecasts, the system enables better scheduling of maintenance activities, reducing unexpected failures and optimizing battery management.

- **Comprehensive Analysis**: The integration of CNN and LSTM allows for a thorough understanding of both short-term and long-term battery performance trends, offering a more complete assessment of battery health.

- **Adaptability to Various Conditions**: The model is designed to handle diverse operational environments and battery types, making it versatile and applicable to different applications and scenarios.

- **Extended Battery Lifespan**: Accurate RUL predictions help in proactive maintenance, which can extend the overall lifespan of lithium-ion batteries by preventing overuse and ensuring timely interventions.

3. TECHNOLOGY OVERVIEW

3.1 CNN-LSTM hybrid method

In our project focused on predicting the remaining useful life (RUL) of lithium-ion batteries, we employ a CNN-LSTM-DNN hybrid method to enhance the accuracy and reliability of our predictive models. Here's an explanation of how each component of this hybrid method contributes to our approach:

Convolutional Neural Network (CNN):

- **Feature Extraction**: CNNs are adept at automatically extracting spatial and temporal features from multidimensional data such as sensor readings over time.
- **In our project**: We utilize CNNs to preprocess and extract meaningful features from the raw battery performance data. This helps in capturing important patterns and essential trends impacting determining battery degradation.

Long Short-Term Memory Network (LSTM):

- **Sequence Modelling**: LSTMs are well-suited for learning dependencies over time in sequential data.
- **In our project**: We implement LSTMs to model the temporal dependencies in the battery degradation process. This allows the model to understand how past states of the battery impact its future degradation, thereby improving the accuracy of RUL predictions.

Integration and Benefits:

- **Hybrid Approach**: By combining CNNs for feature extraction, LSTMs for sequence modelling, and DNNs for prediction refinement, our hybrid method leverages the strengths of each architecture to overcome limitations and improve overall prediction performance.

- **Enhanced Accuracy**: This integrated approach allows us to encompass both spatial and temporal dependencies in the battery data, leading has more focused estimates of remaining battery life.
- **Application**: The CNN-LSTM-DNN hybrid method is particularly effective in complex time-series data scenarios like battery degradation, where understanding both short-term and long-term patterns is crucial for reliable predictions.

4.METHADOLOGY

The methodology for this project involves a multi-step process combining data preprocessing, feature extraction, model development, and evaluation. Initially, data from lithium-ion batteries, including voltage, current, and temperature readings, are collected and preprocessed to ensure quality and consistency. This step includes normalization, noise reduction, and segmentation of time-series data into manageable sequences.

Next, the Convolutional Neural Network (CNN) is employed for feature extraction from the preprocessed data. The CNN's convolutional layers are designed to capture spatial patterns and anomalies in the battery performance metrics, such as degradation trends and operational irregularities. These extracted features are then fed into the Long Short-Term Memory (LSTM) network, which is adept at learning and predicting temporal sequences. The LSTM network processes the sequential data to model the time-dependent behavior of battery degradation, thereby enhancing the prediction of the Remaining Useful Life (RUL).

The combined CNN-LSTM model is trained using historical battery data, with rigorous validation and testing phases to assess its accuracy and robustness. Performance metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used to evaluate the model's predictive capabilities. Finally, the model's effectiveness is demonstrated through comparative analysis with existing methods, showcasing its potential to offer superior RUL predictions and improved battery management solutions.

4.1 Implementation Modules

4.1.1 Data selection

- The input data was obtained from dataset repository.
- In our process, the CALCE dataset is used.
- In this dataset, we have to take four batteries such as CS2_33, CS2_34, CS2_37 and CS2_38.
- In the absence of specific instructions, the discharge cutoff voltage for these batteries was set at 2.7V.
- All CS2 cells were assigned random numbers and named accordingly, with each cell labelled as 'CS2_n', where 'n' represents the cell's number
- All the CS2 cells experienced identical charging profile which Followed a constant current/constant voltage protocol with a constant current rate of 0.5C until the voltage hit 4.2V, after which 4.2V was held until the charging current decreased to under 0.05A.

4.1.2 Data Preprocessing

- Data pre-processing is the process of removing the unwanted data taken from the dataset.

- Pre-processing data transformation tasks are employed to convert the dataset into a format suitable for machine learning.

- This phase includes dataset cleaning to remove irrelevant or corrupted data, enhancing both accuracy and efficiency.

- Missing data removal

- Encoding Categorical data
- Missing data removal: In this process, the null values such as missing values and Nan values are replaced by zero.

4.1.3 Data Splitting:

- Data is necessary during the machine learning process to facilitate learning.
- Along with training data, test data is necessary to assess the algorithm's performance and determine its effectiveness.
- In our approach, 70% of the input dataset was allocated for training, while the remaining 30% was used for testing.
- Data splitting consists of dividing available data into two portions, usually for cross-validator purposes.
- One segment pertaining to the data is utilized to build a predictive model, while another segment is used to assess the model's performance.

4.1.4 Classification:

- In our process, we have to implement the deep learning algorithms such as Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM).

- In our process, to integrate the CNN and LSTM hybrid model.

- LSTM is a type of artificial recurrent neural network architecture employed in deep learning.
- Unlike standard feed forward neural networks, LSTM has feedback connections.
- It is capable of handling not just individual data points but also complete sequences of data.
- LSTM networks are well-suited to classifying, processing and making predictions grounded in time series data, as there may be indeterminate lags between significant events within the series.
- A CNN is a deep learning algorithm that processes input images, assigns learnable weights and biases to different features, and distinguishes between various objects within the image.

4.1.5 Result Generation

The final result is derived from the comprehensive classification and prediction. The effectiveness of this proposed method is assessed using metrics such as:

- **MAE:** In statistics, the **mean absolute error** (MAE) is a way to assess the accuracy of a given model. It is calculated as:

$$\boxed{MAE = (1/n) * \Sigma|y_i - x_i|}$$

Where:

- **Σ:** A Greek symbol that means "sum"
- **y_i:** The observed value for the i^{th} observation
- **x_i:** The estimated value for the ith observation
- **n:** The total number of observations

- **MSE:** The mean squared error (MSE) is a common way to measure the prediction model performance. It is calculated as:

$$\boxed{MSE = (1/n) * \Sigma\,(\text{actual} - \text{prediction})^2}$$

Where:

- **Σ** – a fancy symbol that means "sum"
- **n** – sample size
- **actual** – the actual data value
- **forecast** – the predicted data value

- **RMSE:** The root mean square error (RMSE) is a metric that tells us how far apart our predicted values are from our observed values in a model, on average. It is calculated as:

$$\boxed{RMSE = \sqrt{[\,\Sigma(P_i - O_i)^2 / n]}}$$

Where:

- Σ is a fancy symbol that means "sum"
- P_i is the predicted value for the i^{th} observation
- Oi refers to the actual value for the i^{th} observation.
- n denotes the sample size

5. EXPERIMENTS

The experiments for this project are designed to validate the effectiveness of the hybrid CNN-LSTM model for predicting the Remaining Useful Life (RUL) of lithium-ion batteries. The following experimental phases are conducted:

Data Collection and Preprocessing: High-quality battery data is collected, including variables such as voltage, current, and temperature. This data is then preprocessed to handle missing values, normalize measurements, and segment time-series data into fixed-length sequences suitable for model input

Data Selection

	Data_Point	Test_Time(s)	Date_Time	Step_Time(s)	Step_Index	Cycle_Index	Current(A)
0	1	30.0004	2011-01-03 10:38:25	30.0004	1	1	0
1	2	60.0157	2011-01-03 10:38:55	60.0157	1	1	0
2	3	90.0307	2011-01-03 10:39:25	90.0307	1	1	0
3	4	120.0143	2011-01-03 10:39:55	120.0143	1	1	0
4	5	137.9058	2011-01-03 10:40:13	17.891	2	1	0.5498
5	6	167.9217	2011-01-03 10:40:43	30.0155	3	1	0
6	7	197.9367	2011-01-03 10:41:13	60.0305	3	1	0
7	8	227.9519	2011-01-03 10:41:43	90.0457	3	1	0
8	9	257.9203	2011-01-03 10:42:13	120.0141	3	1	0
9	10	257.9208	2011-01-03 10:42:13	0	4	1	0.6857

Fig 5.1: Data selection

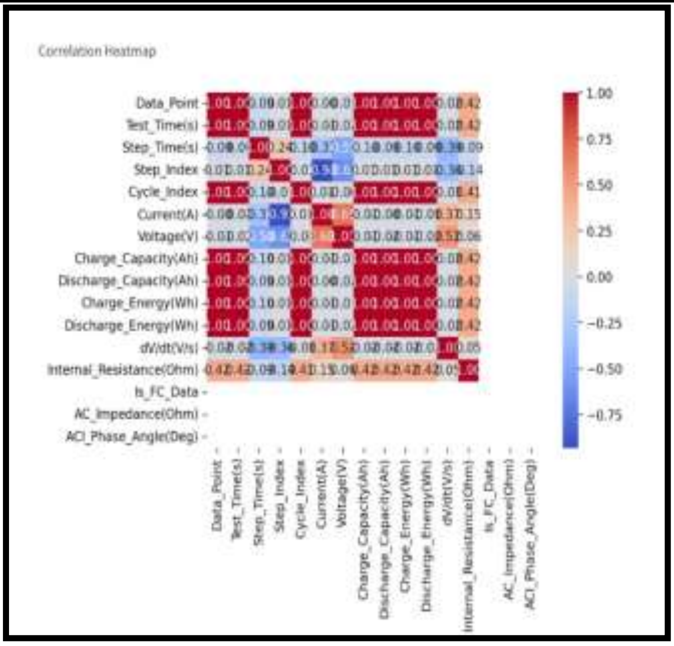

Fig 5.2: Correlation Heatmap

In the RUL prediction project for Li-ion batteries using a CNN-LSTM hybrid model, a correlation heatmap is crucial for identifying relationships between key battery parameters like voltage, current, and temperature. It helps in selecting the most relevant features by highlighting strong correlations, thereby reducing redundancy and avoiding multicollinearity. This ensures that the model focuses on the most impactful data, improving its ability to capture critical patterns over time, leading to more accurate and reliable predictions.

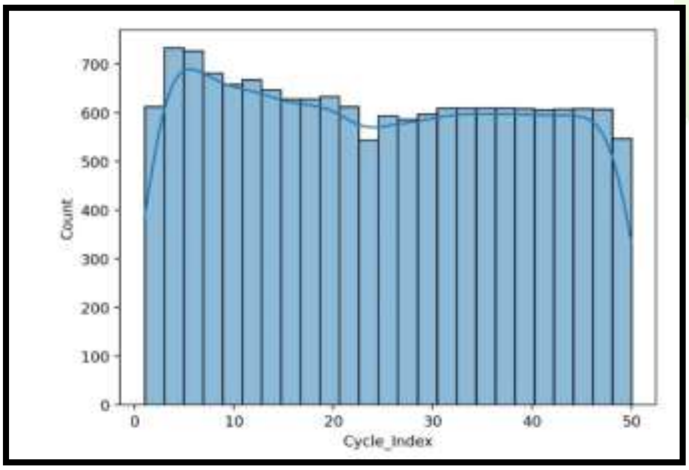

Fig.5.3: Distribution of Cycle Index

In the context of predicting the Remaining Useful Life (RUL) of Li-ion batteries using a CNN-LSTM hybrid model, the "Distribution of Cycle Index" image visualizes how battery cycles are spread across the dataset. This distribution helps to understand the variation in battery degradation over different cycles, which is essential for training the model. A well-distributed cycle index ensures that the model learns from a diverse set of battery conditions, improving its generalization and accuracy in predicting RUL across different battery states and usage patterns. This visualization is key to ensuring the model is robust and applicable to real-world scenarios.

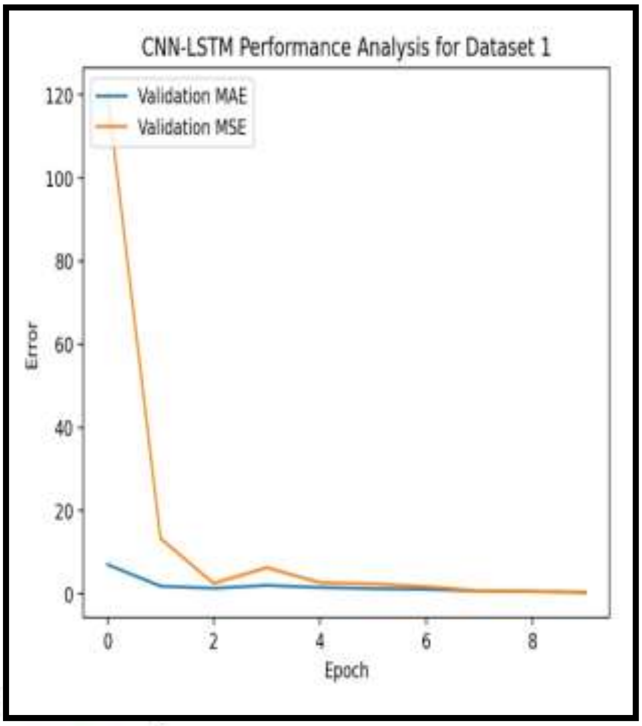

Fig.5.4: Validation Graph

a validation graph plays a crucial role in evaluating the model's performance. The graph typically plots the loss or error metric (such as Mean Squared Error) against the number of epochs during training for both the training and validation datasets. This graph helps in monitoring the model's learning process and detecting overfitting or underfitting. If the validation loss starts increasing while the training loss continues to decrease, it indicates overfitting, meaning the model is learning patterns specific to the training data but failing to generalize to new data. indicating that the model is effectively learning from the data without overfitting.

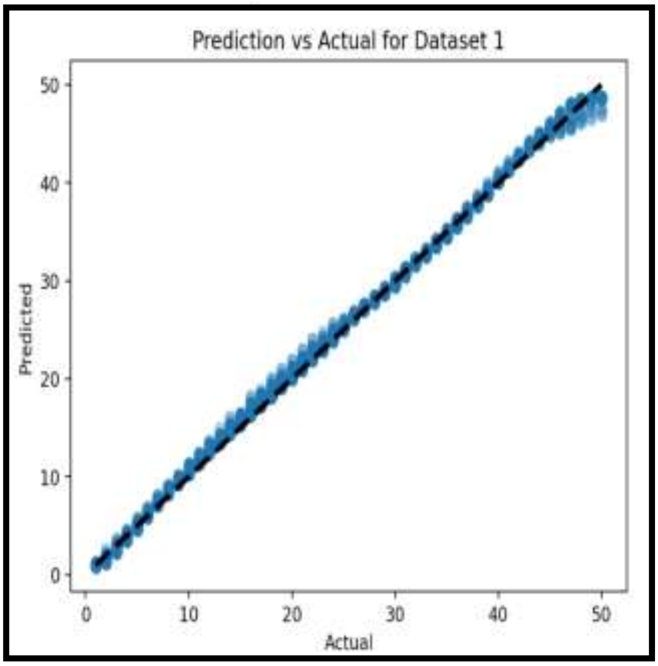

Fig .5.5: Prediction vs actual for dataset 1

The x-axis represents the actual values, while the y-axis represents the predicted values made by the model. **- Black Diagonal Line:** This line represents the ideal scenario where the predicted values perfectly match the actual values (i.e., where `Predicted = Actual`). If all points lie on this line, it indicates a perfect prediction. **- Blue Dots**: These dots represent the actual data points, with their position on the graph indicating how close the predicted values are to the actual values. **Interpretation**: The graph shows that the predicted values closely follow the actual values, as most points lie near or on the black diagonal line. This indicates that the hybrid model is performing well, with high accuracy in predicting the RUL of the batteries. The small deviations suggest minor prediction errors, but overall, the model appears to be robust and reliable.

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============================================================
Performance metrics

Mean Absolute Error 0.7016695447648167

Mean Squared Error: 0.6855847510486563

Root Mean Squared Error: 0.8280004535316731

r squared: 99.29833045523519 %
```

Fig.5.6:Performance metrix

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 15, 100)           40800
_________________________________________________________________
dropout (Dropout)            (None, 15, 100)           0
_________________________________________________________________
conv1d (Conv1D)              (None, 15, 32)            9632
_________________________________________________________________
max_pooling1d (MaxPooling1D) (None, 7, 32)             0
_________________________________________________________________
lstm_1 (LSTM)                (None, 50)                16600
_________________________________________________________________
dropout_1 (Dropout)          (None, 50)                0
_________________________________________________________________
dense (Dense)                (None, 1)                 51
_________________________________________________________________
activation (Activation)      (None, 1)                 0
=================================================================
Total params: 67,083
Trainable params: 67,083
Non-trainable params: 0
_________________________________________________________________
```

Fig.5.7: Model Architecture Summary

8. CONCLUSIONS

The Remaining Useful Life (RUL) assessment of lithium-ion batteries using the CNN-LSTM-DNN hybrid method represents a significant advancement in battery management technology. By integrating real-time data processing, advanced machine learning techniques, and user-friendly interfaces, this system delivers highly precise and actionable predictions. Future enhancements, such as improved visualization tools, expanded compatibility, and robust alerting systems, will further enhance its utility and reliability. Moreover, incorporating cloud computing and IoT integration will streamline data processing and analysis, ensuring faster and more dependable outcomes. These improvements will make the RUL assessment system an indispensable tool for various industries, contributing to more efficient and proactive battery management.

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