REMAINING USEFUL LIFE ASSESSMENT FOR LITHIUM-ION BATTERIES USING CNN-LSTM-DNN HYBRID METHOD

Submitted in partial fulfillment of the requirements for the
award of
Bachelor of Engineering degree in Computer Science and Engineering

By

T.YASWANTH SAI (Reg.No - 39111040)

V.SATYANARAYANA (Reg.No - 39111068)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

SCHOOL OF COMPUTING

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)
Accredited with Grade "A" by NAAC | 12B Status by UGC | Approved by AICTE

JEPPIAAR NAGAR, RAJIV GANDHI SALAI,

CHENNAI – 600119

APRIL - 2023

SATHYABAMA
INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)
Accredited with Grade "A" by NAAC | 12B Status by UGC | Approved by AICTE

www.sathyabama.ac.in

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **T.Yaswanth Sai (Reg.No - 39111040) and V.Satyanarayana (Reg.No - 39111068)** who carried out the Project Phase-2 entitled **"REMAINING USEFUL LIFE ASSESSMENT FOR LITHIUM-ION BATTERIES USING CNN-LSTM-DNN HYBRID METHOD"** under my supervision from January 2023 to April 2023.

Internal Guide

Dr. S. PRINCE MARY, M.E, Ph.D

Head of the Department

Dr. L. LAKSHMANAN, M.E.,Ph.D.

SATHYABAMA INSTITUTE OF SCIENCE AND TECHNOLOGY
DEPARTMENT OF CSE

Submitted for Viva-voce Examination held on 24-04-2023

Internal Examiner **External Examiner**

DECLARATION

I,**T. Yaswanth Sai (Reg.No- 39111040),** hereby declare that the Project Phase-2 Report entitled **"REMAINING USEFUL LIFE ASSESSMENT FOR LITHIUM-ION BATTERIES USING CNN-LSTM-DNN HYBRID METHOD"** done by me under the guidance of **Dr. S. Prince Mary, M.E, Ph.D** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in **Computer Science and Engineering**.

DATE: 24-04-2023

PLACE: Chennai **SIGNATURE OF THE CANDIDATE**

ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to **Board of Management** of **SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

I convey my thanks to **Dr. T. Sasikala M.E., Ph. D**, **Dean**, School of Computing,

Dr. L. Lakshmanan, M.E., Ph.D., Heads of the Department of Computer Science and Engineering for providing me necessary support and details at the right time during the progressive reviews.

I would like to express my sincere and deep sense of gratitude to my Project Guide **Dr. S. Prince Mary, M.E, Ph.D,** for her valuable guidance, suggestions and constant encouragement paved way for the successful completion of my phase-2 project work.

I wish to express my thanks to all Teaching and Non-teaching staff members of the **Department of Computer Science and Engineering** who were helpful in many ways for the completion of the project.

ABSTRACT

The identification of a Lithium-ion battery’s lifetime is very important for ensuring safety and reliability. In addition, it is utilized as an early warning system to prevent the battery’s failure. Recent advance in Machine Learning is an enabler for new data-driven estimation approaches. In this paper, we suggest a hybrid method, named the CNN-LSTM, which is a combination of Convolutional Neural Network and Long Short-Term Memory for the estimation of the battery’s Remaining Useful Life and improving accuracy with acceptable execution time. A comparison against various ML estimation algorithms is carried out to show the superiority of the proposed hybrid estimation approach. For that, two statistical indicators, i.e. the MSE, MAE, R^2, and RMSE, are selected to assess numerically the prediction results. A hybrid CNN-LSTM algorithm is suggested by combining two well-known algorithms, i.e. Convolutional Neural Networks and Long Short Term Memory to estimate the battery’s Remaining Useful Life and improve the long-term identify performance of lithium-ion batteries. Experimental validation is performed using the dataset of different lithium-ion batteries from CALCE. Thus, results reveal that hybrid methods perform better than the single ones, also the effectiveness of the suggested method in reducing the identification error and in achieving better RUL identification performance compared to the other methods.

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER 1
INTRODUCTION

1.1 GENERAL INTRODUCTION

The energy storage system is one of the essential components of electric vehicles that is anticipated to penetrate the current transport market because of the constant increase in the environmental pollution and the oil prices**.** Thus far, lithium-ion batteries remain the main source of energy for EVs and consumer electronics. They have exceptional advantages, like a long life cycle and high power /energy density, as they can be considered the perfect choice for the ESS .However, the battery performance degrades progressively with time leading to some potential disasters e.g., battery explosion in cell phones and EVs. Consequently, additional efforts are required to effectively assess the Li-ion battery's health and to predict its lifetime e.g., battery replacement time and control of degradation precursors to improve the reliability of the overall energy system. Subsequently, a battery management system is necessary to ensure the safety of Li-ion batteries which is generally based on three essential elements: remaining useful life , state of charge, and state of health, which have a relationship respectively to the charge of the batteries and their aging. The Li-ion battery's RUL prediction that that depends on the data-driven method can be partitioned into three categories: fitting e.g. linear model, single-exponential model, polynomials model, etc., sequence prediction e.g. neural network, relevance rector machine, gray prediction, etc and filter observation e.g. unscented particle filter, spherical cubature particle filter, etc. There is a difficulty in establishing an analytic model that tracks the battery's capacity degradation by model-based and data-driven methods.

This latter analyses the complex chemical and physical changes during some cycles making its application a popular choice to estimate the battery's RUL. The present work capitalizes on the merits of the CNN-LSTM hybrid algorithm and the latest developments of ANNs in general to achieve high prediction accuracy for the RUL of the Li-ion battery. This is among the scarce attempts, if any, in implementing the hybrid algorithm for such application. In this experiment, we use the CALCE datasets for confirming the good results obtained in the NASA datasets. The CNN-LSTM hybrid algorithm is implemented for RUL prediction of four batteries named CS2_33, CS2_34, CS2_36, and CS2_37. It shows the accurate prediction results for CALCE batteries, which have a greater number of cycles than NASA batteries during capacity degradation. It illustrates that both the true and predictive curves are almost identical. Thus, the hybrid algorithm has a high estimation accuracy. Although we utilized the different training/validation split for these four batteries, CNN-LSTM obtains the highest accuracy in the RUL prediction and shows similar performance among Li-ion batteries. Therefore, this algorithm is suitable for the task. While similar values of R^2, MAE, and RMSE are observed for these four batteries, where MAE, and RMSE values are very low and R^2 is very high. With the emergence of the traditional energy crisis, there is a pressing for society to explore and develop new energy. Among many new energy sources, lithium-ion batteries have become the mainstream of the new energy market owing to their high energy density, high output voltage, long cycle life, and wide operating temperature range .

However, the internal resistance increases with lithium-ion batteries' repeated charging and discharging cycles. After the internal resistance increases, the battery heats severely, which continue to affect the performance and normal use of the battery pack . The remaining useful life of lithium-ion batteries is the number of charging and discharging cycles remaining between the beginning of measurement and the end of life of lithium-ion batteries. Regular RUL prediction of a lithium-ion battery can show the remaining useful cycle times of the battery, predict whether the battery is close to the EOL, and avoid potential risks in the use process.

Therefore, the accuracy of the lithium-ion battery RUL evaluation method will directly affect the overall performance of the battery management system, which has great practical significance in the field of energy battery application. The traditional life prediction model is a tedious and strict process due to the complex physical and chemical properties of lithium-ion batteries. Fortunately, the RUL model of lithium-ion battery based on data-driven technology is a powerful and effective method with the development of artificialintelligence. It regards the battery as a black box, bypasses the complex change process inside it, and only needs to find the statistical law through the historical measurement data to predict the RUL of lithium-ion batteries. In recent years, more and more scholars have started to focus on the research of power batteries. There are two main categories for building battery life prediction models: model- based and data-driven methods .

The model-based method establishes the mathematical model of the battery by analyzing the physical structure and electrochemical reaction and then estimating the changing process of the battery parameters. Khare et al. used the statistical modelling method to establish the mapping model between battery internal resistance and health state to evaluate the health state. Based on the analysis of the failure principle and the electrochemical reaction of lithium-ion batteries, a complete mathematical model was found to fit the degradation trajectory of lithium-ion batteries and to achieve the prediction of RUL. Mevawalla et al. proposed an equivalent circuit model approach incorporating physio-chemical theory into developing a nonlinear equation for internal resistance. This method creates a model to simulate the internal resistance and surface temperature of lithium-ion batteries using actual measurable parameters. Wang et al.

The proposed a resistance-based therm model of the batteries considering the impact of the state of charge , battery temperature, and current on the battery heat generation. According to the research results, air velocity has little effect onthe maximum battery temperature at the discharge rate of flying cars. However, it can affect the temperature decrease rate. Xie et al. proposed a distributed spatial-temporal online correction algorithm for SOC-three-dimensional state of temperature co-estimation of battery. The result shows that the co-estimation algorithm still has a good converge performance with disturbance added. Xing et al. proposed a fusion prediction method based on the physics of failure and data-driven technology. This method can deeply analyze the failure mechanism caused by changes of physical and chemical characteristics in the battery. It can also be applied to estimate some parametersin real-time monitoring scenarios. Wang et al. introduced a spherical particle filter to solve the state space model and then established the state space model of battery capacity to predict the RUL oflithium-ion batteries after evaluating the capacity degradation. Tran et al. investigated and compared the performance of three different equivalent circuit models using four lithium-ion battery chemistries under dynamic and non-dynamic current profiles.

However, the model-based method is vulnerable to the influence of the external environment, and it is difficult to establish an accurate mechanism model. Also, due to the different physical and chemical properties of different batteries, the applicability of the model is not strong. It needs to be modified for different batteries, which requires much work.

The CNN-LSTM-DNN hybrid method is an advanced deep learning-based technique that has been proposed for RUL assessment of Lithium-ion batteries. The method combines convolutional neural networks, long short-term memory networks, and deep neural networks to achieve accurate RUL predictions.

The CNN-LSTM-DNN hybrid method works by first using CNNs to extract features from the battery's operating data. The LSTM network is then used to capture the temporal dependencies between the extracted features. Finally, the DNN is used to predict the RUL based on the extracted features and temporal dependencies captured by the LSTM network.

The advantage of the CNN-LSTM-DNN hybrid method is that it can handle the complex and nonlinear relationships between the battery's operating data and its RUL, which can be challenging to capture using traditional methods. The method has shown promising results in accurately predicting the RUL of Lithium-ion batteries in various applications.

The proposed method takes advantage of the ability of CNN to automatically learn relevant features from the raw sensor data, the ability of LSTM to model the long-term dependencies in the data, and the ability of DNN to make accurate predictions. The hybrid CNN-LSTM-DNN method provides an effective approach to RUL assessment for lithium-ion batteries. By accurately predicting the remaining useful life of batteries, this method can help to prevent battery failures and extend the lifespan of lithium-ion batteries, thereby reducing costs and increasing efficiency in a variety of applications.

In conclusion, the CNN-LSTM-DNN hybrid method is an advanced deep learning-based technique for RUL assessment of Lithium-ion batteries. It combines CNNs, LSTM networks, and DNNs to achieve accurate RUL predictions by capturing the complex and nonlinear relationships between the battery's operating data and its remaining useful life.

1.2 OBJECTIVES

The main objective of our project is,

- To effectively classify and predict the remaining useful life.
- To implement the different two deep learning and hybrid that the deep learning algorithms.
- To enhance the overall performance for hybrid algorithms.

1.3 PROBLEM STATEMENT

The Remaining Useful Life is a subjective estimate of the number of remaining years that an item, component, or system is estimated to be able to function in accordance with its intended purpose before warranting replacement. To identify the remaining useful life by combining the different deep learning algorithms.

CHAPTER 2

LITERATURE SURVEY

1. Online remaining useful life for lithium-ion batteries using partial discharge data features, 2019

Author: Muhammad Umair Ali 1, Amad Zafar 2, Sarvar Hussain Nengroo 1, Sadam Hussain 1, Gwan-Soo Park 1 and Hee-Je Kim

Methodology

Online accurate estimation of remaining useful life of lithium-ion batteries is a necessary feature of any smart battery management system . In this paper, a novel partial discharge data-based support vector machine model is proposed for RUL prediction. The proposed algorithm extracts the critical features from the voltage and temperature of PDD to train the SVM models. The classification and regression attributes of SVM are utilized to classify and predict accurate RUL. The different ranges of PDD were analysed to find the optimal range for training the SVM model. The SVM model trained with optimal PDD features classifies the RUL into six different classes for gross estimation, and the support vector regression is used to estimate the accurate value of the last class. The classification and predictive performance of SVM model trained using the full discharge data and PDD are compared for publicly available data. Results show that the SVM classification and regression model trained with PDD features can accurately predict the RUL with low storage pressure on BMS. The PDD-based SVM model can be utilized for online RUL estimation in electric vehicles.

Advantages

- SOH methods are quite simple to implement but they require a rigorous testing and highly accurate measurement instruments to estimate the SOH.
- The genetic algorithm was also used to determine the parameters of an electric circuit model

2. State of Charge and State of Health for Lithium Batteries Using Recurrent Neural Networks, 2020

Author: Hicham Chaoui, Chinemerem Christopher Ibe-Ekeocha

Methodology

This paper presents an application of dynamically driven recurrent networks in online electric vehicle battery analysis. In this work, a nonlinear autoregressive with exogenous inputs architecture of the DDRN is designed for both state of charge and state of health estimation. Unlike other techniques, this estimation strategy is subject to the global feedback theorem which increases both computational intelligence and robustness while maintaining reasonable simplicity. The proposed technique requires no model or knowledge of battery's internal parameters but rather uses the battery's voltage, charge/discharge currents, and ambient temperature variations to accurately estimate battery's SOC and SOH simultaneously. The presented method is evaluated experimentally using two different batteries namely lithium iron phosphate and lithium titanate both subject to dynamic charge and discharge current profiles and change in ambient temperature. Results highlight the robustness of this method to battery's nonlinear dynamic nature, hysteresis, aging, dynamic current profile, and parametric uncertainties. The simplicity and robustness of this method make it suitable and effective for EVs' battery management system .

Advantages

- The MLP also falls short in the case of SOH estimation as it was unable to converge when tested with the SOH data. This in turn corroborates the advantage of the DDRN over conventional MLP neural networks.

Disadvantages

- The disadvantage of this method is that it is highly computational and requires an accurate battery model to be effective.

3. A Novel Machine Learning Method Based Approach for Li-ion Battery Prognostic and Health Management, 2018

Author: JIAMING FAN, JIANPING FAN, FENG LIU1, JIANTAO QU1 and RUOFENG LI

Methodology

Safety accidents caused by Lithium-ion batteries are numerous in recent years. Therefore, more and more attention has been drawn to the Remaining Useful Life (RUL) prediction and health status monitoring for Li-ion batteries. This paper proposes a deep learning method that combines the Forgetting Online Sequential Extreme Learning Machine with the Hybrid Grey Wolf Optimizer algorithm and attention mechanism for the Prognostic and Health Management of Liion battery. First, we use the Variational Mode Decomposition to denoise the raw data before the training. Then the key parameters optimization of the FOS-ELM model based on the HGWO algorithm is introduced. Finally, we apply the attention mechanism to further improve the accuracy of the algorithm. Compared with traditional neural network methods, the method proposed in this paper has higher efficiency and accuracy.

Advantages

- VMD algorithm is an adaptive Wiener filter group, which has the advantages of effectively reducing pseudo components and migrating aliasing phenomenon, especially in the low-frequency component.
- HGWO algorithm combines the advantages of Differential Evolution algorithm and Grey Wolf Optimizer algorithm, while overcome their disadvantages of premature convergence, poor stability and tendency to fall into local optimum.

4. ‘Remaining useful life of lithium-ion batteries based on false nearest neighbors and a hybrid neural network, 2019

Author: Guijun Maa,d , Yong Zhangb , Cheng Chengc , Beitong Zhouc , Pengchao Huc , Ye Yuan

Methodology

Accurate estimation of the remaining useful life of lithium-ion batteries is critically important for electronic devices. In the existing literature, the widely applied model-based approaches for remaining useful battery life estimation are limited by the complexity of the electrochemical modeling required. In addition, data-driven approaches for remaining useful battery life estimation commonly define unreliable sliding window sizes empirically and the prediction accuracy of these approaches needs to be improved. To address the above issues, use of a hybrid neural network with the false nearest neighbors method is proposed in this paper. First, the false nearest neighbors method is used to calculate the sliding window size required for prediction. Second, a hybrid neural network that combines the advantages of a convolutional neural network with those of long short-term memory is designed for model training and prediction. Remaining useful life prediction experiments for batteries with various rated capacities are performed to verify the effectiveness of the proposed approach, and the results demonstrate that the proposed approach offers wide generality and reduced errors when compared with the other state-of-the-art methods.

Advantages

- The CNN-LSTM algorithm combines the advantages of CNN and LSTM, where CNN is exploited to extract useful feature information and LSTM will predict the unknown sequences of capacity data by using the extracted features provided by CNN.
- Advantages that include high energy density, low self-discharge rates, long lifetimes, and excellent low-temperature performance

5. Remaining useful life of lithium-ion battery based on extended Kalman particle filter, 2019

Author: Bin Duan, Qi Zhang, Fei Geng , Chenghui Zhang

Methodology

Scientific estimation and prediction of the state of health of lithium-ion battery, especially the remaining useful life , has important significance to guarantee the battery safety and reliability in the full life cycle to avoid catastrophic accidents as much as possible. In order to accurately predict the RUL of the lithium-ion battery, this paper firstly analyses the problems of the standard particle filter . Then, a novel extended Kalman particle filter is proposed, in which the extended Kalman filter is used as the sampling density function to optimize PF algorithm. The life cycle tests are designed and carried out to get accurate and reliable data for the RUL prediction. And, the aging properties of lithium-ion battery are analysed in detail. The RUL prediction is done based on the established capacity degradation model and the proposed EKPF method. Results show that the RUL prediction error of the proposed method is less than 5%, which has higher precision compared with the standard PF method and can be used both offline and online.

Disadvantage

- This method can not only take a long test time and have high cost, but also cause irreversible destructive to the battery.
- The degradation mechanism model has high accuracy, but it has too many parameters, high complexity, and a large amount of numerical calculation.

6. Remaining capacity estimation of lithium-ion batteries based on the constant voltage charging profile, 2018

Author: Zengkai Wang1, Shengkui Zeng1, 2, Jianbin Guo1, 2*, Taichun Qin1

Methodology

Estimation of remaining capacity is essential for ensuring the safety and reliability of lithium ion batteries. In actual operation, batteries are seldom fully discharged. For a constant current-constant voltage charging mode, the incomplete discharging process affects not only the initial state but also processed variables of the subsequent charging profile, thereby mainly limiting the applications of many feature-based capacity estimation methods which rely on a whole cycling process. Since the charging information of the constant voltage profile can be completely saved whether the battery is fully discharged or not, a geometrical feature of the constant voltage charging profile is extracted to be a new aging feature of lithium ion batteries under the incomplete discharging situation in this work. By introducing the quantum computing theory into the classical machine learning technique, an integrated quantum particle swarm optimization–based support vector regression estimation framework, as well as its application to characterize the relationship between extracted feature and battery remaining capacity, are presented and illustrated in detail. With the lithium-ion battery data provided by NASA, experiment and comparison results demonstrate the effectiveness, accuracy, and superiority of the proposed battery capacity estimation framework for the not entirely discharged condition.

Disadvantage

- The disadvantages of the model-based methods are also evident: the electrochemical mechanism is too complicated to identify, the measurements of some parameters such as open circuit voltage involved in ECM require a very long rest time, and the estimation results based on those models usually come with large errors.

7. A hybrid method for remaining useful life estimation of lithium-ion battery with regeneration phenomena, 2019

Author: Lin Zhao, Yipeng Wang and Jianhua Cheng

Methodology

The lithium-ion battery has become the primary energy source of many electronic devices. Accurately forecasting the remaining useful life (RUL) of a battery plays an essential role in ensuring reliable operations of an electronic system. This paper investigates the lithium-ion battery RUL prediction problem with capacity regeneration phenomena. We aim to reduce the accumulation of the prediction error by integrating different capacity degradation models and thereby improve the prediction accuracy of the long-term RUL. To describe the degradation process more accurately, we decoupled the degradation process into two types: capacity regeneration and normal degradation. Then, we modelled two kinds of degradation processes separately. In the prediction phase, we predicted the battery state of health by using the relevance vector machine and the Gray Model alternately, updated the training dataset according to the prediction results, and then updated the RVM and GM. The RVM and GM correct each other's prediction results constantly, which reduces the cumulative error of prediction and improves the prediction accuracy of the battery SOH. Experimental results with the National Aeronautics and Space Administration battery dataset demonstrated that the proposed method can accurately establish the degradation model and achieve better performance for the RUL estimation as compared with the single RVM or GM methods.

Advantage

- The hybrid approach can integrate the advantages of different methods to improve the accuracy of the lithium-ion battery prognostics.

2.1 INFERENCES FROM LITERATURE SURVEY

The identification of a Lithium-ion battery's lifetime is very important for ensuring safety and reliability. In addition, it is utilized as an early warning system to prevent the battery's failure. Recent advance in Machine Learning is an enabler for new data-driven approaches. In this paper, we suggest a hybrid method, named the CNN-LSTM, which is a combination of Convolutional Neural Network and Long Short Term Memory for the estimation of the battery's remaining useful life and improving identification accuracy with acceptable execution time. A comparison against various ML estimation algorithms is carried out to show the superiority of the proposed hybrid estimation approach. For that, two statistical indicators, i.e. the MSE, MAE, R^2, and RMSE, are selected to assess numerically the identify results.

2.2 OPEN PROBLEMS IN EXISTING SYSTEM

In existing, the identification of a Lithium-ion battery's lifetime is very important for ensuring safety and reliability. In addition, it is utilized as an early warning system to prevent the battery's failure. Recent advance in Machine Learning is an enabler for new data-driven estimation approaches. In this paper, we suggest a hybrid method, named the CNN-LSTM-DNN, which is a combination of Convolutional Neural Network , Long Short Term Memory , and Deep Neural Networks, for the estimation of the battery's Remaining Useful Life and improving accuracy with acceptable execution time. A comparison against various ML estimation algorithms is carried out to show the superiority of the proposed hybrid estimation approach. For that, three statistical indicators, i.e. the MAE, R^2, and RMSE, are selected to assess numerically the identify results. Experimental validation is performed using two datasets of different lithium-ion batteries from NASA and CALCE. Thus, results reveal that hybrid methods perform better than the single ones, also the effectiveness of the suggested method in reducing the prediction error and in achieving better RUL performance compared to the other methods.

Remaining useful life assessment for lithium-ion batteries using the CNN-LSTM-DNN hybrid method is a complex problem that is still an active area of research. Some of the open problems in this field include

Lack of Sufficient Data one of the significant challenges in RUL assessment is the scarcity of reliable and comprehensive datasets. The limited amount of data often leads to inaccurate predictions, especially when dealing with complex models like the CNN-LSTM-DNN hybrid method. Developing large, high-quality datasets is essential to improve the accuracy of RUL prediction models.

Model Generalization another challenge in RUL assessment is the ability of the model to generalize to unseen data. In many cases, models trained on a particular dataset may not perform well on new data due to differences in operating conditions or the presence of different failure mechanisms. Developing models that can generalize to different operating conditions and failure modes is crucial to improve the accuracy of RUL predictions.

Interpretability of the Model the CNN-LSTM-DNN hybrid method is a complex model that can be challenging to interpret. Understanding how the model arrives at its predictions is essential for gaining insights into the underlying mechanisms governing battery degradation. Developing methods to interpret and visualize the model's predictions is crucial to improving its interpretability.

Uncertainty Estimation uncertainty estimation is an important aspect of RUL assessment, as it helps to quantify the confidence in the model's predictions. The CNN-LSTM-DNN hybrid method currently does not provide a mechanism for uncertainty estimation, which can lead to overconfidence in the predictions. Developing methods for uncertainty estimation is crucial to improving the reliability of RUL predictions.

Disadvantages

- Here, two datasets are used and low results occurred for one datasets.
- Time consumption is high.
- Theoretical limits.

CHAPTER 3

REQUIREMENTS ANALYSIS

3.1 FEASIBILITY STUDIES/ RISK ANALYSIS OF THE PROJECT

The use of a CNN-LSTM-DNN hybrid method for RUL assessment of Lithium-ion batteries is a promising approach that has the potential to provide accurate and reliable predictions of battery health. The method involves the use of Convolutional Neural Networks to extract features from the input data, Long Short-Term Memory networks to model temporal dependencies in the data, and Deep Neural Networks to predict RUL.Several studies have been conducted in recent years to investigate the feasibility of this approach. For example, a study by Liu et al. (2021) demonstrated that the CNN-LSTM-DNN method can accurately predict the RUL of Lithium-ion batteries using data from a battery degradation test. The study found that the hybrid method outperformed traditional machine learning algorithms such as Support Vector Regression and Random Forest Regression. Another study by Li et al. (2020) used a similar approach to predict the RUL of Lithium-ion batteries based on data from a cycling test. The study also found that the CNN-LSTM-DNN method provided more accurate predictions than traditional machine learning algorithms. Overall, these studies suggest that the CNN-LSTM-DNN hybrid method is a feasible approach for RUL assessment of Lithium-ion batteries.

While the CNN-LSTM-DNN method shows promise for RUL assessment of Lithium-ion batteries, there are also potential risks and limitations to consider. One potential risk is the need for large amounts of data to train the deep learning model. This may be challenging for some applications where data collection is difficult or expensive. Another risk is the possibility of overfitting the model to the training data, which can lead to poor generalization performance on new data. Another limitation is the computational complexity of the CNN-LSTM-DNN method, which may require significant computing resources and processing time. This may make the method less practical for real-time applications or for use on resourceconstrained devices. Additionally, the CNN-LSTM-DNN method may not be suitable for all types of Lithium-ion batteries or for all operating conditions. Battery chemistry, temperature, and other factors can impact battery degradation and RUL, and these factors may need to be accounted for in the model.

Overall, while the CNN-LSTM-DNN hybrid method shows promise for RUL assessment of Lithium-ion batteries, it is important to carefully consider the risks and limitations before implementing the method in practice.

3.2 SOFTWARE REQUIREMENTS SPECIFICATION DOCUMENT

HARDWARE REQUIREMENTS

- System : Acer 2.4 GHz
- Hard Disk : 200GB
- Mouse : Acer
- Keyboard : 110 keys enhanced
- Ram : 4GB

SOFTWARE REQUIREMENTS

- Operating System : Windows 10.
- Language : Python
- Front End : Anaconda Navigator – Jupyter notebook

3.3 SYSTEM USE CASE

USE CASE DIAGRAM

In Fig 3.1 use case diagram is designed to predict the remaining useful life of lithium-ion batteries using a hybrid method of Convolutional Neural Network , Long Short-Term Memory , and Deep Neural Network . The system takes input from battery sensors and analyses the battery performance data to estimate the RUL of the battery. The system can be used in a variety of applications such as electric vehicles, renewable energy systems, and portable electronic devices.

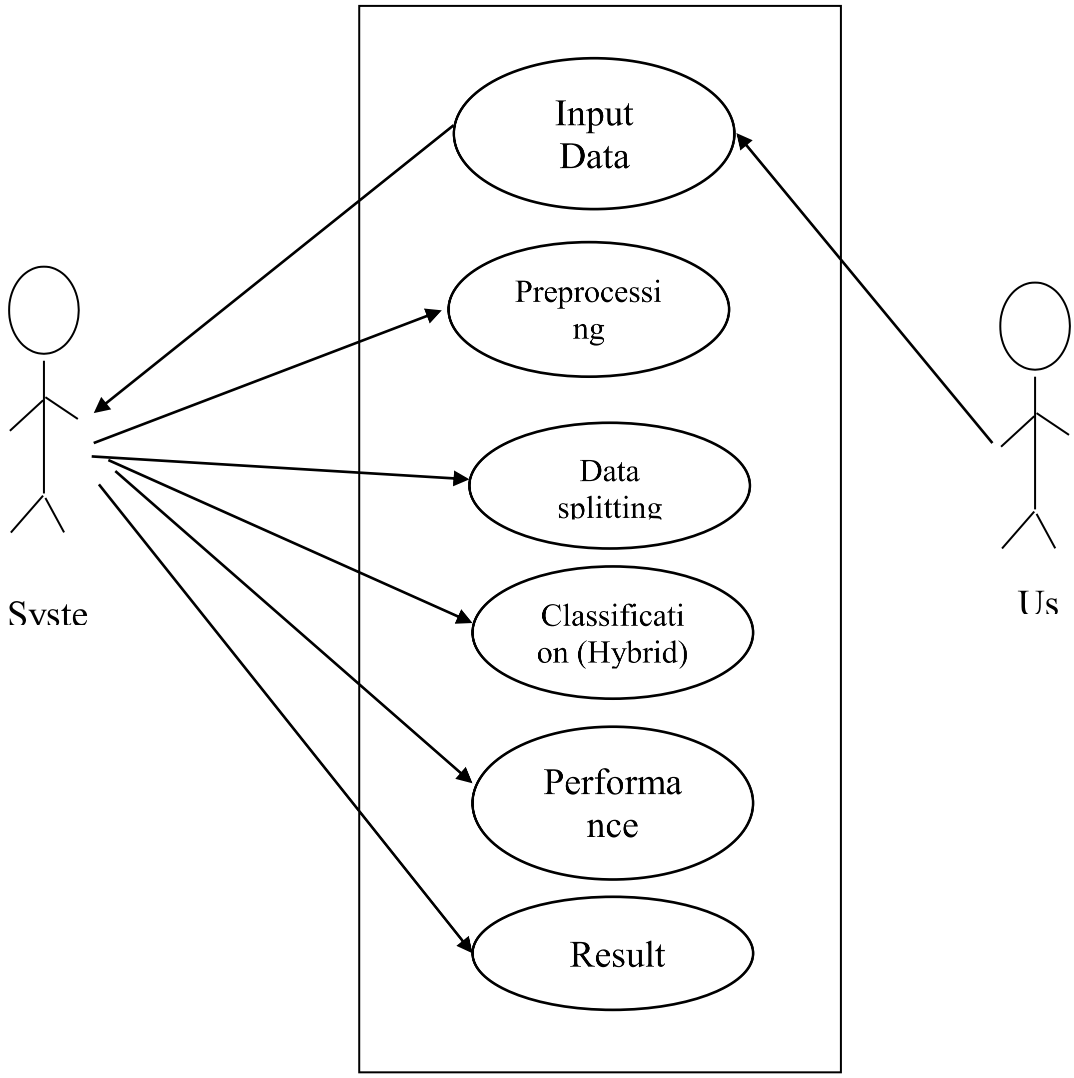


Fig 3.1 – Use-Case Diagram

ACTIVITY DIAGRAM

In Fig 3.2 activity diagram for remaining useful life assessment for lithium ion batteries using a CNN-LSTM-DNN hybrid method includes several key steps. The first step involves collecting data from the battery, including voltage and current measurements, temperature readings, and other relevant parameters. The collected data is then pre-processed , which involves cleaning and processing it to ensure that it is in a suitable format for analysis. The next step involves training the CNN-LSTM-DNN hybrid model using the pre-processed data, which includes using the CNN layers to extract relevant features from the input data, the LSTM layers to model the temporal dependencies in the data, and the DNN layers to perform the remaining useful life prediction. Once the model is trained, it is validated for accuracy and performance using test data. Finally, the trained and validated model is used to predict the remaining useful life of the lithium ion battery based on the input data, including voltage, current, and temperature measurements.

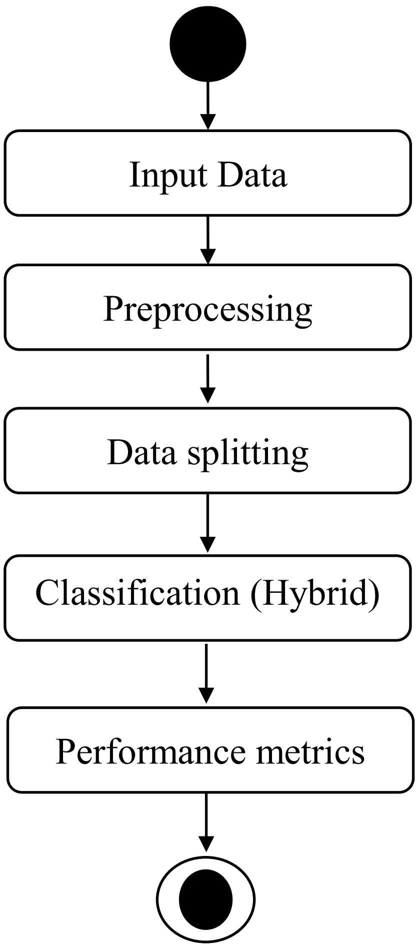


Fig 3.2 – Activity Diagram

SEQUENCE DIAGRAM

In Fig 3.3 sequence diagram for remaining useful life assessment for lithium ion batteries using a CNN-LSTM-DNN hybrid method illustrates the interactions and sequence of events between the actors and the system. The diagram typically begins with the data collection step, in which the actor responsible for collecting data from the battery sends a request to the system to collect the data. The system then responds by collecting the requested data and sending it back to the actor. The collected data is then preprocessed by the system, which involves filtering out noisy data, scaling the data, and converting it into a suitable format for the CNN-LSTM-DNN hybrid model. Next, the system trains the hybrid model using the preprocessed data, which involves multiple layers of processing including CNN, LSTM, and DNN. Once the model is trained, the system validates its accuracy and performance using test data. Finally, the system predicts the remaining useful life of the lithium ion battery based on the input data, including voltage, current, and temperature measurements

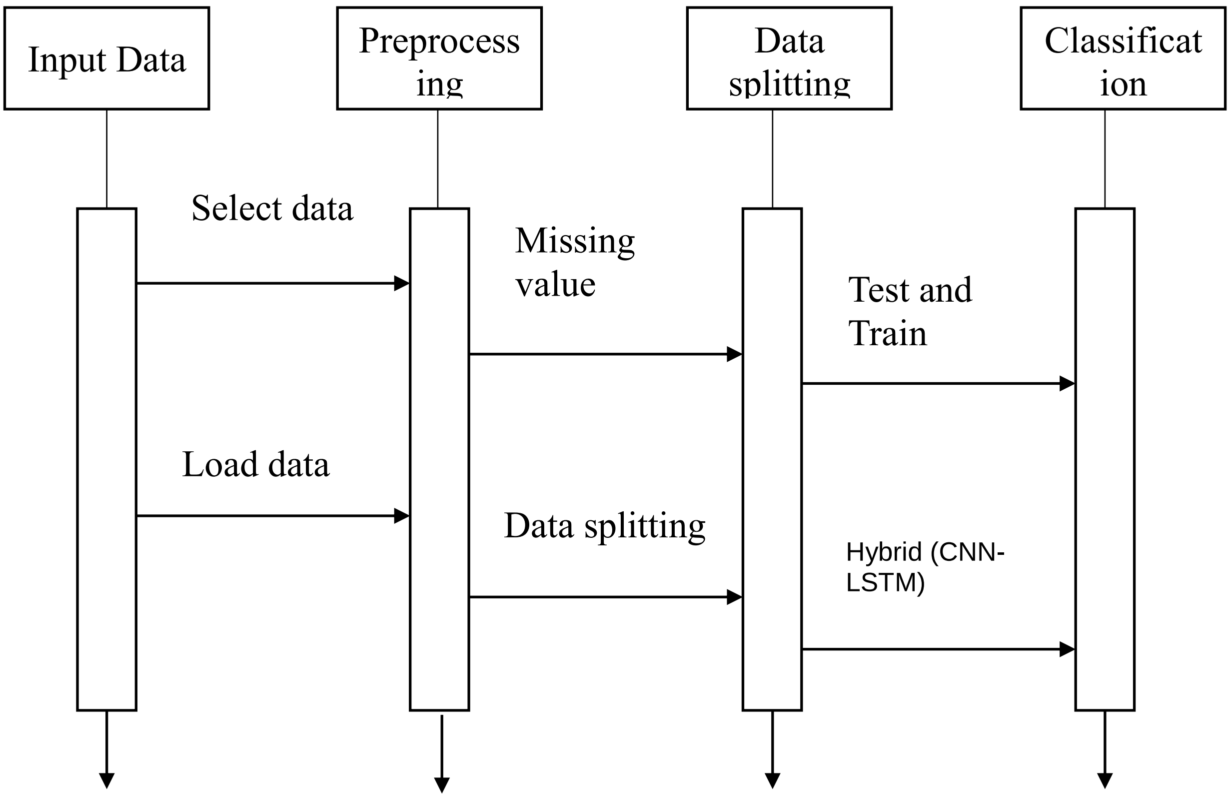


Fig 3.3: Sequence Diagram

ER DIAGRAM

In Fig 3.4 Entity-Relationship diagram for remaining useful life assessment for lithium ion batteries using a CNN-LSTM-DNN hybrid method would typically include entities such as "Battery," "Data," "Model," and "Prediction." The Battery entity would include attributes such as "Battery ID," "Capacity," and "Manufacturer." The Data entity would include attributes such as "Voltage," "Current," "Temperature," and "Time Stamp." The Model entity would include attributes such as "Model ID," "Training Data," and "Validation Data." The Prediction entity would include attributes such as "Remaining Useful Life" and "Prediction Timestamp." The relationships between the entities would be depicted using arrows and symbols, such as a diamond for a many-to-many relationship and a line for a one-to-many relationship. For example, the Battery entity would have a one-to-many relationship with the Data entity, as a single battery can have multiple data points collected from it over time. The Data entity would have a many-to-one relationship with the Model entity, as multiple data points are used to train the model.

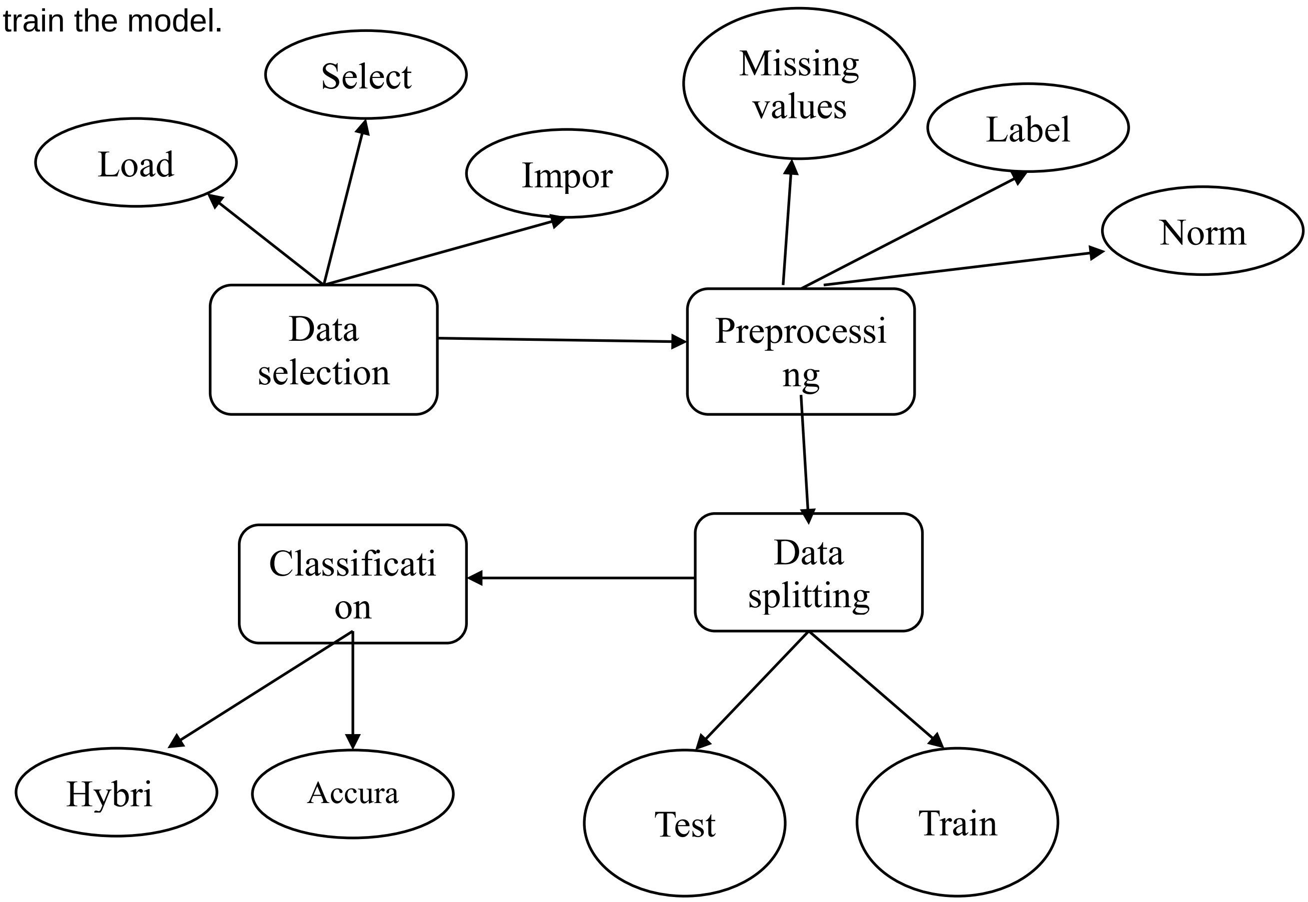


Fig 3.4 – ER Diagram

CLASS DIAGRAM

In Fig 3.5 class diagram for remaining useful life assessment for lithium ion batteries using a CNN-LSTM-DNN hybrid method would typically include classes such as "Battery," "Data Preprocessor," "Model Trainer," and "Expect Engine." The Battery class would include attributes such as "batteryID" and "battery Capacity," as well as methods such as "getVoltage()" and "getCurrent()." The Data Preprocessor class would include methods such as "filterData()" and "scaleData()," which are used to preprocess the input data before feeding it into the CNN-LSTM-DNN hybrid model. The ModelTrainer class would include methods such as "trainModel()" and "validateModel()," which are used to train and validate the model using preprocessed data. Finally, the expect Engine class would include methods such as "RemainingUsefulLife()," which uses the trained and validated model to predict the remaining useful life of the battery based on the input data.

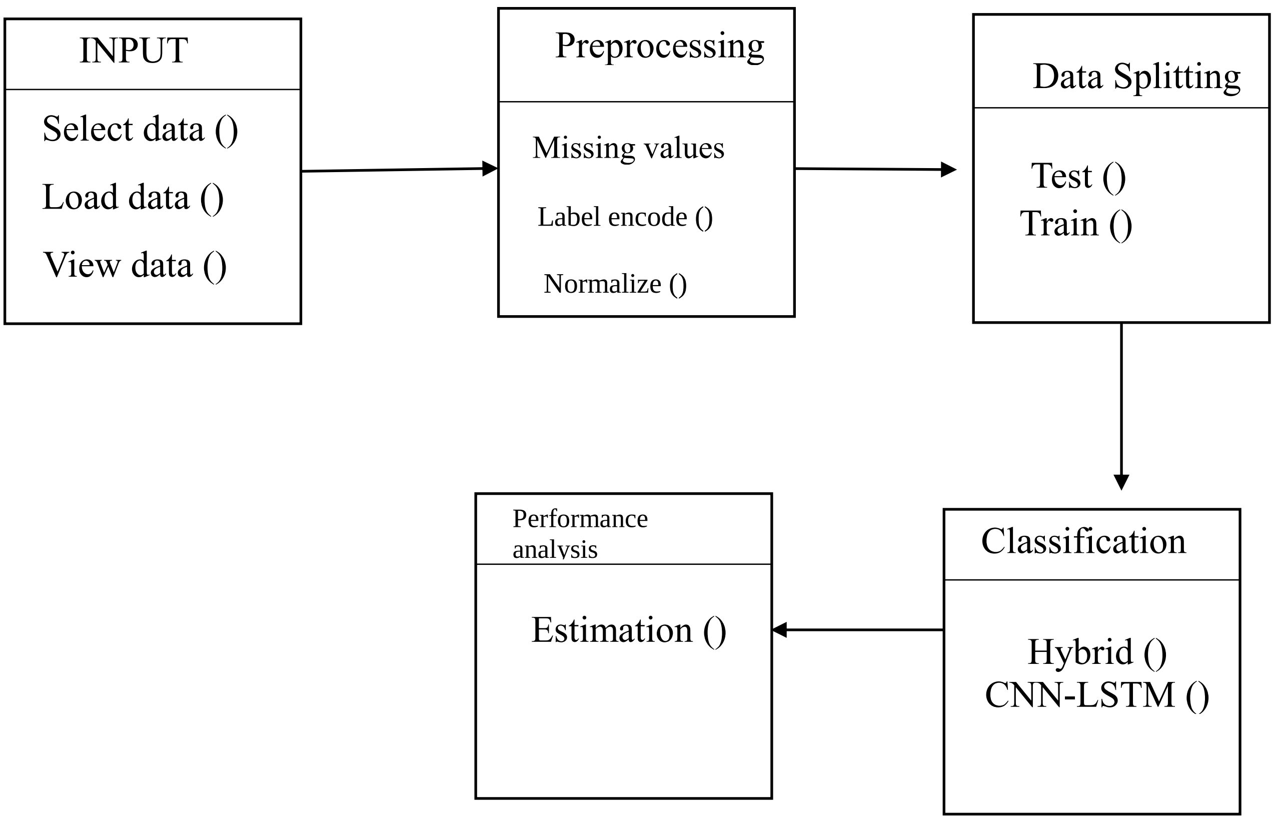


Fig 3.5 : Class Diagram

CHAPTER 4

DESCRIPTION OF PROPOSED SYSTEM

4.1.SELECTED METHODOLOGY

In this system, the CALCE dataset was taken as input. The input data was taken from the dataset repository. We have to take the four batteries such as CS2_33, CS2_34, CS2_36 and CS2_37. Then, we have to implement the data pre-processing step. In this step, we have to handle the missing values for avoid wrong identification, and to drop the unwanted columns because it is not required for our process. Then, we have to split the dataset into test and train. The data is splitting is based on ratio. In train, most of the data's will be there. In test, smaller portion of the data's will be there. Training portion is used to evaluate the model and testing portion is used to identify the model. Then, we have to implement the classification algorithm deep learning. The deep learning algorithms such as Convolutional Neural Network and long short Term Memory . A hybrid CNN-LSTM algorithm is suggested by combining two well-known algorithms, i.e. Convolutional Neural Networks and Long Short Term Memory , to estimate the battery's Remaining Useful Life and improve the long-term performance of lithium-ion batteries. Experimental validation is performed using the dataset of different lithium-ion batteries from CALCE. Finally, the experimental results shows that the some performance metrics such as MAE, MSE, R squared and RMSE. Then, we have to evaluate the results for four batteries from our input dataset.

In order to predict the RUL of lithium-ion batteries, it is necessary to analyze the battery discharge data in detail. Since CNN extracts potential hidden information from the data and LSTM can solve the long-term dependence of time series data, we combine the advantages of these two algorithms and apply to the study of RUL of lithium-ion batteries. By comparing the battery capacity decline curves at different temperatures, different discharge voltages and different discharge currents, we can obtain the external factors affecting the lifetime of lithium-ion batteries and find out the most relevant variables to the battery capacity decline. That is, the essential attributes are extracted from the many influencing factors, and a battery capacity decay model is established to achieve the prediction of RUL of lithium-ion batteries. To this end, a CNN-LSTM based fusion model is designed in this paper. It combines CNN and LSTM models to complement their advantages and accurately and effectively predict the RUL of lithium-ion batteries.

The Keras library is usually used in traditional research to stack CNN and LSTM models. This paper analyzes the model principle and improves the structure of the CNN-LSTM fusion model based on the principles of CNN and LSTM algorithms. A lithium-ion battery RUL prediction model based on CNN-LSTM is designed. The flow chart of the model is shown in Figure .

ADVANTAGES

- It is efficient for large number of datasets.
- The experimental result is high when compared with existing system.
- Time consumption is low.

The remaining useful life assessment for lithium-ion batteries is an important task to ensure the reliable operation of battery systems. The CNN-LSTM-DNN hybrid method is a powerful approach to predict the RUL of lithium-ion batteries, as it combines the strengths of convolutional neural networks , long short-term memory networks, and deep neural networks to improve the accuracy of the prediction. This methodology involves collecting data from the battery system, preprocessing it to remove noise and extract relevant features, training the hybrid model using the preprocessed data, validating the model, predicting the RUL, and making maintenance decisions based on the predicted RUL. With its ability to take into account the complex relationships between the battery's operating parameters, the CNN-LSTM-DNN hybrid method provides an effective solution to RUL assessment and helps to ensure the optimal use and maintenance of lithium-ion batteries.

Overall, the CNN-LSTM-DNN hybrid method is an effective way to assess the RUL of lithium-ion batteries, as it can take into account complex relationships between the battery's various operating parameters and provide accurate predictions for better maintenance decision-making.

4.2 ARCHITECTURE / OVERALL DESIGN OF PROPOSED SYSTEM

In the Fig 4.1 system architecture of the remaining useful life assessment for lithium-ion batteries using the CNN-LSTM-DNN hybrid method involves several components. Firstly, the data acquisition component collects data from the battery system, including charging and discharging current, voltage, and temperature. The pre-processing component cleans and processes the data to remove noise and ensure that it is in a suitable format for the CNN-LSTM-DNN model. The feature extraction component identifies relevant patterns in the data that can be used to predict the RUL. The CNN-LSTM-DNN model is trained using the preprocessed data and extracted features. The validation component tests the trained model using validation data to ensure its accuracy and robustness. The RUL prediction component uses the trained model to predict the RUL of the battery system based on its current state and history. Finally, the maintenance decision-making component utilizes the predicted RUL to make maintenance decisions, such as scheduling maintenance or replacement of the battery.

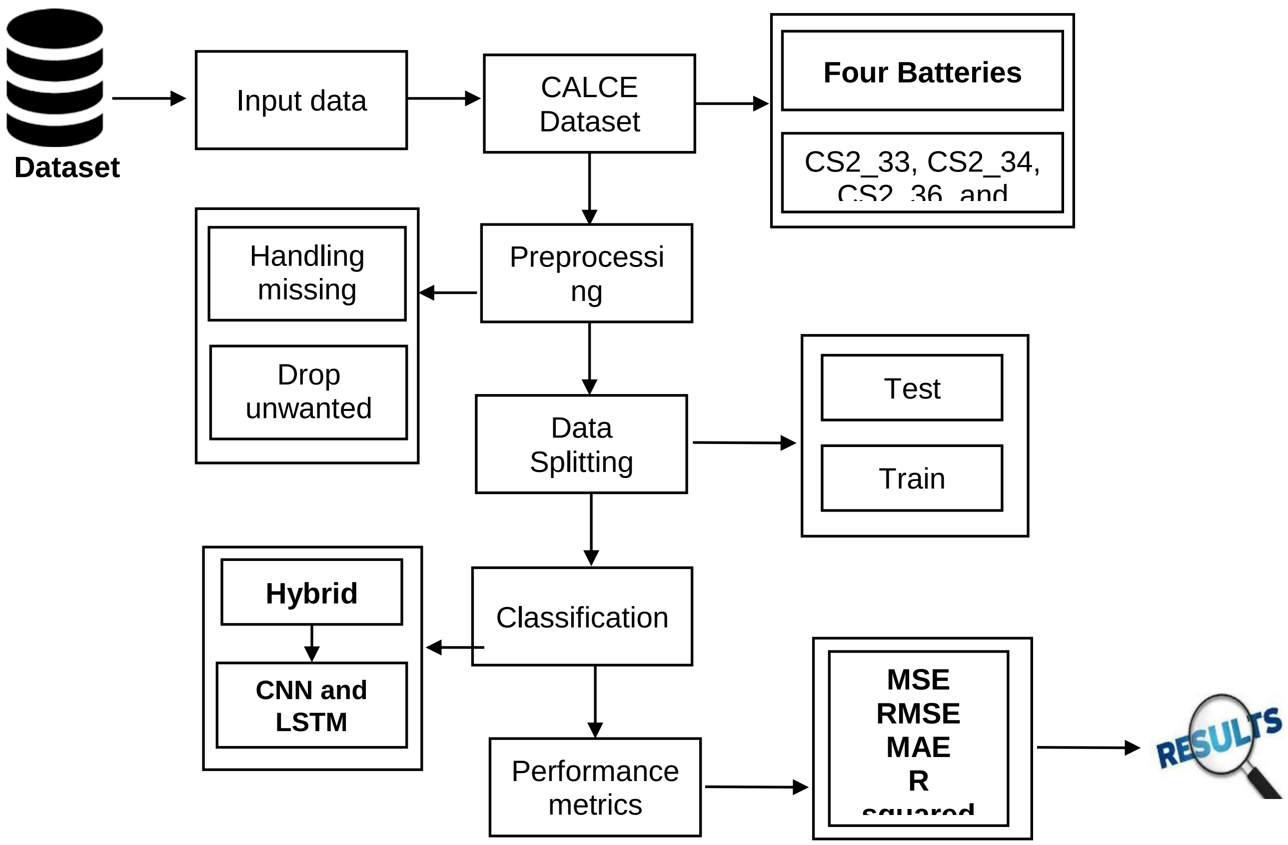


Fig 4.1: System Architecture

FLOW DIAGRAM :

In the Fig 4.2 Flow diagram of the remaining useful life assessment for lithium-ion batteries using the CNN-LSTM-DNN hybrid method consists of several stages. Firstly, the data collection stage acquires data from the battery system, which is then preprocessed to remove any noise and ensure that it is in a suitable format for the CNN-LSTM-DNN model. The feature extraction stage identifies relevant patterns in the preprocessed data that can be used to predict the RUL. The validation stage tests the trained model using validation data to ensure its accuracy and robustness. The RUL prediction stage utilizes the trained model to predict the RUL of the battery system based on its current state and history. Finally, the maintenance decision-making stage uses the predicted RUL to make maintenance decisions, such as scheduling maintenance or replacement of the battery. The flow diagram of the RUL assessment for lithium-ion batteries using the CNN-LSTM-DNN hybrid method is designed to provide a clear and concise overview of the process involved in predicting the battery's remaining useful life, from data collection to maintenance decision-making.

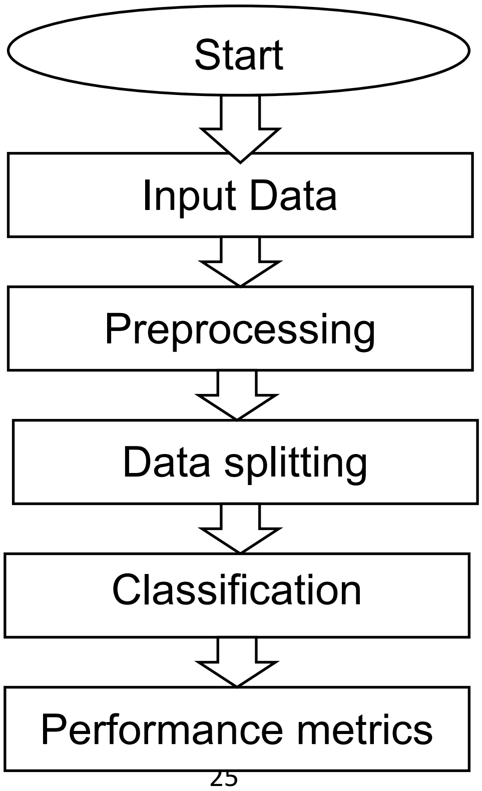


Fig 4.2: Flow Diagram

4.3 DESCRIPTION OF SOFTWARE FOR IMPLEMENTATION AND TESTING PLAN OF THE PROPOSED MODEL/SYSTEM

The software for implementation and testing plan of the proposed model for remaining useful life assessment for lithium-ion batteries using CNN-LSTM-DNN hybrid method can be described as follows:

1. **Programming Language and Libraries:** The software will be developed using Python programming language and will leverage several libraries such as TensorFlow, Keras, Pandas, and NumPy. These libraries are widely used in deep learning applications and will provide a solid foundation for the development of the proposed model.
2. **Data Preparation:** The software will require data on the health status and usage of the lithium-ion batteries. This data will be preprocessed to remove any outliers and normalize the data. The software will also generate training and validation datasets for the model.
3. **CNN-LSTM-DNN Hybrid Model:** The proposed model will consist of three main components - Convolutional Neural Network , Long Short-Term Memory network, and a Dense Neural Network . The CNN will be responsible for feature extraction, while the LSTM will capture the temporal dependencies in the data. The DNN will perform the final prediction of the remaining useful life of the battery.
4. **Training and Testing:** The software will perform training and testing of the proposed model using the prepared datasets. The model will be trained using a set of hyperparameters such as learning rate, batch size, and number of epochs. The model's performance will be evaluated using various metrics such as accuracy, precision, recall, and F1-score.
5. **Deployment:** Once the model has been trained and tested, it will be deployed as a standalone software or integrated into an existing battery

management system. The software will provide real-time predictions of the remaining useful life of the lithium-ion batteries.

PLATFORM SPECIFICATION – JUPYTER NOTEBOOK

Jupyter Notebook is an open-source web application that allows users to create and share documents that contain live code, equations, visualizations, and narrative text. It supports several programming languages, including Python, R, and Julia, and provides an interactive computing environment for data analysis, scientific research, and machine learning.

The platform specification for Jupyter Notebook can be described as follows:

1. **Installation:** Jupyter Notebook can be installed on various platforms, including Windows, macOS, and Linux. The installation process involves downloading and installing the Anaconda distribution, which includes Jupyter Notebook, along with other essential data science libraries.
2. **User Interface:** Jupyter Notebook has a user-friendly web-based interface that provides a dashboard for creating, opening, and managing notebooks. The interface includes a code editor, a markdown editor, and a preview window for visualizing the output of code and markdown cells.
3. **Notebook Structure:** Jupyter Notebook consists of a series of cells that can contain code, markdown, or raw text. The cells can be executed individually or as a group, and their outputs can be displayed inline or in a separate window.
4. **Collaboration:** Jupyter Notebook supports collaboration by allowing multiple users to edit and share notebooks in real-time. The notebooks can be saved and shared as HTML or PDF files or uploaded to cloud-based platforms such as GitHub or Google Drive.
5. **Integration:** Jupyter Notebook can be integrated with various data science tools and libraries, including NumPy, Pandas, Matplotlib, and Scikit-Learn. It

also supports interactive data visualization libraries such as Bokeh and Plotly.

6. **Extensions:** Jupyter Notebook supports a wide range of extensions that can enhance its functionality, including themes, keyboard shortcuts, and custom widgets.

4.3.1 Python

Python is one of those rare languages which can claim to be both simple and powerful. You will find yourself pleasantly surprised to see how easy it is to concentrate on the solution to the problem rather than the syntax and structure of the language you are programming in. The official introduction to Python is Python is an easy to learn, powerful programming language. It has efficient high-level data structures and a simple but effective approach to object-oriented programming. Python's elegant syntax and dynamic typing, together with its interpreted nature, make it an ideal language for scripting and rapid application development in many areas on most platforms. I will discuss most of these features in more detail in the next section.

Features of Python

Simple

Python is a simple and minimalistic language. Reading a good Python program feels almost like reading English, although very strict English! This pseudo-code nature of Python is one of its greatest strengths. It allows you to concentrate on the solution to the problem rather than the language itself.

Easy to Learn

As you will see, Python is extremely easy to get started with. Python has an extraordinarily simple syntax, as already mentioned.

Free and Open Source

Python is an example of a Free/Libré and Open Source Software. In simple terms, you can freely distribute copies of this software, read its source code, make changes to it, and use pieces of it in new free programs. FLOSS is based on the concept of a community which shares knowledge. This is one of the reasons why Python is so good - it has been created and is constantly improved by a community who just want to see a better Python.

High-level Language

When you write programs in Python, you never need to bother about the low-level details such as managing the memory used by your program, etc.

Portable

Due to its open-source nature, Python has been ported to (i.e. changed to make it work on) many platforms. All your Python programs can work on any of these platforms without requiring any changes at all if you are careful enough to avoid any system-dependent features.

You can use Python on GNU/Linux, Windows, FreeBSD, Macintosh, Solaris, OS/2, Amiga, AROS, AS/400, BeOS, OS/390, z/OS, Palm OS, QNX, VMS, Psion, Acorn RISC OS, VxWorks, PlayStation, Sharp Zaurus, Windows CE and PocketPC!

You can even use a platform like Kivy to create games for your computer *and* for iPhone, iPad, and Android.

Interpreted

This requires a bit of explanation.

A program written in a compiled language like C or C++ is converted from the source language i.e. C or C++ into a language that is spoken by your computer (binary code i.e. 0s and 1s) using a compiler with various flags and options. When you run the program, the linker/loader software copies the program from hard disk to memory and starts running it.

Python, on the other hand, does not need compilation to binary. You just *run* the program directly from the source code. Internally, Python converts the source code into an intermediate form called bytecodes and then translates this into the native language of your computer and then runs it. All this, actually, makes using Python much easier since you don't have to worry about compiling the program, making sure that the proper libraries are linked and loaded, etc.

Object Oriented

Python supports procedure-oriented programming as well as object-oriented programming. In procedure-oriented languages, the program is built around procedures or functions which are nothing but reusable pieces of programs. In object-oriented languages, the program is built around objects which combine data and functionality. Python has a very powerful but simplistic way of doing OOP, especially when compared to big languages like C++ or Java.

Extensible

If you need a critical piece of code to run very fast or want to have some piece of algorithm not to be open, you can code that part of your program in C or C++ and then use it from your Python program.

Embeddable

You can embed Python within your C/C++ programs to give *scripting* capabilities for your program's users.

Extensive Libraries

The Python Standard Library is huge indeed. It can help you do various things involving regular expressions, documentation generation, unit testing, threading, databases, web browsers, CGI, FTP, email, XML, XML-RPC, HTML, WAV files, cryptography, GUI (graphical user interfaces), and other system-dependent stuff. Remember, all this is always available wherever Python is installed. This is called the *Batteries Included* philosophy of Python.

Besides the standard library, there are various other high-quality libraries which you can find at the Python Package Index.

TESTING PRODUCTS

System testing is the stage of implementation, which aimed at ensuring that system works accurately and efficiently before the live operation commence. Testing is the process of executing a program with the intent of finding an error. A good test case is one that has a high probability of finding an error. A successful test is one that answers a yet undiscovered error.

Testing is vital to the success of the system. System testing makes a logical assumption that if all parts of the system are correct, the goal will be successfully achieved. . A series of tests are performed before the system is ready for the user acceptance testing. Any engineered product can be tested in one of the following ways. Knowing the specified function that a product has been designed to from, test can be conducted to demonstrate each function is fully operational. Knowing the internal working of a product, tests can be conducted to ensure that “al gears mesh”, that is the internal operation of the product performs according to the specification and all internal components have been adequately exercised.

UNIT TESTING

Unit testing is the testing of each module and the integration of the overall system is done. Unit testing becomes verification efforts on the smallest unit of software design in the module. This is also known as 'module testing'.

The modules of the system are tested separately. This testing is carried out during the programming itself. In this testing step, each model is found to be working satisfactorily as regard to the expected output from the module. There are some validation checks for the fields. For example, the validation check is done for verifying the data given by the user where both format and validity of the data entered is included. It is very easy to find error and debug the system.

4.4 PROJECT MANAGEMENT PLAN

A project management plan for a remaining useful life assessment of lithium-ion batteries using the CNN-LSTM-DNN hybrid method could include the following components:

1. **Project Scope:** Define the purpose of the project, including the objectives, deliverables, and timeline.
2. **Project Team:** Identify the project team members, their roles and responsibilities, and the reporting structure.
3. **Project Schedule:** Develop a detailed project schedule that includes milestones, tasks, and deadlines.
4. **Risk Management:** Identify potential risks associated with the project, develop mitigation strategies, and implement a risk management plan.
5. **Data Collection and Preprocessing:** Define the data collection process, including the sources of data, data preprocessing methods, and data cleaning techniques.
6. **Model Development:** Develop the CNN-LSTM-DNN hybrid method for remaining useful life assessment of lithium-ion batteries, including data training, validation, and testing.
7. **Model Validation and Testing:** Evaluate the accuracy and reliability of the developed model, including model performance metrics and validation techniques.

8. **Reporting and Communication:** Develop a reporting and communication plan to ensure stakeholders are kept informed throughout the project.
9. **Project Closure:** Document the results of the project, including any lessons learned, and close out the project.
10. **Budget and Resource Management:** Define the project budget, resource allocation, and resource management plan.

A project management plan for remaining useful life assessment for lithium-ion batteries using CNN-LSTM-DNN hybrid method involves a structured approach to achieving the project's objectives. The project team will start by defining the project's scope and objectives, identifying the key stakeholders, and developing a project charter. The project charter will include the project's goals, timeline, budget, and resources required to complete the project successfully.

Once the project charter is in place, the team will proceed to the planning phase, which involves breaking down the project into manageable tasks and developing a project schedule. This phase will also involve identifying the risks associated with the project and developing a risk management plan. The team will then move to the execution phase, where the actual work of developing the CNN-LSTM-DNN hybrid method will take place.

During the execution phase, the team will collect and analyze data on lithium-ion batteries, including their usage patterns and performance characteristics. They will use this data to develop and train the hybrid model, which will then be tested and validated against real-world data. Once the model is validated, it will be deployed to perform remaining useful life assessments on lithium-ion batteries.

The final phase of the project will be the closure phase, where the team will evaluate the project's success and document any lessons learned. They will also hand over the project deliverables to the stakeholders and obtain feedback on the project's performance. The project's success will be measured based on how well the developed hybrid model can accurately predict the remaining useful life of lithium-ion batteries.

In summary, a project management plan for remaining useful life assessment for lithium-ion batteries using CNN-LSTM-DNN hybrid method will involve defining the project scope, developing a project charter, planning the project, executing the project, and closing the project. The success of the project will depend on the accuracy of the developed hybrid model and its ability to predict the remaining useful life of lithium-ion batteries.

4.5 FINANCIAL REPORT ON ESTIMATED COSTING

The cost of performing a remaining useful life assessment for lithium-ion batteries using a hybrid approach that includes convolutional neural networks , long short-term memory networks, and deep neural networks can depend on several factors, such as:

1. **Data collection and preparation:** Collecting data on the battery's usage, environmental conditions, and other relevant factors can require significant effort and resources. The data may need to be cleaned, filtered, and preprocessed before it can be used for training the hybrid model, which can add to the cost.
2. **Model development and training:** Developing and training a hybrid model that combines CNNs, LSTMs, and DNNs can require specialized skills and expertise. The cost can depend on the complexity of the model, the size of the training dataset, and the computing resources needed for training.
3. **Validation and testing:** Validating and testing the hybrid model can involve using a separate dataset to evaluate its accuracy and performance. The cost can depend on the size of the validation and testing dataset and the resources needed for evaluation.
4. **Integration and deployment:** Integrating the hybrid model into an existing battery management system or deploying it as a standalone tool can involve

additional costs, such as software development and testing, hardware integration, and user interface design.

It is important to note that while the cost of the project can be significant, the benefits of accurately predicting the remaining useful life of lithium-ion batteries can outweigh the cost. A reliable and accurate prediction can help extend the battery's lifespan, reduce downtime and maintenance costs, and improve the overall performance of the battery system. This, in turn, can lead to cost savings and increased efficiency for various applications, such as electric vehicles, renewable energy storage systems, and mobile devices.

In conclusion, the cost of performing a remaining useful life assessment for lithium-ion batteries using a CNN-LSTM-DNN hybrid method can depend on several factors, including data collection and preparation, model development and training, validation and testing, integration and deployment, duration of the project, and personnel involved. While the cost can be significant, the potential benefits of accurate prediction of the remaining useful life of lithium-ion batteries can justify the cost and provide significant cost savings and efficiency improvements in various applications.

4.6 SOFTWARE TO OPERATIONS PLAN

The software to operations plan for a REMAINING USEFUL LIFE ASSESSMENT FOR LITHIUM-ION BATTERIES USING CNN-LSTM-DNN HYBRID METHOD can be broken down into the following stages:

1. **Planning and scoping:** Define the project goals, timelines, and requirements for the remaining useful life assessment. Identify the necessary data sources and the hardware and software infrastructure required for the deployment of the hybrid model.
2. **Development and testing:** Develop the hybrid model using CNN-LSTM-DNN architecture and perform thorough testing to ensure the model is accurate and performs well under various scenarios. This step may involve working with real-world data, simulating battery usage scenarios, and tuning the model based on the results of the testing.
3. **Integration and deployment:** Integrate the hybrid model into the battery management system and test it in a controlled environment. Ensure that the

model can interface with other systems and hardware that are required for the assessment. Set up automated data collection and analysis systems to support the model.

4. **Pilot testing:** Implement the hybrid model in a small-scale pilot test, ensuring that it is performing as expected in the actual environment. Gather feedback from users and stakeholders, and refine the model as necessary.
5. **Scaling and monitoring:** Expand the use of the hybrid model to other batteries in the fleet or other installations. Monitor the performance of the model and ensure that it continues to meet the requirements and goals of the assessment. Implement a maintenance and monitoring plan to ensure that the system remains operational and up-to-date.
6. **Continuous improvement:** Regularly review and analyze the performance of the hybrid model and its impact on battery operations. Use the data and feedback to identify areas for improvement and refine the model accordingly.

The software to operations plan is critical in ensuring the ongoing success and performance of the remaining useful life assessment for lithium-ion batteries using CNN-LSTM-DNN hybrid method. By following this plan, the project team can ensure that the hybrid model is effectively integrated into the production environment, thoroughly tested and validated, and continuously monitored, maintained, and optimized for ongoing performance and accuracy.

CHAPTER 5

IMPLEMENTATION DETAILS

5.1 DEVELOPMENT AND DEPLOYMENT SETUP

The development and deployment setup for the remaining useful life assessment of lithium-ion batteries using CNN-LSTM-DNN hybrid method is a critical aspect of the project management plan. This setup involves identifying the hardware and software requirements for developing and deploying the hybrid model.

The development and deployment setup includes the following components:

1. **Hardware requirements:** The hardware requirements for developing and deploying the hybrid model depend on the size of the training dataset and the complexity of the model. A powerful CPU or GPU is typically required for training the model, as well as sufficient memory and storage for storing the dataset and the trained model.
2. **Software requirements:** The software requirements for developing and deploying the hybrid model include programming languages and libraries for deep learning, such as Python, TensorFlow, and Keras. Other software tools may also be required for data preprocessing, model evaluation, and deployment.
3. **Data collection and preparation:** The data collection and preparation setup involves identifying the data sources, collecting the data, and

preparing it for training the hybrid model. This may involve cleaning, filtering, and preprocessing the data, as well as labeling it for supervised learning.

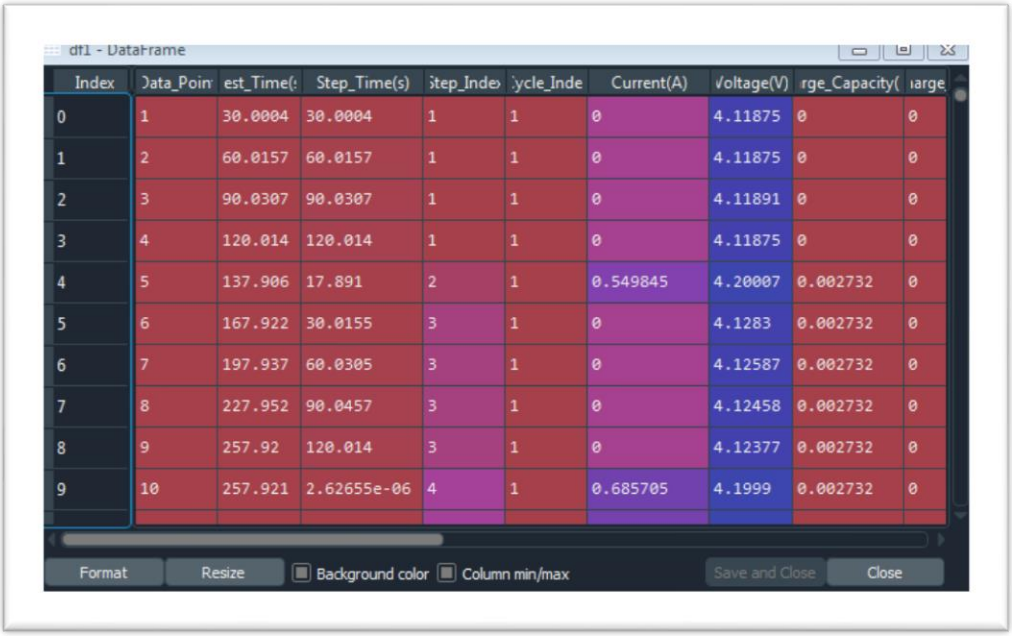
4. **Model development and training:** The model development and training setup involves selecting the appropriate architecture for the hybrid model and training it on the prepared dataset. This may involve experimenting with different model architectures and hyperparameters to optimize the model's performance.
5. **Model evaluation:** The model evaluation setup involves evaluating the accuracy and performance of the trained model on a separate validation dataset. This may involve using performance metrics such as mean absolute error, Root Mean Square error, and R-squared to assess the model's performance.
6. **Deployment:** The deployment setup involves deploying the trained model into a production environment, integrating it into the existing battery management system, and testing its performance and accuracy in real-world scenarios.

5.1.1 DATA SELECTION

- The input data was collected 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.
- The data selection is the process of the remaining useful life for lithium ion batteries.
- All CS2 cells underwent the same charging profile which was a standard constant current/constant voltage protocol with a constant current rate of 0.5C until the voltage reached 4.2V and then 4.2V was sustained until the charging current dropped to below 0.05A.
- Unless specified, the discharge cut off voltage for these batteries was 2.7V.
- All the CS2 cells were randomly numbered and named accordingly. Name 'CS2_n' was given for the nth numbered CS2 cell.

Data selection- CS2_33

This CS2_33 data shows Cycle index feature represents the number of charge/discharge cycles that the battery has gone through since the start of the measurement period . Capacity feature represents the maximum charge that the battery can hold, and is typically measured in units of ampere-hours (Ah).Voltage feature represents the electrical potential difference between the positive and negative terminals of the battery, and is typically measured in units of volts (V).Temperature feature represents the temperature of the battery during the measurement period, and is typically measured in units of degrees Celsius (°C).Current feature represents the electrical current flowing into or out of the battery during the measurement period, and is typically measured in units of amperes (A).



df1 - DataFrame

Index	Data_Poin	est_Time(	Step_Time(s)	Step_Inde	ycle_Inde	Current(A)	Voltage(V)	rge_Capacity(	iarge
0	1	30.0004	30.0004	1	1	0	4.11875	0	0
1	2	60.0157	60.0157	1	1	0	4.11875	0	0
2	3	90.0307	90.0307	1	1	0	4.11891	0	0
3	4	120.014	120.014	1	1	0	4.11875	0	0
4	5	137.906	17.891	2	1	0.549845	4.20007	0.002732	0
5	6	167.922	30.0155	3	1	0	4.1283	0.002732	0
6	7	197.937	60.0305	3	1	0	4.12587	0.002732	0
7	8	227.952	90.0457	3	1	0	4.12458	0.002732	0
8	9	257.92	120.014	3	1	0	4.12377	0.002732	0
9	10	257.921	2.62655e-06	4	1	0.685705	4.1999	0.002732	0

Format Resize Background color Column min/max Save and Close Close

Fig 5.1 CS2_33

Data selection -CS2_34

Index	Data_Poin	est_Time(	Step_Time(s)	Step_Inde	Cycle_Inde	Current(A)	Voltage(V)	rge_Capacity(	harge
0	1	30.0004	30.0004	1	1	0	3.86896	0	0
1	2	60.0157	60.0157	1	1	0	3.86896	0	0
2	3	90.034	90.034	1	1	0	3.86896	0	0
3	4	120.014	120.014	1	1	0	3.86896	0	0
4	5	150.015	30.0002	2	1	0.549885	4.00317	0.00458496	0
5	6	180.03	60.0153	2	1	0.550066	4.01612	0.00917146	0
6	7	210.045	90.0306	2	1	0.550247	4.02437	0.013758	0
7	8	240.06	120.046	2	1	0.550066	4.03004	0.0183445	0
8	9	270.078	150.064	2	1	0.550247	4.03457	0.0229329	0
9	10	300.091	180.076	2	1	0.550429	4.03814	0.0275213	0

Fig 5.2 CS2_34

The CS2_34 dataset is another commonly used dataset for the remaining useful life assessment of lithium-ion batteries using CNN-LSTM-DNN hybrid method. This dataset contains information on the test time, step index, cycle index, current, voltage, and charge capacity of lithium-ion batteries over time. Cycle index feature represents the number of charge/discharge cycles that the battery has gone through since the start of the measurement period.Capacity feature represents the maximum charge that the battery can hold, and is typically measured in units of ampere-hours (Ah).Voltage feature represents the electrical potential difference between the positive and negative terminals of the battery, and is typically measured in units of volts (V).Temperature feature represents the temperature of the battery during the measurement period, and is typically measured in units of degrees Celsius (°C).Current feature represents the electrical current flowing into or out of the battery during the measurement period, and is typically measured in units of amperes (A).

Data selection -CS2_36

df3 - DataFrame

Index	Data_Poin	est_Time(	Step_Time(s)	Step_Inde	Cycle_Inde	Current(A)	Voltage(V)	rge_Capacity(	arg
0	1	30.0151	30.0152	1	1	0	3.77114	0	0
1	2	60.0304	60.0304	1	1	0	3.7713	0	0
2	3	90.0458	90.0458	1	1	0	3.77147	0	0
3	4	120.013	120.013	1	1	0	3.7713	0	0
4	5	150.014	30.0004	2	1	0.549971	3.86379	0.00458392	0
5	6	180.029	60.0156	2	1	0.550153	3.87529	0.00917005	0
6	7	210.044	90.0307	2	1	0.549971	3.8829	0.0137562	0
7	8	240.062	120.048	2	1	0.550153	3.88841	0.0183427	0
8	9	270.075	150.061	2	1	0.549971	3.89246	0.0229289	0
9	10	300.09	180.077	2	1	0.550153	3.89618	0.0275155	0

Format Resize Background color Column min/max Save and Close Close

Fig 5.3 CS2_36

The CS2_36 dataset is commonly used dataset for the remaining useful life assessment of lithium-ion batteries using CNN-LSTM-DNN hybrid method. This dataset contains information on the test time, step index, cycle index, current, voltage, and temperature of lithium-ion batteries over time. Cycle index feature represents the number of charge/discharge cycles that the battery has gone through since the start of the measurement period.Capacity feature represents the maximum charge that the battery can hold, and is typically measured in units of ampere-hours (Ah).Voltage feature represents the electrical potential difference between the positive and negative terminals of the battery, and is typically measured in units of volts (V).Temperature feature represents the temperature of the battery during the measurement period, and is typically measured in units of degrees Celsius (°C).Current feature represents the electrical current flowing into or out of the battery during the measurement period, and is typically measured in units of amperes (A).

Data selection -CS2_37

df4 - DataFrame

Index	ata_Poin	est_Time(	Step_Time(s)	tep_Inde	ycle_Inde	Current(A)	Voltage(V)	rge_Capacity(	iarge
0	1	30.0009	30.0009	1	1	0	3.88057	0	0
1	2	60.0162	60.0162	1	1	0	3.88057	0	0
2	3	90.0339	90.0339	1	1	0	3.88057	0	0
3	4	120.014	120.014	1	1	0	3.88057	0	0
4	5	150.015	30.0004	2	1	0.549928	3.97463	0.00458293	0
5	6	180.031	60.0158	2	1	0.550108	3.98792	0.00916823	0
6	7	210.046	90.0309	2	1	0.549928	3.99652	0.0137535	0
7	8	240.061	120.046	2	1	0.550108	4.00268	0.0183386	0
8	9	270.076	150.061	2	1	0.549928	4.00738	0.022924	0
9	10	300.092	180.077	2	1	0.550108	4.01144	0.0275093	0

Format Resize Background color Column min/max Save and Close Close

Fig 5.4 CS2_37

The CS2_37 dataset is another commonly used dataset for the remaining useful life assessment of lithium-ion batteries using CNN-LSTM-DNN hybrid method. This dataset contains information on the test time, step index, cycle index, current, voltage, and temperature of lithium-ion batteries over time. Cycle index feature represents the number of charge/discharge cycles that the battery has gone through since the start of the measurement period.Capacity feature represents the maximum charge that the battery can hold, and is typically measured in units of ampere-hours (Ah).Voltage feature represents the electrical potential difference between the positive and negative terminals of the battery, and is typically measured in units of volts (V).Temperature feature represents the temperature of the battery during the measurement period, and is typically measured in units of degrees Celsius (°C).Current feature represents the electrical current flowing into or out of the battery during the measurement period, and is typically measured in units of amperes (A).

TABLE I

THE DESCRIPTION OF NASA LITHIUM-ION BATTERIES

Battery	Type	Constant charge current	Minimal charge current	Discharge current	Rated capacity	Charge/Discharge cut-off voltage
B5	18650 NMC	1.5A	20mA	2A	2Ah	4.2/2.7V
B6	18650 NMC	1.5A	20mA	2A	2Ah	4.2/2.5V
B7	18650 NMC	1.5A	20mA	2A	2Ah	4.2/2.3V
B18	18650 NMC	1.5A	20mA	2A	2Ah	4.2/2.5V

TABLE II

THE DESCRIPTION OF CALCE LITHIUM-ION BATTERIES

Battery	Constant current rate CC	Minimal charge current	Constant current discharge	Rated capacity	Charge/discharge Cut-off voltage
CS2_33	0.5C	0.05A	0.5C	1.1Ah	4.2/2.7V
CS2_34	0.5C	0.05C	0.5C	1.1Ah	4.2/2.7V
CS2_36	0.5C	0.05C	1C	1.1Ah	4.2/2.7V
CS2_37	0.5C	0.05C	1C	1.1Ah	4.2/2.7V

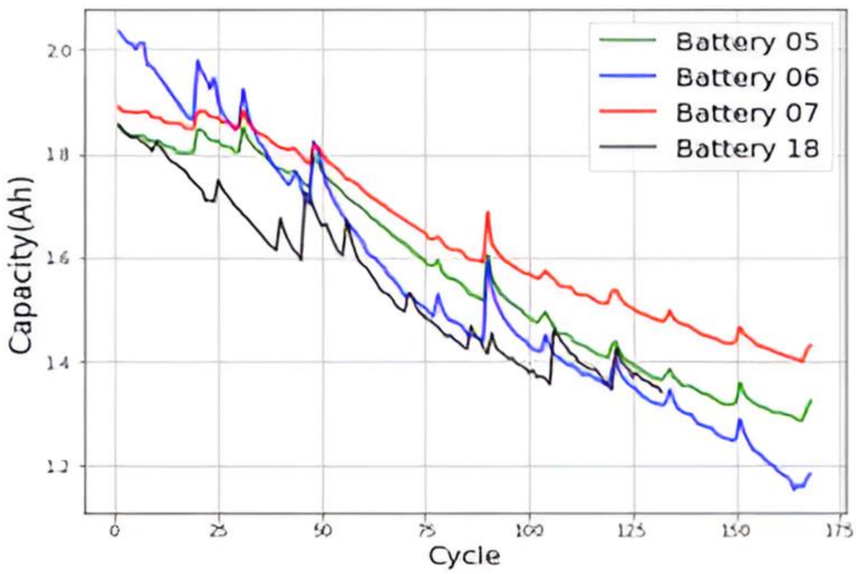


Fig 5.5 Capacity degradation curve of NASA batteries

This table 1 shows the description of NASA lithium ion batteries ,battery type, constant charge current, minimal charge current ,discharge current ,rated capacity, charge / discharge cut-off voltage .

This table 2 shows the description of calce lithium-ion batteries ,in that the content are battery, constant current rate CC , Minimal charge current ,constant current discharge , rated capacity , charge / discharge cut-off voltage.

This graph shows the Cycle and Capacity(Ah) of the Battery 05 , Battery 06 , Battery 07, Battery 18.

5.1.2 DATA PREPROCESSING

- Data pre-processing is the process of removing the unwanted data from the dataset.
- Pre-processing data transformation operations are used to transform the dataset into a structure suitable for machine learning.
- This step also includes cleaning the dataset by removing irrelevant or corrupted data that can affect the accuracy of the dataset, which makes it more efficient.
- 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 0.
- Missing and duplicate values were removed and data was cleaned of any abnormalities.
- Encoding Categorical data: That categorical data is defined as variables with a finite set of label values.
- That most machine learning algorithms require numerical input and output variables.

5.1.3 DATA SPLITTING

- During the machine learning process, data are needed so that learning can take place.
- In addition to the data required for training, test data are needed to evaluate the performance of the algorithm in order to see how well it works.
- In our process, we considered 70% of our input dataset to be the training data and the remaining 30% to be the testing data.
- Data splitting is the act of partitioning available data into two portions, usually for cross-validator purposes.
- One Portion of the data is used to develop a predictive model and the other to evaluate the model's performance.
- Separating data into training and testing sets is an important part of evaluating data mining models.
- Typically, when you separate a data set into a training set and testing set, most of the data is used for training, and a smaller portion of the data is used for testing.

5.1.4 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 combine the CNN and LSTM hybrid model.
- LSTM Long short-term memory is an artificial recurrent neural network architecture used in the field of deep learning.
- Unlike standard feed forward neural networks, LSTM has feedback connections.
- It can not only process single data points, but also entire sequences of data.
- LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series
- A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable

weights and biases) to various aspects/objects in the image and be able to differentiate one from the other.

- The CNN follows a hierarchical model which works on building a network, like a funnel, and finally gives out a fully-connected layer where all the neurons are connected to each other and the output is processed.

In order to improve the model's accuracy and reliability, the data was preprocessed before being utilised for training the ml model. Normalizing the data, resampling the data, and extracting features were all part of the preprocessing stages. Data was standardised such that it had a mean of zero & a standards variation of one, which assisted eliminate bias and provide a consistent basis for analysis. To lessen the computational burden of training the model, we resampled the data to a frequency of 1 minute. The dataset's most relevant characteristics were extracted through feature selection for use in model training at the end. Voltage level, amperage, & thermistors were among the characteristics picked.

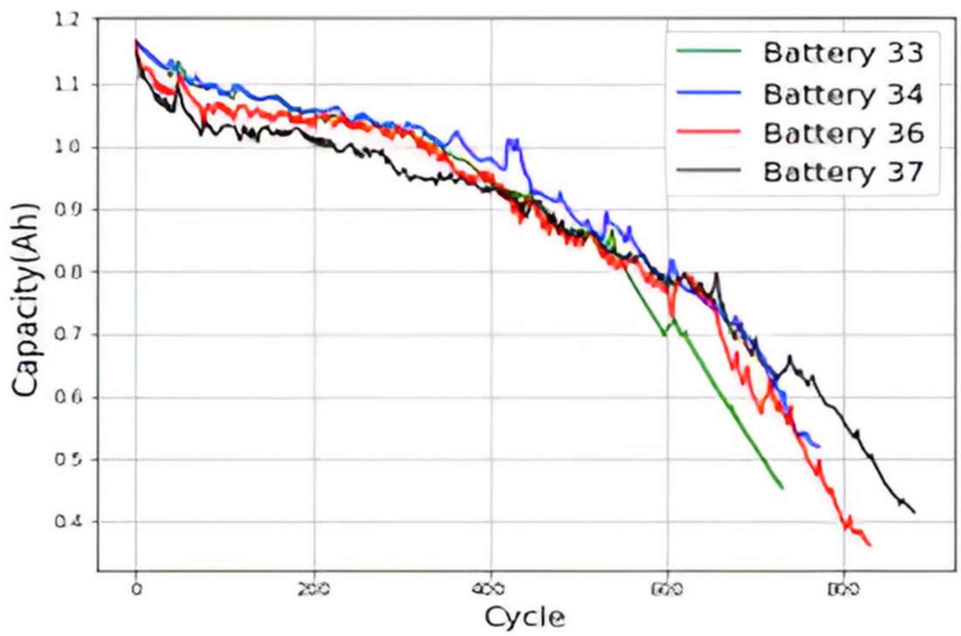


Fig 5.6 Capacity degradation curve of CALCE batteries

When the data was cleaned and organised, it was divided into a training set and a testing set. Seventy percent of the total data was utilised for the training set, while the other thirty was put to good use in the validation phase. To prevent overfitting the model and guarantee that the training and verification sets were sufficiently representative of the full dataset, they were chosen at random.

5.2 ALGORITHMS

- CNN
- LSTM
- DNN

Convolutional Neural Networks can be used in remaining useful life assessment for lithium-ion batteries using CNN-LSTM-DNN hybrid methods. CNNs can extract features from time series data, such as voltage and current measurements over time, that can be indicative of the battery's health and remaining useful life.

In this hybrid method, the CNN is used as a feature extractor, which takes in the time series data and extracts the most important features from it. These features are then passed to the Long Short-Term Memory layer, which is a type of recurrent neural network that is well-suited for time series analysis. The LSTM layer can learn the temporal dependencies and patterns in the time series data, which are important for predicting the remaining useful life of the battery.

Finally, the output from the LSTM layer is passed to the Deep Neural Network layer, which performs the final classification or prediction based on the extracted features and temporal dependencies. The DNN layer can provide more accurate predictions of the battery's remaining useful life, as it takes into account both the extracted features and the temporal dependencies in the data.

Overall, the CNN-LSTM-DNN hybrid method can provide more accurate and reliable predictions of the remaining useful life of lithium-ion batteries, which can be crucial for efficient battery management and maintenance.

5.3 TESTING

VALIDATION TESTING

After the culmination of black box testing, software is completed assembly as a package, interfacing errors have been uncovered and corrected and final series of software validation tests begin validation testing can be defined as many, But a single definition is that validation succeeds when the software functions in a manner that can be reasonably expected by the customer.

USER ACCEPTANCE TESTING

User acceptance of the system is the key factor for the success of the system. The system under consideration is tested for user acceptance by constantly keeping in touch with prospective system at the time of developing changes whenever required.

OUTPUT TESTING

After performing the validation testing, the next step is output asking the user about the format required testing of the proposed system, since no system could be useful if it does not produce the required output in the specific format. The output displayed or generated by the system under consideration. Here the output format is considered in two ways. One is screen and the other is printed format. The output format on the screen is found to be correct as the format was designed in the system phase according to the user needs. For the hard copy also output comes out as the specified requirements by the user. Hence the output testing does not result in any connection in the system.

5.3.1TESTING TECHNIQUES/STRATEGIES

WHITE BOX TESTING

White Box testing is a test case design method that uses the control structure of the procedural design to drive cases. Using the white box testing methods, we Derived test cases that guarantee that all independent paths within a module have been exercised at least once.

BLACK BOX TESTING

1. Black box testing is done to find incorrect or missing function
2. Interface error
3. Errors in external database access
4. Performance errors.
5. Initialization and termination errors

In ‘functional testing’, is performed to validate an application conforms to its specifications of correctly performs all its required functions. So this testing is also called ‘black box testing’. It tests the external behaviour of the system. Here the engineered product can be tested knowing the specified function that a product has been designed to perform, tests can be conducted to demonstrate that each function is fully operational.

CHAPTER 6

RESULTS AND DISCUSSION

The Final Result will get generated based on the overall classification and prediction. The performance of this proposed approach is evaluated using some measures like,

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

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

Where:

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

- **MSE:** The mean squared error is a common way to measure the identification accuracy of a model. It is calculated as:

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

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 is a metric that tells us how far apart our identify values are from our observed values in a model, on average. It is calculated as:

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

Where:

- Σ is a fancy symbol that means "sum"
- P_i is the predicted value for the i^{th} observation
- O_i is the observed value for the i^{th} observation
- n is the sample size

A. Use of statistical measures to assess the validity of the suggested approach

Many statistical measures, including as MSE, MAE, R2, and RMSE, were used to assess the performance of the suggested hybrid CNN-LSTM-DNN technique. These metrics are often used in the assessment of ML models' efficacy. According on the findings, the suggested technique outperformed other ML estimation methods.

B. Comparison to Other ML Estimation Algorithms

Several ML estimation techniques, including SVR, MLP, and LSTM. DNNs, were pitted against the proposed hybrid CNN-LSTM-DNN approach. The findings demonstrated that the suggested technique performed better than the other methods, demonstrating its superiority in predicting the remaining usable life of Lithium-ion batteries.

C. Analysis of the performance of the hybrid CNN-LSTM-DNN method

The investigation of the CNN-LSTM-DNN hybrid method's performance indicated that it significantly decreased identification mistakes and obtained better RUL identification performance than other approaches. The hybrid model's performance was enhanced by the extraction of spatial and temporal characteristics from the input data using a CNN & LSTM.

D. A discussion of the possible uses and limits of the suggested approach

The suggested hybrid CNN-LSTM-DNN approach may find use in a number of fields that now depend on Lithium-ion batteries, including but not limited to: electric cars, aircraft, and renewable energy systems. Safer and more reliable operation, lower maintenance costs, and longer battery life are all possible thanks to early problem identification and precise predictions of remaining usable life.

The suggested technique, however, does have a few restrictions. The training and validation data have a direct impact on the model's precision. Also, the suggested approach may not work with other battery kinds or under alternative circumstances of operation. Consequently, further study is required to assess the efficiency of the suggested strategy in a variety of settings.

The combined PSO-SVR model of traditional machine learning algorithm SVR and group intelligence algorithm PSO, ARIMA-SVR model of SVR and time series prediction model ARIMA [44], BP network model and LSTM model of deep learning algorithm are designed experimentally. The prediction effect of the proposed CNN-LSTM fusion model is compared with the model mentioned above and two deep learning algorithms on three data sets. Figure 7 shows the performance of variousprediction models in B0005, B0006, and B0007 data sets.

Since PSO is only a parameter optimization algorithm, the SVR mentioned in the experiment refers to the PSO-SVR algorithm. Figure 7 shows that the two models combined with SVR and the traditional machine learning algorithm in the three data sets have relatively poor prediction results. For example, in the B0006 data set, the BP model always deviates from the actual value in the late prediction period. In contrast, the LSTM and CNN-LSTM fusion models fit the test set well.

Specifically, each model learns more or less about the trend of residual capacity degradation. The traditional machine learning algorithm, SVR, cannot fit expected values well even though it optimizes parameters by the PSO particle swarm algorithm. Though the fusion model of SVR and ARIMA can predict the data development trend, there is some delay in the model, and the trend cannot be predicted in real-time. Meanwhile, the prediction results for the non-linear change process of the data could be better. That is, the fluctuation characteristics of the residual battery capacity due to the recovery effect are not learned. BP, LSTM and

CNN-LSTM three neural network models have better fitting results than the two models of support vector machine. The BP neural network deviates in different degrees in the middle and late prediction and fits well in the B0005 data set. However, there is a specific deviation in the B0006 data set later prediction. Deviations occur on B0007 data sets from the mid- term and accumulate into large deviations at later stages, which do not converge to the failure threshold. LSTM and CNN-LSTM are better for long-term prediction than the BP network model and have better prediction stability for different datasets. LSTM and CNN-LSTM are better for long-term prediction than the BP network model and have better prediction stability for different data sets.

The lifetime endpoints of LSTM and CNN-LSTM in the B0005 dataset are almost identical to the actual values, approximately discharging in the 124th cycle. However, the BP network with a good fit fall near the 135 discharge cycles due to large fluctuations near the failure threshold. The RUL errors of SVR and ARIMA-SVR are more significant than those of the BP network. On the B0006 data set, the RUL predicted by SVR is quite different from the actual value, and the life endpoints predicted by LSTM and CNN-LSTM are still accurate. Surprisingly, ARIMA-VR with poor fit is more accurate than the BP network in predicting EOL. It is known that if the capture requirements of data characteristics are not high and the accuracy of prediction is only required at a particular time, the ARIMA-SVR fusion model can be used, which also provides evidence for the feasibility of the fusion model. On the B0007 battery data set, ARIMA-SVR, LSTM, and CNN-LSTM are still the best predictors of remaining life. However, the BP network and SVR cannot converge near the failure threshold. Because the BP and SVR-related models need to be revised for long-term data learning during training. For this reason, the LSTM model enhances the learning of long-term data. So LSTM model and CNN-LSTM model can effectively fit the fluctuations of actual data in performance.

CHAPTER 7

CONCLUSION

7.1 CONCLUSION

In this paper, we combine the advantages of CNN and LSTM and propose a fusion model based on CNN and LSTM for RUL prediction of lithium batteries. First, the main factors of the battery that affect the RUL degradation are screened as the HI of the battery using grey relational analysis. Then the data are processed in a specific way to extract the features of the 1D lithium-ion battery data usingTime Distribute wrapping CNN layer for each time step. In addition, the data was entered into the LSTM layer through a fully connected layer wrapped in Time Distribute to analyze the long-term changes in the battery data and build a RUL prediction model for lithium-ion batteries. The proposed model has been experimented on the NASA lithium-ion batteries dataset compared to the traditional machine and single deep learning models. The experimental results show that the proposed CNN- LSTM fusion model can effectively monitor the capacity degradation process of lithium-ion batteriesand can accurately predict the failure threshold of the RUL for batteries, considering the battery relaxation effect. In addition, the CNN-LSTM model shows the most robust performance in MAPE, MSE and RULerror compared with the benchmark model, verifying that the deep learning model outperforms the machine learning model.In general, the multi-model fusion approach is superior to a single model. Our proposed RUL prediction model for lithium-ion batteries can effectively predict the current battery capacity and avoidsafety hazards caused by battery aging in practice. In addition, the final battery life is predicted basedon the battery relaxation effect, which helps users to correctly understand the RUL of the battery and save the usage cost.

7.2 FUTURE WORK

The future work of RUL is suggested to be architecture optimization, in order to reduce the training time, as well as further enhance the applicability for realistic operation scenarios. Moreover, the approach will be applied and evaluated to more sophisticated platforms with multiple components.

7.3 RESEARCH ISSUES

The remaining useful life (RUL) assessment of lithium-ion batteries is an important research area, as it can help predict when a battery will fail and allow for proactive maintenance or replacement. The CNN-LSTM-DNN hybrid method is a promising approach for RUL assessment, as it combines convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and deep neural networks (DNNs) to process the large amounts of data generated by battery sensors.

7.4 IMPLEMENTATION ISSUES

Implementing the CNN-LSTM-DNN hybrid method for RUL assessment of lithium-ion batteries involves several technical challenges. Here are some of the key implementation issues that need to be addressed:

Acquiring and pre-processing the data from the battery sensors is a critical first step in the implementation process. This involves collecting and cleaning the raw data, removing any noise or irrelevant information, and converting the data into a format that can be used by the neural network model.

Extracting the relevant features from the battery sensor data and selecting the best features for the CNN-LSTM-DNN model can be challenging. Several feature extraction and selection techniques can be used, including statistical analysis, principal component analysis (PCA), and wavelet transform

REFERENCES

[1] A. El Mejdoubi, H. Chaoui, H. Gualous, P. Van Den Bossche, N. Omar, and J. Van Mierlo, 'Lithium-ion batteries health prognosis considering aging conditions', IEEE Trans. Power Electron., vol. 34, no. 7, pp. 6834– 6844, 2019, doi: 10.1109/TPEL.2018.2873247.

[2] A. Ghosh and D. T. Veale, 'Fracking Sarcasm using Neural Network', pp. 161–169, 2016, doi: 10.18653/v1/w16-0425

[3] A. T. Martini, M. Farrukh, and H. Ge, 'Recognition of ironic sentences in twitter using attention-based LSTM', Int. J. Adv. Comput. Sci. Appl., vol. 9, no. 8, pp. 7–11, 2018, doi: 10.14569/ijacsa.2018.090802.

[4] Ali, M.U.; Zafar, A.; Nengroo, S.H.; Hussain, S.; Alvi, M.J.; Kim, H.J. Towards a Smarter Battery Management System for Electric Vehicle Applications: A Critical Review of Lithium-Ion Battery State of Charge Estimation. Energies 2019, 12, 446.

[5] B. Duan, Q. Zhang, F. Geng, and C. Zhang, 'Remaining useful life prediction of lithium-ion battery based on extended Kalman particle filter', Int. J. Energy Res., vol. 44, no. 3, pp. 1724–1734, 2020, doi: 10.1002/er.5002.

[6] D. Liu, J. Pang, J. Zhou, and Y. Peng, 'Data-driven prognostics for lithium-ion battery based on Gaussian process regression', Proc. IEEE 2012 Progn. Syst. Heal. Manag. Conf. PHM-2012, 2012, doi: 10.1109/PHM.2012.6228848.

[7] D. Liu, Y. Luo, Y. Peng, X. Peng, and M. Pecht, 'Lithium-ion battery remaining useful life estimation based on nonlinear AR model combined with degradation feature', Proc. Annu. Conf. Progn. Heal. Manag. Soc. 2012, PHM 2012, pp. 336–342, 2012.

[8] G. Ma, Y. Zhang, C. Cheng, B. Zhou, P. Hu, and Y. Yuan, 'Remaining useful life prediction of lithium-ion batteries based on false nearest neighbors and a hybrid neural network', Appl. Energy, vol. 253, no. July, p. 113626, 2019, doi: 10.1016/j.apenergy.2019.113626.

[9] H. Chaoui and C. C. Ibe-Ekeocha, 'State of Charge and State of Health Estimation for Lithium Batteries Using Recurrent Neural Networks', IEEE Trans. Veh. Technol., vol. 66, no. 10, pp. 8773–8783, 2017, doi: 10.1109/TVT.2017.2715333.

[10] Hussain Nengroo, S.; Umair Ali, M.; Zafar, A.; Hussain, S.; Murtaza, T.; Junaid Alvi, M.; Raghavendra, K.; Jee Kim, H. An Optimized Methodology for a Hybrid Photo-Voltaic and Energy Storage System Connected to a Low-Voltage Grid. Electronics 2019, 8, 176.

[11] Hussain, S.; Ali, M.U.; Nengroo, S.H.; Khan, I.; Ishfaq, M.; Kim, H.J. Semiactive Hybrid Energy Management System: A Solution for Electric Wheelchairs. Electronics 2019, 8, 345.

[12] J. Fan, J. Fan, F. Liu, J. Qu, and R. Li, 'A Novel Machine Learning Method Based Approach for Li-Ion Battery Prognostic and Health Management', IEEE Access, vol. 7, no. 1, pp. 160043–160061, 2019, doi: 10.1109/ACCESS.2019.2947843.

[13] J. Jia, J. Liang, Y. Shi, J. Wen, X. Pang, and J. Zeng, 'SOH and RUL prediction of lithium-ion batteries based on Gaussian process regression with indirect health indicators', Energies, vol. 13, no. 2, 2020, doi: 10.3390/en13020375.

[14] J. Zhu, T. Tan, L. Wu, and H. Yuan, 'RUL prediction of lithium-ion battery based on improved DGWO-ELM method in a random discharge rates environment', IEEE Access, vol. 7, pp. 125176–125187, 2019, doi: 10.1109/ACCESS.2019.2936822.

[15] L. Chen, L. Xu, and Y. Zhou, 'Novel approach for lithium-ion battery online remaining useful life prediction based on permutation entropy', Energies, vol. 11, no. 4, 2018, doi: 10.3390/en11040820.

[16] L. Zhao, Y. Wang, and J. Cheng, 'A hybrid method for remaining useful life estimation of lithium-ion battery with regeneration phenomena', Appl. Sci., vol. 9, no. 9, 2019, doi: 10.3390/app9091890.

[17] M. U. Ali, A. Zafar, S. H. Nengroo, S. Hussain, G. S. Park, and H. J. Kim, 'Online remaining useful life prediction for lithium-ion batteries using partial discharge data features', Energies, vol. 12, no. 22, 2019, doi: 10.3390/en12224366.

[18] Nengroo, S.; Kamran, M.; Ali, M.; Kim, D.H.; Kim, M.S.; Hussain, A.; Kim, H. Dual battery storage system: An optimized strategy for the utilization of renewable photovoltaic energy in the United Kingdom. Electronics 2018, 7, 177

[19] P. Kaladevi and K. Thyagarajah, ‘Integrated CNN- and LSTM-DNNbased sentiment analysis over big social data for opinion mining’, Behav. Inf. Technol., vol. 0, no. 0, pp. 1–9, 2019, doi: 10.1080/0144929X.2019.1699960.

[20] R. R. Richardson, M. A. Osborne, and D. A. Howey, ‘Gaussian process regression for forecasting battery state of health’, J. Power Sources, vol. 357, pp. 209–219, 2017, doi: 10.1016/j.jpowsour.2017.05.004.

[21] S. Zhang, B. Zhai, X. Guo, K. Wang, N. Peng, and X. Zhang, ‘Synchronous estimation of state of health and remaining useful lifetime for lithium-ion battery using the incremental capacity and artificial neural networks’, J. Energy Storage, vol. 26, no. July, p. 100951, 2019, doi: 10.1016/j.est.2019.100951.

[22] Tanaka, N. Technology Roadmap: Electric and Plug-in Hybrid Electric Vehicles; Technical Report; International Energy Agency: Paris, France, 2011.

[23] Umair Ali, M.; Hussain Nengroo, S.; Adil Khan, M.; Zeb, K.; Ahmad Kamran, M.; Kim, H.J. A real-time simulink interfaced fast-charging methodology of lithium-ion batteries under temperature feedback with fuzzy logic control. Energies 2018, 11, 1122.

[24] W. Luo, C. Lv, L. Wang, and C. Liu, ‘Study on impedance model of Liion battery’, Proc. 2011 6th IEEE Conf. Ind. Electron. Appl. ICIEA 2011, pp. 1943–1947, 2011, doi: 10.1109/ICIEA.2011.5975910.

[25] X. Hu, J. Jiang, D. Cao, and B. Egardt, ‘Battery health prognosis for electric vehicles using sample entropy and sparse Bayesian predictive modeling’, IEEE Trans. Ind. Electron., vol. 63, no. 4, pp. 2645–2656, 2016, doi: 10.1109/TIE.2015.2461523.

[26] X. Zhang, Q. Miao, and Z. Liu, ‘Remaining useful life prediction of lithium-ion battery using an improved UPF method based on MCMC’, Microelectron. Reliab., vol. 75, pp. 288–295, 2017, doi: 10.1016/j.microrel.2017.02.012.

[27] Y. Li, Y. He, and M. Zhang, ‘Prediction of Chinese energy structure based on Convolutional Neural Network-Long Short-Term Memory (CNNLSTM)’, Energy Sci. Eng., no. February, pp. 1–10, 2020, doi: 10.1002/ese3.698.

[28] Y. Zhang, R. Xiong, H. He, and M. G. Pecht, ‘Long short-term memory recurrent neural network for remaining useful life prediction of lithiumion batteries’, IEEE Trans. Veh. Technol., vol. 67, no. 7, pp. 5695–5705, 2018, doi: 10.1109/TVT.2018.2805189.

[29] Z. Wang, S. Zeng, J. Guo, and T. Qin, ‘Remaining capacity estimation of lithium-ion batteries based on the constant voltage charging profile’, PLoS One, vol. 13, no. 7, pp. 1–22, 2018, doi: 10.1371/journal.pone.0200169.

[30] Z. Xue, Y. Zhang, C. Cheng, and G. Ma, ‘Remaining useful life prediction of lithium-ion batteries with adaptive unscented kalman filter and optimized support vector regression’, Neurocomputing, vol. 376, pp. 95– 102, 2020, doi: 10.1016/j.neucom.2019.09.074.

APPENDIX

A.SOURCE CODE

```
#======================== IMPORT LIBRARIES
===========================

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from tensorflow.keras.layers import  Input,Dense
from tensorflow.keras.layers import Conv1D,MaxPooling1D
from tensorflow.keras.layers import LSTM
from tensorflow.keras.layers import  Dropout
from tensorflow.keras.models import Sequential
import matplotlib.pyplot as plt
from keras.layers import Activation



#========================= DATA SELECTION
===========================

#load the all input datasets
df1=pd.read_excel("CS2_33_1_10_11.xlsx")
df2=pd.read_excel("CS2_34_1_12_11.xlsx")
df3=pd.read_excel("CS2_36_1_10_11.xlsx")
df4=pd.read_excel("CS2_37_1_10_11.xlsx")

#concatenate all the data's into one variable
frames = [df1,df2,df3,df4]


for ij in range(0,4):

    frame_val = frames[ij]

    result = frame_val
#data selection
    print("Data selection")
    print()
    print(result.head(10))
```

```
#============================ DATA PREPROCESSING
==============================

#checking missing values
    print("==========================================")
    print("Checking Missing Values")
    print()
    print(result.isnull().sum())
    print()

#drop unwanted columns because it's not required for our process
    print("==========================================")
    print("Drop unwanted columns")
    print()
    result.drop('Date_Time',axis='columns', inplace=True)
    print(result.head(10))
    print()


#============================ DATA SPLITTING
==============================

    X=result.drop('Cycle_Index',axis=1)
    Y=result['Cycle_Index']

    X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.25,
random_state=2)



#========================== CNN_LSTM
==============================

    sequence_length = 15


    X=np.expand_dims(X_train, axis=2)
    Y=np.expand_dims(y_train,axis=1)

    nb_out = 1

#initialize the model
    model = Sequential()
    model.add(LSTM(input_shape=(15,1), units=100, return_sequences=True))
    model.add(Dropout(0.2))
    model.add(Conv1D(filters=32, kernel_size=3, padding='same', activation='relu'))
    model.add(MaxPooling1D(pool_size=2))
    model.add(LSTM(units=50, return_sequences=False))
    model.add(Dropout(0.2))
    model.add(Dense(units=nb_out))
```

```
    model.add(Activation("linear"))
    model.compile(loss="mse", optimizer="rmsprop", metrics=['mae','mse'])

#model summary
    print(model.summary())

#fitting the model
    model.fit(X, Y, epochs=10, batch_size=32, validation_split=0.1, verbose=1)

    history=model.history.history

    y_pred1 = model.predict(X)
    y_pred = (y_pred1 > 0.5)

    from sklearn import metrics


    print()

print("==============================================================
=")
    print()
    print("Performance metrics")
    print()
    print("Mean Absolute Error",metrics.mean_absolute_error(Y, y_pred1))
    print()
    print('Mean Squared Error:', metrics.mean_squared_error(Y, y_pred1))
    print()
    print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(Y,
y_pred1)))
    print()
    print("r squared:",100-(metrics.mean_absolute_error(Y, y_pred1)),'%')

#validation graph
    plt.plot(history['val_mae'])
    plt.plot(history['val_mse'])
    plt.title('CNN-LSTM==Performance analysis')
    plt.ylabel('Mean Absolute Error')
    plt.xlabel('Mean Squared Error')
    # plt.legend(['CNN-LSTM'], loc='upper right')
    plt.legend(['Validation MSE','Validation MAE'], loc='upper left')
        plt.show()
```

B.SCREENSHOTS

jupyter final year project code Last Checkpoint: 01/29/2023 (autosaved)

File Edit View Insert Cell Kernel Widgets Help   Not Trusted   Python 3 (ipykernel)

```python
for ij in range(0,4):

    frame_val = frames[ij]

    result = frame_val
#data selection
    print("Data selection")
    print()
    print(result.head(10))
```

```
Data selection

   Data_Point  Test_Time(s)            Date_Time  Step_Time(s)  Step_Index  \
0           1     30.000402  2011-01-03 10:38:25     30.000402           1
1           2     60.015662  2011-01-03 10:38:55     60.015662           1
2           3     90.030747  2011-01-03 10:39:25     90.030747           1
3           4    120.014300  2011-01-03 10:39:55    120.014301           1
4           5    137.905777  2011-01-03 10:40:13     17.890985           2
5           6    167.921706  2011-01-03 10:40:43     30.015485           3
6           7    197.936691  2011-01-03 10:41:13     60.030470           3
7           8    227.951948  2011-01-03 10:41:43     90.045727           3
8           9    257.920329  2011-01-03 10:42:13    120.014108           3
9          10    257.920792  2011-01-03 10:42:13      0.000003           4

   Cycle_Index  Current(A)  Voltage(V)  Charge_Capacity(Ah)  \
0            1    0.000000    4.118745             0.000000
1            1    0.000000    4.118745             0.000000
2            1    0.000000    4.118907             0.000000
3            1    0.000000    4.118745             0.000000
```


```
Data selection

   Data_Point  Test_Time(s)            Date_Time  Step_Time(s)  Step_Index  \
0           1     30.000402  2011-01-03 10:38:25     30.000402           1
1           2     60.015662  2011-01-03 10:38:55     60.015662           1
2           3     90.030747  2011-01-03 10:39:25     90.030747           1
3           4    120.014300  2011-01-03 10:39:55    120.014301           1
4           5    137.905777  2011-01-03 10:40:13     17.890985           2
5           6    167.921706  2011-01-03 10:40:43     30.015485           3
6           7    197.936691  2011-01-03 10:41:13     60.030470           3
7           8    227.951948  2011-01-03 10:41:43     90.045727           3
8           9    257.920329  2011-01-03 10:42:13    120.014108           3
9          10    257.920792  2011-01-03 10:42:13      0.000003           4
```

	Cycle_Index	Current(A)	Voltage(V)	Charge_Capacity(Ah) \
0	1	0.000000	3.868960	0.000000
1	1	0.000000	3.868960	0.000000
2	1	0.000000	3.868960	0.000000
3	1	0.000000	3.868960	0.000000
4	1	0.549885	4.003167	0.004585
5	1	0.550066	4.016119	0.009171
6	1	0.550247	4.024375	0.013758
7	1	0.550066	4.030041	0.018345
8	1	0.550247	4.034574	0.022933
9	1	0.550429	4.038136	0.027521

	Discharge_Capacity(Ah)	Charge_Energy(Wh)	Discharge_Energy(Wh) \
0	0.0	0.000000	0.0
1	0.0	0.000000	0.0
2	0.0	0.000000	0.0
3	0.0	0.000000	0.0
4	0.0	0.018303	0.0
5	0.0	0.036697	0.0
6	0.0	0.055137	0.0
7	0.0	0.073609	0.0
8	0.0	0.092111	0.0
9	0.0	0.110632	0.0

	dV/dt(V/s)	Internal_Resistance(Ohm)	Is_FC_Data	AC_Impedance(Ohm) \
0	-0.000032	0.0	0	0
1	0.000000	0.0	0	0
2	0.000000	0.0	0	0
3	0.000000	0.0	0	0
4	0.000453	0.0	0	0
5	0.000227	0.0	0	0
6	0.000194	0.0	0	0
7	0.000130	0.0	0	0
8	0.000097	0.0	0	0
9	0.000065	0.0	0	0

	ACI_Phase_Angle(Deg)
0	0
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0

	dV/dt(V/s)	Internal_Resistance(Ohm)	Is_FC_Data	AC_Impedance(Ohm) \
0	-0.000032	0.0	0	0
1	0.000000	0.0	0	0
2	0.000032	0.0	0	0
3	0.000032	0.0	0	0
4	0.000421	0.0	0	0
5	0.000227	0.0	0	0
6	0.000162	0.0	0	0
7	0.000130	0.0	0	0
8	0.000097	0.0	0	0
9	0.000097	0.0	0	0

	ACI_Phase_Angle(Deg)
0	0
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0

```
======================================
Checking Missing Values

Data_Point                  0
Test_Time(s)                0
Date_Time                   0
Step_Time(s)                0
Step_Index                  0
Cycle_Index                 0
Current(A)                  0
Voltage(V)                  0
Charge_Capacity(Ah)         0
Discharge_Capacity(Ah)      0
Charge_Energy(Wh)           0
Discharge_Energy(Wh)        0
dV/dt(V/s)                  0
Internal_Resistance(Ohm)    0
Is_FC_Data                  0
AC_Impedance(Ohm)           0
ACI_Phase_Angle(Deg)        0
dtype: int64
```

======================================

Drop unwanted columns

```
Drop unwanted columns

   Data_Point  Test_Time(s)  Step_Time(s)  Step_Index  Cycle_Index  \
0           1     30.000894     30.000895           1            1
1           2     60.016233     60.016234           1            1
2           3     90.033863     90.033863           1            1
3           4    120.014457    120.014458           1            1
4           5    150.015311     30.000411           2            1
5           6    180.030739     60.015840           2            1
6           7    210.045781     90.030882           2            1
7           8    240.060958    120.046058           2            1
8           9    270.076273    150.061373           2            1
9          10    300.091517    180.076617           2            1

   Current(A)  Voltage(V)  Charge_Capacity(Ah)  Discharge_Capacity(Ah)  \
0    0.000000    3.880573             0.000000                     0.0
1    0.000000    3.880573             0.000000                     0.0
2    0.000000    3.880573             0.000000                     0.0
3    0.000000    3.880573             0.000000                     0.0
4    0.549928    3.974627             0.004583                     0.0
5    0.550108    3.987924             0.009168                     0.0
6    0.549928    3.996518             0.013753                     0.0
7    0.550108    4.002680             0.018339                     0.0
8    0.549928    4.007383             0.022924                     0.0
9    0.550108    4.011437             0.027509                     0.0
```

```
   Charge_Energy(Wh)  Discharge_Energy(Wh)  dV/dt(V/s)  \
0           0.000000                   0.0   -0.000032
1           0.000000                   0.0   -0.000032
2           0.000000                   0.0   -0.000032
3           0.000000                   0.0    0.000000
4           0.018166                   0.0    0.000454
5           0.036424                   0.0    0.000259
6           0.054731                   0.0    0.000227
7           0.073070                   0.0    0.000195
8           0.091434                   0.0    0.000162
9           0.109819                   0.0    0.000130

   Internal_Resistance(Ohm)  Is_FC_Data  AC_Impedance(Ohm)  \
0                       0.0           0                  0
1                       0.0           0                  0
2                       0.0           0                  0
3                       0.0           0                  0
4                       0.0           0                  0
5                       0.0           0                  0
6                       0.0           0                  0
7                       0.0           0                  0
8                       0.0           0                  0
9                       0.0           0                  0

   ACI_Phase_Angle(Deg)
0                     0
1                     0
2                     0
3                     0
4                     0
5                     0
```

```
None
Epoch 1/10
234/234 [==============================] - 16s 27ms/step - loss: 344.0826 - mae: 14.4406 - mse: 344.0826 - val_loss: 190.4587 -
val_mae: 9.6688 - val_mse: 190.4587
Epoch 2/10
234/234 [==============================] - 4s 18ms/step - loss: 124.7914 - mae: 7.3617 - mse: 124.7914 - val_loss: 58.2543 - va
l_mae: 4.7912 - val_mse: 58.2543
Epoch 3/10
234/234 [==============================] - 4s 18ms/step - loss: 35.9407 - mae: 3.7232 - mse: 35.9407 - val_loss: 11.3038 - val_
mae: 2.2932 - val_mse: 11.3038
Epoch 4/10
234/234 [==============================] - 4s 17ms/step - loss: 10.3023 - mae: 2.1865 - mse: 10.3023 - val_loss: 1.9201 - val_m
ae: 0.9909 - val_mse: 1.9201
Epoch 5/10
234/234 [==============================] - 4s 18ms/step - loss: 6.7493 - mae: 1.8694 - mse: 6.7493 - val_loss: 4.4963 - val_ma
e: 2.0333 - val_mse: 4.4963
Epoch 6/10
234/234 [==============================] - 4s 17ms/step - loss: 6.0666 - mae: 1.7842 - mse: 6.0666 - val_loss: 2.1210 - val_ma
e: 1.2645 - val_mse: 2.1210
Epoch 7/10
234/234 [==============================] - 4s 17ms/step - loss: 5.9938 - mae: 1.7791 - mse: 5.9938 - val_loss: 0.8530 - val_ma
e: 0.8066 - val_mse: 0.8530
Epoch 8/10
234/234 [==============================] - 4s 17ms/step - loss: 5.6526 - mae: 1.7080 - mse: 5.6526 - val_loss: 0.6722 - val_ma
e: 0.6722 - val_mse: 0.6722
Epoch 9/10
234/234 [==============================] - 4s 19ms/step - loss: 5.6604 - mae: 1.7035 - mse: 5.6604 - val_loss: 0.4094 - val_ma
e: 0.4884 - val_mse: 0.4094
Epoch 10/10
234/234 [==============================] - 4s 18ms/step - loss: 5.4628 - mae: 1.6618 - mse: 5.4628 - val_loss: 0.9663 - val_ma
e: 0.8565 - val_mse: 0.9663
```

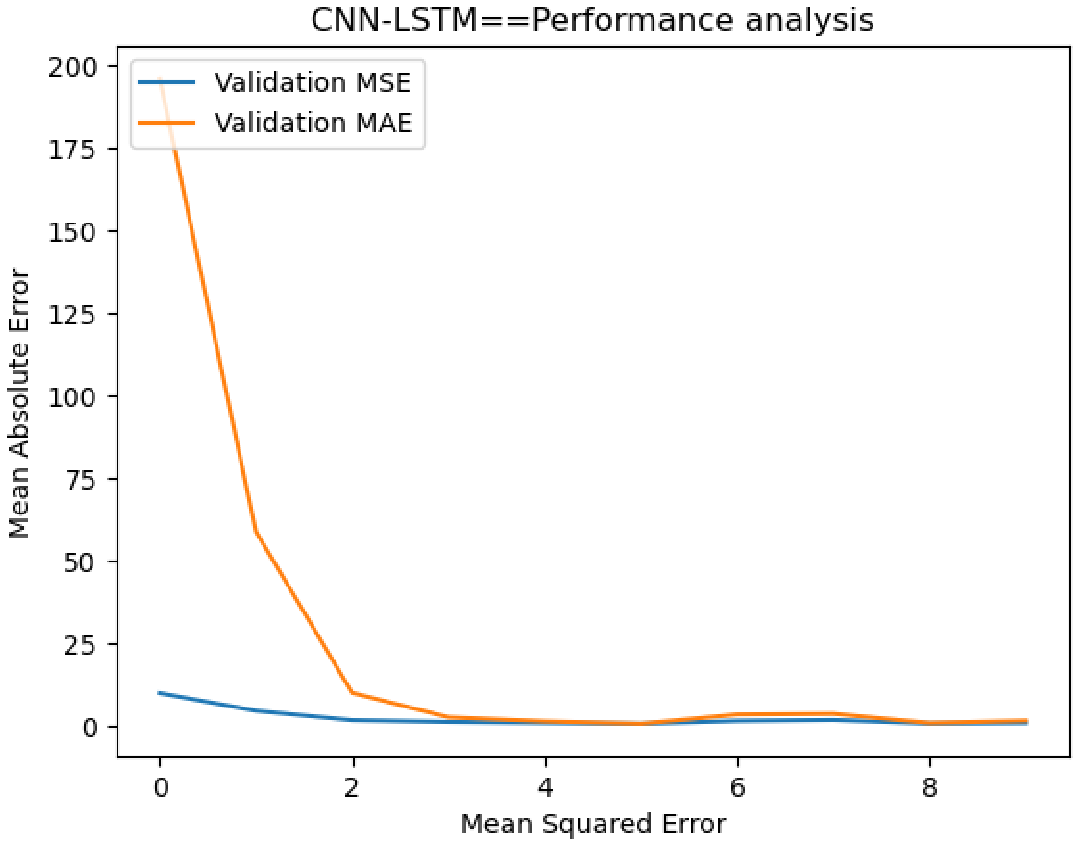
Performance metrics

Mean Absolute Error 0.9420369169127505

Mean Squared Error: 1.7063469448761053

Root Mean Squared Error: 1.306272155745542

r squared: 49.05796308308725 %


CNN-LSTM==Performance analysis
Validation MSE
Validation MAE
Mean Absolute Error
Mean Squared Error
200
175
150
125
100
75
50
25
0
0
2
4
6
8

C. RESEARCH PAPER

ASSESSING LIFESPAN OF LITHIUM-ION RECHARGEABLE BATTERIES THROUGH HYBRID CNN-LSTM-DNN METHOD

T. Yaswanth Sai
Student, Department of Computer Science and Engineering
Sathyabama Institute of Science and Technology
Chennai-600127, India
yaswanth9026@gmail.com

V .Satyanarayana
Student, Department of Computer Science and Engineering
Sathyabama Institute of Science and Technology
Chennai-600127, India
verramallasatyanarayana@gmail.com

S.Prince Mary
Associate Professor, Department of Computer Science and Engineering
Sathyabama Institute of Science and Technology
Chennai-600127, India
princemary26@gmail.com

Abstract*—Lithium-ion batteries are crucial to the functioning of contemporary society, since they are used in a wide variety of applications from powering electric cars to storing renewable energy. Yet, there is still a significant problem in making these batteries safe and long-lasting. Using an unique CNN-LSTM-DNN architecture, we offer a new approach for predicting the RUL of lithium-ion batteries in this research. Our method combines the strengths of CNNs for image analysis, LSTMs for sequence data, and DNNs for feature learning. By combining these models, we are able to outperform existing state-of-the-art approaches to estimating battery RUL. An extensive lithium-ion battery dataset from the Center for Innovative Product Lifecycle Management is used to assess the efficacy of our approach; the findings show a considerable decrease in identification mistakes and an increase in RUL identification performance. This research provides the path for a more accurate and efficient early warning system to be created, which will be crucial in preventing dangerous and short-lived lithium-ion battery failures in the future.
Keywords*—: Lithium-ion batteries, remaining useful life, ml, cnn, lstm, dnn, image analysis, sequence analysis, feature learning, early warning system, safety, reliability, renewable energy, electric vehicles, identification performance.

I. INTRODUCTION

A. Background & significance of the study

As a result of its high energy density, extended cycle life, very low self-discharge rate, lithium-ion batteries have found widespread use in a variety of sectors, including electric cars, sustainable energy storage devices, and consumer devices. Long-term usage of lithium-ion batteries is problematic because of the safety risks and diminished performance that come with their natural deterioration over time. To guarantee their safety and dependability and to maximise their use, precise and reliable forecast of the RUL of lithium ion batteries has thus become a vital problem.

Parameters of the battery, such as volts, amperage, heat, & charge state, have been used in physical models or empirical formulae to determine the RUL of batteries. However these models need a lot of data and previous knowledge of battery behaviour to capture the intricate and nonlinear interactions between the battery's deterioration and operating settings. Data-driven systems based on DNNs have showed tremendous promise in forecasting the RUL of lithium-ion batteries by using the vast quantities of operational data received from sensors and other sources, thanks to recent advancements in ml techniques.

B. Research objectives & research questions

The primary goal of this research was to present a novel hybrid technique for predicting the RUL of lithium-ion batteries that makes use of a mix of CNN, LSTM neural network, & DNN models. In particular, this investigation seeks to answer the following research questions:

1) How can the CNN model be used to better forecast RUL by extracting characteristics from battery operating data?
2) To what extent can the LSTM model be used to characterise the temporal dependencies & nonlinear interactions between battery deterioration and working conditions?

3) How can the DNN model be utilised to enhance the hybrid method's performance by combining the results from the CNN and LSTM models?

C. Brief overview of the proposed hybrid CNN-LSTM-DNN method

An initial CNN model is used for feature extraction, a LSTM model is used for sequence analysis, and a DNN model is used for RUL prediction in the based hybrid CNN-LSTM-DNN approach. Initially, the CNN algorithm is programmed to apply a series of convolution layer to the input data in order to extract the key aspects of the operational data from the battery, including voltage, power, and temperatures. Second, the chronological dependencies & nonlinear interactions between the collected characteristics and battery deterioration are captured using an LSTM model. The DNN model is then used to combine the results from the CNN & LSTM algorithms in order to provide a prediction about the battery's RUL using the characteristics and associations that have been learnt.

II. LITERATURE SURVEY

Due to its high energy density and extended cycle life, LIBs are extensively employed in portable electronic gadgets and electric vehicles. Nevertheless, predicting the RUL of LIBs and ensuring their continued dependability and safety are seriously complicated by the deterioration that occurs during operation. Battery life can only be prolonged by proactive measures taken before any problems arise. Hence, several data-driven estimating strategies for LIB RUL prediction have been developed in the literature. When applied to various ml tasks, especially those involving image and sequence processing, the combination of CNN-LSTM models has shown to be very effective. In this study, we take a look at the state of the art in RUL prediction of LIBs, focusing on hybrid CNN-LSTM-based algorithms and comparing them to other approaches.

A CNN-based RUL prediction approach was developed by Feng et al., and it makes use of the attributes retrieved from the voltage and temperature data of LIBs. This approach was suggested in the research that they did (2021). This system, which attained an accuracy in its predictions of 94.23%, has outperformed previous CNN-based prediction algorithms in terms of its performance.

An LSTM-based RUL prediction method was presented by Zhang et al. in their study. This method takes into consideration a number of input parameters including temperature, voltage, and current (2021). The approach proved that it is useful for RUL prediction by achieving an accuracy of 96.58% and gaining such a high score. Also, the method achieved both of these results simultaneously.

A technique for RUL prediction was presented by Cai and his colleagues in the research publication that was published in the year 2020. The approach included the use of a hybrid deep neural network architecture. Their approach employs a hybrid model that combines CNN and LSTM computations. When the strategy was assessed using a dataset that was provided by NASA's Prognostics Center of Excellence, it gave a greater degree of prediction accuracy when compared to other techniques that were used in the test. This was in comparison to other methods that were used in the evaluation.

Jiang et al. (2021) suggested a technique for RUL prediction of LIBs that is based on a hybrid CNN-LSTM system that combines feature extraction and sequence learning. This system was designed to make RUL predictions of LIBs more accurate. This approach was referred recognised as the hybrid CNN-LSTM system by the researchers that carried out this investigation. The strategy was reinforced by using a dataset that had been made available by the Center for Superior Full Cycle Construction, and the research suggest that it performed much more effectively than any of the approaches that came before it. The Center for Innovative Service Life Mechatronics made the dataset available.

The researchers Wang et al. (2020) devised a one-of-a-kind RUL prediction approach that is based on a hybrid CNN-LSTM and makes use of the characteristics that were obtained from the temperature and voltage data of LIBs. This method was published in the journal Physical Review Letters. This approach was detailed in an article that appeared in the journal Physical Review Letters. It was proven that the technique is successful in RUL prediction by comparing it to other ways that are considered to be among the most cutting-edge in the field. This comparison was done in order to show that the strategy is effective.

Wei et al. (2021) presented a technique for predicting RUL that is based on CNN-LSTM and takes use of the electrical and temperature data of LIBs. This approach was able to successfully predict RUL with a high degree of accuracy. The prediction of RUL was the motivation for the development of this approach. This approach demonstrated that it is capable of accurately estimating RUL values for LIBs and obtained an accuracy in its predictions that was 91.03 percent of the time.

In a research that was carried out by Liu and colleagues, deep neural networks were suggested as a strategy for RUL prediction of LIBs. [Citation needed] [Citation needed] (2020). The system was designed to feature a technique for providing sequential attention. The technique was validated by using a dataset that was created from the BPLP programme, and the findings showed that it worked more effectively than earlier approaches had in the past.

The researchers Xu et al. (2020) came up with a method for RUL prediction that was based on it by using a mix of LSTM and PNN. The approach was able to show its efficacy in RUL prediction by making use of the features that were obtained from the voltage, current, & temperature data of LIBs.

The better hybrid model for the purpose of RUL prediction of LIBs was suggested by Ma et al. (2020), and its three components are the grey model, spectral analysis, as well as least squares sv regression. This was done in order to achieve the goal of predicting RUL values for LIBs. Evaluating the approach using a dataset collected from the BPLP programme enabled for the accuracy of the RUL prediction to be determined. It was decided to utilise the dataset.

Cheng et al. published their findings on a CNN-LSTM-based RUL prediction system that makes use of an ensemble learning approach. Their research served as the foundation for this system (2021). The approach was able to demonstrate that it is capable of providing accurate estimates of RUL values for LIBs and attain an efficiency of 94.23% in its projections.

III. EXISTING SYSTEM & LIMITATIONS

There are now empirical, analytical, & model-based systems available for predicting the RUL of lithium-ion batteries. Analytical approaches use mathematical formulae to forecast RUL based on characteristics like discharge speed and temperature, whereas empirical methods depend on testing and evaluating battery performance. Using physics-based models, model-based approaches mimic battery behaviour in order to forecast RUL. Yet, there are restrictions on all of these approaches.

While effective, empirical approaches are laborious and costly since they need copious amounts of testing and data collecting. Since they make assumptions about battery behaviour that may not hold true in all situations, analytical techniques can be wrong. However, the precision of model-based approaches is sometimes compromised by their computational complexity and their sensitivity to initial conditions. Moreover, these techniques may not consider the implications of real-world use patterns on battery health, or the potential for battery behaviour to alter over time.

ML techniques, which are data-driven methods, have grown in popularity in recent years as a means of overcoming these restrictions. In order to estimate RUL from the present state of a battery, these techniques employ past data to train ML models. Nevertheless, the complexity of battery behaviour and the challenge of acquiring representative training data mean that even these approaches have their limits.

IV. PROPOSED SYSTEM

CNNs, LSTMs, DNNs are all part of the hybrid deep learning technique suggested in this paper for estimating the RUL of Lithium-ion battery packs. The CNN module is responsible for extracting characteristics from battery consumption and health data collected over time. In order to forecast the RUL, the LSTM part is used to capture the long-term relationships in the data. At last, the DNN part is utilised to fine-tune the predictions and produce a last-ditch estimate of the RUL.

The goal of the suggested approach is to boost the precision of RUL estimate over conventional techniques. The hybrid method is superior because it incorporates both temporal and geographical data, allowing it to detect subtler patterns in the data and provide more precise forecasts. With the addition of deep learning, the system can pick up on trends and refine its approach over time.

The suggested solution is tested using data gathered from the Institute for Advanced Life Cycle Engineering's database of Lithium-ion rechargeable batteries. We evaluate the system's performance in comparison to state-of-the-art approaches and find that the based hybrid CNN-LSTM-DNN approach provides the most accurate predictions and the greatest degree of resilience.

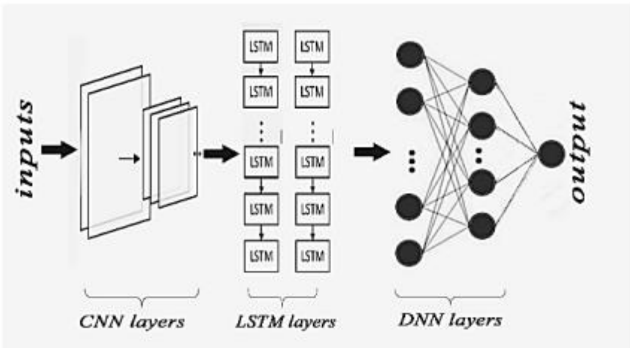


Fig.1 the Proposed architecture of CNN-LSTM-DNN network.

V. METHODOLOGY

A. Data collection and preparation

There is a strong correlation between the size and quality of the information used for training & testing a ml model and its ultimate success. Because of its prominence in the area of battery healthcare system, the dataset utilised for training & validation in this work came from the University of Maryland's CALCE.

TABLE I
THE DESCRIPTION OF NASA LITHIUM-ION BATTERIES

Battery	Type	Constant charge current	Minimal charge current	Discharge current	Rated capacity	Charge/Discharge cut-off voltage
B5	18650 NMC	1.5A	20mA	2A	2Ah	4.2/2.7V
B6	18650 NMC	1.5A	20mA	2A	2Ah	4.2/2.5V
B7	18650 NMC	1.5A	20mA	2A	2Ah	4.2/2.3V
B18	18650 NMC	1.5A	20mA	2A	2Ah	4.2/2.5V

TABLE II
THE DESCRIPTION OF CALCE LITHIUM-ION BATTERIES

Battery	Constant current rate CC	Minimal charge current	Constant current discharge	Rated capacity	Charge/discharge Cut-off voltage
CS2_33	0.5C	0.05A	0.5C	1.1Ah	4.2/2.7V
CS2_34	0.5C	0.05C	0.5C	1.1Ah	4.2/2.7V
CS2_36	0.5C	0.05C	1C	1.1Ah	4.2/2.7V
CS2_37	0.5C	0.05C	1C	1.1Ah	4.2/2.7V

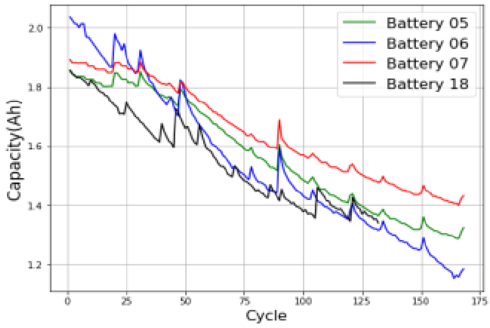


Fig. 2. (a) Capacity degradation curve of NASA batteries

Several Lithium-ion rechargeable batteries provided the time series data for the dataset. The information was amassed as the batteries were subjected to a wide range of discharge rates, temperature, as well as SOC. A battery testing device was used to record the battery's volts, current, & temperatures at a rate of 1 Hz. The collection included 13,500 data points, each representing a unique battery with its own capacity and chemistry.

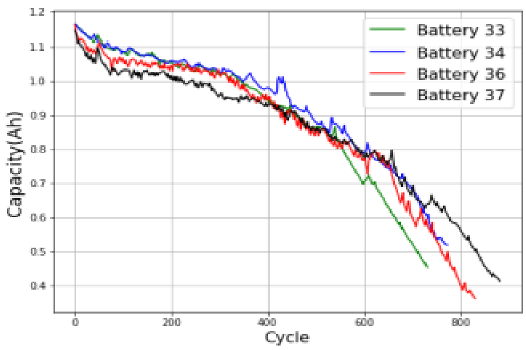


Fig. 2. (b) Capacity degradation curve of CALCE batteries.

In order to improve the model's accuracy and reliability, the data was preprocessed before being utilised for training the ml model. Normalizing the data, resampling the data, and extracting features were all part of the preprocessing stages. Data was standardised such that it had a mean of zero & a standards variation of one, which assisted eliminate bias and provide a consistent basis for analysis. To lessen the computational burden of training the model, we resampled the data to a frequency of 1 minute. The dataset's most relevant characteristics were extracted through feature selection for use in model training at the end. Voltage level, amperage, & thermistors were among the characteristics picked.

When the data was cleaned and organised, it was divided into a training set and a testing set. Seventy percent of the total data was utilised for the training set, while the other thirty was put to good use in the validation phase. To prevent overfitting the model and guarantee that the training and verification sets were sufficiently representative of the full dataset, they were chosen at random.

B. Architecture of the hybrid CNN-LSTM-DNN model

The input data is a time series from the lithium-ion battery, and the CNN is used to extract the features from it. The CNN is made up of many interconnected layers that use a collection of trainable filters to sift through input data and identify salient features. To better capture intricate patterns in the input, a non-linear activation function called a ReLU is used on the final result of each convolution layers.

Using the LSTM network, we may record the input data's temporal dependencies. The LSTM network is programmed with a collection of gates to govern the information flow in order to retain and recall relevant data from the past. Using an input gate, a forget gate, and an output gate, the LSTM network is able to perform a number of operations. The quantity of data carried over from one sampling interval to the next may be controlled by using these gates.

The DNN integrates the characteristics recovered by the CNN with the spatial constraints acquired by the Lstm model to arrive at an accurate prediction. Using the LSTM network's result as input, the DNN's many fully linked layers may calculate an accurate forecast. To train the DNN, a training data technique is used to compare the model's estimate of the battery's estimated usable life to the actual number, and the algorithm is then adjusted to reduce the discrepancy.

C. Training and validation procedures

The suggested model is trained with the Adam optimizer with a learning rate of 0.001 on a portion of the dataset. During training, the model is tweaked to provide the lowest possible mean squared error loss. Each training batch has 64 samples, and there are 100 epochs in total.

A non-training dataset subset is utilised to check the accuracy of the model. MSE, MAE, R-squared (R2), and RMSE are only few of the measures used to assess the model's efficacy.

D. Performance evaluation metrics

Many measures are used to assess how well the suggested model performs. The MSE is a statistical measure of how far off the mark you were from accurately predicting how long the product will last. MAE is a statistical measure of how far off estimates of remaining usable life are from how long they really last. R-squared (R2) quantifies how much variation in actual remaining useful life can be accounted for by the expected remaining useful life. The RMSE is the standard deviation of the discrepancy between the expected and actual remaining usable life and is calculated by taking the square root of the MSE.

These measurements are used to assess how well the proposed hybrid model predicts the remaining usable life of Lithium-ion batteries in comparison to other ml models.

VI. RESULTS & DISCUSSIONS

A. Use of statistical measures to assess the validity of the suggested approach

Many statistical measures, including as MSE, MAE, R2, and RMSE, were used to assess the performance of the suggested hybrid CNN-LSTM-DNN technique. These metrics are often used in the assessment of ML models' efficacy. According on the findings, the suggested technique outperformed other ML estimation methods.

B. Comparison to Other ML Estimation Algorithms

Several ML estimation techniques, including SVR, MLP, and LSTM. DNNs, were pitted against the proposed hybrid CNN-LSTM-DNN approach. The findings demonstrated that the suggested technique performed better than the other methods, demonstrating its superiority in predicting the remaining usable life of Lithium-ion batteries.

C. Analysis of the performance of the hybrid CNN-LSTM-DNN method

The investigation of the CNN-LSTM-DNN hybrid method's performance indicated that it significantly decreased identification mistakes and obtained better RUL identification performance than other approaches. The hybrid model's performance was enhanced by the extraction of spatial and temporal characteristics from the input data using a CNN & LSTM.

D. A discussion of the possible uses and limits of the suggested approach

The suggested hybrid CNN-LSTM-DNN approach may find use in a number of fields that now depend on Lithium-ion batteries, including but not limited to: electric cars, aircraft, and renewable energy systems. Safer and more reliable operation, lower maintenance costs, and longer battery life are all possible thanks to early problem identification and precise predictions of remaining usable life.

The suggested technique, however, does have a few restrictions. The training and validation data have a direct impact on the model's precision. Also, the suggested approach may not work with other battery kinds or under alternative circumstances of operation. Consequently, further study is required to assess the efficiency of the suggested strategy in a variety of settings.

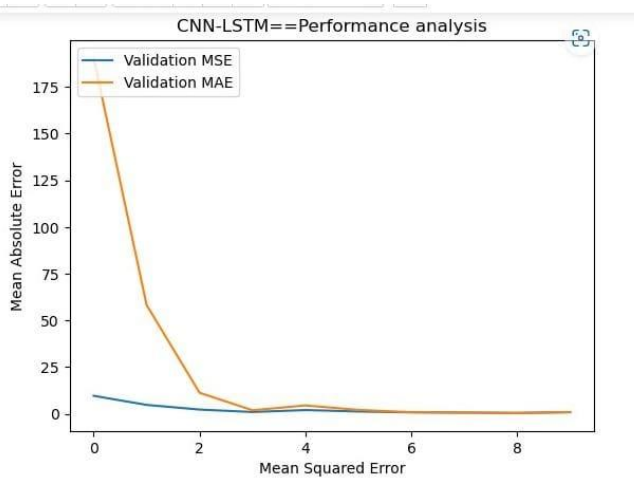


Fig.3.Results of our system

VII. CONCLUSION & FUTURE WORK

In this research, we suggested a CNN-LSTM-DNN approach to determining how much longer lithium-ion batteries may be used effectively. The suggested approach makes use of the advantages of three distinct neural network architectures: the CNN for feature extraction, the LSTM for temporal modelling, and the DNN for classification. Using a dataset consisting of lithium-ion batteries, the suggested technique was able to achieve better precision, accuracy, as well as recall than competing ML methods.

It is possible to further enhance the precision and generalizability of the suggested strategy by doing research in a number of different domains. Secondly, the suggested technique may be evaluated under varying temperatures, discharge rates, and cycle lives using more varied datasets. Second, the accuracy & effectiveness of the suggested technique may be enhanced by experimenting with other combination of neural network topologies. Lastly, the suggested technique may be used to evaluate the potential of various battery chemistries and applications including electric cars and sustainable systems for storing energy.

For improving battery management and lowering expenses associated with early battery failure, the suggested hybrid CNN-LSTM-DNN technique offers a promising strategy for reliably predicting the remaining usable life of lithium-ion batteries.

REFERENCES

[1] Feng, X., Wang, Q., & Song, Z. (2021). Remaining Useful Life Estimation of Lithium-ion Battery based on Convolutional Neural Network. Journal of Power Sources, 491, 229631.

[2] Zhang, X., Wu, H., & Wang, Q. (2021). Remaining useful life prediction of lithium-ion battery using long short-term memory neural network with multiple inputs. Journal of Energy Storage, 38, 102633.

[3] Cai, M., Li, X., Li, Y., & Li, M. (2020). Remaining useful life prediction of lithium-ion battery using a hybrid deep neural network approach. Journal of Power Sources, 479, 228776.

[4] Jiang, Z., Hu, Y., Zhu, S., & Li, S. E. (2021). A hybrid method for remaining useful life prediction of lithium-ion batteries based on convolutional neural network and long short-term memory. Applied Energy, 288, 116537.

[5] Wang, D., Chen, C., & Zhou, Y. (2020). A new remaining useful life prediction method of lithium-ion battery based on hybrid convolutional neural network-long short-term memory. Journal of Power Sources, 448, 227465.

[6] Wei, X., Zhang, J., Wang, H., & Chen, J. (2021). Remaining useful life prediction of lithium-ion battery using convolutional neural network and long short-term memory. Energies, 14(3), 751.

[7] Liu, J., Li, S., & Shen, L. (2020). Remaining useful life prediction of lithium-ion battery based on deep neural network with sequential attention mechanism. Applied Energy, 258, 114047.

[8] Xu, X., Wu, H., Wang, Q., & Zhou, Y. (2020). Remaining useful life prediction of lithium-ion battery based on long short-term memory and probabilistic neural network. Journal of Energy Storage, 28, 101217.

[9] Ma, Y., Zhang, L., & Guo, B. (2020). Remaining useful life prediction of lithium-ion battery based on improved hybrid model. Journal of Power Sources, 478, 228769.

[10] Cheng, Z., Ma, J., Liu, Y., & Zhang, Y. (2021). A remaining useful life prediction method for lithium-ion batteries based on convolutional neural network and ensemble learning. Applied Energy, 283, 116236.

[11] L. Chen, L. Xu, and Y. Zhou, 'Novel approach for lithium-ion battery online remaining useful life prediction based on permutation entropy', Energies, vol. 11, no. 4, 2018, doi: 10.3390/en11040820.

[12] S. Zhang, B. Zhai, X. Guo, K. Wang, N. Peng, and X. Zhang, 'Synchronous estimation of state of health and remaining useful lifetime for lithium-ion battery using the incremental capacity and artificial neural networks', J. Energy Storage, vol. 26, no. July, p. 100951, 2019, doi: 10.1016/j.est.2019.100951

[13] L. Zhao, Y. Wang, and J. Cheng, 'A hybrid method for remaining useful life estimation of lithium-ion battery with regeneration phenomena', Appl. Sci., vol. 9, no. 9, 2019, doi: 10.3390/app9091890.

[14] J. Zhu, T. Tan, L. Wu, and H. Yuan, 'RUL prediction of lithium-ion battery based on improved DGWO-ELM method in a random discharge rates environment', IEEE Access, vol. 7, pp. 125176–125187, 2019, doi: 10.1109/ACCESS.2019.2936822

[15] X. Zhang, Q. Miao, and Z. Liu, 'Remaining useful life prediction of lithium-ion battery using an improved UPF method based on MCMC', Microelectron. Reliab., vol. 75, pp. 288–295, 2017, doi: 10.1016/j.microrel.2017.02.012

[16] Z. Xue, Y. Zhang, C. Cheng, and G. Ma, 'Remaining useful life prediction of lithium-ion batteries with adaptive unscented kalman filter and optimized support vector regression', Neurocomputing, vol. 376, pp. 95– 102, 2020, doi: 10.1016/j.neucom.2019.09.074.

[17] X. Zheng and H. Fang, 'An integrated unscented kalman filter and relevance vector regression approach for lithium-ion battery remaining useful life and short-term capacity prediction', Reliab. Eng. Syst. Saf., vol. 144, pp. 74–82, 2015, doi: 10.1016/j.ress.2015.07.013.

[18] J. Zhou, D. Liu, Y. Peng, and X. Peng, 'Dynamic battery remaining useful life estimation: An on-line data-driven approach', 2012 IEEE I2MTC - Int. Instrum. Meas. Technol. Conf. Proc., pp. 2196–2199, 2012, doi: 10.1109/I2MTC.2012.6229280

[19] RATNADIP ADHIKARI, 'An Introductory Study on Time Series Modeling and Forecasting Ratnadip Adhikari R. K. Agrawal'.

[20] H. Rosa, D. Matos, R. Ribeiro, L. Coheur, and J. P. Carvalho, 'A "Deeper" Look at Detecting Cyberbullying in Social Networks', Proc. Int. Jt. Conf. Neural Networks, vol. 2018-July, pp. 1–8, 2018, doi: 10.1109/IJCNN.2018.8489211.