Summer Internship Project Report

Detecting Anomalous Degradation Behaviour in Lithium-ion Batteries using Machine Learning

Submitted by

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Certificate

This is to certify that the Project entitled **"Detecting Anomalous Degradation Behaviour in Lithium-ion Batteries"**, submitted by **Anghsuman Chanda, Saumyen Prateek Deka, Washim Akram** and **Rahul Pathori** to the Indian Institute of Technology Guwahati, for the in Technology Innovation Hub, is a record of the original, bona fide research work carried out by them under my supervision and guidance. The project has met the standards fulfilling the requirements of the project guidelines.

The results contained in this project have not been submitted in part or in full to any other University or Institute for the award of any degree or diploma to the best of our knowledge.

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Dr. Anindita Borah
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Declaration

We declare that this written submission represents our ideas in our own words. Where others' ideas and words have been included, we have adequately cited and referenced the original source. We declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated, or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will cause disciplinary action by the Institute and can also evoke penal action from the source which has thus not been properly cited or from whom proper permission has not been taken when needed.

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Contents

1 Introduction

Lithium-ion batteries (Li-ion batteries) are pivotal in powering a myriad of modern applications, ranging from portable electronics to electric vehicles and large-scale renewable energy storage systems. Known for their high energy density, long cycle life, and relatively low self-discharge rate, Li-ion batteries have become the technology of choice across various sectors. Despite these advantages, Li-ion batteries are prone to degradation over time, which can impact their performance, reduce their lifespan, and, in some cases, lead to safety hazards.

Degradation in Li-ion batteries can result from several factors, including thermal instability, overcharging, deep discharging, and manufacturing defects. This degradation manifests as capacity fading, increased internal resistance, and other performance issues, which, if undetected, can lead to catastrophic failures such as thermal runaway. Therefore, the early detection and diagnosis of anomalous degradation behaviors are crucial to ensuring the safe and efficient operation of Li-ion batteries.

Fault diagnosis in Li-ion batteries involves identifying and predicting abnormal conditions or failures within the battery system. Modern diagnostic techniques employ advanced data analysis and machine learning algorithms to monitor key battery parameters. Accurate fault diagnosis not only prevents unexpected battery failures but also extends the operational life of the batteries.

In this project, we focus on utilizing advanced machine learning techniques to detect anomalous degradation behaviors in Li-ion batteries. Specifically, we employ Long Short-Term Memory (LSTM) networks, Bidirectional LSTM (Bi-LSTM) networks, Gated Recurrent Unit (GRU) networks, and primarily, LSTM-based forecasting models. These techniques are particularly well-suited for time series analysis, enabling them to capture the complex temporal dependencies and non-linearities inherent in battery degradation data.

LSTM networks, a type of recurrent neural network (RNN), are capable of learning long-term dependencies in sequential data, making them ideal for modeling battery performance over time. Bi-LSTM networks enhance this capability by processing data in both forward and backward directions, providing a more holistic understanding of the temporal dynamics. GRU networks offer a simpler alternative to LSTMs with comparable performance in many cases. In this study, we used LSTM forecasting to evaluate its performance against the other models in predicting future degradation behaviors based on historical data.

By leveraging these advanced machine learning models, we aim to accurately detect and predict anomalous degradation behaviors in Li-ion batteries. This approach enhances the reliability and safety of battery systems, supporting the development of more robust and efficient energy storage solutions. The insights gained from this research will contribute to the advancement of battery technology and promote the broader adoption of sustainable energy practices.

2 Background

Machine learning algorithms have proven to be highly effective in analyzing time series data, which is crucial for monitoring the performance and predicting the degradation of Li-ion batteries. This project employs several advanced machine learning models, including Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), Gated Recurrent Unit (GRU), LSTM Autoencoder, and LSTM Forecasting. Each of these models offers unique advantages in capturing the temporal dependencies and complex patterns in the degradation data.

Recurrent Neural Networks (RNN)

RNNs are a class of neural networks designed to recognize patterns in sequences of data. They are well-suited for time series analysis due to their ability to maintain information across different time steps. However, standard RNNs suffer from limitations such as the vanishing gradient problem, which hampers their ability to learn long-term dependencies in data [1, 2].

Long Short-Term Memory (LSTM)

LSTM networks, a type of RNN, were developed to address the limitations of standard RNNs. LSTMs can effectively learn long-term dependencies by using a memory cell that can maintain information over extended sequences. This makes LSTMs particularly suitable for modeling sequential data, such as the time series data of battery degradation [2, 3].

Bidirectional LSTM (Bi-LSTM)

Bi-LSTM networks extend the capabilities of LSTM networks by processing the input data in both forward and backward directions. This bidirectional approach allows Bi-LSTMs to capture information from both past and future states, providing a more comprehensive understanding of the temporal dynamics in the data [4, 5].

Gated Recurrent Unit (GRU)

GRU networks are another variant of RNNs that simplify the architecture of LSTMs while retaining their ability to capture long-term dependencies. GRUs combine the forget and input gates into a single update gate, which reduces the computational complexity and training time, often providing comparable performance to LSTMs [6].

LSTM Autoencoder

LSTM Autoencoders are specialized models used for unsupervised learning tasks, particularly anomaly detection. They consist of an encoder that compresses the input sequence into a fixed-size vector and a decoder that reconstructs the input sequence from this vector. By training on normal behavior data, LSTM Autoencoders can learn to identify deviations from the normal patterns, making them effective for detecting anomalies in battery degradation [7, 8].

LSTM Forecasting

LSTM Forecasting involves using LSTM networks to predict future values in a time series based on historical data. This technique is particularly useful for anticipating the future degradation behavior of Li-ion batteries. By training the LSTM model on past degradation data, we can forecast future performance metrics and identify potential anomalies before they lead to critical failures [2, 9].

Application of Machine Learning in This Project

In this project, we utilized LSTM, Bi-LSTM, GRU, LSTM Autoencoder, and primarily LSTM Forecasting to detect anomalous degradation behaviors in Li-ion batteries. These models were chosen for their ability to handle sequential data and capture complex temporal dependencies. By comparing the performance of these models, we aimed to evaluate their effectiveness in accurately detecting and predicting degradation behaviors.

The insights gained from this research will contribute to enhancing the reliability and safety of Li-ion battery systems. This will support the development of more robust and efficient energy storage solutions, ultimately promoting the broader adoption of sustainable energy practices.

3 Related Work

Battery anomaly detection has garnered significant attention in recent years due to its critical role in enhancing the reliability and safety of battery systems across various applications. Several approaches and methodologies have been explored in the literature to address this challenge, with a particular focus on leveraging advanced machine learning techniques such as LSTM autoencoders.

Traditional Methods

Traditional methods for anomaly detection in battery systems often rely on threshold-based techniques or rule-based systems. These approaches set predefined thresholds for battery parameters such as voltage, current, and temperature. Anomalies are detected when these parameters exceed or fall below their designated thresholds. While simple to implement, these methods may struggle to adapt to dynamic and complex operating conditions, leading to limited accuracy in anomaly detection.

Machine Learning Approaches

Machine learning (ML) techniques have shown promise in improving the accuracy and robustness of battery anomaly detection systems. Supervised learning algorithms, such as support vector machines (SVM) and decision trees, have been applied to classify anomalies based on labeled datasets. However, the effectiveness of supervised approaches heavily relies on the availability of comprehensive and accurately labeled data, which can be challenging to obtain in practical scenarios.

Unsupervised Learning with Autoencoders

Unsupervised learning techniques, particularly autoencoders, have emerged as a powerful tool for anomaly detection in battery systems. Autoencoders are neural network architectures designed to learn efficient representations of input data by compressing it into a latent space and then reconstructing the original data. Anomalies are identified based on significant reconstruction errors between the input and the reconstructed output.

LSTM Forecasting for Time-Series Data

Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), are well-suited for handling time-series data with long-term dependencies. LSTM networks can capture temporal patterns and dynamics in battery performance metrics, making them effective for anomaly detection tasks. When employed in forecasting architectures, LSTM networks can predict future operational behavior of battery systems based on historical data. By identifying deviations between predicted and actual performance, LSTM forecasting models can detect anomalies with high accuracy, providing early warnings of potential issues.

Recent Advances and Challenges

Recent research has focused on enhancing the efficiency and scalability of LSTM autoencoder models for battery anomaly detection. Techniques such as transfer learning, which leverage pre-trained models from related domains, and ensemble methods have shown promise in improving model performance and generalization across different battery types and operating conditions.

Several datasets for lithium-ion battery performance and anomaly detection are available for research purposes. The Center for Advanced Life Cycle Engineering (CALCE) at the University of Maryland provides open access to experimental test data on various types of lithium-ion batteries, including cylindrical, pouch, and prismatic form factors with chemistries such as LCO, LFP, and NMC. The datasets include continuous full and partial cycling, storage conditions, dynamic driving profiles, open circuit voltage measurements, and impedance measurements [10].

For instance, Dataset 1 consists of qualification and ongoing reliability testing data on INR 18650-20R batteries, where samples were subjected to rigorous cycling and evaluated for their degradation trends. Dataset 2 provides capacity fade data for lithium-ion batteries with a nominal capacity of 350 mAh, focusing on ongoing reliability testing to detect early signs of degradation [10].

This dataset is invaluable for battery state estimation, remaining useful life prediction, accelerated degradation modeling, and reliability analysis in the context of anomaly detection in Li-ion batteries. For more details and access to the dataset, interested researchers can visit the CALCE Battery Anomaly Detection Data webpage [10].

However, challenges remain, including the need for large and diverse datasets for training robust models, computational complexity, and the interpretability of model outputs. Addressing these challenges is crucial for the widespread adoption of LSTM autoencoders in real-world battery management systems.

4 Methodologies/approach(es) applied:

In this project we used a variety of methodologies to detect battery anomalies prediction in the battery cycle.In this case we have used LSTM autoencoder model.At first we collected the datasets for training and testing purpose which were in excel formats from calce,umd -University of Maryland website .It consisted one column for cycles and other 6 columns for 6 batteries giving capacity after each cycle in each of the datasets.Then we converted them into three columns that are cycle ,battery id,and capacity.

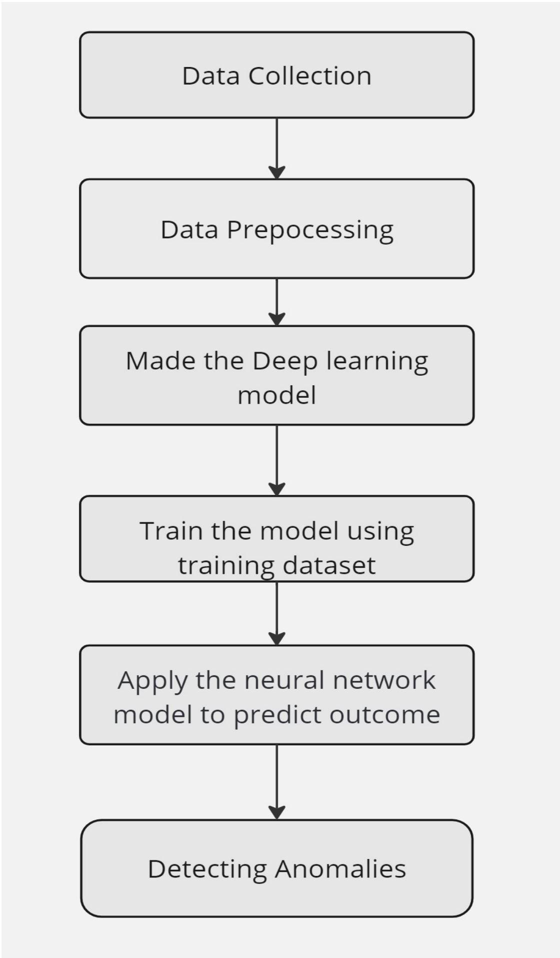

Figure 1: Flowchart for Battery-Anomaly Detecion

To capture the temporal dynamics of battery health, we prepared sequences of length 20 for each battery ID. Multiple LSTM layers with ReLU activations, dropout layers to prevent overfitting, and a TimeDistributed dense layer for output sequences made up our LSTM autoencoder model.

The model was trained with early stopping and model checkpoint callbacks to track performance, using the Adam optimizer and MSE loss. We determined the anomaly detection threshold by utilizing the percentile approach and reconstruction error included in the training set.

We performed a similar preprocessing on the testing data for evaluation, computed reconstruction errors, and compared these errors to the threshold to identify abnormalities. To check our model efficiency, we have used Accuracy, Precision, Recall and F1 score.

Lastly, we displayed the anomalies and reconstruction loss for every BatteryID, differentiating between normal and anomalous sequences using color coding.

4.1 Data Collection

This project's dataset was acquired from the University of Maryland's Centre for Advanced Life Cycle Engineering (CALCE). The CALCE Battery Anomaly Detection Data contains various battery performance metrics which are essential for developing and testing our machine learning models for detecting anomalies in Li-ion batteries [10]. These tests were conducted following industry-standard battery testing protocols, and the data was sourced from a combination of research laboratories, published datasets, and proprietary sources. The data was unorganised and had to be organised into 3 columns named - BatteryID, Cycle, Capacity.

The primary attributes collected were:

Battery ID:A unique identifier for each battery, ensuring that data from different batteries could be tracked and analyzed individually.
Cycle: The number of charge-discharge cycles a battery has undergone.
Capacity: The amount of charge that a battery can hold is indicated by its capacity, which is expressed in milliampere-hours (mAh) or ampere-hours (Ah).

Data was stored in Excel files after preprocessing and cleaning to facilitate easy manipulation. The training dataset comprised several hundreds of cycles (each battery in training datset has 495 cycles) from multiple batteries to provide a robust base for model training. The testing dataset was similarly extensive to ensure consistent and reliable evaluation of the model's performance.

4.2 Data Preparation

Data preparation was a crucial step in ensuring the precision and accuracy of the LSTM autoencoder model for battery health monitoring and anomaly identification. In order to transform unstructured raw data into a clean, structured format suitable for machine learning, a variety of tasks were finished during this phase.

To begin with, data cleaning and preprocessing was necessary to address any outliers and missing values. If there was too much missing data to reliably impute, it was removed. If any capacity readings were diverged, they were normalized using statistical techniques like min-max scalar method. Using statistical methods and domain expertise, outliers that could seriously distort the model's performance were found and eliminated, guaranteeing that the remaining data correctly depicted typical battery behavior.

4.3 Proposed Method

The proposed method for battery health monitoring and anomaly detection utilizes a Long Short-Term Memory (LSTM) model to analyze battery capacity data and identify deviations indicative of potential issues. To dive deep into the LSTM world, we first uses the LSTM Autoencoder model to detect anomalies. This approach leverages the strengths of LSTM networks in capturing temporal dependencies and the capability of autoencoders to learn robust representations of normal behavior, making it particularly suited for sequential data such as battery cycles.

The core of the proposed method is an LSTM forecasting model. This model is designed to predict future values of time series data based on past observations, which is crucial for monitoring the performance and detecting anomalies in Lithium-ion batteries. The architecture of the LSTM forecasting model used in this project includes the following components:

Input Layer: Two LSTM layers that process the input sequences sequentially have 128 and 64 units, respectively.

Output Layer: The output layer provides the forecasted values of the battery parameters for the specified future time steps.

To avoid overfitting, there are dropout layers with a rate of 0.2 after each LSTM layer.

A **TimeDistributed Dense** layer with a single unit and linear activation to output reconstructed sequences.

Activation Function: Recurrent Linear (ReLu) Unit was used.

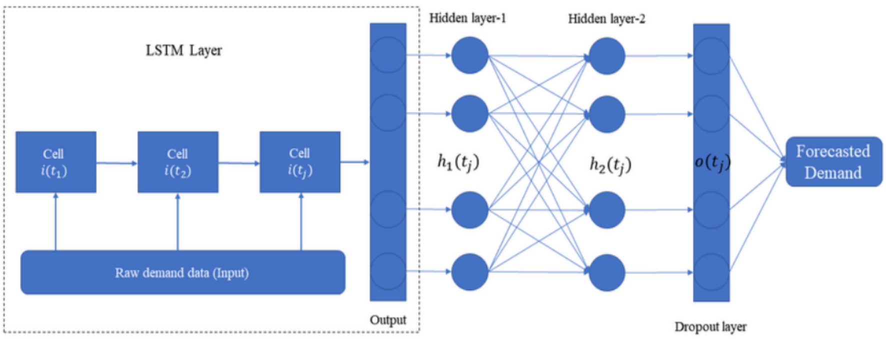

Figure 2: LSTM Forecasting Architecture

The LSTM forecasting model operates as follows:

Training Phase: During the training phase, the model learns to predict future capacity by minimizing the error between the predicted and actual values of the battery parameters. The training process involves backpropagation and optimization algorithms such as Adam to update the model weights iteratively.

Forecasting Phase: In the forecasting phase, the trained model takes historical data as input and generates predictions for future time steps. These predictions are used to predict the capacity of the next battery in the cycle and also monitor the difference between the actual capacity value and predicted capacity value. If the predicted value has a huge difference then a particular threshold, it is announced as an anomaly.

In summary, the LSTM forecasting model forms the backbone of our proposed method, offering a powerful and efficient approach for predicting future battery capacity in next cycle and detecting anomalies in Lithium-ion batteries.

5 Experimental Results

Model	Optimizer	Activation Function	Epoch	Loss
LSTM Autoencoder	ADAM	ReLu	1	0.3748
LSTM Autoencoder	ADAM	ReLu	10	0.1228
LSTM Autoencoder	ADAM	ReLu	20	0.080
LSTM Autoencoder	ADAM	ReLu	30	-
LSTM Autoencoder	ADAM	ReLu	40	-
LSTM Autoencoder	ADAM	ReLu	50	-

Table 5.1: Performance of LSTM Autoencoder Model

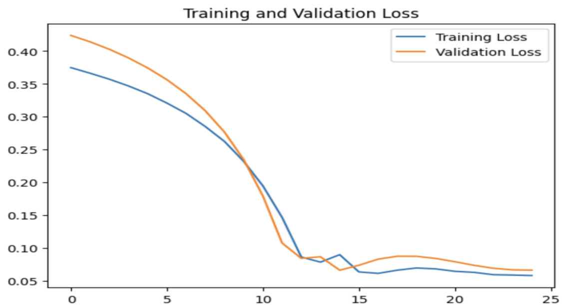

Figure 5.3: Epoch vs Loss Graph of LSTM Autoencoder

Training of the model ended in epochs before 30, due to early stopping.

Model	Optimizer	Activation Function	Epoch	Loss
Bi-LSTM	ADAM	ReLu	1	0.3780
Bi-LSTM	ADAM	ReLu	10	0.0541
Bi-LSTM	ADAM	ReLu	20	0.0546
Bi-LSTM	ADAM	ReLu	30	0.0476
Bi-LSTM	ADAM	ReLu	40	0.0467
Bi-LSTM	ADAM	ReLu	50	-

Table 5.2: Performance of Bi-LSTM Model

Figure 5.4: Epoch vs Loss Graph
of Bi-LSTM

Training of the model ended in epochs before 50, due to early stopping.

Figure 5.5: Epoch vs Loss Graph of GRU

Model	Optimizer	Activation Function	Epoch	Loss
GRU	ADAM	ReLU	1	1.9425
GRU	ADAM	ReLU	10	1.3958
GRU	ADAM	ReLU	20	1.0536
GRU	ADAM	ReLU	30	0.8395
GRU	ADAM	ReLU	40	0.6636
GRU	ADAM	ReLU	50	0.5244

Table 5.3: Performance of GRU Model

Training of the model does not end. All epochs are used to train the model.

Model	Optimizer	Activation Function	Epoch	Loss
LSTM Forecasting	ADAM	ReLu	1	0.3758
LSTM Forecasting	ADAM	ReLu	10	0.2584
LSTM Forecasting	ADAM	ReLu	20	-
LSTM Forecasting	ADAM	ReLu	30	-
LSTM Forecasting	ADAM	ReLu	40	-
LSTM Forecasting	ADAM	ReLu	50	-

Table 5.4: Performance of LSTM Forecasting Model

Figure 5.6: Epoch vs Loss Graph of LSTM Forecasting

Training of the model ended in epochs before 20, due to early stopping.

Machine learning models are trained using an early stopping method to avoid overfitting. It keeps track of a validation metric, like validation loss or accuracy, and halts training when the metric begins to deteriorate even after many epochs have passed. Therefore, not all epochs are completed because training terminates early based on predefined criteria, ensuring that the model does not learn noise or specific features of the training data that do not generalize well to unseen data.

We evaluated the performance of our four models—LSTM Autoencoder, Bi-LSTM, GRU, and LSTM Forecasting, in detecting anomalies in Lithium-ion batteries.

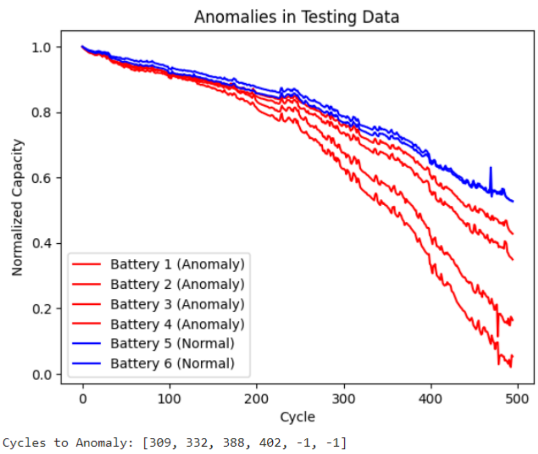

Figure 5.7: LSTM Autoencoder

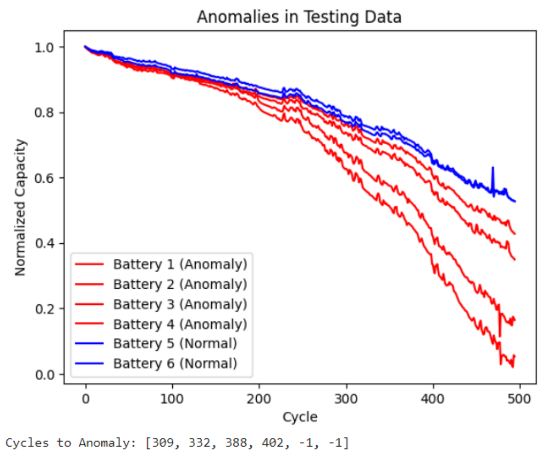

Figure 5.8: Bi-LSTM

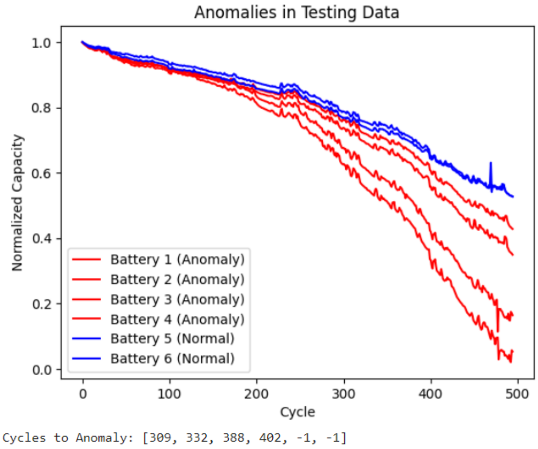

Figure 5.9: GRU

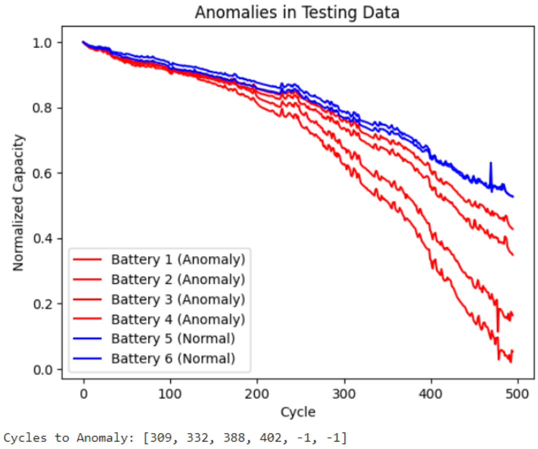

Figure 5.10: LSTM Forecasting

It can be observed that all the models have been able to identify the anomalous batteries correctly. Thus, depicting all models were accurate in predicting the anomalous batteries. As being unlabeled dataset, the accuracy of all models were same and perfect in terms of classification outcomes, i.e. - True Positive, True Negative, False Positive and False Negative. So, we have evaluated the performance based on the number of anomalies found using each model.

Model	No. of anomalies	Threshold
LSTM Autoencoder	1621	0.18892406672239304
Bi-LSTM	1717	0.16223962604999542
GRU	1626	0.1796199381351471
LSTM Forecasting	2180	0.013470607995986936

Table 5.5: Number of Anomalies detected

On the basis of the above table, it can be observed that LSTM Forecasting model predicts the highest number of anomalies whereas LSTM Autoencoder predicts the lowest number of anomalies.

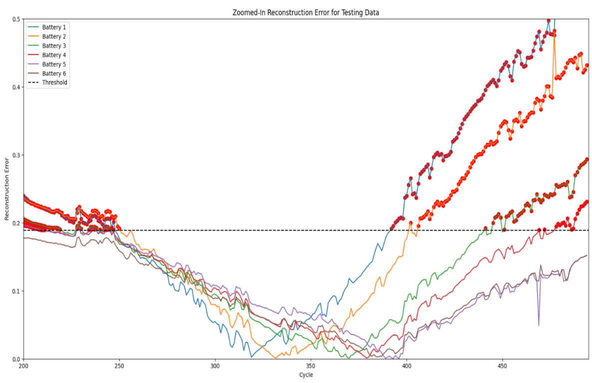

Figure 5.11: LSTM Autoencoder from 200-500 cycles

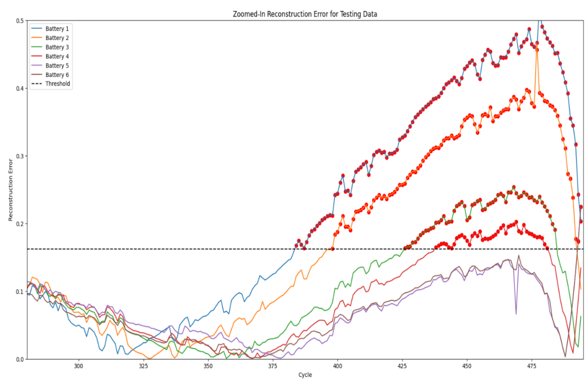

Figure 5.12: Bi-LSTM from 200-500 cycles

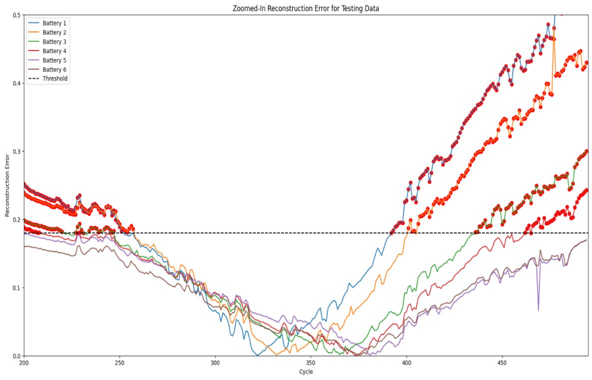

Figure 5.13: GRU from 200-500 cycles

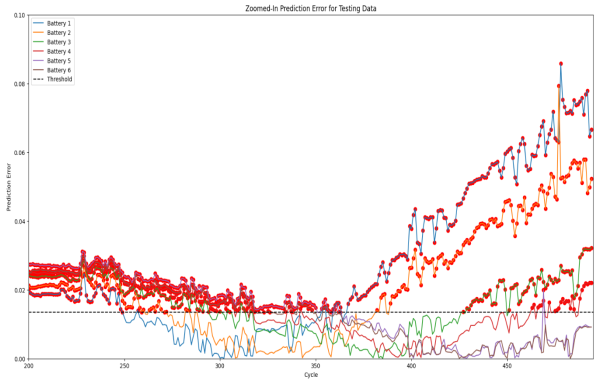

Figure 5.14: LSTM Forecasting from 200-500 cycles

Thus, it shows that reducing the anomaly detection threshold results in a higher count of anomalies being identified. This relationship underscores the sensitivity of the model to deviations from normal patterns in the data. As the threshold decreases, the models becomes more discerning, identifying even subtle deviations as anomalies, which is critical for enhancing the system's reliability in detecting potential issues early.

6 Conclusion and Future Work

We investigated the use of Long Short-Term Memory (LSTM) Forecasting for anomaly detection in battery systems in this study. The primary objective was to effectively discover anomalies that would indicate potential malfunctions or performance issues in battery systems by utilizing the time-series data handling capabilities of LSTM networks.

Our study demonstrated that LSTM Forecasting could effectively learn the normal operational patterns of battery systems and identify deviations indicative of anomalies with high accuracy. The model was able to identify anomalies based on considerable forecasting errors since it could capture temporal dependencies and predict future input sequences.

The results obtained from our experiments show that LSTM forecasting can significantly improve the reliability and safety of battery management systems. By detecting anomalies in real-time, this approach facilitates proactive maintenance strategies, ultimately extending the lifespan and optimizing the performance of batteries in various applications, including electric vehicles, renewable energy storage, and portable electronics.

Future Work

Although the project's results are encouraging, there are a number of directions that further study and development, that are needed, to improve the reliability and usefulness of LSTM autoencoders for battery anomaly detection:

- **Data Augmentation and Diversity**: Acquiring larger and more diverse datasets covering different battery types, usage scenarios, and environmental conditions will help improve the model's generalization and performance. Data augmentation techniques can also be explored to enrich the training data.
- **Hybrid Models**: Investigate the integration of LSTM forecasting models with other machine learning techniques, such as convolutional neural networks (CNNs) or traditional statistical methods, to develop hybrid models that can leverage the strengths of multiple approaches for more accurate anomaly detection.
- **Transfer Learning**: Explore transfer learning techniques to utilize pre-trained models from related domains or other battery systems. This can make the training time less and enhance the model's functionality, particularly in situations where there is a lack of labeled data.
- **Interpretability**: Developing methods to interpret and explain the decisions made by the LSTM forecasting models is crucial for gaining user trust and understanding the underlying causes of detected anomalies.
- **Implementation in real time and scalability:**: Implementing the LSTM forecasting models in real-time battery management systems and testing their scalability in practical applications will be essential for their adoption. Optimization techniques to reduce computational complexity and improve real-time performance will be necessary.

- **Adaptive Learning**: Investigating adaptive learning methods that allow the model to continuously learn and update its parameters based on new data can enhance its ability to detect emerging and evolving anomalies.
- **Cross-domain Applications**: Exploring the application of LSTM forecasting models in other domains, such as health monitoring systems or industrial equipment, can provide insights into the versatility and effectiveness of the approach across different anomaly detection tasks.

The potential of LSTM forecasting models for battery anomaly detection can be fully realized by addressing these future research objectives, which will also advance the field of anomaly detection generally and lead to more dependable and effective battery management systems.

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