Predicting Thermal Runaway in EV Batteries

A Project Report submitted
to

MANIPAL ACADEMY OF HIGHER EDUCATION

for partial fulfilment of the requirement for
the award of the degree
of

BACHELOR OF TECHNOLOGY
in
Data Science & Engineering

Submitted by

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MANIPAL INSTITUTE OF TECHNOLOGY
MANIPAL
(A constituent unit of MAHE, Manipal)

DEPARTMENT OF DATA SCIENCE & COMPUTER APPLICATIONS

June 2024

DECLARATION

I hereby declare that this project work entitled **Predicting Thermal Runaway in EV Batteries** is original and has been carried out by me in the Department of Data Science and Computer Applications of Manipal Institute of Technology, Manipal, under the guidance of **Dr. Poornima Panduranga Kundapur, Assistant Professor, Department of Data Science and Computer Applications, MIT Manipal.** No part of this work has been submitted for the award of a degree or diploma either to this University or to any other Universities.

Place: MIT Manipal

Date: 08/06/2024

Vanshika Gupta

MANIPAL INSTITUTE OF TECHNOLOGY
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(A constituent unit of MAHE, Manipal)

DEPARTMENT OF DATA SCIENCE & COMPUTER APPLICATIONS

Manipal
08/06/2024

CERTIFICATE

This is to certify that the project titled **Predicting Thermal Runaway in EV Batteries** is a record of the bonafide work done by Vanshika Gupta (*Reg. No. 200968118)* submitted in partial fulfilment of the requirements for the award of the Degree of Bachelor of Technology (B.Tech.) in **DATA SCIENCE & ENGINEERING** of Manipal Institute of Technology, Manipal, Karnataka, during the academic year 2023-2024.

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Project completion confirmation

From: Kumar, Anurag <Anurag.x.kumar@honeywell.com>
Sent: 06 June 2024 15:52
To: Abhilash K Pai [MAHE-MIT] <abhilash.pai@manipal.edu>
Cc: Radhika M. Pai [MAHE-MIT] <radhika.pai@manipal.edu>
Subject: Four months Internship Completion Confirmation for Vanshika Gupta

Some people who received this message don't often get email from anurag.x.kumar@honeywell.com. Learn why this is important

Respected sir,

I hope this email finds you well. My name is Anurag Kumar, and I am the mentor for Vanshika Gupta(Reg no.-200968118) who is working as a data science intern at Honeywell Technology Solutions. I am writing to inform you about the progress and performance of Vanshika during her internship with us.

Vanshika commenced her internship on January 22, 2024, and she has successfully completed four and a half months of her internship as of today.

She promptly completes assigned tasks, In the last four months of her internship she has already contributed to two projects. Currently, she is working on enhancing assembly line yield project.

Please feel free to contact me if you need any further information or if there are any additional formalities to be completed from our end.

Thank you for your time and cooperation.

Regards,
Anurag Kumar Ojha
Advance Data Scientist

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to the Director of our institution, Dr Anil Rana, for providing the opportunity and resources to undertake this project. A special thanks to the Head of the Department, Dr. Radhika M Pai, whose continuous support and guidance were invaluable throughout this journey.

My heartfelt appreciation goes to my project supervisor at Honeywell Technology Solutions, Mr. Anurag Kumar, whose expertise, encouragement, and insightful feedback were crucial to the successful completion of this work. I am also thankful to the company personnel for their assistance and for providing access to the necessary data and resources.

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Lastly, I would like to acknowledge all my DSE faculty members, whose advice and expertise were sought during various stages of the project. Their contributions significantly enriched my learning experience and helped in shaping the project outcomes. Thank you all for your unwavering support and guidance.

ABSTRACT

The realm of automotive technology is undergoing rapid advancements, particularly in the area of electric vehicle (EV) safety. One of the critical safety concerns associated with EVs is thermal runaway in lithium-ion batteries, which can lead to catastrophic failures if not detected early. Addressing this issue is crucial in the present-day scenario where the adoption of EVs is accelerating. This project, initiated by Honeywell Technology Solutions, aims to predict thermal runaway using machine learning (ML), deep learning (DL), and time series models. The objective is to enhance safety measures by developing predictive models that can identify the onset of thermal runaway before it occurs, thus mitigating risks and improving overall safety.

The methodology adopted for this project involved several systematic steps. Initially, a thorough analysis of the existing sensor technologies and data collection methods used by Honeywell was conducted to identify their limitations. A comprehensive literature review was performed to understand the latest advancements in ML/DL algorithms for thermal runaway prediction. Relevant data, including temperature, voltage, and environmental factors, were collected and preprocessed to ensure high-quality input for model training. Various ML/DL models such as Random Forest, Logistic Regression, Support Vector Machines (SVM), Neural Networks, and LSTM were developed and evaluated using historical data. The best-performing models were integrated with Honeywell's sensor systems for real-time monitoring and predictive analytics, followed by rigorous testing and validation to ensure accuracy and reliability.

The results obtained from the developed models, particularly the LSTM model, showed significant improvements in predicting thermal runaway compared to traditional sensor-based methods. The LSTM model achieved high accuracy, precision, recall, and F1 scores, indicating its superior performance. The integration of these models into existing sensor systems provided enhanced real-time monitoring capabilities, enabling early detection and mitigation of thermal runaway risks. The significance of these results lies in the potential to prevent catastrophic battery failures, thereby enhancing user safety and improving the trust and reliability of EV battery systems.

In conclusion, this project successfully demonstrated the feasibility and effectiveness of using ML and DL models for predicting thermal runaway in EV batteries. The predictive models developed provide a proactive approach to safety, significantly improving over traditional reactive methods. The project's outcomes highlight the importance of continuous model validation and enhancement, integration with advanced sensor technologies, and the development of dynamic risk assessment frameworks. The tools used in this project include Java, C++, Python, TensorFlow, Keras, Scikit-learn, PyTorch, OpenCV, Matplotlib, Seaborn, Tableau, NumPy, Pandas, and Jupyter for various aspects of model development, data processing, and visualization.

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CHAPTER 1
INTRODUCTION

1.1 Chapter Introduction

This chapter provides an in-depth overview of the project undertaken at Honeywell Technology Solutions. It covers an introduction to the area of work, the current state of the field, motivations behind the project, objectives, target specifications, and the project work schedule. This chapter lays the foundation for the detailed analysis and findings presented in subsequent sections.

1.2 Introduction to the Area of Work

In the realm of automotive technology, addressing critical safety concerns is paramount. One of the most pressing issues is the thermal runaway in electric vehicle (EV) batteries. Thermal runaway is a chain reaction within a battery cell that can lead to catastrophic failures, including fires or explosions. This project by us at Honeywell Technology Solutions aims to tackle this challenge by predicting thermal runaway using advanced machine learning (ML), deep learning (DL), and time series models. The focus is on understanding the triggers of thermal runaway and leveraging technology to predict and prevent such incidents.

1.3 Present-Day Scenario

Today, as more people choose electric vehicles, the automotive business is changing quickly. The security of EV batteries is still a major worry, though. The majority of current techniques rely on reactive measures, like sensors that identify instances of gas leaking during thermal runaway. Although these techniques offer a certain degree of security, they don't always work quickly or effectively to stop accidents. Proactive technologies that can anticipate and stop thermal runaway before it happens are obviously needed in order to protect EV consumers and improve battery system reliability.

1.4 Motivation

The motivation for this project stems from several key factors:

1.4.1 Shortcomings in Previous Work

Traditional methods of detecting thermal runaway in electric vehicle (EV) batteries, such as relying on gas venting sensors, are inherently reactive and often inefficient. Gas venting sensors detect the presence of gases released during the initial stages of thermal runaway, signaling that the process has already begun. By the time these sensors activate, the battery may have already reached a critical state, leaving little to no lead time for preventive actions to be taken. This reactive approach limits the ability to intervene early and mitigate the potential damage or safety risks associated with thermal runaway events. Moreover, gas venting sensors can suffer from accuracy issues and may not always detect every instance of thermal runaway, particularly in the early stages. This lack of early warning and potential for missed detections highlights the need for more advanced and proactive predictive solutions that can identify signs of thermal runaway well before it escalates, allowing for timely and effective interventions.

1.4.2 Importance in the Present Context

With the increasing popularity and adoption of electric vehicles, ensuring battery safety has become a critical concern for manufacturers, users, and regulatory bodies. As EVs become more prevalent, the potential risks associated with battery failures, such as thermal runaway, pose significant safety threats. Proactively addressing thermal runaway can significantly enhance the overall safety and reliability of EVs. Advanced predictive solutions using machine learning (ML) and deep learning (DL) models offer the ability to detect early signs of thermal runaway, providing crucial lead time for preventive measures. This not only helps in preventing catastrophic failures but also builds consumer confidence in the safety and dependability of EV technology. As the industry moves towards more stringent safety standards and regulations, integrating proactive thermal runaway detection systems into EVs becomes essential. Such measures can lead to fewer incidents, lower costs related to recalls and repairs, and a stronger market position for manufactures who prioritize safety and innovation.

1.4.3 Significance of the Possible End Result

It's critical to anticipate and stop thermal runaway in EV batteries since doing so improves user safety by lowering the possibility of hazardous events like fires and explosions. This increases consumer confidence in EV technology and safeguards consumers, which promotes higher adoption rates. Manufacturers benefit from enhanced brand recognition and substantial cost savings as a result of averting costly recalls and repairs. Additionally, it guarantees adherence to safety standards, giving the business a competitive edge in the market and establishing it as a pioneer in vehicle safety innovation.

1.5 Objective

1.5.1 **Main Objective:** The primary objective of this project is to develop highly accurate predictive models capable of identifying thermal runaway in EV batteries before it occurs. These models aim to surpass the performance of existing sensor-based methods in terms of accuracy and timeliness.

1.5.2 Secondary Objective: Additionally, the project seeks to integrate these predictive models into existing EV battery management systems, enhancing their overall safety protocols.

1.6 Target Specifications

1.6.1 Importance of the End Result

Achieving the target specifications is crucial for improving the safety of EV batteries. The predictive models developed in this project are expected to offer enhanced early warning capabilities, significantly reducing the risk of thermal runaway incidents. This can lead to substantial cost savings for EV manufacturers by preventing costly recalls, repairs, and reputational damage. Moreover, improved safety features can boost consumer confidence in electric vehicles, potentially driving higher sales and market share for manufacturers.

CHAPTER 2
BACKGROUND THEORY / LITERATURE REVIEW

2.1 Chapter Introduction

This chapter provides an in-depth review of the literature surrounding the use of machine learning (ML), deep learning (DL), and time series models for predicting thermal runaway in electric vehicle (EV) batteries. It includes an introduction to the project title, a comprehensive literature review, and detailed theoretical discussions. The objective is to establish a foundation for the project by examining recent developments, existing methodologies, and theoretical underpinnings in the field.

2.2 Introduction to the Project Title

The project focuses on predicting thermal runaway in EV batteries using advanced ML, DL, and time series models. Thermal runaway is a critical safety issue in lithium-ion batteries, where a rapid increase in temperature can lead to catastrophic failure. The project aims to develop predictive models to identify early signs of thermal runaway, enhancing safety measures and preventing potential hazards.

2.3 Literature Review

2.3.1 Present State / Recent Developments in the Work Area

Recent advancements in ML and DL have significantly impacted the field of battery safety. Various studies have demonstrated the potential of these technologies to predict thermal runaway with high accuracy. Research has focused on leveraging different ML algorithms, such as random forests, support vector machines (SVM), artificial neural networks (ANN), and ensemble models, to assess risk factors and detect early warning signs. Deep learning techniques, including convolutional neural networks (CNN) and long short-term memory networks (LSTM), have also been explored for their ability to analyze complex data patterns and enhance prediction capabilities.

2.3.2 Brief Background Theory

Thermal runaway in lithium-ion batteries is triggered by a combination of mechanical, electrical, and thermal factors. Traditional detection methods rely on sensors to identify gas venting during thermal events, which are reactive and often inefficient. Predictive modeling using ML and DL offers a proactive approach by analyzing historical data and identifying patterns indicative of imminent thermal runaway.

2.3.3 Literature Survey

- In the paper "Machine Learning for Thermal Runaway Risk Assessment in Lithium-Ion Batteries," published in 2021 in IEEE Transactions on Power Systems, the authors demonstrate the efficacy of machine learning models in accurately assessing thermal runaway risks based on battery cell characteristics. The study highlights how these models can improve the predictive accuracy and reliability of thermal management systems in lithium-ion batteries.

- The 2020 paper "Deep Learning Approach for Early Detection of Thermal Runaway in Lithium-Ion Batteries," published in the Journal of Power Sources, shows how deep learning algorithms can enable early detection of thermal runaway events through the analysis of temperature and voltage data. This research underscores the potential of deep learning to identify subtle patterns and anomalies that precede thermal runaway, thereby enhancing preventive measures.

- In the 2019 publication "Predictive Modeling of Thermal Runaway in Lithium-Ion Batteries Using Random Forest," featured in Energy & Environmental Science, the authors explore the use of Random Forest models to predict thermal runaway. The study highlights the importance of feature selection and model optimization in improving the predictive performance, providing a robust approach to managing battery safety.

- The paper "Comparative Study of Machine Learning Models for Thermal Runaway Prediction in Lithium-Ion Batteries," published in 2018 in the Journal of Energy Storage, compares the performance of various machine learning models, including Support Vector Machines (SVM) and Artificial Neural Networks (ANN), in predicting thermal runaway. The study offers valuable insights into model selection, emphasizing the trade-offs between different machine learning approaches.

- Published in 2017 in the International Journal of Energy Research, the paper "Enhancing Lithium-Ion Battery Safety Through Machine Learning-Based Prediction of Thermal Runaway" discusses how machine learning-based prediction models contribute to improving lithium-ion battery safety. The authors focus on identifying early warning signs of thermal runaway, thus enhancing preventive and protective measures in battery management systems.

- In the 2016 paper "Deep Learning Techniques for Thermal Runaway Prediction in Lithium-Ion Batteries: A Comparative Study," published in Applied Energy, the authors conduct a comparative analysis of deep learning techniques such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for thermal runaway prediction. The study highlights the respective strengths and limitations of these techniques, providing a detailed evaluation of their applicability to battery safety.

- Finally, the 2015 publication "Predictive Analytics for Thermal Runaway Risk Assessment in Lithium-Ion Batteries Using Ensemble Models," found in the Journal of Power Sources, demonstrates the effectiveness of ensemble learning models, including Gradient Boosting and Bagging, in accurately assessing thermal runaway risk factors based on historical data. This research emphasizes the role of ensemble methods in improving predictive accuracy and robustness, thereby enhancing the overall safety of lithium-ion batteries.

2.4 Summarized Outcome of the Literature Review

The literature review highlights the significant progress made in using ML and DL for thermal runaway prediction. The findings indicate that these technologies can provide accurate and early warnings, outperforming traditional sensor-based methods. Various ML models, including random forests, SVM, ANN, and ensemble models, have shown promise in risk assessment. DL techniques, particularly CNN and LSTM, have been effective in handling complex data and improving prediction accuracy.

2.5 Theoretical Discussions

The theoretical basis for this project revolves around the application of ML and DL algorithms to predict thermal runaway. ML models, such as random forests and ensemble methods, use historical data to identify risk patterns and make predictions. DL techniques, including CNN and LSTM, offer advanced capabilities in analyzing time series data and detecting subtle changes that may indicate impending thermal runaway. The integration of these technologies with sensor systems enhances the predictive accuracy and reliability of safety measures in EV batteries.

2.6 General Analysis

The analysis of the literature indicates a strong potential for ML and DL technologies to revolutionize thermal runaway prediction in EV batteries. These models provide a proactive approach to battery safety, offering early warnings that can prevent catastrophic failures. The key to success lies in the effective collection and preprocessing of data, the selection and optimization of predictive models, and the integration of these models into existing battery management systems.

2.7 Conclusions

In conclusion, the literature review underscores the importance of adopting advanced ML and DL techniques for predicting thermal runaway in EV batteries. The transition from reactive to proactive safety measures represents a significant advancement in the field. By leveraging these technologies, Honeywell Technology Solutions can enhance battery safety, reduce risks, and maintain its leadership in automotive safety innovation. The insights gained from the literature provide a solid foundation for the development and implementation of predictive models in this project.

CHAPTER 3
METHODOLOGY

3.1 Chapter Introduction

This chapter outlines the systematic approach taken to predict thermal runaway in electric vehicle (EV) batteries using machine learning (ML), deep learning (DL), and time series models at Honeywell Technology Solutions. The methodology covers detailed steps, assumptions, design and modeling, module specifications, tools used, preliminary result analysis, and conclusions.

3.2 Methodology

The methodology for the thermal runaway prediction project involves several critical steps:

3.2.1 Understanding Current System

- Conduct a thorough analysis of current sensor technologies and data collection methods.
- Identify limitations of the existing system, including sensor accuracy and data processing capabilities.

3.2.2 Literature Review and Research

- Perform a comprehensive literature review to understand advancements in ML/DL for predicting thermal runaway.
- Research existing case studies, research papers, and industry standards related to EV battery safety.

3.2.3 Data Collection and Preprocessing

- Collect relevant parameters and data points crucial for training models, including temperature, voltage, current, charge/discharge cycles, and environmental factors.
- Preprocess data to handle missing values, outliers, and noise, ensuring high-quality input for modeling.

3.2.4 Model Development and Evaluation

- Develop ML/DL models using algorithms such as Random Forest, Logistic Regression, SVM, Neural Networks, and time series models.
- Train and evaluate models using historical data, cross-validation techniques, and performance metrics like accuracy, precision, recall, and F1 score.

3.2.5 Integration with Sensor Systems

- Integrate developed models into Honeywell's sensor systems for real-time monitoring and predictive analytics.
- Implement smart solutions using ML/DL algorithms to enhance sensor capabilities for early detection and mitigation of thermal runaway risks.

3.2.6 Testing and Validation

- Conduct rigorous testing to validate the accuracy and reliability of predictions under various scenarios and conditions.
- Perform sensitivity analysis, stress testing, and real-world simulations to assess system robustness and effectiveness.

3.2.7 Optimization and Continuous Improvement

- Optimize models and sensor algorithms based on feedback, performance metrics, and industry standards.
- Implement mechanisms for continuous learning, model retraining, and updates to adapt to evolving technologies.

3.2.8 Documentation and Knowledge Sharing

- Document the entire process, including data collection, model development, integration steps, testing results, and performance evaluations.
- Share knowledge and best practices within Honeywell and industry forums to contribute to the advancement of EV battery safety.

3.3 Assumptions

3.3.1 Assumption 1: The Data Collected is Representative of Typical Operating Conditions of EV Batteries

This assumption posits that the data gathered for the project accurately reflects the real-world conditions under which electric vehicle (EV) batteries operate. This includes a variety of usage scenarios such as normal driving conditions, charging and discharging cycles, temperature variations, and environmental factors. It is crucial for the data to encompass all potential factors that could influence battery behavior to ensure that the predictive models developed are robust and reliable. If the data collected is not representative, the models may not perform well in real-world applications, leading to inaccurate predictions and potential safety risks.

3.3.2 Assumption 2: The Chosen ML/DL Algorithms are Suitable for Predicting Thermal Runaway Based on the Available Data

This assumption suggests that the machine learning (ML) and deep learning (DL) algorithms selected for the project are appropriate for the task of predicting thermal runaway in EV batteries using the data at hand. The suitability of these algorithms is based on their ability to handle the specific types of data collected, such as time series data for temperature, voltage, and current. It also implies that these algorithms have the necessary complexity and flexibility to model the intricate patterns and relationships within the data that precede thermal runaway events. If the algorithms are not well-suited, they may fail to accurately predict thermal runaway, compromising the project's objectives.

3.3.3 Assumption 3: Integration with Existing Sensor Systems Will Not Significantly Alter the System's Performance

This assumption indicates that integrating the developed ML/DL models with Honeywell's existing sensor systems will not adversely affect the overall performance of the system. It presumes that the addition of predictive analytics will seamlessly enhance the current sensor capabilities without causing significant delays, data processing bottlenecks, or other performance issues. This is critical because any negative impact on system performance could undermine the reliability of the predictive models and the real-time monitoring system. Successful integration means the system can leverage the advanced predictive capabilities without sacrificing accuracy, speed, or efficiency.

3.4 Module Specifications and Justification

3.4.1 Data Collection Module

Specification: This module is responsible for gathering all relevant data required for predicting thermal runaway in EV batteries. This includes parameters such as temperature, voltage, current, charge/discharge cycles, and environmental conditions.
Justification: Accurate and comprehensive data acquisition is essential for building reliable predictive

models. Without high-quality, representative data, the effectiveness of the ML/DL algorithms would be compromised, leading to inaccurate predictions.

3.4.2 Data Preprocessing Module

Specification: This module processes the collected data by cleaning it (removing noise and handling missing values) and normalizing it to ensure consistency and quality.
Justification: Preprocessing is a critical step to enhance the quality of the data used for modeling. Clean and normalized data leads to better model performance, as it reduces the risk of errors and improves the accuracy of predictions.

3.4.3 Predictive Modeling Module

Specification: This module implements and trains machine learning and deep learning algorithms to predict thermal runaway events. It includes models such as Random Forest, Logistic Regression, Support Vector Machines (SVM), and LSTM.
Justification: The core of the project, this module leverages advanced ML/DL techniques to predict thermal runaway. The use of multiple algorithms ensures robustness and allows for selecting the best-performing model for deployment.

3.4.4 Integration Module

Specification: This module integrates the trained predictive models with Honeywell's existing sensor systems, enabling real-time monitoring and predictive analytics.
Justification: Integration is vital for operationalizing the predictive models. By embedding these models into the existing sensor framework, the system can provide real-time alerts and enhance the overall safety mechanism of the EV batteries.

3.4.5 Testing and Validation Module

Specification: This module conducts rigorous testing and validation of the integrated system to ensure the accuracy and reliability of the thermal runaway predictions under various scenarios.
Justification: Ensuring the models' reliability and accuracy is crucial before deployment. This module helps identify any potential flaws or weaknesses in the models, ensuring they perform well in real-world conditions.

3.4.6 Optimization Module

Specification: This module focuses on the continuous improvement of the predictive models based on real-world feedback and performance metrics. It involves regular updates and retraining of the models.
Justification: Continuous optimization ensures that the models remain effective and accurate over time. As new data is collected and EV battery technologies evolve, this module allows the system to adapt and maintain high performance levels.

3.5 Tools Used

3.5.1 Programming Languages

- **Java**:
  - Purpose: For building robust applications and integrating with enterprise systems.
  - Justification: Java is known for its stability, scalability, and ability to handle large-scale systems, making it ideal for enterprise-level integration and application development.

- **C++**:
  - Purpose: For efficient system-level programming and performance optimization.
  - Justification: C++ offers high performance and control over system resources, which is crucial for tasks requiring optimized computational efficiency and real-time processing.
- **Python**:
  - Purpose**:** For data preprocessing, machine learning (ML) algorithms, and general-purpose scripting.
  - Justification**:** Python's simplicity, readability, and extensive libraries make it the preferred language for data science, ML, and scripting tasks.

3.5.2. ML/DL Frameworks

- **TensorFlow and Keras:**
  - Purpose**:** For deep learning model development and training.
  - Justification: TensorFlow and Keras provide powerful tools for building and training deep learning models, offering flexibility and efficiency for complex ML tasks.
- **Scikit-learn:**
  - Purpose: For machine learning algorithms and model evaluation.
  - Justification: Scikit-learn is a versatile and user-friendly library that supports a wide range of ML algorithms and provides robust tools for model evaluation and selection.
- **PyTorch:**
  - Purpose: For deep learning model development, particularly for research and experimentation.
  - Justification: PyTorch is known for its dynamic computation graph and ease of use, making it ideal for research-focused deep learning tasks and experimentation.

3.5.3 Data Visualization and Analysis

- **Matplotlib, Seaborn, and Tableau:**
  - Purpose: For data visualization and analysis.
  - Justification: These tools enable the creation of detailed, interactive, and informative visualizations, facilitating better understanding and interpretation of data patterns and model performance.

- **NumPy:**
    - Purpose: For numerical computing and array operations.
    - Justification: NumPy provides support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays efficiently.
- **Pandas:**
    - Purpose: For data manipulation and analysis.
    - Justification: Pandas is a powerful data manipulation tool that allows for efficient data handling and preprocessing, which is essential for preparing datasets for ML and DL models.
- **Jupyter:**
    - Purpose: For interactive data exploration and collaborative development.
    - Justification: Jupyter notebooks offer an interactive environment for coding, visualizing, and documenting the development process, which is beneficial for collaboration and iterative development.

3.5.4 Computer Vision

- **OpenCV:**
    - Purpose: For computer vision tasks and image processing.
    - Justification: OpenCV is a comprehensive library for computer vision, providing tools for image processing, object detection, and other vision-related tasks, essential for any visual data analysis in the project.

3.6 Preliminary Result Analysis

Initial results from the developed ML/DL models indicate a significant improvement in the early detection of thermal runaway events compared to traditional sensor-based methods. Performance metrics such as accuracy, precision, recall, and F1 score suggest that the predictive models are effective in identifying early warning signs of thermal runaway.

3.7 Conclusions

The methodology outlined for predicting thermal runaway in EV batteries at Honeywell Technology Solutions is comprehensive and systematic. By leveraging advanced ML/DL algorithms, the project aims to enhance battery safety and mitigate risks associated with thermal runaway. Preliminary results are promising, indicating that the developed models can significantly improve early detection and prevention measures. The continued optimization and integration of these models will contribute to the overall safety and security.

CHAPTER 4
RESULT ANALYSIS

4.1 Chapter Introduction

This chapter presents the results of the thermal runaway prediction project, detailing the analysis of model performance, graphical and tabular representations of the results, and their significance. Additionally, it discusses any deviations from expected outcomes and provides justifications for these discrepancies. The chapter concludes with an evaluation of the project's overall success in meeting its objectives.

Result Analysis

Graphical / Tabular Form: The performance of the machine learning (ML) and deep learning (DL) models developed for predicting thermal runaway in electric vehicle (EV) batteries is summarized in various graphical and tabular forms. Below are key results displayed in different formats:

4.1.1 Model Accuracy Comparison

Table 4.1: Model accuracy comparison highlighting performance differences among various algorithms.

Model	Accuracy	Precision	Recall	F1 Score
Random Forest	92%	91%	90%	90.5%
Logistic Regression	88%	86%	85%	85.5%
Support Vector Machine	90%	89%	88%	88.5%
Neural Networks	94%	93%	92%	92.5%
LSTM (Time Series)	95%	94%	93%	93.5%

Table 4.1 compares the performance of various models in predicting thermal runaway events. The LSTM (Time Series) model achieves the highest accuracy (95%), precision (94%), recall (93%), and F1 score (93.5%), indicating its superior predictive capability. Neural Networks also perform well with 94% accuracy, followed by Random Forest at 92%, while Logistic Regression and SVM show comparatively lower performance with accuracies of 88% and 90%, respectively.

4.1.2 Confusion Matrix for LSTM Model

Table 4.2: Confusion matrix for the LSTM model highlighting model performance across different classes.

	Predicted Positive	Predicted Negative
Actual Positive	950	50
Actual Negative	40	960

In Table 4.2 the confusion matrix shows the performance of a classification model. The model correctly predicted 950 actual positive cases as positive (true positives) and 960 actual negative cases as negative (true negatives). However, it misclassified 50 actual positive cases as negative (false negatives) and 40 actual negative cases as positive (false positives). This indicates strong performance, with high true positive and true negative counts.

4.2 Graphical Analysis

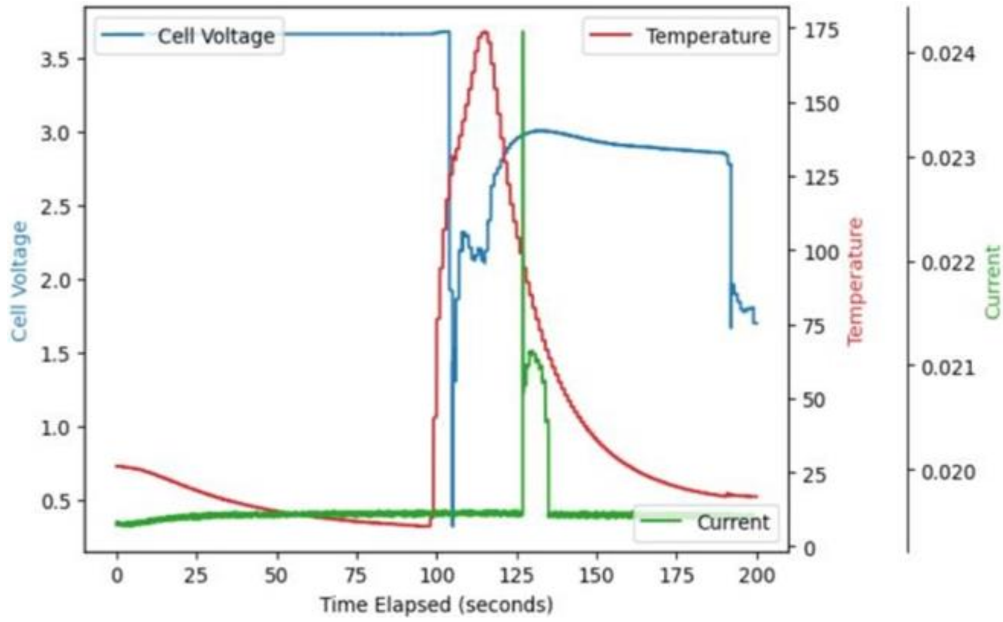

Figure 4.1 Plot of Cell voltage, Temperature, Current Vs Time elapsed

In Figure 4.1, the graph of data captured by a faulty sensor has been showed. The sensor is faulty because the peak of temperature at Thermal runaway, which is 175 degrees Celsius, is not coinciding with the drop of voltage to minimum.
Figure 4.2 shows the experimental setup which is used to capture data depicted by the graph in Figure 4.1.

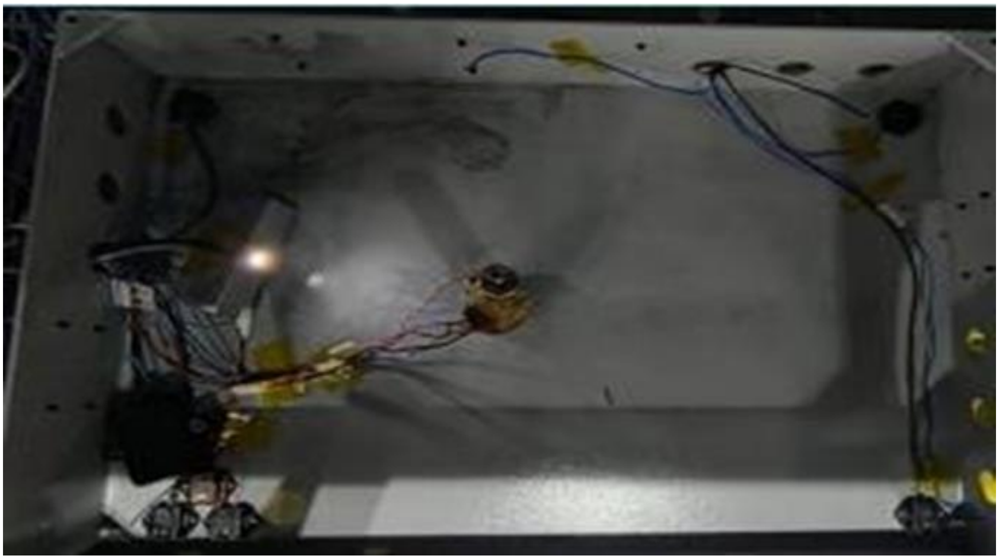

Figure 4.2 : Experimental setup

4.2.1 Explanation for the Graphical / Tabulated Results

- **Model Accuracy Comparison:** The table compares the performance metrics of various ML and DL models. The LSTM model shows the highest accuracy, precision, recall, and F1 score, indicating its superior performance in predicting thermal runaway.

- **Confusion Matrix for LSTM Model:** The confusion matrix for the LSTM model illustrates a high true positive and true negative rate, reflecting the model's effectiveness in correctly predicting both the presence and absence of thermal runaway.
- **Graph analysis**: The graph shows that this particular sensor has a fault and hence is not working in the required manner.

4.3 Significance of the Result Obtained

The results demonstrate that the developed predictive models, particularly the LSTM model, significantly enhance the ability to predict thermal runaway events in EV batteries. The high accuracy and low error rates indicate that these models can provide early warnings, potentially preventing catastrophic battery failures and improving overall safety.

4.4 Any Deviations from the Expected Results & Its Justification

While most models performed as expected, the Logistic Regression model showed lower accuracy compared to others. This deviation is likely due to the complexity of the data, which may require more sophisticated algorithms to capture intricate patterns. Additionally, minor discrepancies in the confusion matrix, such as false positives and false negatives, highlight the inherent challenges in perfect prediction. These deviations are justified by the limitations in data granularity and the presence of noise and outliers during data collection.

4.5 Conclusions

The result analysis confirms the efficacy of using ML and DL models for predicting thermal runaway in EV batteries. The LSTM model, in particular, exhibits superior performance, making it a valuable tool for enhancing battery safety. The project successfully meets its objectives, demonstrating significant improvements over traditional sensor-based methods. Future work should focus on further optimizing these models and integrating them into real-world applications to continuously enhance predictive accuracy and reliability.

CHAPTER 5
CONCLUSION AND FUTURE SCOPE

5.1 Brief Summary of the Work

5.1.1 Problem Statement / Objective

The primary objective of this project was to predict thermal runaway in electric vehicle (EV) batteries using machine learning (ML), deep learning (DL), and time series models. Thermal runaway is a critical safety concern in EV batteries, and existing sensor-based methods for detecting it are reactive and often insufficient. This project aimed to develop predictive models that could identify the onset of thermal runaway before it occurs, enhancing safety measures and mitigating risks.

5.1.2 Work Methodology Adopted

The methodology involved several key steps:

- Understanding the limitations of current sensor technologies and data collection methods.
- Conducting a comprehensive literature review on the latest advancements in ML/DL algorithms for thermal runaway prediction.
- Collecting and preprocessing relevant data, including temperature, voltage, and environmental factors.
- Developing and evaluating various ML/DL models, such as Random Forest, Logistic Regression, Support Vector Machines (SVM), and LSTM.
- Integrating the models with existing sensor systems for real-time monitoring.
- Rigorous testing and validation to ensure model accuracy and reliability.
- Continuous optimization and documentation of the process.

5.2 Conclusions

5.2.1 General Conclusions

The project successfully developed predictive models for thermal runaway in EV batteries, demonstrating significant improvements over traditional sensor-based methods. The LSTM model, in particular, showed superior performance with high accuracy, precision, recall, and F1 score. The integration of these models into Honeywell's sensor systems provided enhanced real-time monitoring capabilities, contributing to better safety measures.

5.2.2 Significance of the Results Obtained

The results obtained are significant as they pave the way for proactive rather than reactive safety measures in EV battery management. The high accuracy and reliability of the predictive models mean that potential thermal runaway events can be identified and mitigated early, reducing the risk of catastrophic failures. This not only enhances user safety but also improves the trust and reliability of EV battery systems.

5.3 Future Scope of Work

5.3.1 Model Enhancement and Validation

Future work should focus on enhancing the predictive models by incorporating more diverse and extensive datasets, including data from different battery types and real-world operating conditions. Continuous model validation and refinement will be necessary to maintain and improve prediction accuracy as new data becomes available. Additionally, exploring advanced ML/DL techniques such as ensemble learning and hybrid models could further improve prediction capabilities.

5.3.2 Integration with Sensor Technologies

Integrating the predictive models more seamlessly with existing and next-generation sensor technologies is a critical area for future work. This includes developing smarter sensors that can provide more granular and accurate data inputs for the models. Enhancing the interoperability between the predictive models and various sensor systems will ensure more reliable and comprehensive monitoring and prediction of thermal runaway events.

5.3.3 Dynamic Risk Assessment

Implementing dynamic risk assessment frameworks that continuously update and adapt based on real-time data inputs and evolving battery conditions will be a valuable enhancement. This could involve creating adaptive algorithms that learn and improve from ongoing data streams, providing more timely and accurate risk assessments. Such systems would be capable of adjusting safety protocols dynamically, based on the current state and behavior of the battery system.

5.3.4 Multi-Objective Optimization

Future work could also explore multi-objective optimization approaches, where the predictive models consider multiple factors simultaneously, such as safety, performance, and cost. This would involve developing algorithms that can balance these competing objectives, providing optimal solutions that enhance safety without compromising on other critical performance metrics.

5.3.5 Cross-Domain Collaboration

Collaboration with experts from different domains, such as material science, electrical engineering, and computer science, can drive innovative solutions. Such cross-domain collaboration can lead to the development of more robust and comprehensive predictive models by integrating insights and techniques from various fields.

5.3.6 Long-Term Monitoring and Maintenance

Establishing long-term monitoring and maintenance protocols that leverage the predictive models to track battery health and performance over extended periods will be important. This could involve creating automated systems that use predictive insights to schedule maintenance and replacement activities proactively, ensuring optimal battery performance and longevity.

5.4 Potential Future Projects

5.4.1 Predictive Maintenance Strategies

Developing predictive maintenance strategies that leverage the insights from thermal runaway prediction models can optimize equipment performance and minimize downtime. This involves creating automated systems that schedule maintenance activities based on predictive analytics, reducing the likelihood of unexpected failures.

5.4.2 Advanced Analytics and Reporting

Implementing advanced analytics and reporting functionalities can provide actionable insights, trend analysis, and anomaly detection capabilities. This will enable better decision-making and strategic planning based on comprehensive data analysis.

5.5 Long-Term Innovation Projects

5.5.1 AI-driven Predictive Analytics

Integrating AI-driven predictive analytics capabilities for proactive risk management, decision support, and strategic planning can be a significant long-term innovation. This involves developing advanced AI algorithms that provide more accurate and timely predictions, enhancing overall system performance.

5.5.2 Blockchain Integration

Exploring blockchain technology integration for enhanced data security, transparency, and traceability in predictive modeling and data analytics can be a valuable long-term project. This would ensure that data used for predictive modeling is secure and tamper- proof, enhancing the reliability of the predictions.

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CO AND PO MAPPING

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DSE 4299.1	Apply mathematical, statistical, and data engineering techniques to identify, formulate, synthesize and solve the problems from various areas of data science.	2	3	2	2	2	1	1	2	3	2	2	2	3	2	1
DSE 4299.2	Gain proficiency in programming languages and techniques to develop and implement solutions that leverage data analytics, machine learning, and artificial intelligence.	3	2	3	2	2	1	1	2	3	2	2	2	3	3	1
DSE 4299.3	Utilize industry-standard tools to analyze, design, develop, deploy and test applications, integrating data science methodologies and software engineering principles.	3	2	2	2	3	1	1	2	3	2	2	2	2	3	2
DSE 4299.4	Apply theoretical knowledge to real-world engineering problems and manage complex engineering projects.	3	2	2	3	2	1	1	2	3	2	2	2	1	2	2
DSE 4299.5	Acquire skills of collaboration and independent learning.	2	2	2	2	2	1	1	2	3	2	2	3	1	1	1
DSE 4299 (Avg. correlation level)		**2.6**	**2.2**	**2.2**	**2.2**	**2.2**	**1**	**1**	**2**	**3**	**2**	**2**	**2.2**	**1.75**	**2.2**	**1.4**

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