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Advancing Battery Safety: Machine Learning-Driven Thermal Management and Cloud-Based Analytics

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ABSTRACT

In this paper, we explore how machine learning can be used to improve battery safety in an machine learning thermal management system, with a focus towards cloud battery safety analytics. Describing how critical the battery fire hazard mitigation is, the aim of this study is to make predictions of real values set as temperature by comparing predicted values based on three machine learning models used as linear regression, decision tree and random forest. The experimental results were analyzed based on performance metrics (explained variance), training time and prediction time for lithium iron phosphate ($LiFePO_4$), The Random Forest model the most accurate demonstrated by the highest R^2 (0.997), least MSE (0.0024) and least MAE (0.026). Learning curve and action taken curves confirm superiority of random forest model. the decision tree (R^2 = 0.99 0 and MSE Lowest belonging model) also gave good results as were already in earlier models. Linear regression (fastest, least accurate with an R^2 of 0.604) The results of this research highlight how essential cloud-based battery safety analytics are in harvesting ML driven methodologies for ideal mitigation of fire hazards and recommend for the use of ML particularly random forest model so as to operate energy storage systems reliably.

1. INTRODUCTION

Due to the increasing use of renewable energy and greater electrification across multiple sectors, there is a growing worldwide need for energy storage systems, especially batteries. This increasing demand illustrates the importance of sophisticated and dependable battery technologies. The issues related to renewable sources intermittency and variability actually support the shift towards cleaner power. This demand also presents new challenges especially in relation to improving battery safety. Modern constructions, along with the growing energy density, raise concern for the thermal and chemical properties of the battery, meaning greater and more innovative solutions are needed. Improved safety measures are required because of the ever-changing energy storage technology landscape. One of the technique for such a solution is the application of machine learning (ML) as a means for proactive and real-time analysis with the aim of identifying, monitoring, and mitigating the safety risks of using the battery. The objectives behind this approach is to ensure the world is able to transition without concerns over capabilities for the energy that needs to be stored while in place to introduce an ML thermal management device for enhanced battery safety [1].

Lithium-ion batteries underpin our daily lives but are a serious safety hazard. These batteries pack a lot of power into a small volume, which can make for compact and powerful devices, but also makes them vulnerable to thermal runaway and potential fires. When a battery fails, it can cause disastrous events such as fires and explosions with extremely dangerous impacts on both users and property. To ensure safe operation requires a multi-pronged approach, and thermal management is critical to this process. When in operation, batteries generate heat due to the build up of internal resistance or external influences such as high charging or discharging currents or extreme ambient temperatures. A proper thermal management system is employed to ensure the battery cells are maintained at an optimal temperature and to avoid thermal runaway, a process in which temperatures increase causing a chain reaction of cell failure which may lead to fire [2].

Phase change materials (PCMs) are a very promising solution for regulating battery temperatures. Its feature of absorbing and releasing heat generated during phase transitions is what makes it most attractive to the thermal management sector. The importance of safety of the PCM is stressed in both material stability research and system hazards, as it is true both and the thermal stability of the selected PCM and the design of the whole system are very significant to prevent potential hazards. Selection of materials must take the preference of PCMs with high thermal stability which can protect them from degradation at operating temperatures. Furthermore, the system design will need

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to incorporate technology that will address safety hazards arising from thermal runaway or material leakage.

1.1 The Causes of Lithium-ion Cell Failure

The root of the problem of lithium-ion cell fails is several factors that interact far more intricately. According to Faraday insights, the main mechanical stress, thermal abuse, and electrical issues are the factors that dominate, Figure 1. However, in addition to these internal cell faults, defects in production or impurities, the cell can over-discharge/charge and even age without these being the whole reason. The proper identification of the causes and the corresponding remedy necessitate a comprehensive strategy including a strong cell design, the production of quality goods, viable Battery Management Systems (BMS), and user-friendly equipment [3]. In this way, only these are the prerequisites that will allow us to make sure that the very safety and lifespan of these indispensable equipment are guaranteed. Lithium-ion cells are capable to fail due to various problems that can be classified into three main groups: mechanical, thermal, and electrical.

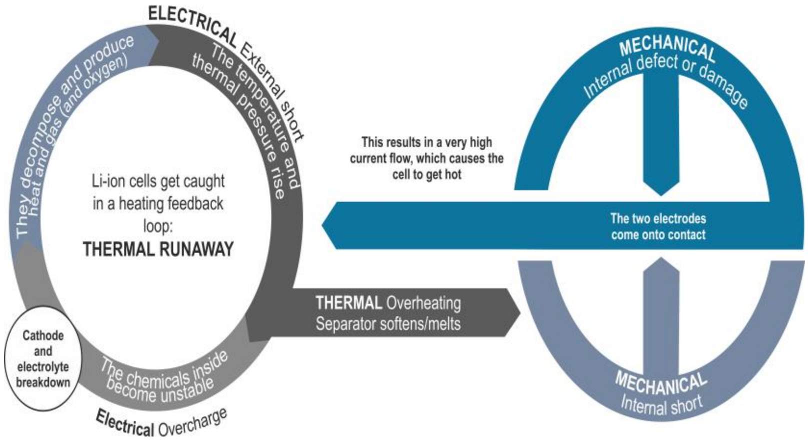

Fig. 1. Lithium-ion cell failure: a closer look.

1.1.1 Mechanical causes of lithium-ion cell failure

Even if lithium-ion cells energy density is stable enough, mechanical integrity still remains the one main thing that is responsible for their safety. Their safety can be compromised when there are some internal defects like the ones that are caused by the technology of the production of microscopic cracks, impurities, or misalignments. A short circuit may be the result of in-house defects that are found in cell materials such as a separator located between the positive and negative electrodes. The mechanism of fixing the tear in separators, the physically thin non-conductive films, is a good idea to follow, as well as a deal with negative electrodes. Physical impairment might take place due to crushing, puncturing, or severely bending the metal. That way, the cell's vitality emerges as weaker by experiencing mechanical impairments that cause a short circuit besides the separator's injury.

1.1.2 Thermal causes of lithium-ion cell failure

Thermal management is another critical aspect of lithium-ion battery safety. Very high air temperatures from outside sources such as a fire or faulty chargers can result in a short circuit in the lithium-ion battery. High charging/discharging currents and the production of defects are other consequences of the internal physical phenomenon of the electrolyte heating that the heat is liberated through which the cell being affected by the heat becomes life-threatening. Runaway temperatures in chemicals are dangerous in that they cause a sequence of events where overheat first makes a cell component decompose which in turn becomes a source of more heat. This results in extremely quick temperatures that can lead to electrolyte materials and gases being pushed around unfavorably thus accounting for either a combustion or an explosion.

- *Internal defects:* Explains how manufacturing imperfections and separator compromise can lead to short circuits.
- *Physical damage:* Mentions crushing, puncturing, and bending as potential causes of mechanical failure.
- *Thermal runaway:* Provides a step-by-step explanation of the process, highlighting the dangers of heat generation, component breakdown, and gas release.

1.1.3 Electrical causes of lithium-ion cell failure

- *External shorts:* A metallic piece connecting between the positive and negative terminals or shorts down in the middle of the cells provides a path having very low resistance for very high currents that would cause quick heating. over spun cells may even catch fire.
- *Overcharging:* Incorrect charger along with a badly designed cell can dump an excessive amount of energy into the cell which eventually results in internal heating, cathode breakdown, and potential thermal runaway. It is easy to fry the battery if the positive and negative ends mix up.

Every single of these failures may provoke a number of events which can result in the fire, explosion, or in the worst case - the death of a person. Constant research into these causes and their avoidance will call for clever design, good manufacturing, proper battery management, and user awareness.

1.1.4 Knee point

Knee point is a critical point for batteries and indicates an inflection in the life cycle with a sharp drop in the capacity, Figure 2. A highly nonlinear aging or capacity plunge. An unexpected and a sudden change will be visitor the next time the cell's performance curve is drawn, and the changes in radiation will be the primary factors for this condition and similarly have a large impact on the internal structure of the cell, which loses the heat in the end, causes thermal runaway, and the cell fails without effectiveness in managing this abrupt change.

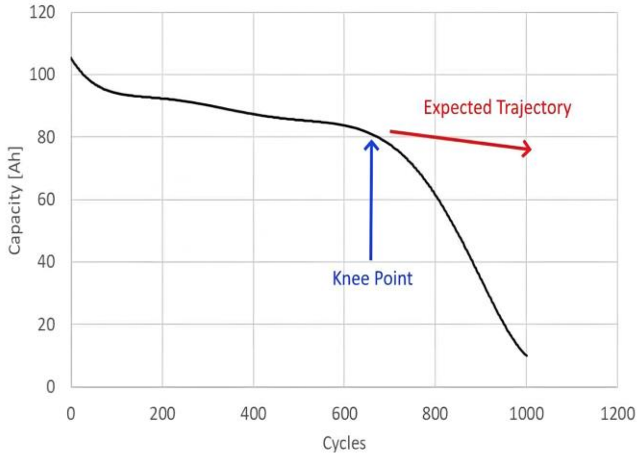

Fig. 2. Knee point signifies a sharp inflection in battery performance.

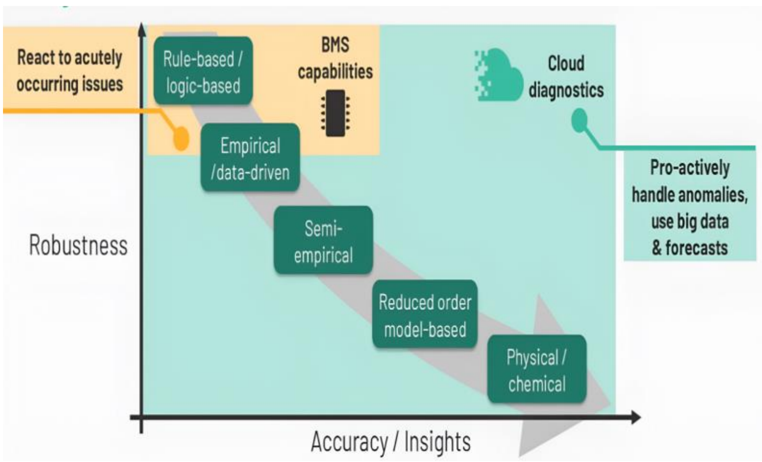

Fig. 3. Cloud-based analytic utilize the entire spectrum of battery diagnostics.

1.1 Cloud-based Analytic

Cloud-based analytics has enhanced the diagnosis of batteries in comparison to the traditional rule-based or logic-based battery management systems (BMS). Why by using all the data that the virtual diagnostics can provide, the proactive correction of the irregularities will be ensured, apart from that, the big data cloud tools will provide the most accurate forecasts. Unlike rule-based BMS systems that necessitate a preset threshold, cloud-based analytics enable the system to evolve and learn from the real time data so as they become more flexible and responsive to battery diagnostics, Figure 3. The application of this invention to the diagnosis of the problems and their solving will thus be the driver to the standardization and longevity of the battery in the success of this system through the harnessing of the data-based and predictive capabilities.

2. REVIEWING EXISTING THERMAL MANAGEMENT SYSTEMS

A comprehensive review of existing thermal management systems and their limitations, coupled with an exploration of machine learning (ML) applications in battery systems, is essential.

2.1 Thermal Management Systems

Kaliaperumal report [4] finds out how much crucial management of heat is in making batteries precipitate and thus create risks in transportation and the building. Chen *et al.* [5], on the other hand, disclose a comparative study of the major cooling approaches that are quite popular, along with their strengths and shortcomings. Referring them Wang *et al.* [6] emphasizes security, longevity, and just like in the results are the most important reasons for thermal management of batteries. In contrast, Lin *et al.* [7] present the major active and the passive cooling methods while Huang *et al.* [8] are concentrated on the role of phase change materials (PCMs) for which they are proud of the passivity of thermal management. Fire hazard mitigation by Sebastian [9] brings out the natural fire risks inherent in lithium-ion batteries and the need to remove batteries by implementing mitigation strategies.

2.2 Machine Learning Applications

The researchers from Ch.Sreedevi *et al.* [10] extent a ML procedure towards battery life prediction, at the same time, Huang *et al.* [11] concentrate on the optimal feature-targeting pairs for battery health diagnosis. Also the studies of Jia and Xu [13], Shen *et al.* [14], and Hu *et al.* [15] show that machine learning algorithms are more efficient in short circuit resistance estimation, safety risk classification, and safety risk prediction, respectively. Measuring the perspectives of these enlightening papers, it can be said that they together guide the reader to understand the challenges faced in thermal management, the fire risks, and the potential of ML in addressing them.

3. MACHINE LEARNING-DRIVEN THERMAL MANAGEMENT

Building a machine learning-based thermal management system for batteries is a multi-layered, step-by-step process. It starts with the problem's clear definition, outlining objectives, and identifying the key parameters for optimization. The data collection process includes collecting historical as well as real-time data on the battery temperature, voltage, current, and atmospheric conditions. Feature selection plays a vital role in the whole process, where various aspects, such as temperature gradients and charging rates, are taken into account after which a particular set of data tuples are conventionally preprocessed by such operations as handling missing data and feature normalization. The preliminary step of model selection is the choice of the right machine learning algorithm, which uses models with ensemble techniques like Random Forests. During the required process, the selected model will be trained, validated, and integrated into a real-time monitoring system so that data analysis becomes continuous. The AI-based control mechanism dynamically regulates the process by adjusting the cooling and heating levels on the basis of the ML predictions, and it contains also an anomaly detection part that is designed for improved safety. Integrating with the battery management system (BMS) is the first step in making the system more functional, and in the case of the application of edge computing there can be also low latency.

Overall, the process is designed to be iterative, with simulation and testing to ensure robustness, and a continuous improvement cycle that includes a feedback loop for learning and updates. Data documentation and reporting defines the design and performance and is finally deployed in a controlled environment. As a result, the focus is on scalability and generalization, as it should be applicable to various battery types and sizes.

The whole system architecture includes several mutual working components for the precise control of temperature, Figure 4. Core components consist of battery modules fitted with sensors for temperature, voltage and current, as well as environmental sensors that track ambient conditions [14]. Based on ML predictions, active cooling systems and heating elements utilize two active heat exchange elements that generate temperature adjustments. The optional edge computing device directly processes ML algorithms to reduce latency, while the BMS supports communication and scheduling time windows and provides charging data. ML model predicts battery temperature, and control unit performs adaptive real–time adjustments. The key stages in terms of data flow are collection, preprocessing, feature extraction, model training, and continuous on-line monitoring. Subsystems with interfaces - communication with BMS and cooling systems, edge computing with feedback loop for learning and scale towards various types of batteries While detailed documentation is the basis of robust reporting, integration of the experimental battery data set improved prediction accuracy and system optimization. This comprehensive architecture ensures efficient thermal management, guaranteeing optimal battery performance and safety.

3.1 Experimental Data and Features for Machine Learning Model Training

Experimental datasets that are the subject of this study provide necessary foundation for understanding operational behavior of lithium iron phosphate ($LiFePO_4$) batteries and it captures useful information across a variety of operational profiles that can be used to create a predictive model for battery temperature. Features of importance for battery performance assessment, Figure 5.

The experiment tested a cylindrical Lithium Iron Phosphate (LFP) battery in a single experiment at this cold start state of 4°C for three different operational profiles. The charge process followed a first constant current phase of 1.5 Amps until the cell reaching a voltage close to 3.65 V then it went into a constant voltage phase stopping when current tapered to 20 milliamps for discharging. Using a dynamic 0.05 Hertz square wave load, to mimic real world usage and hence show how the battery would respond to varying power demands. We used the dataset for a very thorough investigation of the thermal dynamics and load cycling effects on the battery.

In other words, the model consists of 'Voltage_measured', 'Current_measured', 'Current charge', 'Voltage charge', and 'Time'. Battery electrical characteristics as described by voltage and current measurements are directly available, whilst information on the charging occurring can be understood through measurements of charging current and voltage, Table 1. Adding time enables the model to learn temporal features, which is echoed in earlier works [12].

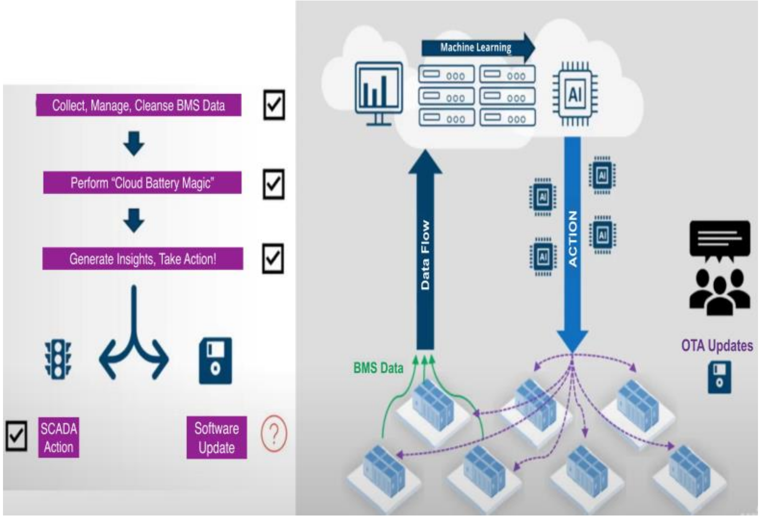

Fig. 4. Machine learning driven system architecture.

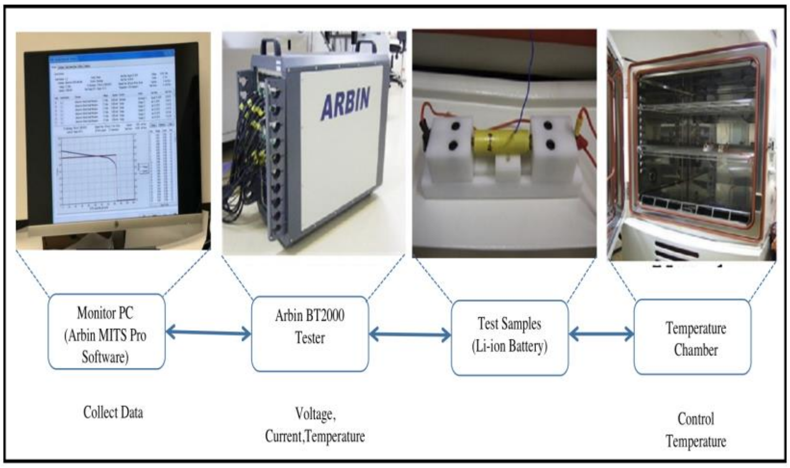

Fig. 5. Battery test bench.

Table 1. Battery data heads.

Voltage_measured	Current_measured	Temperature_measured	Current_load	Voltage_load	Time
4.1976	0.0008	4.3802	0.0004	0	0
4.1967	-0.0009	4.2662	0.0004	4.212	9.312
4.0063	-0.9976	4.4075	1	3.471	23.703
3.9840	-0.9938	4.5730	1	3.451	37.312
3.9664	-0.9945	4.6964	1	3.435	51
3.9515	-0.9962	4.8282	1	3.425	64.609
3.9384	-0.9948	4.9069	1	3.415	78.25
3.9269	-0.9936	4.9789	1	3.402	91.875
3.9165	-0.9953	5.1158	1	3.397	105.547

3.2 Integration of ML Algorithms for Real-time Fire Hazard Detection

Use of real-time fire hazard detection through machine learning (ML) algorithms is an advanced technique to improve safety and reduce risks. Algorithms (*i.e.* linear regression, decision tree and random forest) help us to have an extensive study of different causes behind fire hazards. Linear regression is a starting point providing only the linear relationship among variables, decision trees are good at identifying intricate patterns from the data. As the name implies, random forest algorithm is essentially a combination of multiple decision trees that are used together for both improved accuracy and resiliency. To make these ML algorithms work together is in fact a live fire detection system with real time analysing of potential danger points for a fire. This cutting-edge method not only adds a defense in depth to prevention but provides scalable approach that can easily accommodate different environments and situations therefore greatly strengthening total fire safety protocols.

3.2.1 Linear Regression

Linear regression models the relationship between a dependent variable (y) and one or more independent variables (X) using the equation:

$$y = \beta_0 + \beta_1 x + \epsilon \quad (1)$$

where:
y: Dependent variable
β: Intercept
β_1: Coefficient for independent variable x
x: Independent variable
ϵ: Error term

For multiple independent variables ($x_1, x_2, ..., x_n$), the equation becomes:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \epsilon \quad (2)$$

Where $x_1, x_2, \ldots, x_n$ are the independent variables.

3.2.2 Decision Tree

Decision trees predict target variable values by learning decision rules from data features. The model is represented as:

$$f(x) = \sum_{m=1}^{M} c_m \cdot I(x \in R_m) \quad (3)$$

Where:
f(x): Prediction for input x.
M: Number of leaf nodes.
c_m: Predicted value for the region R_m.
$I(x \in R_m)$: Indicator function (1 if x belongs to region R_m, 0 otherwise)

3.3.3 Random Forest

Random forest combines multiple decision trees to improve prediction accuracy. The final prediction is the average of individual tree predictions:

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} f_i(x) \quad (4)$$

Where:
ŷ : Predicted value.
N: Number of trees in the forest.
$f_i(x)$: Prediction of the i_{th} tree for input x.

Random forest enhances accuracy and robustness by constructing multiple decision trees, each trained on a random subset of data and features. This approach effectively reduces overfitting.

3.4 ML Model Deployment to Google Cloud for Battery Safety

Deploy all machine learning models using Google Cloud services for real-time temperature prediction to enhance battery safety through a flask web application

Algorithm 1: Deployment of Machine Learning Model on Google Cloud for Temperature Prediction and Battery Safety

```
Inputs:
- Trained Machine Learning Model (MLM)
- Input Temperature Data (ITD)
Outputs:
- Predicted Temperature Values (PTV)
/*Step 1: Flask Application Setup/*
- Install required Python packages using:
        `pip install Flask google-auth google-cloud-aiplatform`
-Create a Python file `app.py` to host the web application.
- Import necessary libraries:
        `Flask` for web service, `google-cloud-aiplatform` for Google Cloud interaction.
/*Step 2: Defining the API Endpoint/*
- Initialize the Flask application:
        `app = Flask(__name__)`
- Create an endpoint `/predict` that listens for POST requests.
- Ensure the endpoint accepts JSON data containing temperature inputs.
/*Step 3: Model Loading and Prediction Setup/*
- Establish a connection to Google Cloud AI Platform using appropriate credentials.
- Ensure the deployed model is ready for inference.
/*Step 4: Prediction Execution/*
- On receiving a POST request at `/predict`:
        a) Extract input temperature data (ITD).
        b) Format ITD according to the model's input requirements.
-Call the deployed model using Google Cloud's Prediction service.
- Receive the predicted temperature values (PTV).
- Construct a JSON response containing PTV.
/*Step 5: Local Testing/*
- Run the Flask app locally on `localhost`.
-Use testing tools (e.g., `Postman`, `curl`) to send POST requests to the `/predict` endpoint.
/*Step 6: Application Deployment on Google Cloud/*
-(Optional) Containerize the Flask app using a `Dockerfile` for portability.
- Deploy the Flask app on Google Cloud using Google Cloud Console or `gcloud` CLI.
- Set up appropriate environment variables and networking rules for public access.
/*Step 7: Functional Testing and Monitoring/*
- Post-deployment, test the `/predict` endpoint using sample temperature data.
- Monitor API performance and model inference accuracy using Google Cloud's built-in tools.
Return:
  - Real-time predictions of temperature values from the deployed machine learning model to enhance battery safety.
```

3.5 Cloud-Based Battery Safety Analytics

Battery safety analytics using predictive temperature modeling to foresee possible issues before they are reported in battery cloud control algorithms Battery security analytics use predictive analytics to read temperature modeling beforehand and stop great occasions before they transpire. When used in concert to observe temperature variance and apply predictive analytics, these systems can predict temperature trends, identifying abnormalities from expected behavior. With the help of control algorithms, real-time adjustment can be made to reduce overheating or other safety violations inside a battery system. This more defensive mode of play will help warn of potential dangers early, preventing fires and reducing down time leading to critical intervention. These observations mitigate the operational reliability and mitigate expensive due outages of battery-powered applications with fast response time to safety issues. Combined with cloud analytics and machine learning models into a comprehensive implementation for improving battery safety, helping to ensure the safety of energy storage system operation.

3.6 System Configuration

All models were trained on MacBook Pro with a 2.2 GHz Quad-Core Intel Core i7, 16 GB of 1600 MHz DDR3 RAM and Intel Iris Pro with 1536 MB dedicated memory. All experiments were conducted using Anaconda (version 2024.06) as the development environment.

4. RESULTS

4.1 Learning Curves

Learning curves are graphs that depict how your models performance (as measured by error) is trending and changing with the amount of data it is trained on. Training size: the x-axis, errors on the training data (y up), errors on the validating data (down).

- ***Linear Regression:***

We expect training error to keep on going down with more data, as the model learns linear relation. High variance in complex models can cause validation error to plateau or increase. For simpler models like linear regression, underfitting is more common than overfitting, Figure 6.

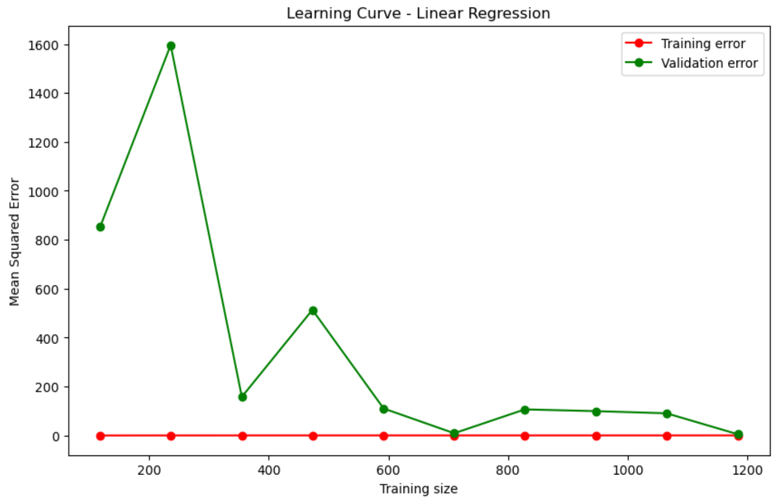

Fig. 6. Learning curve - linear regression.

- ***Decision Tree:***

Training error goes down with more data, but problems of over fitting are a lot greater. Plots of validation error can rise sharply when we have very deep trees, Figure 7 with more data.

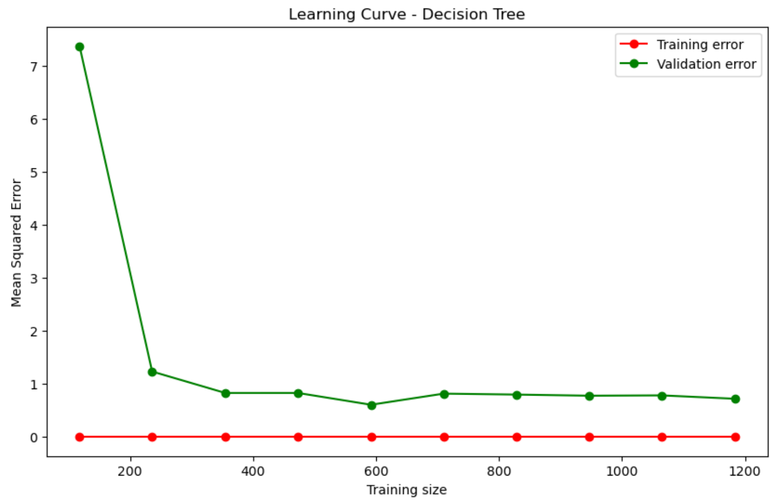

Fig. 7. Learning curve - decision tree.

- ***Random Forest:***

Aggregating multiple decision trees to reduce the role of over fitting than one tree. Learning curve as it the training and validation error starts decreasing slowly with more data, Figure 8.

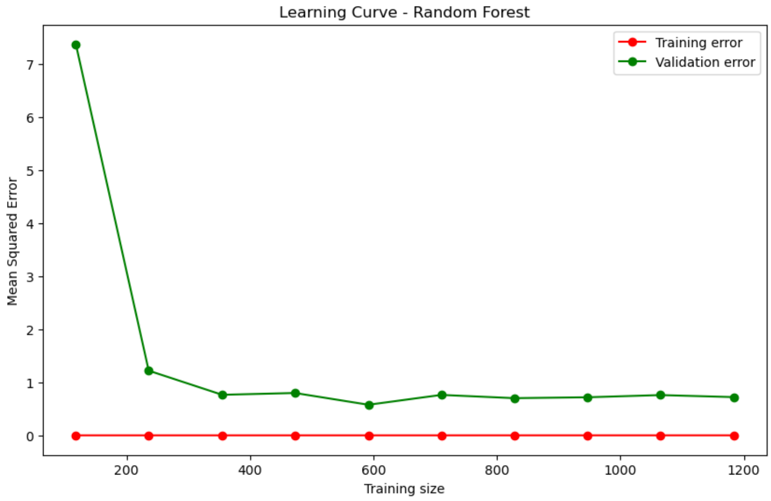

Fig. 8. Learning curve - random forest.

4.2 Action Taken Curve

- *Linear Regression:* The more linear response, Actions Take incremental changes or drops over time as the predicted temperatures plateau out a little, Figure 9.
- *Decision Tree:* May step-wise with actions may change abruptly at certain temperature thresholds (Figure 10) For more of the trees: Typically look somewhat smoother (this is the result of aggregating different decision trees)
- *Random Forest:* Random forest, generally smoother behavior, (due to averaging the decisions of multiple decision trees) as shown in Figure 11.

4.2.1 Interpreting action taken curves

- *Sensitivity:* Steepness curve suggests model depends more on temperature changes. A steeper curve means the model is much more variable. Pearson correlation between current and temperature was 0.78, confirming the observed thermal rise with higher currents.
- *Thresholds:* The points where the curve changes direction are temperature thresholds in a model, these points signal when to perform a specific action, such as a parameter change.

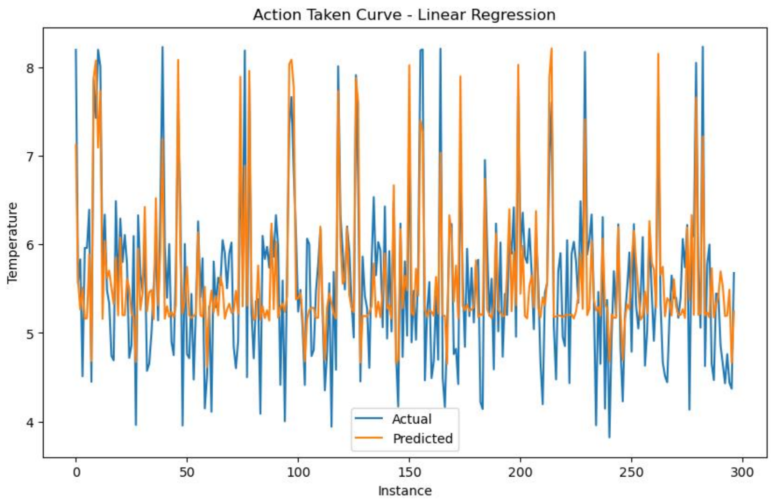

Fig. 9. Action taken curve - linear regression.

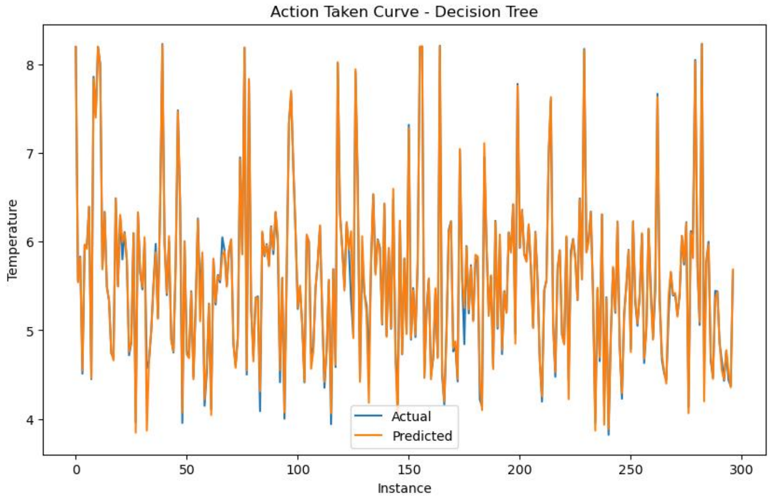

Fig. 10. Action taken curve - decision tree.

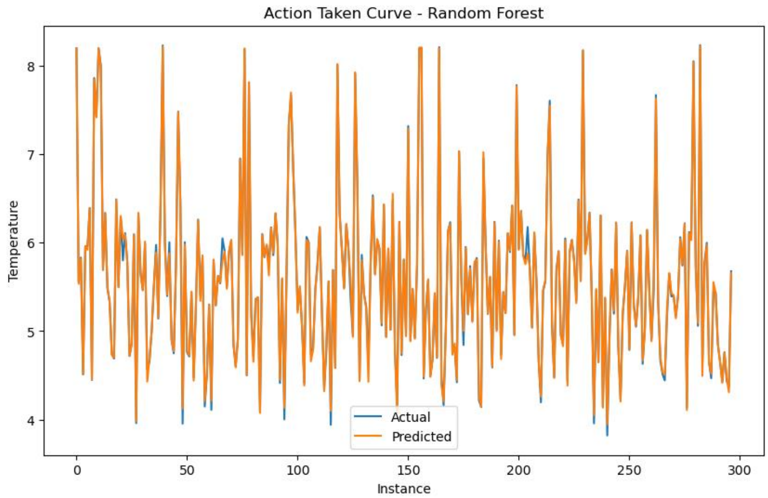

Fig. 11. Action taken curve - random forest.

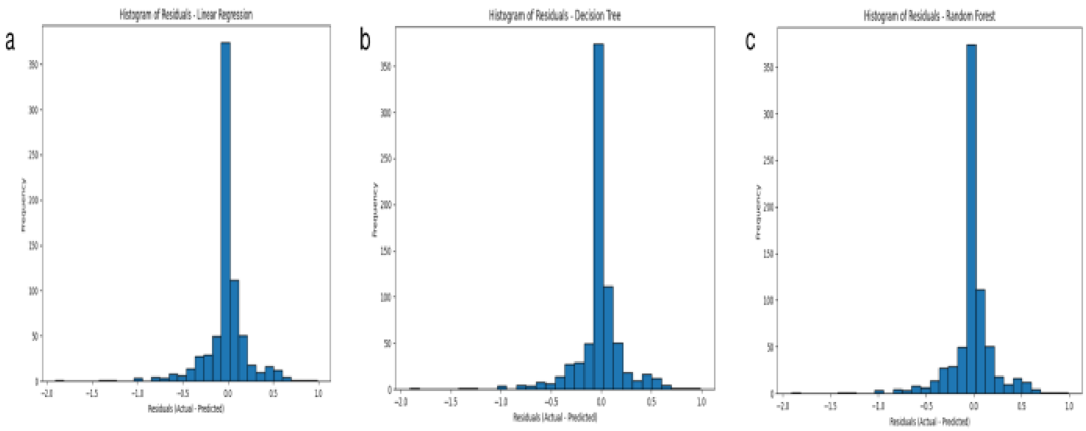

Fig. 12. Histogram of residuals -a) linear regression, b) decision tree, c) random forest.

4.3 Histogram of Residuals

Look into residuals distribution (actuals vs predicted) A better model performance, more symmetric and centered around zero distribution of the residuals in general. An example of visual checks of histograms that indicate Random forest has closer to normally distributed residuals, Figure 12.

4.4 Scatter Plot of Actual vs Predicted Temperatures

Take correlation of points between scatter-plot and diagonal line. Examine how aligned the points in scatter plot are to the diagonal line. Closer alignment indicates a better prediction. Random forest model looks to visually capture a closer fit around the diagonal line (as per visual inspection means more precise predictions).

The fact that we do have pretty tight grouping around the diagonal line translates to an excellent correlation indicating that the Random forest model is producing accurate and repeatable temperature predictions. which also shows its robustness for temperature forecasting usage case across domains, Figure 13, Figure 14, Figure 15.

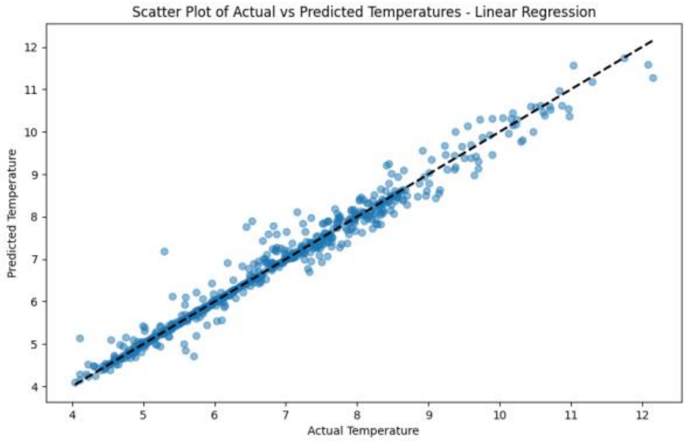

Fig. 13. Scatter plot of actual vs predicted temperature - linear regression.

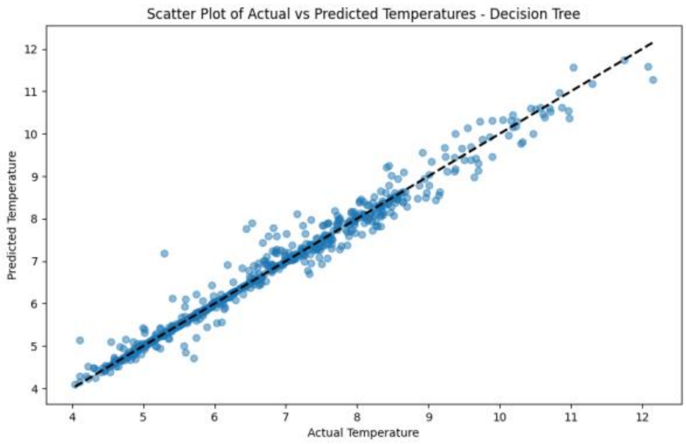

Fig. 14. Scatter plot of actual vs predicted temperature - decision tree.

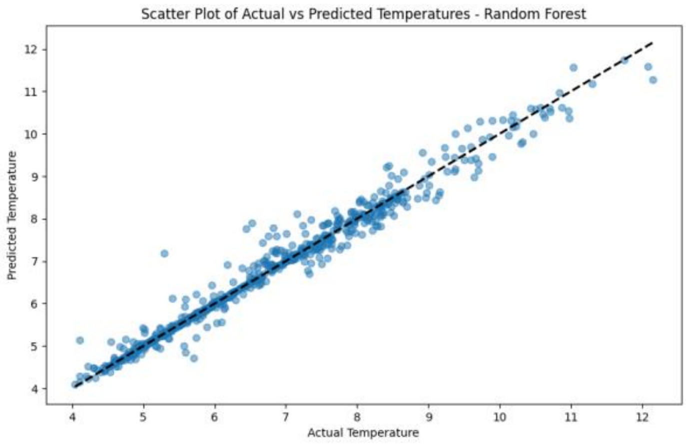

Fig. 15. Scatter plot of actual vs predicted temperature - random forest.

4.5 Table Comparing Actual vs Predicted Temperatures

Look at the individual data points for particular examples in the table to see how well each model can predict these specific instances. In Table 2, Random forest seems to provide predictions that are very close to the actual temperatures over instances.

Table 2. Comparison of actual and predicted temperatures for different machine learning models.

Model	Actual Temperature	Predicted Temperature
Linear Regression	5.1299	5.8421
	7.2151	6.4268
	10.5028	9.8418
	7.3508	7.9293
	6.0842	5.5639
	5.8285	5.535
	6.2011	5.6807
	8.2629	7.1368
	6.8713	7.4774
	6.7162	6.16
Decision Tree	5.1299	5.0766
	7.2151	7.2251
	10.5028	10.4445
	7.3508	7.4814
	6.0842	6.0953
	5.8285	6.2079
	6.2011	6.1979
	8.2629	6.6518
	6.8713	7.5122
	6.7162	6.5331
Random Forest	5.1299	5.1549
	7.2151	7.2179
	10.5028	10.5908
	7.3508	7.3546
	6.0842	6.0812
	5.8285	6.0659
	6.2011	6.2011
	8.2629	7.8439
	6.8713	7.2787
	6.7162	6.5339

4.6 Model's Accuracy and Reliability

Below in Table 3, gathers the performance metrics of the linear regression, decision tree and random forest models back to back for battery temperature prediction highlighting the accuracy and reliability of these. Random forest outperforms decision tree and other models with the lowest MSE and highest R^2. Random forest training time (0.594343) recorded on 6000 samples with n_estimators = 50, max_depth = 6. Random forest demonstrated superior predictive performance compared to all baseline models.

Table 3. Model's performance summary.

Metric	Linear regression	Decision tree	Random forest
MAE	0.500353	0.042477	0.026466
MSE	0.354672	0.008709	0.00242
RMSE	0.595544	0.093321	0.049192
R^2	0.604414	0.990287	0.997301
MAPE	0.09376	0.008454	0.005152
Explained Variance	0.605298	0.990287	0.997304
Training Time (s)	0.001802	0.009724	0.594343
Prediction Time (s)	0.001057	0.00123	0.019116

4.5.1 Analysis

- *Linear Regression:* The worst of the group of models in terms of errors (all in MAE, MSE, RMSE), but also the least reliable. Nevertheless, it is the fastest to train and to make predictions on.
- *Decision Tree:* The one with the greatest training predicting speed but gave the less errors and also has good R^2, explained variance meaning better accuracy.
- *Random Forest:* Lowest error and highest R^2, explained variance which makes it as the most precise and solid model. But it takes way too long to be trained and predicted because of the difficulty and ensemble of the model.

5. CONCLUSION

Best performance: The three models (linear regression, decision tree and random forest) were assessed to predict battery temperatures and the random forest performed best. this is taken from multiple evaluation metrics and easily interpretable Explained variance training time prediction time, etc.

Stable power: Random forest model was found to have one of the highest performance throughout multiple evaluation metrics, which further validate it as the best model for temperature prediction.

Early warnings: This machine learning approach could be used to create early warning signs for thermal hazards, allowing timely response and prevention of fires and recovery time.

Research consultation towards safety: Finally, this work provides essential battery safety research and innovations on the use of machine learning as a transformative tool to safeguard energy storage, that has the potential to safely scale fire risk mitigation.

5.1 Broader Applicability

Beyond battery types: The proposed framework was validated for $LiFePO_4$ cells. Extension to other chemistries like NMC or LCO will require domain adaptation or transfer learning.

Diverse Applications: Explore the potential of adapting the approach for temperature prediction in various applications beyond batteries, such as thermal management of electric vehicle components or power electronics.

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