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AI-BASED EARLY PREDICTION OF THERMAL RUNAWAY USING MULTI-SENSOR BATTERY FEATURE DATA

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Abstract

Lithium-ion batteries, the technology of choice in the energy storage industry today, are unable to totally prevent thermal runaway (TR) incidents. In this sense, using real-time monitoring as well as warning mechanisms for the batteries is not just crucial but also extremely beneficial as they enable the identification of the battery's protection state and the prompt removal of any potential safety hazards. The presented research describes a novel way for the thermal runaway prediction in lithium-ion batteries to be detected at an early stage using the NASA Battery Dataset from Kaggle. The dataset comprises the voltage, current, temperature, and EIS time series measurements altogether, stored in MATLAB .mat files and organized according to battery cell and then cycle number. A very thorough pre-processing of the data was done—missing values were replaced, Z-score normalization was applied, and outliers were removed. To enhance the model's performance, a convolutional neural network (CNN) using Bat Optimization was proposed. The model was exceptionally accurate with an R^2 score of 99.8% and very low values of RMSE and MAE, thus surpassing the existing methods like SVM, Random Forest, and 1D models. Visualization results indicated that the actual and the predicted capacity trends had very close alignment, and there was also reliable RUL estimation and stable learning behaviour. Thus, the CNN optimized by Bat has proved to be a strong predictor, the possessing of superb learning capability, and the high reliability making it the ideal solution for battery systems' early thermal runaway prediction.

Keywords: Lithium-ion Batteries, Predictive Maintenance, Battery Health Monitoring, Thermal Runaway, RUL Estimation.

I. INTRODUCTION

The lithium-ion battery (LIB) has emerged as the primary energy storage medium across different sectors such as transport, electric power grid and personal electronics due to its significant breakthroughs in efficiency and cost reduction during the last ten years. However, battery malfunctions result in major issues like explosions and fires in robotics, cellphones, and aero planes [1]. The primary indicators of serious battery failure include mechanical, electrical, thermal, as well as electrochemical misuse. A battery cell's unregulated chemical reaction known as thermal runaway can result in a devastating fire. If a battery above certain temperature thresholds, chain reactions involving heat, temperature, as well as chemical reactions may take place [2][3]. Because of their pressure build-up design, cylindrical cells are particularly vulnerable to explosion. Thermal runaway prediction models depending on the cellular inner workings are espoused in the search for quicker warning system for known truthful ways.

The sensor that is not functioning properly in the battery management systems (BMSs) leads to important errors in state estimation, hence affecting the reliability of the system. In particular, if voltage sensors do not function correctly, the BMS not be able to set the correct charge limits. This, in turn, leads to overcharging/undercharging cycles, which are operational anomalies. Such deviations make the cells deteriorate faster because they exposed to non-ideal electrochemical conditions and eventually, internal short circuits might happen. The current errors in sensors have a direct effect on the calculations of the state of charge (SOC), thus, making it impossible for the BMS to exercise proactive equalization management.

The precise evaluation of battery health and the creation of battery systems with dependable operation and maintenance are the most important factors in increasing battery life and safety. It is widely acknowledged that predictive maintenance is the bedrock application in adhering to the "IT" manufacturing vision; being based upon the proactive practice of diagnosing potential equipment faults by utilizing data analysis and artificial intelligence (AI) [4]. This necessitates the uninterrupted supervision of the state of the machines, the evaluation through artificial intelligence, and the forecast of the breakdowns of the machines for the preventive maintenance to be carried out in time [5]. The conventional battery management system (BMS) usually uses external sensors (voltage, current, and temperature) for battery monitoring. These systems can be enhanced with a large amount of publicly available sensor data. For the purpose of analyzing this sensor data, the implementation of certain advanced data analysis techniques is being considered [6], to deal with extensive multidimensional data and automatically pick up complex behavioral pattern strands. Supervised machine learning capabilities have been exploited to perform greater accuracy in classification and handle non-linear relationships in datasets efficiently, hence making them suitable for separating behaviors Deep learning (DL) is a division of machine learning (ML) that stresses on the utilization of multilayered neural networks (NNs) for learning which in fact, comprise a great number of parameters. Deep learning, through its multiple layers of abstraction, is capable of collecting features directly from raw data [7], thereby, pattern recognition becomes more complex, it can even detect the non-linear traits of batteries in real-time, thus proving its high adaptability to different battery types.

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A. Motivation and Contribution of the Study

In a lot of critical applications, Lithium-ion batteries have become the best choice and along with this, safety problems like thermal runaway need very precise early detection systems. Conventional BMS sensors are not very dependable and hence they lead to wrong state estimation, thereby heightening the risk of failure. So, it is the right time for the machine learning-assisted smart, data-driven methods to take over, which could make it possible to achieve real-time monitoring, predictive maintenance, and safer battery operations. The following are the primary findings of this study

- Leveraged the NASA Battery Dataset on time-series Li-ion battery aging patterns with close and broad-based time measurements.
- The thorough pre-processing outline briefly involved processing from early stages for missing-values management (removal), Z-score normalization, and outlier detection.
- Proposed a novel structure that merges Convolutional Neural Network (CNN) with the Bat Algorithm in a controlling manner for the purpose of forecasting enhanced results.
- This model brought an impressive R2 of 99.8% and had very low RMSE and MAE values.

B. Significance of the Study

This investigation is significant as it marks a strong and accurate strategy for predicting the thermal runaway in Lithium-Ion batteries at an initial phase, resulting in a safe and healthy management of the batteries. Additionally, the technique integrates CNN with Bat Optimization to boost forecasting accuracy, full preventive maintenance support, and the provision of a solution that is advantageous to the energy storage and electric vehicle industries in actual scenarios.

C. Organization of the Research

The organization of the paper is as follows: In Section II, the existing studies on Early Prediction of Thermal Runaway in Sensor Batteries are reviewed, Section III describes the methodology which consists of dataset and model implementation, Section IV discusses performance, results and comparisons of the models, and finally Section V wraps up with insights and future research directions.

II. LITERATURE REVIEW

The various research articles highlight the usage of ML and optimization techniques for the timely prediction of thermal runaway in sensor-equipped battery systems, with special attention to health estimation, RUL forecasting, SoC prediction, and energy management.

Daniels, Kumar and Prabhakar's (2024) work aims to optimize the temperature sensors for all the chosen sensor distribution patterns, which could be further used to develop an ML model and test its accuracy in predicting the cell position undergoing TR in the battery domain within the multiple operation conditions. To identify the optimized sensors, the Pearson Correlation Coefficient (heat map) optimization strategy is implemented by analyzing the correlations between temperature sensors and potential fault positions based on the coefficient limiting threshold of 0.85 [8].

Huang et al. (2024) the validation of the method was done with the NASA battery dataset and then it was assessed through different representative machine-learning techniques for an accurate battery health evaluation. Some performance metrics have been used, in order to validate the methodology. It has been revealed that the models trained with the suggested features are more accurate than the models trained with a single feature, as the prediction metrics are below 4% [9].

Xie et al. (2024). This framework merges a group of RVFL neural networks that are enhanced with domain adaptation in order to yield precise estimates. Cross-validation skill has been conducted on battery data sets NASA and CALCE which were publicly available. The verification results show that the proposed framework can ensure that the root mean square error (RMSE) is less than 2% in the absence of target labels [10].

Pan and Ji (2024) finally, the algorithm model validation is carried out with NASA and CACLE battery dataset, & the findings outlines that the model prediction method based on the charging IC curve and BOA-ELM can predict the RUL of battery more accurately than other models, and the values of MAE and RMSE are lower than 2%, with better prediction accuracy and robustness [11].

Chen et al. (2023) The heat flow has a positive relationship with the temperature differential on the HFS membrane's bottom surface. The temperature difference grew from 0.034 K to 0.251 K as the measured thickness of the thermal resistance layer increased from 2 μm to 15 μm. Furthermore, there is a strong linear correlation (R2 = 0.99996) between the temperature variation as well as the thickness of the thermally resistant layer, indicating that the thin-film heat flux sensors' effectiveness is additionally optimized when the thickness of the layer varies [12].

Li et al. (2021) the battery's remaining capacity is then assessed in real time by feeding the calculated RC model parameters through a multivariate regression model. With an overall inaccuracy of 2.57%, which is larger than conventional approaches that just employ ohmic internal resistance for their indication, results from studies employing the NASA battery database demonstrate the reliability of the suggested approach [13].

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The relevant systems present Table I for the research background on methodology, dataset/environment, problems addressed by the researchers, performance, and prior/future work.

TABLE I. REVIEW OF LITERATURE ON EARLY PREDICTION OF THERMAL RUNAWAY IN SENSOR BATTERIES

Author	Methodology	Dataset	Problem Addressed	Performance	Future Work / Limitation
Daniels, Kumar & Prabhakar (2024)	Pearson Correlation Coefficient with heatmap for sensor optimization	Sensor distribution patterns in battery systems	Optimize temperature sensors to detect TR (thermal runaway) positions	Correlation threshold of 0.85 used to identify optimal sensors	Future ML model development and validation under varied operating conditions
Huang et al. (2024)	ML-based battery health assessment using extracted features	NASA Battery Dataset	Accurate battery health prediction	Prediction metrics below 4%	Needs more real-world validation and generalization across battery types
Xie et al. (2024)	Swarm of RVFL neural networks with domain adaptation	NASA & CALCE open-source datasets	Estimation without target labels	RMSE < 2%	Requires further improvement on unlabeled data robustness
Pan & Ji (2024)	BOA-ELM model with IC curve features	NASA & CACLE battery datasets	Accurate RUL prediction	MAE & RMSE < 2%	Further enhancement of robustness and model adaptability
Chen et al. (2023)	Thin-film heat flux sensor optimization using thermal resistance variation	Thermal experiments on HFS membrane	Improve sensor sensitivity and heat flux response	$R^2 = 0.99996$ indicating strong linearity	Needs scaling to practical battery systems
Li et al. (2021)	Recursive Least Squares with regression model	NASA Battery Dataset	Real-time battery capacity estimation	Avg. error = 2.57%	Better indicators needed beyond internal resistance

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III. METHODOLOGY

This project's major focus is to establish a quick and precise framework for the early identification of thermal runaway in lithium-ion batteries utilizing sensors & the NASA Battery Database. Research is done with a goal of merging CNN and Bat Optimization to increase the dependability of predictions, support preventive maintenance, and moreover, the safety and reliability of the batteries in real-life scenarios. The technique flowchart described in the section is seen in Figure 1.

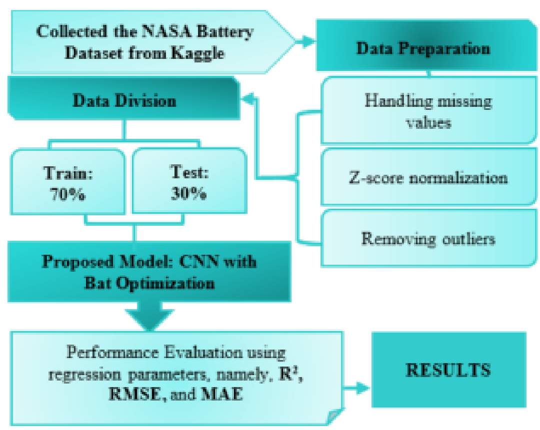

Fig. 1. Flowchart Representation of the Early Prediction of Thermal Runaway in Sensor Batteries

Every step of the flowchart is briefly explained in this section:

A. Data Analysis

This study employed NASA Battery Dataset sourced from Kaggle . The collection consists of Li-ion battery aging trials conducted in MATLAB and supplied in .mat file format. It has a size of approximately 210 MB and is categorized according to battery cell, cycle number and measurement time steps and some cells even have up to 168 cycles, instead of a single flat table.

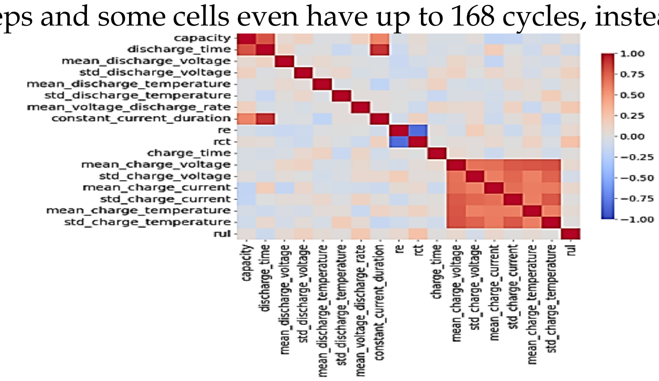

Fig. 2. Correlation Heatmap

The correlation heatmap of battery features is displayed in Figure 2, showing that there are strong positive relationships among the charge-related variables and strong negative correlations between RUL and several features. The discharge metrics also show different patterns, which contribute to the identification of the major factors that affect battery health and aging.

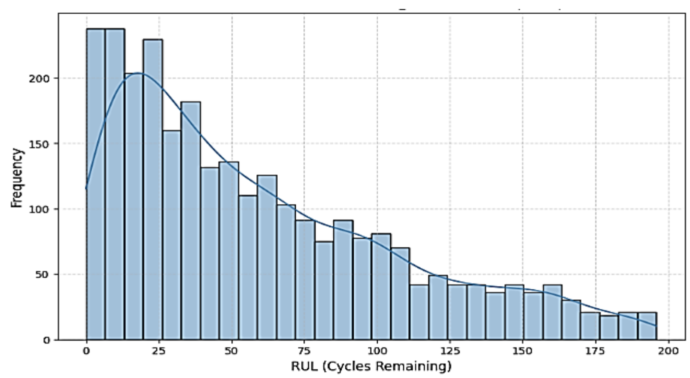

Fig. 3. Distribution of Remaining Useful Life (RUL)

In Figure 3, a histogram of RUL (remaining cycles) is shown, which indicates a strong skew toward the lower side, while the majority of the samples are below the 50-cycle mark. With the increase in RUL, frequency steadily drops, meaning that there are fewer and fewer batteries coming with long remaining life. The trend line reinforces the general degradation mode.

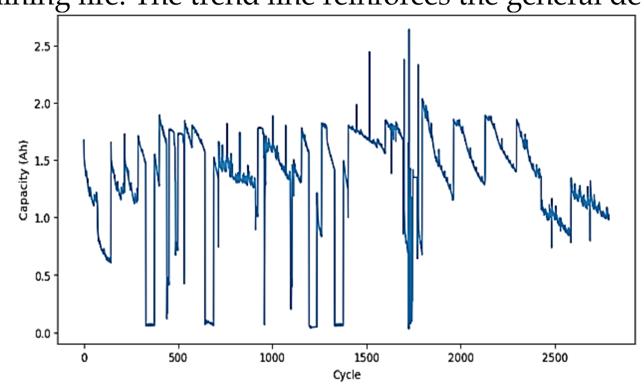

Fig. 4. Capacity Degradation

In Figure 4, the battery capacity is displayed against cycles and a clear degradation trend over time is shown. Despite the gradual decrease in the overall capacity, there are still some fluctuations and occasional sharp drops, which suggest that certain cycles behaved irregularly. Thus, the battery aging process was non-linear and unstable, as indicated by this pattern.

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B. Data Preprocessing

To get the dataset ready for investigation and modelling, completed a number of crucial activities throughout the data preparation step. The pre-processing steps involved in this study are defined below:

- **Handling Missing Values:** Inaccurate findings with more serious repercussions might arise from missing data values caused by uncontrolled circumstances, including faulty data collecting, transmission, or storage systems. Ignoring missing data might result in serious issues with managing an asset that provides a service in an essential electrical network.
- **Z-score normalization**: Zero normalization, or Z-score normalization, is achieved by dividing the mean as well as the standard deviation of each feature in a training set by a number of variables. For every attribute, the mean & standard deviation are calculated. The generic Equation (1) specifies the process to be carried out:

$$c = \frac{c-\mu}{\sigma} \qquad (1)$$

where, the average of c is μNd its standard deviation is σ.

- **Removing Outliers:** Outlier removal consists of identifying and eliminating data points that are much different from the remaining data points. As a result, the data's reliability has enhanced, noise is lowered, and consequently, analysis and model performance are more accurate.

C. Data Splitting

Training as well as testing databases are produced from the analyzed data. In this instance, the split ratio is 70-30%. The system has been trained using 70% of the data, and its efficiency is tested using the remaining 30%.

D. Proposed Approach: CNN with Bat Optimization

CNN is a popular deep learning method for applications like image categorization and identification [14], as well as image regression. Convolutional, pooling, & fully linked layers make up a CNN. Convolutional elements and fully linked layers, which operate identically to a basic ANN, make up a CNN [15], using several layers of neurons for learning after receiving the data produced from the convolutional layers. Equation (2) refers to the formula that the convolutional layers use to execute convolution procedures on the input images:

$$z_{i,j,k}^{l} = w_k^{l^T} \cdot x_{i,j}^{l} + b_k^{l} \qquad (2)$$

where x_(i,j)^l is the input group situated in the l-th layer with the centre position at (i,j) , w_k^l and b_k^l Are the weight vector and bias term of the k-th convolution kernel of the l-th layer, respectively, and , z_(i,j,k)^lis the value at (i,j) In the k-th feature map of the l-th layer.

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Bats use their mouths to produce ultrasonic vibrations. The bat's ears pick up the echo created when the ultrasonic vibrations bounce off barriers or prey [16]. The bat can fly free as well as hunt successfully in the darkness because it depends on the echoes for precise placement. It's fascinating to note that the size of the prey and the wavelength of the ultrasonic waves bats generate are quite similar. The author originally put forward the concept and fundamental structure of the BA in 2010, motivated by this circumstance. The global optimal solution may be found using the heuristic algorithm BA.Equation (3) may thus be used to determine the bat's flying speed.

$$V_i^t = V_i^{t-1} + (S_i^{t-1} - BestS) \times Q_i \quad (3)$$

The BA offers an excellent worldwide discovery and optimization capability by arbitrarily varying the frequency. The local exploitation capability is enhanced by varying the pulse emission rate and loudness. The BA controls the community's unpredictable behavior using tuning tools.

IV. EXPERIMENTAL SIMULATIONS AND PERFORMANCE

The operating system for the model was Ubuntu 22.04, and it was developed using the PyTorch 2.2.0 framework. The hardware setup was made up of an AMD EPYC 7402 24-Core Processor and an NVIDIA GeForce RTX 4090 GPU with 24GB of memory, both situated in Santa Clara, California, USA.

A. Performance Measures

Leveraging the NASA database, the generated RUL prediction system underwent rigorous testing to verify its accuracy and robustness. The effectiveness of the suggested method is assessed using three main metrics: root means square error (RMSE), mean absolute error (MAE), and R2-score (coefficient of determination). The algorithm is frequently assessed using a variety of performance indicators, such as MAE, R2-score, and root mean squared error (RMSE). Improved performance is shown by lower MAE & RMSE values, whereas an elevated R2-score denotes a better capacity for forecasting outcomes. An R2-score around 1 denotes a more precise estimation, but the prediction accuracy rises as RMSE and MAE go closer to zero. Equations (4) (6) provide the following formulations for performance metrics:

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(y_k - \hat{y}_k)^2} \quad (4)$$

$$MAE = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{(\hat{y}_k - y_k)}{y_k}\right| \quad (5)$$

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$$R^2 = 1 - \frac{\sum_{k=1}^{n}(y_k - \hat{y}_k)^2}{\sum_{k=1}^{n}(y_k - \bar{y}_k)^2} \quad (5)$$

B. Result Demonstrations

The performance of the Bat-optimized CNN model for predicting early thermal runaway was very strong, as indicated by Table II. This is evidenced by the high R^2 value of 99.8% and the very low RMSE and MAE, which indicate great accuracy and nearly no prediction errors.

TABLE II. MODEL PERFORMANCE FOR EARLY PREDICTION OF THERMAL RUNAWAY IN SENSOR BATTERIES

Metrics	CNN with Bat Optimization
R2	99.8
RMSE	0.0065
MAE	0.0043

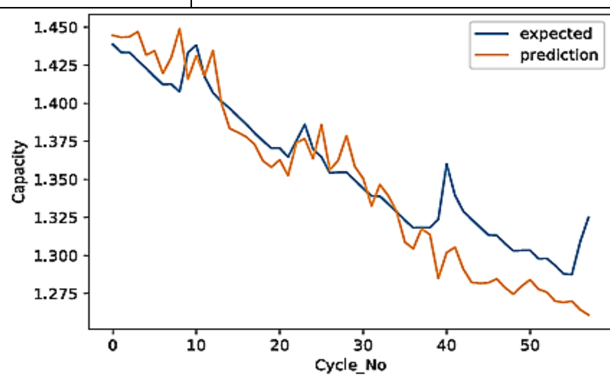

Fig. 5. Actual vs. Predicted Capacity prediction of the Battery

Figure 5 visualizes the actual vs predicted simulations of the approach. The falling trend of both curves suggests that the capacity has been losing its quality over the cycles. Although predicted ratios are quite similar to the expected measurements, they often fall short of the expected capacity values. In later cycles, they are falling short of the expected values the most.

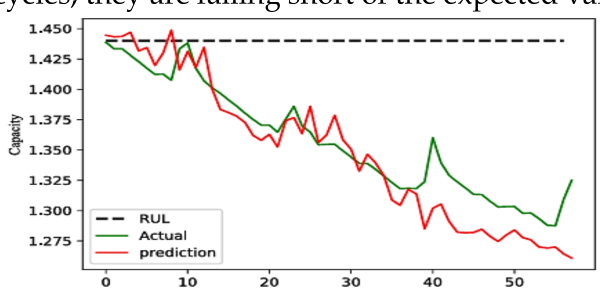

Fig. 6. RUL prediction of the Capacity of the Battery

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Figure 6 shows the comparison of actual and predicted battery capacity against cycles along with a dotted line illustrating the RUL threshold. The two curves, though fluctuating, are declining and the prediction is very close to the actual trend but slightly underestimates capacity in the later cycles, which is helpful in the assessment of remaining useful life.

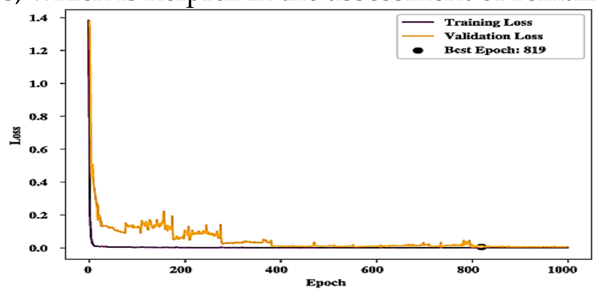

Fig. 7. Learning Curve of the Model with Best Epoch

Training & validation losses are plotted against epochs in Figure 7, and the result is a very quick drop at the beginning followed by the convergence to a very low value. Validation loss, while fluctuating, is gradually getting stabilized and epoch 819 is marked as the one with the highest performance.

C. Comparative Evaluation

A comparison of early thermal runaway prediction methods through datasets and machine learning models is shown in Table III. The suggested CNN with Bat Optimization model applied on NASA Battery Data obtains the best R^2 value of 99.8%, leaving behind other techniques like the 1D model (87.0%), SVM (79.0%), Random Forest (92.4%), and Decision Tree (91.0%). Thus, it was able to prove its superior prediction performance.

TABLE III. COMPARATIVE ANALYSIS ON EARLY PREDICTION OF THERMAL RUNAWAY IN SENSOR BATTERIES

Reference	Dataset	Approach	R2
[17]	EVERLASTING Data	1D model (NN1)	87.0
[18]	Open Battery Failure Data	SVM	79.0
[19]	Real-World Data	RF	92.4
[20]	Original Data from Lithium Iron Phosphate Battery	DT	91.0
Proposed	NASA Battery Data	CNN with Bat Optimization	99.8

The CNN model that was recently proposed and incorporated with Bat Optimization not only immensely surpasses the existing methods but also asserts its strengths in the areas of precision, generalization, and alignment with the actual fluctuations in battery capacity. Consequently, it has been an amazing and trustful tool for the prediction of thermal runaway at its very early stage.

V. CONCLUSION AND FUTURE SCOPE

Through the use of sensors, it is possible to supervise characteristics, including voltage and temperature, throughout the battery's life cycle. It provides an opportunity for the system of thermal test warning systems that looks for abnormal behavior in the parameters under supervision. In fact, the suggested Bat-optimized CNN model turned out to be a very useful instrument for the early detection of thermal runaway in lithium-ion batteries. With the help of the NASA Battery Dataset and good pre-processing techniques, the model not only reached a high level of accuracy in making predictions but also exhibited robustness, as indicated by the R^2 value of 99.8% and very small RMSE and MAE. The model's excellent generalization and ability to adapt to actual battery degradation patterns were once again confirmed by the projections' excellent agreement with the true capacity as well as RUL trends. Its superiority over alternative techniques was further confirmed by the comparison research, resulting in a promising and reliable choice for preventative safety systems as well as battery health monitoring. This mechanism is a big help in ensuring that batteries last long and operate safely for critical operations.

The future research can possibly target utilizing real-time battery monitoring, multi-sensor fusion and transfer learning instead to improve the generalization capacity over different battery types. Furthermore, the augmentation of the dataset along with trials in real-life scenarios might lead to increased reliability. On top of that, the combination of different optimization methods and explainable AI could lead to more accurate and interpretable predictions for the purpose of deployment in a real-world environment.

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