Temperature Prediction of Electric Vehicle Battery Using Attention based Adaptive Convolution Neural Network

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***Abstract*— Electric Vehicle (EV) battery temperature prediction is a critical component of efficient battery management and optimal vehicle performance. Accurate SOC estimation ensures safe operation, maximizes battery lifespan, and enhances the overall driving experience. Traditional methods, such as model-based approaches and equivalent circuit models, have been widely used but often struggle with complex battery dynamics and degradation over time. While deep learning approaches, particularly Recurrent Neural Networks (RNNs), have gained popularity due to their ability to model temporal dependencies, they face significant challenges such as high computational complexity, poor generalization to new datasets, and sensitivity to initial error states. These limitations hinder their practical applicability in real-world EV battery management systems. To address these challenges, proposing a novel approach for temperature prediction using an Adaptive Convolutional Neural Network (ACNN). The ACNN leverages the hierarchical feature extraction capabilities of convolutional layers, which are highly effective in capturing spatial and temporal patterns in battery data. Additionally, the ACNN incorporates adaptive mechanisms that dynamically adjust to varying battery conditions, such as temperature fluctuations, aging effects, and different operating modes. Attention channel-based Convolutional Neural Network enables improved feature representation through Input Based Kernel Adaption, higher accuracy of prediction up to 85% in comparing to other models with minimal learning rate,bettter generalisation and efficient computation. This adaptability ensures robust convergence, even when the model is initialized with significant initial errors, and significantly improves generalization across diverse datasets and operating conditions.**

***Keywords*— Electric vehicle battery, temperature prediction, deep learning, Adaptive Convolutional Neural Network , battery management.**

I. INTRODUCTION

The worldwide transformation to electric vehicles (EVs) is primarily driven by the need to reduce climate pollutants, reduces dependence on fossil fuels, and foster environmentally friendly transportation. As EV utilization increases to rise, streamlining battery usage and performance becomes a key factor in enhancing overall vehicle functionality and user satisfaction. Battery integrity, particularly its thermal management, significantly influences electricity demand, operational distance, and durability. Poor thermal management can result in thermal overload, fast deterioration, and lower effectiveness. Managing battery temperature is particularly challenging due to constantly changing driving conditions, ambient temperature variations, and fluctuating power demands.

Excessive heat can increase power usage due to extra cooling demands, while extremely cold temperatures can reduce battery efficiency and limit driving range. As a result, an effective and responsive thermal management system is crucial for keeping the battery within its optimal temperature range, ultimately improving both efficiency and lifespan. Recent advancements in machine learning, especially deep learning, have demonstrated promising potential in predictive modeling across different fields. Deep learning algorithms can process complex, high-dimensional data and uncover intricate patterns that traditional methods may struggle to identify .

Utilizing deep learning techniques for thermal prediction enables accurate forecasting of temperature variations under different conditions, facilitating precise control of the battery's thermal state. Proposed research introduces an innovative approach that applies deep learning models to predict the thermal behavior of EV batteries. By leveraging sensor data, including temperature, voltage, and current, the objective is to forecast battery temperature profiles in real-time, thereby supporting optimal thermal management. The overarching goal is to enhance battery efficiency, extend lifespan, and improve overall EV performance.

To improve the continuity and efficacy of EVs, it is essential to develop intelligent systems capable of managing battery temperature across varying driving conditions. Effective thermal management is vital in preventing overheating, which can damage the battery and increase the energy consumption of cooling systems. Conversely, low temperatures can reduce the battery's discharge efficiency, ultimately limiting the vehicle's driving range. Therefore, a dynamic and adaptive thermal management system is essential for optimizing energy use and extending battery lifespan .

Accurately predicting battery temperature profiles is a complex task influenced by various factors, including driving patterns, weather conditions, battery load, and charge/discharge cycles. Variables like voltage, current contribute to temperature fluctuations that require continuous monitoring and real-time adjustments. Traditional thermal management approaches are often reactive, addressing temperature deviations only after they become critical.

In contrast, leveraging machine learning, particularly deep learning techniques, enables real-time prediction of battery thermal behaviour. Predictive models can forecast temperature variations in advance, allowing for proactive regulation of heating and cooling systems to prevent overheating or excessive cooling.

II. LITERATURE REVIEW

Temperature fluctuations in batteries affect their performance, cycle life, and safety. To maintain optimal performance, it is essential to predict temperature changes accurately and implement precise cooling/heating solutions. Researches conducted a study on the role of battery temperature in EV performance, proposing a model for thermal management that integrates computational fluid dynamics and cooling systems. Their findings showed that adaptive thermal control could improve battery efficiency and longevity [1-6].

The effectiveness of deep learning models, such as Long Short-Term Memory and Recurrent Neural Networks, in forecasting battery temperatures and other crucial battery parameters. These models leverage time-series data to predict future temperature behavior under varying conditions. Later in advancement applied LSTM networks for temperature forecasting based on historical data from the battery, ambient conditions, and driving patterns [7-9]. Deep learning techniques have emerged as a battery temperature and optimize thermal management systems. Their model showed that the accuracy of thermal predictions improved by 15% compared to traditional thermal modelling techniques, contributing to better thermal control and improved battery lifespan. introduced a deep neural network model to predict the state of charge (SOC) and temperature during rapid charge/discharge events. Their research demonstrated that real-time predictions helped to regulate temperature fluctuations and prevent battery overheating, increasing operational efficiency [10-12].

Different thermal management strategies for electric vehicle (EV) batteries, including passive cooling, active cooling, and the use of phase change materials (PCMs). Additionally, it examines various temperature prediction models, particularly those based on machine learning techniques such as artificial neural networks (ANN), Gaussian process regression (GPR), and deep learning methods. A comparative analysis of these models, highlighting their advantages and drawbacks in terms of prediction accuracy and computational efficiency [13]. Advanced techniques for managing battery temperature and predicting thermal behavior in electric vehicles. It examines both model-based and data-driven approaches, with a strong emphasis on machine learning and hybrid methods. The paper also includes case studies where data-driven models, such as neural networks and fuzzy logic[14-15], have been utilized to forecast battery temperatures under different driving and charging scenarios.

Deep learning brings exceptional precision and adaptability to temperature prediction. It's successful deployment requires addressing key challenges such as data availability, computational demands, and model generalization. The incorporation of deep learning into hybrid frameworks, highlights its role as an enhancement rather than a replacement—leveraging the advantages of both traditional and modern approaches.

Deep learning models, such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, are particularly effective for this application as they can process time-series data and recognize patterns over time [16-18]. By integrating sensor data—including temperature, voltage, current, and environmental conditions—these models provide highly accurate predictions of the battery's future thermal state. Additionally, as more data becomes available, the model continuously adapts to changing conditions, enhancing both performance and reliability. The above methods have challenges such as high computational demands, limited generalization to new datasets, and sensitivity to initial error states [19-20]. These limitations reduce their effectiveness for real-world EV battery management applications. The proposed methodology for temperature prediction of a battery using an Adaptive Convolution Neural Network (ACNN) overcomes the challenges.

The ACNN employ the hierarchical feature extraction capabilities of convolution layers, which are highly effective in capturing spatial and temporal patterns in battery data. Moreover, the ACNN makes use of adaptive mechanisms that continuously adjust to changing battery conditions, including temperature variations, aging effects, and different operational modes. This flexibility enhances the model's ability to achieve stable convergence, even when starting with substantial initial errors, mean while improving its generalization across a wide range of datasets and operating scenarios.

III. PROPOSED WORK

Adaptive convolution neural networks(ACNN)

Adaptive CNNs constructs on the traditional CNN architecture by introducing dynamic components that adjust their behaviour based on input data. The primary goal is to optimize performance without compromising computational efficiency.

Adaptive Features

1. Input-Based Kernel Adaptation

Adaptive Convolutional Neural Networks (CNNs) adjust their convolutional kernels dynamically according to the characteristics of the input data to diminish the noise. For example, an image with high contrast may require a distinct kernel configuration compared to one with more subtle features. This adaptive Attention mechanism enhances the model's ability to extract relevant features by capturing patterns efficiently across diverse inputs which is acting as dynamic noise filter that reduces over fitting.

2. Multi-Level Adaptation

These networks dynamically modify their architecture at various levels, adjusting factors such as layer depth, filter sizes, and activation thresholds based on the input's complexity. This hierarchical adaptation enhances the model's ability to generalize effectively across diverse datasets.

Computational complexity for traditional models makes use of step-by-step process over time with Time complexity of $O(N*HS^2)$ i.e total length of N and Hidden size HS but is expensive with the increase of size, while ACNNs make use of Convolution filters with Time complexity as $O(K*N*F)$ where K denotes Kernel Size, N denotes input size and F denotes number of Filters.

3. Efficient Architecture Design

Adaptive CNNs frequently utilize lightweight architecture shown in Fig:1, making them suitable for deployment on devices with limited computational resources, such as smartphones or IoT devices. This optimization ensures efficient performance without compromising accuracy. ACNN architecture with multiple convolution branches using different kernel sizes (3, 5, 7) to adaptively capture features at different scales. It also includes an attention mechanism to focus on the most informative channels along with Dropout and hidden layers for prediction and accuracy improvement. Thus Adaptive CNN applies multiple kernel sizes in parallel (multi-branch) and combines them with attention, allowing the model to adaptively focus on relevant features. It improves generalization and feature extraction for time-series problems like SOC prediction.

This approach not only enhances temperature regulation but also improves the overall energy efficiency of EVs by minimizing energy losses caused by excessive heating or cooling. As a result, it extends battery lifespan, reduces operational expenses, and supports greater sustainability in electric vehicles. Therefore, integrating machine learning with thermal forecasting presents significant potential for advancing EV technology in the future.

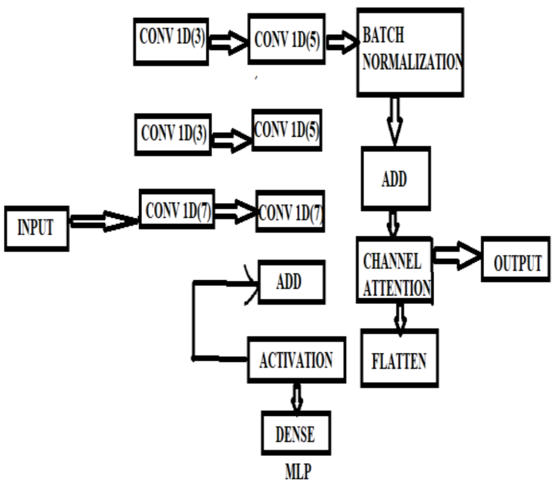

Fig 1: Architecture of ACNN

The proposed method is substantiated using real-world Li-ion battery data, which includes voltage, current, and temperature measurements collected under various driving cycles and environmental conditions. A comprehensive data filtering pipeline is designed to handle the unique characteristics of battery datasets. This approach includes noise filtering to remove measurement artifacts, feature normalization to standardize input data, handling missing data through advanced imputation techniques, and extracting temporal patterns such as voltage gradients and cumulative current. These preprocessing steps ensure that the input data is clean, consistent, and representative of the underlying battery dynamics. Batch Normalization regularizes the convolutional layer outputs to maintain zero mean and unit variance, improving gradient flow and accelerating training. In the proposed work, it is applied around the attention module to ensure stable, well-scaled features, enabling more effective focus on important patterns.

To enhance understanding and readability, data visualization techniques are employed at every stage of the prediction. For instance, raw and filtered voltage data are visualized to explain the effectiveness of noise filtering, while histograms of normalized features highlight the impact of feature scaling. Temporal patterns, such as cumulative current and voltage trends, are plotted to provide insights into battery behaviours over time. These visualizations not only aid in debugging and refining the preprocessing pipeline but also help stakeholders understand the data-driven nature of the proposed approach. ACNN violates temporal modeling but combines it into a unified spatial-temporal feature extraction process. Unlike traditional methods that separate temporal and spatial analysis, ACNN jointly captures both through adaptive convolutions.

The adaptive nature of the proposed framework ensures consistent performance across varying battery conditions, addressing key challenges in temperature predictions for Li-ion batteries. By combining advanced deep learning techniques with robust data preprocessing and visualization, this work paves the way for more reliable and efficient EV battery management systems.

IV. METHODOLOGY AND RESULTS

The accurate temperature prediction of an EV battery is a critical factor in ensuring optimal battery management, performance, and longevity. Temperature prediction mainly gives the remaining charge in a battery relative temperature to its maximum capacity, akin to a fuel gauge in conventional vehicles. However, its estimation poses significant challenges due to the complex and dynamic behaviours exhibited by lithium-ion batteries under varying environmental conditions and usage patterns. Adaptive Convolutional Neural Networks (ACNN), an advanced machine learning architecture, present a promising solution to these challenges. By capturing non-linear dependencies and learning directly from data, ACNN provides a robust mechanism to predict temperature with high accuracy and reliability, offering a significant leap forward in battery technology and electric vehicle management systems.

A. *Data Augmentation and Preprocessing*

The process begins with data augmentation, a technique crucial for enhancing the diversity and volume of available data. This step is particularly important for given datasets typically available in the field of battery management in reference to Fig.2. Data augmentation involves generating new samples from the existing dataset by applying transformations such as noise addition, scaling, and temporal shifts. The augmented data not only improves the robustness of the ACNN model but also ensures its adaptability across various real-world scenarios, including extreme operational conditions.

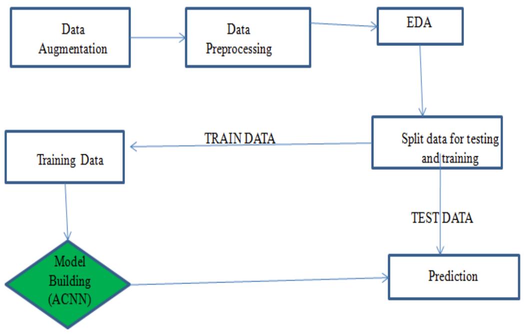

Fig 2: Implementation process flow Diagram of ACNN

Once augmented, the data undergoes preprocessing to prepare it for analysis and modelling. Preprocessing is a meticulous step that entails cleaning the raw dataset, normalizing feature scales to ensure uniformity, and filtering outliers to remove potential sources of error. Additionally, feature engineering is performed to extract critical parameters such as voltage, current, temperature, and historical temperature values. These features, representative of the battery's state and performance, are pivotal in enabling the ACNN to learn effectively and make accurate predictions.

B. *Exploratory Data Analysis (EDA) and Insights*

Before proceeding with model training, Exploratory Data Analysis (EDA**)** is performed to thoroughly examine the dataset. This process employs statistical and graphical techniques to uncover patterns, relationships, and anomalies within the data. For example, correlation matrices help identify dependencies between temperature prediction and variables such as voltage, temperature, and current as directed. Additionally, time-series analysis provides insights into how these parameters fluctuate across different drive cycles and operating conditions. The findings from EDA play a crucial role in shaping the subsequent modeling approach, ensuring that the ACNN architecture is optimized for the dataset's unique characteristics. By detecting biases and potential issues early, EDA establishes a solid groundwork for developing a reliable predictive model.

C. *Training and Adaptive Features of the ACNN Model*

The foundation of training of an Adaptive Convolutional Neural Network (ACNN) model incorporates convolutional layers specifically designed to capture both spatial and temporal patterns within the input data. The ACNN is its adaptive mechanism, which dynamically modifies kernel parameters in response to the complexity of the data. This flexibility enables the model to effectively accommodate various operating conditions, ranging from mild discharges to significant temperature fluctuations. As a result, the ACNN delivers precise temperature predictions across a wide spectrum of scenarios.

The Adaptive Convolutional Neural Network (ACNN) is trained by optimizing a carefully selected loss function, such as Mean Absolute Error (MAE) offers a clear metric for average prediction error, making it valuable for evaluating thermal risks when both overestimation and underestimation are equally critical initially computed to 0.001016 using ACNN and in Fig 4a the MAE obtained is 0.004, Root Mean Square Error (RMSE) gives greater weight to larger errors, which is vital in battery management systems where sharp temperature rises can be hazardous. It helps to assess the ACNN's ability to handle abrupt and nonlinear thermal variations with less amount to about 0.700%. The model parameters are recursively updated using advanced optimization techniques like backpropagation and gradient descent. To enhance generalization and mitigate overfitting, the dataset is strategically split, with 70-80% used for training and the remaining 20-30% allocated for validation and testing as shown in Fig [3a and 3b]. Predicted structure approach ensures that the model not only learns effectively from the training data but also maintains strong performance on unseen test data—an essential factor for real-world applications. Accuracy performance metric indicates the proportion of predictions within a defined error margin (e.g., ±1°C), reflecting the model's reliability for real-time thermal control and alignment with safety and regulatory standards.

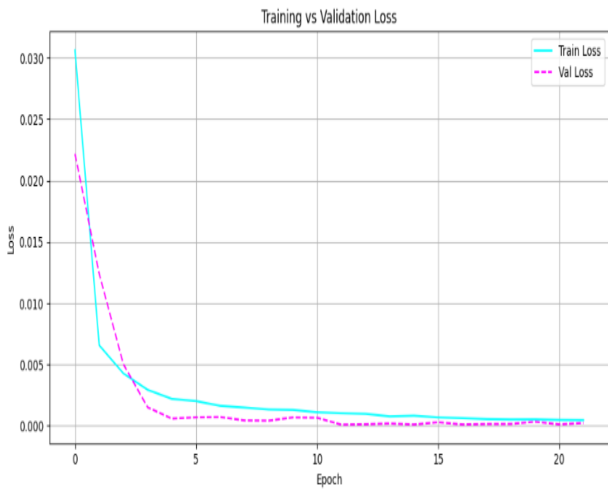

Fig 3a: Plot of Training and Validation Loss

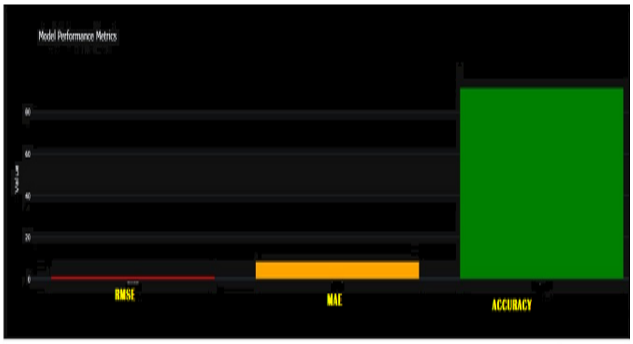

Fig 3b: Model Performance Metrics (RMSE, MAPE, Accuracy)

D. *Prediction and Post Processing*

Once trained, the ACNN model is employed to predict the temperature of EV batteries under varying conditions. The input features such as real-time voltage,

Test Case ID	Test Description	Input	Expected Output	Actual Output
TC01	File Upload Functionality	CSV file containing SOC and voltage data	File should be uploaded and data previewed	File uploaded successfully and displayed in table
TC02	Data Preprocessing	Raw data with missing values	Cleaned and normalized data	Missing values handled and data normalized
TC03	Model Training Execution	Training dataset	Model should begin training and show accuracy/loss curves	Model trained successfully with convergence
TC04	SOC vs Voltage Prediction	Test data file	Predicted SOC values based on input	Model generated accurate predictions
TC05	Graph Plotting (SOC vs Voltage)	Prediction results	Correctly plotted SOC vs Voltage graph	Graph plotted with expected format and values
TC06	Time vs Dynamic Current Plot	Time-series input	Line graph with current fluctuation over time	Accurate and readable plot displayed
TC07	Error Handling for Invalid File	Upload of .txt or malformed CSV	Display error message	"Invalid file format" message displayed
TC08	Model Evaluation Metrics Display	Model prediction results	Display of accuracy, RMSE, and error metrics	All metrics shown with correct values

current, temperature and other data are fed into the model, which processes them through its layered architecture to generate temperature estimates clearly shown in Table:1. To further enhance the accuracy and reliability of these predictions, post- processing techniques are applied. Ensemble averaging, for example, combines predictions from multiple trained models to mitigate individual biases and reduce overall error margins as clearly shown above. Thresholding techniques are also employed to ensure that temperature prediction values remain within physically plausible bounds, typically ranging from 0% to 100%.

Table1:Test Case implementation for various descriptions of input to Actual and Predicted values is as follows with all passed status:

SOC Estimation, Actual vs Predicted	
Actual SOC (%)	**Predicted SOC (%)**
78.23	76.04
93.35	93.84
13.79	14.16
85.54	85.55
35.92	33.94
1.24	1.21
30.01	28
78.16	77.24
52.76	52.35
84.62	83.49

Table2 :Tabular Form For State Of Charge Estimation For Actual Vs Predicted

E. *Evaluation Metrics and Model Performance*

The performance of the ACNN model is rigorously evaluated using a combination of statistical and practical metrics. Accuracy is defined as the proportion of temperature predictions falling within an acceptable error range, serves as a primary benchmark. MAE quantifies the average deviation between predicted and actual temperature prediction values, offering a straightforward measure of predictive reliability. RMSE, meanwhile, provides a more nuanced assessment by penalizing larger errors more heavily, reflecting the model's consistency and robustness. By achieving high scores across these metrics, the ACNN demonstrates its efficacy as a state-of-the-art tool for temperature prediction is shown in [Fig:4a(Traditional Analysis) and 4b(ACNN Analysis)]. The comparative analysis of Traditional models and temperature prediction for non linear circuits using ACNN.

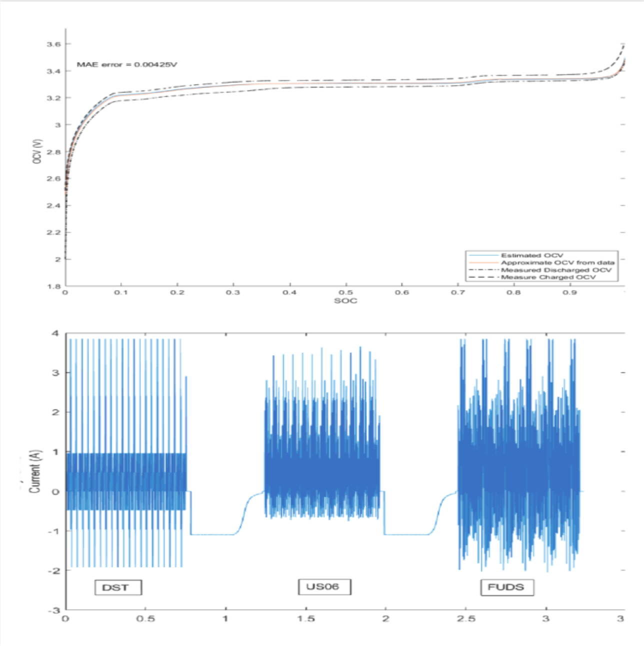

Fig: 4a OCV vs SOC and Current Vs Time plots of Li-ion Batteries Using Traditional methods

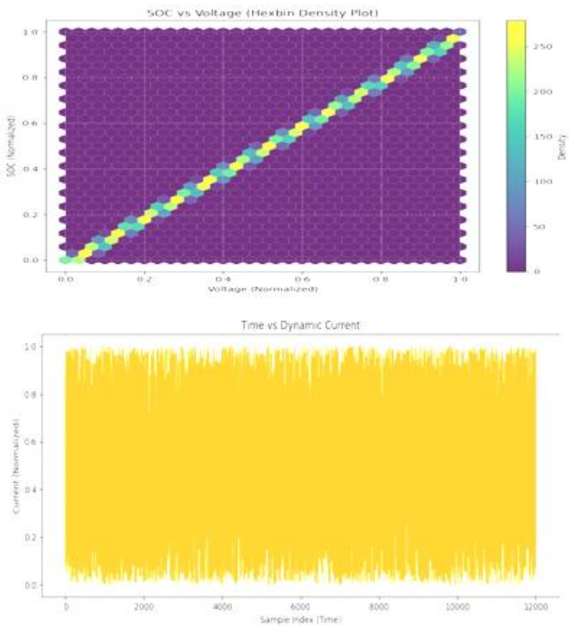

Fig: 4b OCV vs SOC and Current Vs Time plots of Li-ion Batteries Using ACNN

Implications and Advantages

Implementing Adaptive Convolutional Neural Networks (ACNNs) for temperature prediction brings several significant benefits. The model's resilience to noisy or incomplete datasets makes it highly suitable for real-world applications, where sensor inaccuracies and data gaps frequently occur. Its ability to provide real-time predictions enhances its integration into dynamic battery management systems, while its adaptability to changing conditions ensures compatibility across various electric vehicle (EV) models and environments is finally resulted in Fig:5. Furthermore, by enhancing battery temperature prediction accuracy, ACNN plays a crucial role in extending battery lifespan and optimizing energy consumption, addressing key challenges in the pursuit of more sustainable transportation solutions.

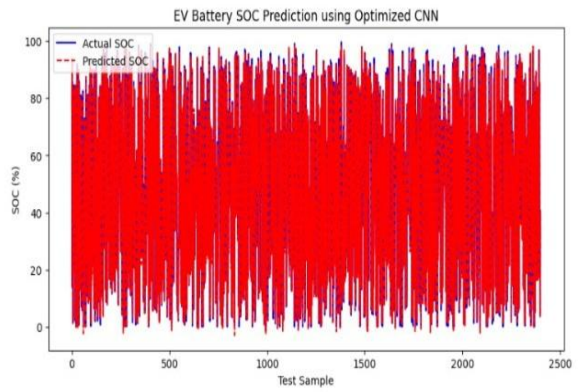

Fig 5: EV Battery SOC Prediction Using Adaptive Convolution Neural Network(ACNN)

The proposed system has the following advantages:

Reduced Memory Usage: Adaptive networks often reduce the number of parameters while balancing performance measures.

Efficiency: Faster computations make these models suitable for real-time applications.

Versatility: Enhanced performance on varied datasets.

By plotting the graph of Actual and predicted temperatures using Adaptive Convolution Neural Networks can help us to identify the various levels of temperature faults that effects the longevity of the battery can be identified easily.

V. Conclusions

Deep learning-based temperature prediction techniques to enhance the battery life and efficiency of electric vehicles (EVs). By leveraging advanced deep learning models for thermal management, we demonstrated how accurate temperature predictions can optimize the performance of lithium-ion batteries, leading to better thermal control and improved overall battery longevity. Our findings highlight that precise thermal forecasting not only helps in maintaining the ideal operating temperature but also minimizes the risks of overheating and thermal runaway, thereby enhancing both the safety and efficiency of EV batteries. Additionally, the integration of thermal prediction models enables more effective battery management, ensuring that EV batteries operate within optimal conditions, thus extending their useful life and maximizing energy efficiency.

ACNNs dynamically adjust kernels, enabling better generalization across varied driving scenarios, though handling high-dimensional or multi-sensor data by traditional methods is rectified. Building ACNNs requires moderate to high development effort, advanced frameworks (like PyTorch/TensorFlow), and large, labeled datasets, all contributing to expensive for real time prediction. The use of Adaptive Convolutional Neural

Networks (ACNNs) has greatly enhanced the accuracy of battery temperature prediction and thermal management. However, continuous optimization and refinement are essential to effectively handle real-world challenges, such as temperature fluctuations and charging cycles. Future research can further explore the impact of environmental conditions and integrate hybrid modeling approaches to improve prediction reliability.

By utilizing ACNNs for battery temperature estimation, this approach contributes to enhancing performance, safety, and sustainability in electric vehicle (EV) batteries. As a result, it plays a key role in developing more efficient and dependable EV technologies. Enhancing ACNN architectures to improve prediction accuracy across various battery types and operating conditions. Developing light weight deep learning models for real-time deployment on embedded battery management systems (BMS). Integrating hybrid approaches by combining deep learning with physics-based models for more reliable predictions. The proposed work can also be extended further to Deploy Model on Edge AI Devices in Optimizing for low-power hardware like Raspberry Pi for real-time Charge estimation. **Hardware Requirements** includes Training demands powerful GPUs, while real-time EV deployment is feasible on edge AI hardware with model optimization for speed and energy efficiency.

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