AI-Powered Thermal Profiling for Battery Management

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***Abstract*—Battery safety is an important issue in the design of contemporary electronic systems, particularly electric vehicles (EVs), mobile phones, and renewable energy systems. Overheating is one of the most common and risky battery faults, which may result in degraded performance, reduced lifespan, and even catastrophic failure like thermal runaway. Legacy systems are based on threshold-based controls that are reactive and usually not capable of real-time prediction of thermal behavior. This work introduces a new AI-based battery safety monitoring system with a Generative AI model implemented using the Long Short-Term Memory (LSTM) networks to forecast battery temperature fluctuations beforehand. The model learns dynamic thermal patterns by examining multivariate sensor readings—voltage, current, state of charge, ambient temperature, and time—and predicts future temperature states. Real-time forecast is complemented by a voice warning system that categorizes battery conditions into phases such as "normal," "heating up," or "overheating," allowing for effective and user-friendly intervention for safety. The system proves to be highly accurate in detecting abnormal temperature patterns before they become threats. Integration of forecasting AI with integrated voice notifications is a new advance in intelligent energy management systems, with possible usage in EVs, IoT devices, and energy storage technologies. This contribution helps to promote battery safety and assists in sustainable development objectives by increasing reliability, minimizing electronic waste, and fostering responsible energy consumption.**

Keywords - Battery Safety, Thermal Prediction, LSTM, State of Charge, Voice Alert System

I. Introduction

The increased demand for electric cars (EVs), alternative energy-based systems, and mobile electronic equipment all over the world has turned batteries into an integral part of contemporary technology. Yet safety issues with batteries are serious because of incidents such as overheating, thermal runaway, and eventual battery failure, which can cause drastic decline in performance, reduced battery life, or even dangerous accidents [1]. Monitoring and management of battery temperatures hence become important to guarantee safety, reliability, and longevity. The conventional battery management systems (BMS) usually depend upon pre-defined temperature ranges or rule-based control strategies, which cannot self-adapt to changing operating conditions [2]. These methods might not be able to issue advance warnings prior to entering a dangerous condition. Now, with the emergence of artificial intelligence, especially deep learning, there is a chance of designing forecasting systems with the capacity to predict unsafe behavior of the battery beforehand. This project is suggesting a Battery Safety Monitoring System based on AI utilizing a Generative AI model in the form of a Long Short-Term Memory (LSTM) network to predict future battery temperature from real-time inputs like voltage, current, state of charge, ambient temperature, and time [3]. The system not only provides future thermal predictions but also issues smart voice-based warnings based on the severity of the predicted condition. This anticipatory strategy enables systems or users to take instant safety precautions, averting probable malfunction or damage. Through the combination of deep learning, real-time analytics, and interactive alerting, the suggested system shows how AI can greatly improve battery safety monitoring [4]. The model is light and deployable on edge devices and has potential applications in both the industrial and consumer markets. This work is aligned with recent trends in green energy and smart embedded systems and has immediate application for industries that seek to enhance safety in battery-powered systems.

A. Novelty and Contribution

The new system provides a unique combination of Generative AI in the form of LSTM networks and a real-time battery safety system [5] with the following unique contributions:

- **Predictive Thermal Monitoring:** In contrast to existing systems that respond to threshold violations, this system predicts future battery temperature based on real-time sensor inputs, allowing proactive safety management.
- **Multivariate Time-Series Modeling:** The model accepts several input parameters—temperature, current, voltage, state of charge, and time—providing high accuracy based on learning intricate interdependencies that influence battery behavior.
- **Voice-Based Alert System:** In a novel deployment, the system alerts through voice feedback such as ”Battery is overheating,” providing simple and timely warnings in even non-visual monitoring contexts [6].
- **Visual Representation of Battery Condition:** The software features a dynamic visual indication of the battery’s thermal condition, facilitating easier interpretation by users of the current status.
- **End-to-End Integration on Edge-Supported Framework:** The entire solution from data ingestion and prediction to visualization and alerting is made to be light in weight and ready for deployment on embedded boards such as Raspberry Pi or ESP32.
- **Potential for Real-World Application:** The model is generalizable and scalable, with immediate applications in renewable energy storage systems, electric vehicles, portable electronics, and IoT-based battery packs.

B. Contribution of the Proposed System Towards Sustainable Development Goals

The AI-based Battery Safety Monitoring System strongly resonates with a number of the United Nations Sustainable Development Goals (SDGs) by ensuring safer, more efficient, and sustainable battery use. It most directly supports SDG 7 (Affordable and Clean Energy) by allowing the safe and reliable functioning of batteries in renewable energy systems and making energy storage solutions efficient and hazard-free [7]. With the help of predictive analytics, the system improves battery life and eliminates wastage of energy. Consistent with SDG 9 (Industry, Innovation, and Infrastructure), the project proposes a novel AI-based solution for real-time battery monitoring in aid of developing smart and robust infrastructure in the energy, transportation, and electronic industries [8]. The system also facilitates SDG 12 (Responsible Consumption and Production) by avoiding battery degradation and failures, hence cutting down the frequency of replacements and reducing the amount of electronic waste [9]. Additionally, by making electric vehicles and clean energy technologies safe to use, the system indirectly supports SDG 13 (Climate Action) by promoting the large-scale use of green technologies [10]. Overall, the project indicates how AI can be utilized effectively in contributing to sustainable development by way of improved safety, efficiency, and resource management in battery-powered systems.

II. Related Work

A detailed comparison of existing AI models [11] is presented in the table I and Fig. 1.

TABLE I
COMPARISON OF AI MODELS FOR BATTERY TEMPERATURE PREDICTION

Model	Use Case	Limitations
LSTM	Time-series prediction	Slower training
GRU	Faster time-series prediction	May miss complex patterns
Transformer	Long sequence modeling	High computational cost
GAN	Synthetic data generation	Difficult to train
VAE	Anomaly detection	Poor long-term forecasting
ARIMA	Linear trend forecasting	Not suitable for nonlinear data

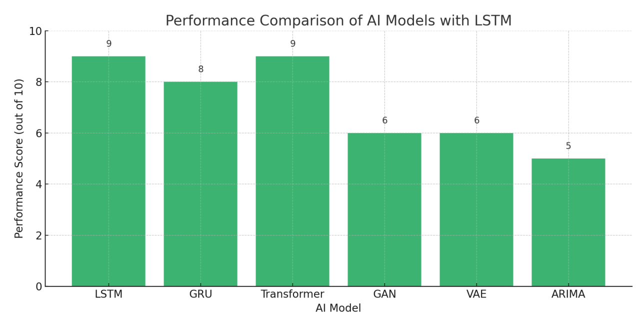

Fig. 1. Performance comparison of LSTM with other AI models for battery temperature prediction.

III. Implementation

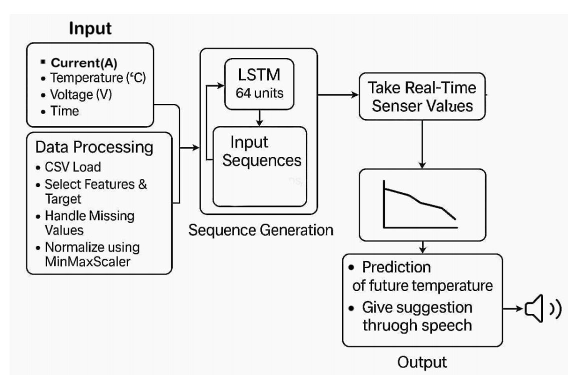

Fig. 2. LSTM-based system for real-time temperature prediction and voice-based suggestions using sensor data.

A. LSTM and Loss Functions

The core of the proposed AI-powered battery safety monitoring system is a Long Short-Term Memory (LSTM) neural network, which is well-suited for modeling multivariate time-series data. LSTM networks are capable of learning long-term dependencies and temporal patterns from sequential data, overcoming the vanishing gradient issues present in traditional RNNs.

In this project, the LSTM is trained on time-series data from battery sensors—voltage, current, temperature, and time—to predict future thermal behavior [12]. The model leverages the internal memory cell to retain relevant historical information and issue accurate forecasts for upcoming temperature values.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$

Here, eq(1) represents the Forget gate of the LSTM model.

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{2}$$

$$\tilde{C}_t = \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \tag{3}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{4}$$

Here, eq(2), eq(3) and eq(4) represents the input gate of the LSTM model.

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{5}$$

$$h_t = o_t * \tanh(C_t) \tag{6}$$

Here. eq(5) and eq(6) represents the output gate of the LSTM model

For the implemented LSTM model, the training process uses the Mean Squared Error (MSE) loss function to evaluate prediction accuracy:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{7}$$

From eq(2) y_i is the actual temperature and $\hat{y}_i$ is the predicted value. MSE is well-suited for continuous value regression, ensuring the model learns to minimize temperature prediction error effectively, which is critical for real-time safety alert generation in the system [13].

B. Li-Ion Battery

Lithium-ion batteries are used extensively in contemporary technologies such as electric transport, mobile electronics, and renewable energy systems because they boast high energy density, high cycle life, and efficiency. In spite of these benefits, lithium-ion cells have the inherent characteristic of being sensitive to thermal and electrical stress, hence susceptible to overheating, short circuit, and thermal runaway. Such failures are usually initiated by internal defects or external factors including overcharging, excessive current loads, or inadequate thermal control. Due to the severe safety risks involved, more and more sophisticated smart battery monitoring systems that can sense initial thermal anomaly warnings are needed.

To address this challenge, the suggested AI-Powered Battery Safety Monitoring System leverages real-time sensor measurements and an LSTM-based predictive model to anticipate temperature fluctuations in lithium-ion cells [14]. Through detection of abnormally rising heating trends before they become hazardous, the system allows for proactive intervention, thus improving operational safety and battery lifespan. This predictability is especially crucial for lithium-ion use, where unanticipated overheating can jeopardize device integrity and user safety.

C. Sensors

The proposed system employs three major sensors — temperature sensor, voltage sensor, and current sensor—to track the state of operation of lithium-ion batteries and feed inputs into the predictive LSTM model.

a. Temperature Sensor The temperature sensor keeps a continuous check on the surface or ambient temperature of the lithium-ion battery. The data is utilized as an input feature as well as a ground truth label while training the model. In real-time, forecasted temperature values are matched against actual measurements to evaluate the accuracy of the model as well as to initiate safety notifications when overheating is expected [15].

b. Voltage Sensor Voltage sensors pick up the point terminals' instant voltage of the battery. These values characterize the charge-discharge cycles and are input into the model as features affecting thermal behavior. Fluctuations in voltage, particularly during fast charging or discharging, can be related to increasing internal temperatures, so voltage becomes an essential input for predicting possible overheating.

c. Current Sensor The real-time charging and discharging current are measured by the current sensor. Current levels are most indicative of load status, and abrupt peaks will cause higher internal resistance and temperature accumulation. The system compensates for load-induced temperature variations using current information.

D. Text-to-image

The text-to-image feature dynamically displays the forecasted temperature by creating a simulated battery graph with a tagged temperature reading. This enables users to rapidly determine thermal status through easy-to-understand visual indicators, enhancing situational awareness. The image is updated according to forecasted temperature and gives an at-a-glance awareness of battery condition [16].

E. Text-to-speech

The voice module, with gTTS used to implement it, is used to translate predictive safety information into voice alerts [17]. It informs the user verbally, based on the predicted temperature range, whether the battery is in the normal, warning, or overheating condition. The voice alerting system aids accessibility and allows response in real time without constant visual scrutiny.

IV. Methodology

The system proposed employs an LSTM neural network for predicting future temperature patterns in lithium-ion batteries from real-time sensor readings [18]. The process involves the following major steps:

a. Data Acquisition: Temperature, voltage, and current sensor data from lithium-ion batteries are gathered during charging and discharging operations. This information mirrors the battery's operating and thermal characteristics.

b. Preprocessing: The time-series data obtained is preprocessed by cleaning it and normalizing it with Min-Max scaling [19]. It is organized into sequences with a sliding window method. Each sequence of historical values is utilized to forecast the subsequent temperature reading.

c. Model Design: An LSTM model is trained on the sequential data with the Mean Squared Error (MSE) loss function [20]. The model learns to predict temperature based on electrical and thermal parameter trends.

d. Prediction and Alert System: The trained model gives real-time temperature values prediction. By applying threshold-based classification, the safety status of the battery is classified, and alert is sent to the user if overheating is expected.

e. User Interface and System Deployment: A Gradio interface is built to achieve user-friendly input of data and display of output. Being lightweight, it is deployable in the edge device for real-time applications of battery monitoring.

V. Results and Discussions

The suggested AI-based battery safety monitoring system was tested with real-time input values of temperature, voltage, current, and time. The model was assessed through a web interface where users provide operational data, which in turn triggers real-time prediction and visualization.

a. Temperature Prediction Results: Upon entering a temperature of 50°C, voltage of 3.7V, current of 1.5A, and time of 1000 seconds into the system (Fig. 3), the AI model, powered by LSTM, forecasted the battery's future thermal behavior over a 24-step horizon. The predicted temperature curve (Fig. 4) shows a continued increase, reaching approximately 23°C and trending upward, indicating a thermal profile that is escalating beyond optimal safety thresholds. This suggests that the battery is undergoing thermal stress, and the model has effectively captured this dangerous trend.

b. Battery Condition Assessment: Based on the latest prediction, the battery is no longer in a "Normal" state. As illustrated in (Fig. 5), the battery temperature currently stands at around 23.2°C, and predictions indicate a continued rise.

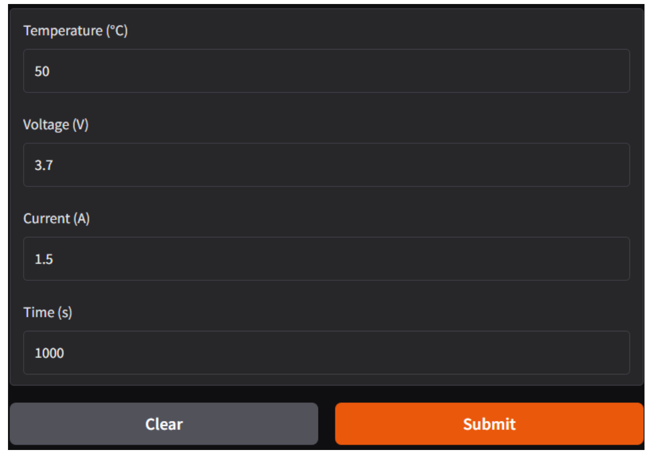

Fig. 3. User Input Interface for Battery Monitoring

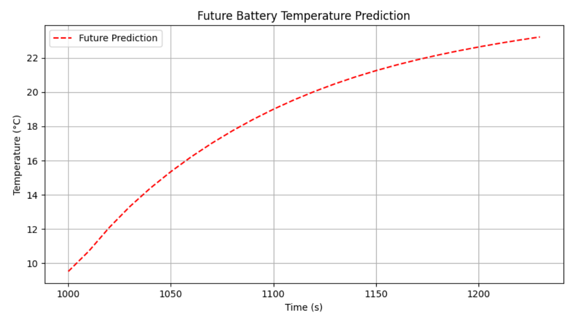

Fig. 4. The graph predicting battery temperature over time illustrates stable thermal behavior and indicates no signs of overheating

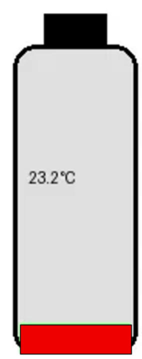

Fig. 5. Simulated Battery Status Indicator

This behavior indicates the onset of an overheating condition, potentially pushing the system into an unsafe thermal zone. The battery is therefore flagged as "Overheating", necessitating immediate corrective actions such as cooling mechanisms, load reduction, or shutdown to avoid safety risks.

c. System Responsiveness and Usability: The system responded quickly with the forecasted temperature values and visual feedback. The interface's combination of real-time data entry, visual battery representation and temperature prediction supports rapid user interpretation. For real-world deployment in EVs or energy storage systems, this system can be life-saving by issuing alerts before the battery crosses critical limits, thereby enhancing safety and usability.

d. Model Performance Discussion: In this high-temperature scenario, the LSTM model's ability to predict the impending overheating condition showcases its strength in real-time hazard anticipation. Trained on multivariate time-series data, the model accurately recognizes unsafe thermal trends in advance. This early prediction capability makes it a powerful tool for proactive thermal management and battery protection, allowing operators to intervene before catastrophic failure occurs.

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