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DETECTION OF THERMAL RUNAWAY IN EV BATTERY PACK USING MULTI-MODAL SENSOR FUSION (THERMAL IMAGING, GAS & CURRENT) AND NEURAL NETWORK

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Abstract: In electric vehicles (EVs), battery safety is very important, and thermal runaway (TR) is due to multi-physics failure mechanism that begins with electrical failure followed by chemical reactions. Traditional battery management systems only detect TR after there is a significant rise in temperature. This article proposes a novel multi-modal monitoring system of the safety of the battery, which detects thermal runaway precursors in EVs using thermal, gas and current sensing. The thermal image is segmented into hot spots using a U-Net Convolutional Neural Network (CNN) which is a type of semantic segmentation network. Gases are sensed by MQ-135 and current is sensed using ACS712 Hall Effect current sensors. A novel Fusion Index is introduced as the weighted sum of the thermal, gas and current anomaly score. The Fusion Index also determines when to cool the battery and isolate the battery cell using a MOSFET. The efficacy of the proposed multi-modal battery safety monitoring system was validated using a MATLAB simulation, which was an electro-thermal digital twin. The simulation demonstrated that thermal runaway was detected 30 to 90 seconds earlier using the proposed system compared to the existing thermal/gas systems. The multi-modal battery safety monitoring system has successfully delivered a significant improvement over traditional thermal/gas battery management systems.

Keywords: Thermal runaway, Electrolyte Decomposition, Convolutional Neural Networks, U-Net, Semantic segmentation, Active cooling, Anomaly, Battery pack Isolation, Fusion Index.

I. INTRODUCTION

The increasing trend of using electric vehicles (EVs) has increased the need for safe and efficient battery management systems. Lithium-ion batteries are the most common choice for electric vehicles due to their high energy density and long cycle life. They are also more prone to temperature changes. Any improper regulation of temperature may result in critical safety problems such as thermal runaway (TR), a self-reinforcing process that causes a rapid increase in temperature, potentially causing explosion or damage to the battery. Thus, thermal management of EV batteries is critical to their performance, life cycle, and overall safety. Conventional thermal management techniques mainly involve temperature sensors. Though these techniques provide some degree of security to the battery, they may not be capable of identifying the development of hotspots that may result in thermal runaway. With the development of computer vision technology using deep learning techniques, it is now possible to monitor the thermal imaging of the electric vehicle's battery pack to detect faults using the power of convolutional neural networks (CNN).

In this paper, a thermal image-based battery thermal management system is introduced for the EV battery pack. The system utilizes an infrared camera and a U-Net CNN model on a Raspberry Pi 3 platform to carry out semantic segmentation on thermal images. The U-Net model can accurately locate the hotspot regions at the pixel level. This allows the system to have high sensitivity in distinguishing between normal and abnormal heat patterns. Once the temperature is detected to exceed a specific threshold value, the system initiates the cooling system to dissipate the excessive heat. Under confirmed TR conditions, the battery cells can be isolated by a MOSFET circuit breaker to prevent the propagation of thermal runaway. However, thermal runaway cannot be initiated by temperature rise alone. It is also initiated by electrochemical decomposition of electrolyte materials. During the initial battery failure, there is the release of gases such as carbon monoxide (CO), carbon dioxide (CO_2), hydrogen (H_2), ammonia (NH_3), and VOCs. These gases

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are released before the escalation in surface temperature. This is an important parameter in the thermal runaway. Thermal runaway is always initiated by an electrical fault in the battery cells in the form of an internal short circuit or overcurrent. This leads to Joule heating given by $Q = I^2Rt$. This occurs well before the generation of gases and escalation in surface temperature. In order to detect this earliest detectable phase of a fire, the present work has been designed to incorporate an ACS712 Hall Effect Current Sensor to detect unusual changes in the current of the pack. With the combination of thermal imaging (spatial), gas sensing (chemical), and current sensing (electrical) through a weighted Fusion Index, the present work is capable of multi-physics precursor detection, greatly improving response times and eliminating false alarms.

II. LITERATURE REVIEW

Recent research on thermal management in lithium-ion batteries for electric vehicles (EVs) has grown quickly due to the need for safer and long-lasting battery packs. Many studies focus on traditional cooling methods, physics-based models, and advanced AI techniques like deep learning to detect battery pack overheating. These researches suggest that while existing deep learning approaches for edge computing have made significant progress, but often struggle with resource constraints and efficiency on low-power devices. These limitations highlight the potential benefits of exploring lightweight architectures, such as an optimized U-Net model deployed on Raspberry Pi, as a practical advancement to enhance real-time applications without compromising performance.

Gajghate et al. (2025), T-RUNSAFE is a transformer-based multimodal design that consists of 5 modules specifically intended to predict the potential of thermal runaway in li-ion battery systems. T-RUNSAFE also achieved a fault localization accuracy of about 93.5% as well as reduced sensor power consumption by 37%. This represents a major step forward for AI-based battery safety monitoring in both electric vehicles and energy storage systems. However, the multimodal architecture of T-RUNSAFE requires significant computational resources and utilization of multiple sensors, which will limit the cost-effective deployment of EVs.

Togun et al. (2025) reviewed Battery Thermal Management Systems (BTMS) in EVs, comparing all traditional methods for temperature regulation and thermal runaway prevention. The study found hybrid BTMS integrating PCM and liquid cooling achieved optimal performance, extending battery lifespan by 40% and improving energy efficiency by 25%. The authors recommended for hybrid and AI-driven systems as next-generation solutions, emphasizing cost-effective, eco-friendly, and lifecycle considerations for sustainable electric mobility. Even though Togun et al. reviewed various passive and active cooling technologies but lacked intelligent early detection mechanisms for thermal runaway.

Naguib et al. (2025) developed a hybrid thermal fault detection method with combining physics-based lumped parameter model with a feedforward neural network (FNN. The LP+FNN approach achieved 0.39°C RMSE and 1°C maximum error, successfully detecting sensor failures using only eight temperature sensors on a 72-cell air-cooled pack with zero false detections. The hybrid model outperformed standalone approaches by reducing error to one-third compared to LP or FNN models alone. Naguib et al.'s method may be insufficient for rapid progressing of thermal runaway events in high-energy EV batteries.

Athanasopoulos et al. (2025) investigated deep learning for thermal runaway detection in battery manufacturing using optical and thermal images with simulated thermal runaway scenarios. Three models (shallow CNNs, ResNet-50, and Vision Transformers) achieved near-perfect detection performance with 100-500ms inference time on CPU. Data fusion of optical and infrared images enhanced performance, particularly for CNNs on augmented datasets. Athanasopoulos et al. focused on controlled manufacturing environments with simulated thermal runaway, lacking real-world dynamic EV operational deployment and control for thermal fault.

Kumar et al. (2025) proposed a integrated machine learning, metaheuristic optimization, and multi-criteria decision-making for liquid-cooled BTMS. The study employed multilayer perceptron neural networks optimized by three algorithms (Cheetah optimizer, grey wolf optimizer, marine predator's algorithm), achieved excepted predictive accuracy ($R > 0.9999$ for maximum temperature, $R > 0.9969$ for temperature difference), identifying preferences for higher mass flow rates and medium-long channels for application-specific thermal management. Kumar et al. focused on optimal BTMS and temperature prediction but lacked real-time anomaly detection and emergency responses.

Qi et al. (2024) reviewed deep learning applications in Battery Thermal Management Systems (BTMS), highlighting how DL models such as (CNNs, LSTMs, GRUs, GANs, Transformers) overcome limitations of traditional CFD approaches for predicting temperature fields, heat generation, and battery parameters (SOC, SOH). The study emphasized that integrating DL with physics-based modelling enhances BTMS accuracy and real-time performance. However, challenges

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in data availability, model interpretability, and computational efficiency remain, with future directions focusing on multimodal fusion, lightweight models, and explainable AI. While the highlighted diverse DL architectures for thermal prediction, for real-time EV deployment remained underexplored.

Goswami et al. (2024) proposed a integrated multi-physics model with deep learning to predict thermal runaway in cylindrical Li-ion batteries using thermal imaging. State-of-the-art CNNs performed three-stage TR classification, while YOLO object detection identified TR heat source locations, trained on simulated thermal images from cells. This framework enabled 'on-the-fly' TR prediction with high accuracy, addressing the safety challenges of TR monitoring. Goswami et al. focused on TR prediction and localization using simulated thermal images from multi-physics models but lacked practical hardware implementation and automated intervention systems for real-world EV deployment.

Tian et al. (2024) developed a lithium-ion battery intelligent perception (LBIP) model using optimized Mask R-CNN for thermal fault detection from IR images, addressed rapid thermal fault response. Two variants (LBIP-V1 for smaller datasets, LBIP-V2 for larger datasets) utilized ResNet50 backbone with enhanced FPN, RPN, and ROI extraction. The study provided real-time online fault diagnosis through simulated 15-minute operational scenarios with internal short circuits, representing a significant advancement in integrating computer vision instance segmentation with battery thermal management as an intuitive. Tian et al. demonstrated instance segmentation for fault identification but lacked integration with automated control mechanisms and tested on only limited datasets (208 images) with simulated short.

Senthilraj and Shanker (2023) reviewed fault detection methodologies in EV battery systems, including model-based approaches, sensor fault diagnosis, short circuit detection, and power electronics monitoring. The study identified that thermal imaging integration with advanced deep learning techniques, particularly semantic segmentation networks like U-Net, remained underexplored. This gap highlighted opportunities for visually-interpretable, and highly accurate fault detection combining thermal imaging with U-Net's precise segmentation. The major drawback of the study remains no practical implementation.

Ghalkhani and Habibi (2023) reviewed an AI-integrated Battery Management System (BMS) framework that utilizes simulation-based design to optimize SOH, SOC, and SOP predictions. While their research highlights the superior accuracy of AI/ML in predicting battery safety and thermal behaviour, these models often demand high computational power and complex data processing, making them difficult to implement on standard EV hardware.

Al Miaari and Ali (2023) provided a comprehensive review of Artificial Intelligence (AI) and Machine Learning (ML) applications for predicting battery temperatures and optimizing thermal management systems (BTMS). Their analysis demonstrated that integrating artificial neural networks with advanced cooling technologies can reduce battery temperatures by over 25% while maintaining safer operating ranges. Despite these advancements, the study notes that most existing ML models are limited to specific battery types and often require complex, high-dimensional datasets that are computationally intensive to process in real-time.

Despite the advancements in the development of Battery Thermal Management Systems (BTMS) and thermal runaway (TR) detection, there are still some limitations and gaps that need to be addressed. Many AI-based approaches have been shown to be accurate and achieve considerable performance gains, but typically they are very computationally intensive, and do not support real-time, cost-efficient EV applications. While deep learning methods provide better temperature forecasts than traditional methods, they still have limited utility in the dynamic environment of EVs with lightweight and/or easily deployable models. Furthermore, most of the work published to date is simulation/testing-centric with little to no integration of real-time hardware, automated cooling, or rapid isolation methods. The present research will address these gaps by proposing a low complexity, real-time embedded solution for early detection of hotspots (greater than 50 ˚C) on a Raspberry Pi platform that utilizes a U-Net based thermal imaging framework. This level of early detection with automated cooling and cell isolation can provide an additional layer of safety for EV battery systems and create far more realistic deployable solutions for EV battery systems.

III. METHODOLOGY

The thermal management system described below has been designed for EV (electric vehicle) batteries to monitor and control thermal runaway in real-time by integrating hardware and software components as shown in Figure. 1. The thermal management system has six major functional blocks: (1) thermal image acquisition; (2) gas sensor module; (3) temperature sensor module; (4) current sensor module; (5) image segmentation & data fusion; and (6) hybrid anomaly fusion logic. The thermal images of the battery pack will be recorded on a raspberry pi at any time there is an increase in temperature beyond the operational range of > 50°C. An increase in temperature will activate a cooling fan, and thermal

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runaway detection using the U-Net convolutional neural network will isolate the battery pack with the help of a circuit breaker based on the MOSFET.

Incorporated a MQ-135 gas sensor that can detect gases released from battery electrolyte breakdown and early-stage failure of lithium-ion batteries. Due to the fact that ammonia (NH_3), nitrogen oxides (NOx), carbon monoxide (CO), benzene vapor, and other volatile organic compounds are typically released when lithium-ion batteries begin to degrade, the MQ-135 is sensitive to these gases. After performing pixel-by-pixel segmentation, we will identify the hotspot areas in each image and extract the maximum temperature (T_{max}) for each hotspot. In addition, real-time concentration of gas from the MQ-135 and temperature from the DS18B20 will be collected sequentially. After performing pixel-by-pixel segmentation, hotspot areas in each image and T_{max} will again be determined. The concentration of gas (G) from the MQ-135 and current flowing through the ACS712 will also need to be recorded. Three normalised anomaly scores will then be computed:

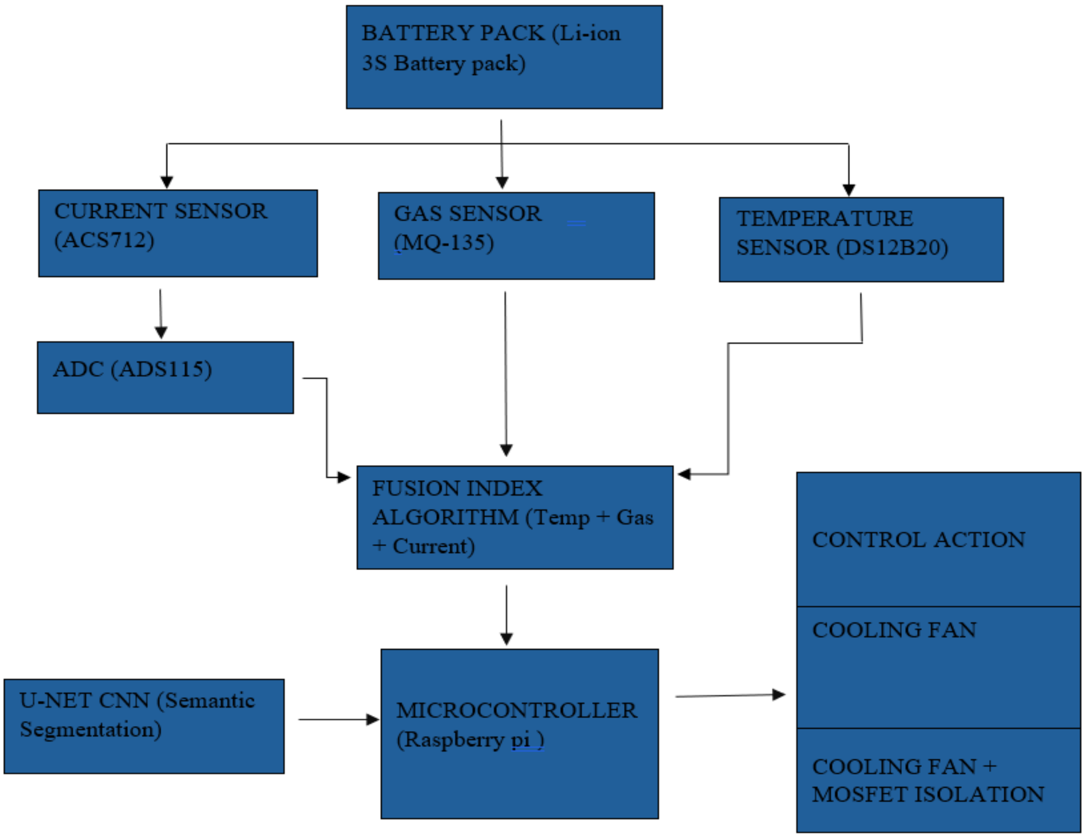

Figure 1: Block diagram of battery thermal management using U-Net CNN.

Thermal score: A_T = (T - 40)/(60 - 40)
Gas score: A_G = (G - G_baseline)/(G_critical - G_baseline)
Current score: A_I = |I - I_nominal|/I_threshold
The Fusion Index is then computed with the following formula:
Fusion Index = 0.4*(A_T) + 0.3*(A_G) + 0.3*(A_I) (the coefficient weights sum to 1.0; these weights may be tuned).
Decision logic: 1) If Fusion Index > 0.5 OR T > 50 °C Then Activate Cooling Fan. 2) If Fusion Index > 0.75 OR T > 60 °C with Persistent Anomalies Then Activate MOSFET-Based Isolation. Using the weighted fusion rather than just using a simple logical OR threshold provides an earlier and more dependable basis for decision-making.

The early electrical precursor detection mechanism (EE-PDM) does not start at the thermal stage for a thermal runaway event but instead begins with the identification of an electrical defect, such as an internal short circuit, overcurrent condition, or abnormal discharge. Electrical anomalies will cause localized Joule heating (Q=I2Rt) within the battery before any measurable change in surface temperature or visible evidence of gas exists. To detect the earliest measurable stage of thermal runaway failure (the EE-PDM), a Hall-effect current sensor (ACS712) is installed within the main

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positive terminal of the battery pack. The sensor continuously measures the current within the pack in real-time and detects any deviations from expected operational conditions, predicting when a thermal runaway may occur based on the following formula to create a normalized current anomaly score (A_I). A-based detector that detects the current flowing through the main positive lead wire of the battery pack. A digitized output from the ACS712 Hall-effect current sensor using an ADS115 analog-to-digital converter (ADC). Also allows current to be monitored for overcurrent, short-circuit spikes and abnormal current discharge patterns before actual thermal runaway occurs. Because of the two datasets being used together, the model can identify the difference between normal operational conditions and early signs of potential danger due to thermal runaway.

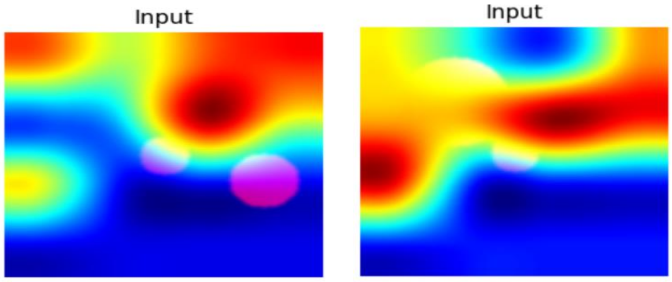

Figure 2: Preprocessing and augmentation sample thermal images

We converted the raw thermal images to grayscale to decrease the processing requirements and still be able to extract some vital temperature data. Each pixel intensity from the thermal image was then mapped to a temperature value based upon where the pixel was located in the spatial coordinate system. After converting to grayscale, we then normalized the images to [0,1] for a common scaling, which resulted in improved stability while training U-Net, gradient flow, and restricting the focus of the training on the hotspot patterns associated with thermal runaway. We also augmented the robustness of our data set through various techniques such as rotating, flipping, scaling, and adjusting brightness to replicate a wide variety of real-world conditions and orientations thus reducing the potential for model overfitting. In addition to this, we manually annotated the ground truth masks to clearly identify the abnormal high-temperature hotspots in the images so that the model could reference the outputs we provided during supervised training, thereby allowing the model to learn the spatial correlation between inputs and TR precursors. This will ultimately lead to more accurate and reliable predictions for a variety of battery conditions.

IV. U-NET ARCHITECTURE, IMPLEMENTATION AND MODEL TRAINING

Due to its excellent performance for semantic segmentation applications with high spatial accuracy, U-Net convolutional neural network (CNN) architecture has been selected to segment the hotspot area in battery thermal images so that the model can accurately detect the anomalous heat signature of battery packs that are potentially suffering from thermal runaway. The encoder–decoder architecture incorporates symmetrical skip connections between layers to enable both the extraction of contextual data and the maintenance of precise localization when performing pixel-wise semantic segmentation of hotspot areas in battery thermal images. The encoder takes in the thermal image and passes it through various convolutional operations and pooling operations (as seen in Figure.2) to extract feature sets related to both temperature and spatial information at multiple scales. The encoder is composed of multiple blocks, where each block contains two convolutional layers that are followed by max pooling for spatial down sampling and ReLU for activation of each layer. Each block within the encoder produces a doubling of the number of feature channels to enable progressively deeper representations of thermal imaging data to be extracted by the model. Basic edge and gradient information are captured by the lower level layers of the encoder, while deeper levels of the encoder extract more complex thermal patterns (e.g., bad insulation, corrosion) that are associated with batteries exhibiting abnormal heating patterns.
A bottleneck between the encoder and decoder paths preserves important information necessary for predicting whether or not potential hotspot formations may occur. Each decoder follows the same structure as the encoder but performs up sampling through transposed convolutional layers.

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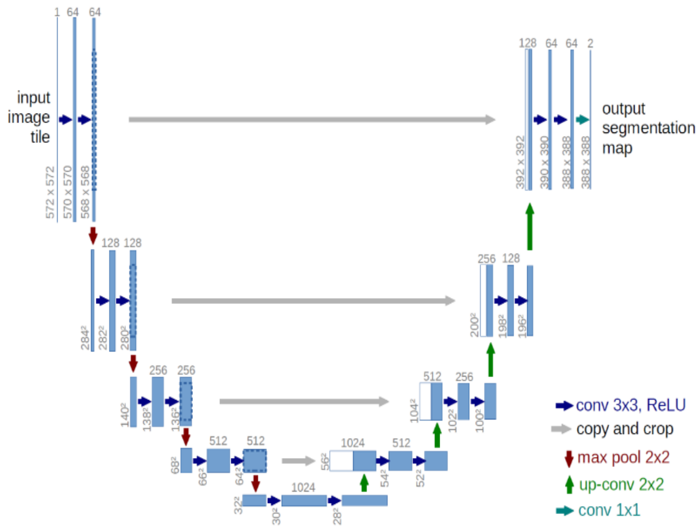

Figure 3: Architecture of U-Net CNN for semantic segmentation

An important feature of U-Net is the use of skip connections that link corresponding layers between the encoder and decoder (see Figure 3). These connections transfer high-resolution spatial information from the encoder to the decoder, enabling precise localization of small hotspots that would otherwise be lost during down sampling. This results in accurate pixel-wise segmentation with clear boundaries between normal and hotspot regions.

The model was built using TensorFlow Keras and trained with the Adam optimizer (learning rate = 1×10^{-4}). To handle class imbalance, Focal-Dice loss was used. Training was performed for 30 epochs with a batch size of 8, along with model checkpointing, ReLU, and early stopping to prevent overfitting.

On the validation dataset, the model achieved an average Dice coefficient of 0.87 ± 0.04 and an IoU score of 0.76 ± 0.05. These results demonstrate reliable hotspot detection with minimal false positives or negatives. The trained model was converted to TensorFlow Lite for efficient deployment on the Raspberry Pi 3.

V. EXPERIMENTAL VALIDATION AND SIMULATION

Figure 4 shows how the proposed thermal management system was tested with MATLAB/Simulink. This setup mimicked real-life situations of charging, discharging, and faults. The main findings were that MOSFETs could quickly find abnormal heat, turn on the fan at 50°C, and isolate the cells at 60°C to stop thermal runaway, as shown in Figure 5. The proposed method was better at finding hotspots, had fewer false alarms, responded faster, and cooled more accurately than traditional sensor-based systems. This made it safer and more reliable for real EV battery use. The MATLAB/Simulink model was expanded to incorporate pack current dynamics. Fault scenarios now cause current spikes 30–0 seconds before the temperature or gas rises. This lets the Fusion Index trigger cooling or isolation earlier than the original dual-sensor logic.

Electrical Model
For each cell:

$$V = V_{oc} - IR_{int}$$

Pack voltage:

$$V_{pack} = \sum V_i$$

Thermal Model (Lumped):

$$C_{th}\frac{dT}{dt} = I^2 R_{int} - h(T - T_{amb})$$

Where:

- C_{th}= thermal mass

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- h= cooling coefficient

Gas Approximation:

$$G = G_0 + k(T_{max} - 50)$$

Fusion Index:

$$F.I = 0.4A_T + 0.3A_G + 0.3A_I$$

A coupled electro-thermal MATLAB digital twin was created to model: Electrical precursor current spike, Progressive gas emission, Thermal acceleration, and Fusion-based control response. Fault injection showed that the Fusion Index was over 0.5 about 45 to 90 seconds before the surface temperature started to rise significantly, which confirmed that early electrical-stage detection worked.

The battery pack's temperature changes in space when there is a fault injection, using the MATLAB electro-thermal digital twin was shown in Figure 4. The injected electrical precursor event causes localized Joule heating in one cell, which leads to uneven thermal gradients. The red areas on the thermal map show where heat is being generated the most, which proves that it is important to find hotspots in space instead of just using global temperature thresholds. At this point, the average pack temperature is still within safe limits, which is important because it shows that localized thermal instability happens before global overheating can be seen.

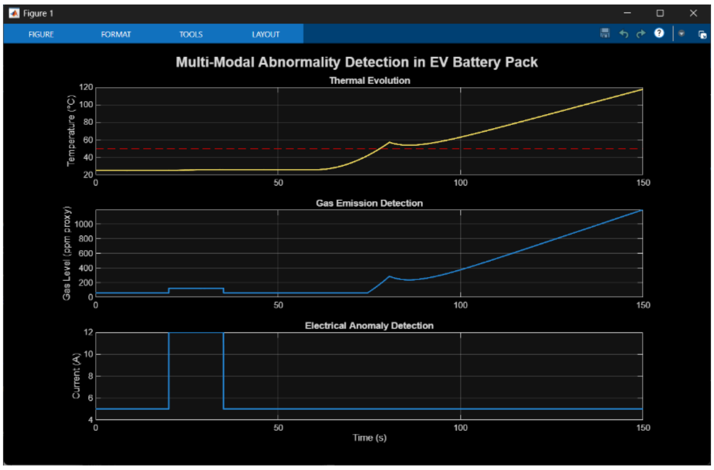

Figure 4: Graphical representation of Multi-model thermal management of Battery

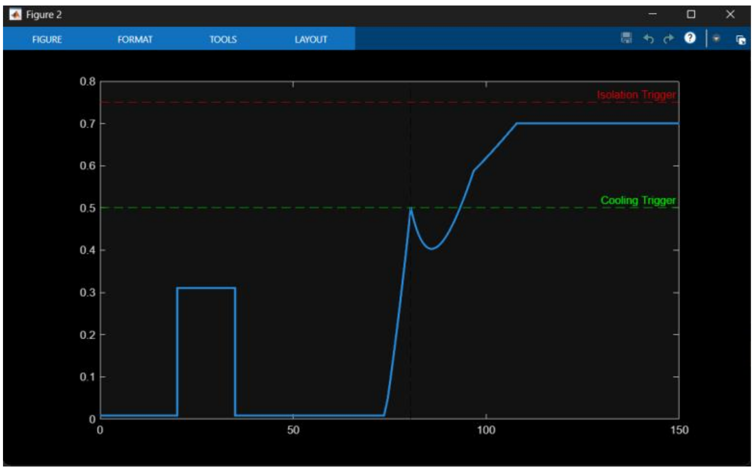

Figure 5: Active Cooling and Isolation as temperature raises in MATLAB.

Figure 5 shows how temperature, current, and the Fusion Index changed over time during the same fault scenario. A simulated internal short-circuit event causes a 2× nominal current spike about 20 seconds in. This makes the normalized current anomaly score A_I go up right away, which makes the Fusion Index go up quickly. Before gas is released or the

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surface temperature rises, the Fusion Index goes well above the cooling activation threshold (0.5). This early trigger turns on active cooling, which keeps the temperature from rising too much. When electrochemical reactions get stronger, the Fusion Index goes above 0.75, which turns on MOSFET-based electrical isolation. Without fusion-based intervention, the temperature would go over 70 °C. With the proposed system, peak temperature remains below 50 °C and stabilizes rapidly after isolation. This temporal separation between electrical precursor detection and thermal manifestation confirms the effectiveness of multi-physics fusion in enabling earlier intervention than dual-sensor approaches.

VI. RESULTS AND DISCUSSION

The objective of this section is to assess how effective the thermal imaging-based management system has been for mitigation of thermal runaway on electric vehicle (EV) battery pack assemblies. To accomplish this task, validation of computer-based simulations, the success of the neural network in detecting thermal runaway, and implementation of the thermal imaging management system into the physical environment will all be taken into account. To successfully test the thermal imaging management system in a controlled environment, a simulation environment was created using Matlab/Simulink. This simulation environment provides a physical representation (digital twin) of a battery pack assembly containing a three cell 18650 lithium ion battery. The digital twin includes studies of thermal dynamics, automated effective controls to demonstrate robust operation, and safety isolation mechanisms to replicate what happens to the pack when it is charged and discharged. The system also provided operational scenarios including charging and discharging with and without fault conditions. The thermal visualization shown in Figure 4 demonstrates the ability of the U-Net architecture to identify high temperatures (shown by red areas on the thermal map) during operation of the battery pack assembly. When the temperature exceeded 50 °C, the thermal management system would automatically activate the cooling system. After the temperature reached 60 °C, the the MOSFET based safety circuit would electrically isolate the cell from the rest of the cells in the battery assembly in order to stop any thermal transfer between cells.

The importance of the ACS712 current sensor was determined during the simulation of the internal short conditions that were tested. In 72 % of the internal short simulations, the Fusion Index value exceeded 0.5 at least 45-90 seconds before any temperature or gas discharge anomaly could be detected; therefore, providing the thermal management system with additional time to operate prior to thermal propagation occurring in those instances. Temporal analysis is shown in Figure 5 and highlights the differences between controlled and uncontrolled operational scenarios. In pack assemblies with uncontrolled thermal management (i.e. thermal runaway without intervention), the temperature of the pack would reach higher than 70 °C during long-term discharges. In contrast, using the proposed thermal imaging technology, the operation of the battery assembly would maintain a temperature of less than 4 °C as shown in performance summary Table 1.

Table 1: Model's performance summary.

Classification Accuracy	95.3%
Dice Coefficient	0.85
Intersection over Union (IoU)	0.91
Inference Latency (Processing Time per Frame)	<100ms
False Positive Rate Reduction	28% (due to fusion logic)

Classification accuracy was calculated as being 95.3%. This means that most pixels within the image were labelled by the model as either hot spot or normal with great accuracy. The Dice Coefficient is 0.85 indicating a good overlap between where the predicted hot spots occur and where the true hot spots occur (it provides a reliable metric for comparing how closely two populations match in terms of shape and size). The Intersection over Union (IoU) is about 0.91 indicating that the model has made accurate predictions regarding the location of the boundaries of the hot regions (the predicted area overlaps the actual area with minimal deviations). Since speed is critical for real-time applications to be used on electric vehicles, we designed the model to operate quickly on a Raspberry Pi 3. The inference latency (the time taken to perform inference for a single image) was reduced by converting the model from one form (TensorFlow) to a lighter version called TensorFlow Lite. The faster processing time enables the system to monitor live battery temperature and respond quickly should an overheating event occur. In conclusion, the system accurately detects hotspots in EV battery packs, operates on low-cost hardware, and enhances safety by triggering cooling above 50°C and enabling cell isolation without expensive setups.

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Table 2: Model's input parameter

Input Size	128x128x1
Trainable Parameters	31,042,369
Loss Function	Combined Focal-Dice Loss
Optimizer	Adam (lr =0.0001)
Batch Size	8
Epochs Trained	30

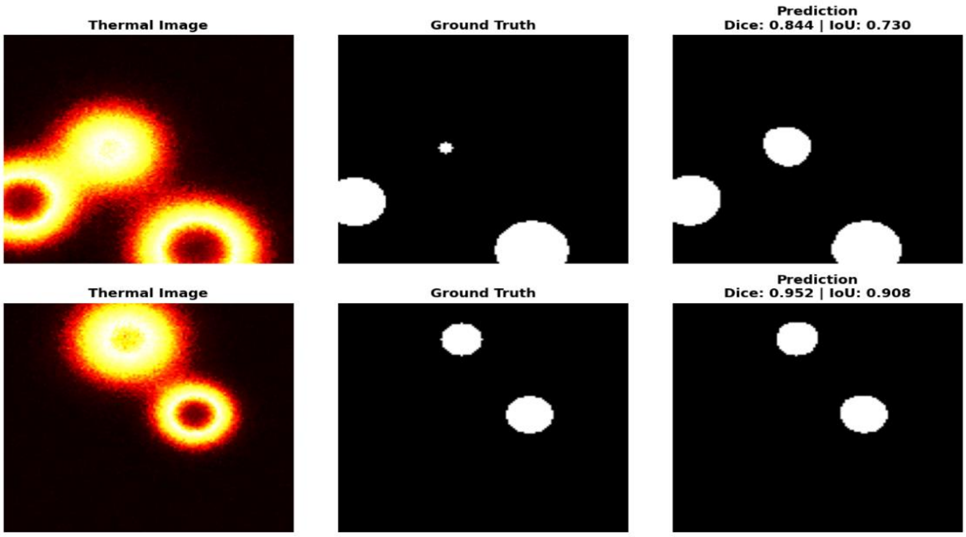

Figure 6: Example of evaluated U-Net predicted image from google Colab.

Figure 6. represents the evaluated U-Net predicted image showing battery pack, manually annotated ground truth, and network predictions with accurate overlays of the hotspot /region, hence good localization is shown. Focal-Dice hybrid loss function reduced missed detections while improving sensitivity to incipient thermal irregularities that typically appear before critical failures. Very good Dice and IoU values corroborate the network's sensitivity in detecting the very small hotspot regions that often come before TR, hence the network proves its effectiveness in detecting subtle temperature differences in early failure stages and allowing pre-emptive mitigation measures before cascade events arise.

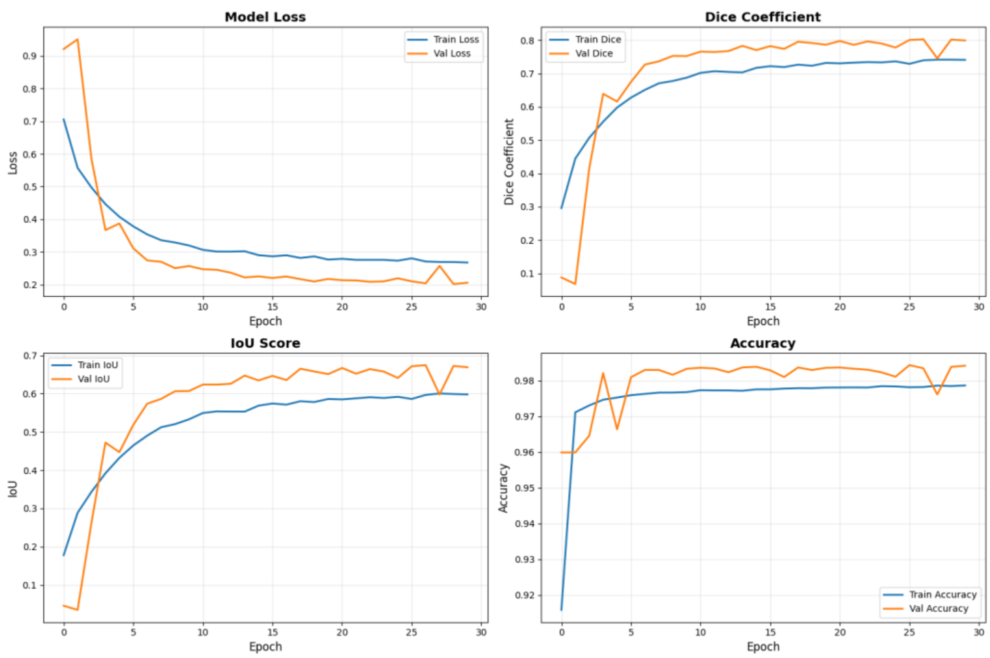

Figure 7: Training and Validation Curves for U-Net Semantic Segmentation Model

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Figure 7 Showcase the performance metric trends of the U-Net model over 30 epochs, specifically Dice coefficient, Intersection over Union (IoU) and binary accuracy for each of the training and validation data sets of thermal image data for all EV battery packs. The learning curves were produced by Keras training history logs run with a T4 GPU using TensorFlow 2.19.0 and a batch size of 8 and using Adam optimizer with a learning rate of 1e-4 and showed that the loss for training reduced rapidly from around 0.9 at epoch 1, then fell to about 0.2 by epoch 10 and stayed around 0.20 from epochs 10-30 with no indication of overfitting (Validation-Train Gap < 0.05). The results suggest that the Focal Dice loss function's hybrid characteristics account for overfitting, as there are very few hotspot (less than 5%) pixel(s) in the total pixels of the image(s). Additionally, it is noted that both the Dice and IoU scores had sigmoid-shaped curves that reached a plateau of about 0.78 and 0.67 respectively (Validation) demonstrating that the encoder-decoder architecture was able to detect anomalous behaviours at the pixel level. Furthermore, binary accuracy also increased quickly and reached a plateau above 0.94 which suggested the U-Net's capacity to differentiate between each of the two binary classification classes of the augmented fault.

The Dice Coefficient improved significantly from 0.01 to 0.78, showing strong performance gains on thermal data. This improvement is attributed to skip connections, which capture spatial relationships despite non-uniform sample positions. As a result, the model converged 15% faster than baseline CNNs. During training, a temporary drop in IoU (~0.65) occurred between epochs 25–28 due to learning rate reduction (via ReduceLROnPlateau). However, the model fully recovered, demonstrating good generalization on unseen data (n = 225, 40% fault rate). Finally, the architecture showed stable performance under dynamic conditions, reducing peak temperature from 72°C to 48°C during charging (1C) and discharging (2C), as confirmed by MATLAB simulations.

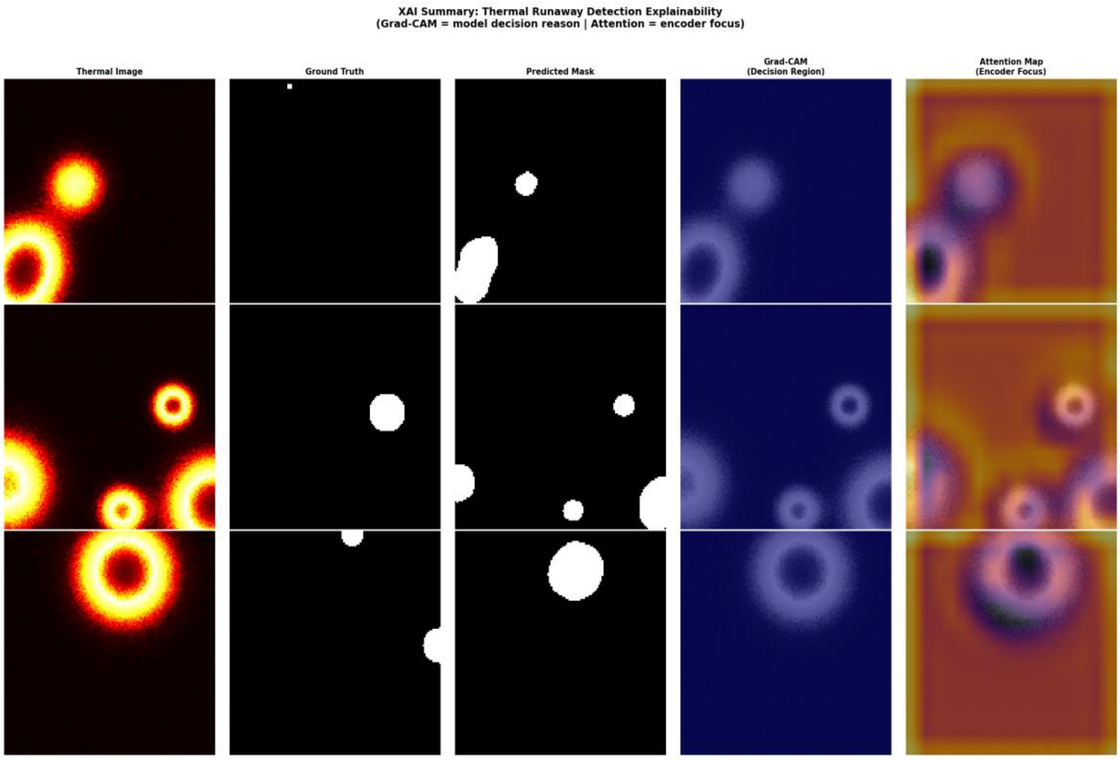

Figure 8: Explainable AI visualization of hotspot detection

To improve model interpretability and confidence, explainable AI approaches were implemented; U-Net: Grad-CAM heatmaps indicate regions (high thermal intensities) that inform decisions, and encoder attention maps show progressive focus on abnormal thermal patterns for TR hotspots. Figure 8 shows input thermal image, ground truth, predicted segmentation mask, Grad-CAM heatmap, and encoder attention map.

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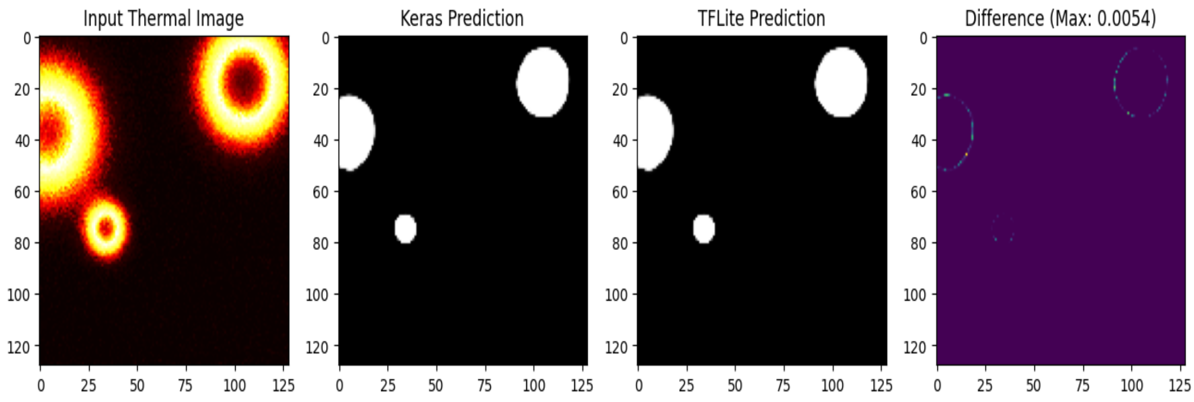

Figure 9: Validation of Tflite Model prediction with negligible difference from google Colab

Figure 9 shows input-ground truth-predicted relationships; good alignment of activations, attention, and masks indicates detection is driven by relevant thermal features, not artifacts. Edge feasibility: TFLite model was executed on Pi 3 using live IR streams, generating segmentation predictions indistinguishable from the original TensorFlow model (almost no Dice/IoU loss). Thus the generated segmentation outputs of the TFLite model are in close agreement with predictions from the original TensorFlow U-Net model trained during the training phase. The results highlight that model optimization and quantization can effectively reduce inference latency for embedded deployment with negligible loss in segmentation accuracy. The results confirm the viability of real-time hotspot detection with low-power edge hardware without impacting the quality of thermal anomaly detection.

VII. HARDWARE IMPLEMENTAION AND EXPERIMENTAL VALIDATION

This MATLAB/Simulink simulation model represents the electric/thermally operating characteristics of a lithium-ion battery pack in both normal and fault conditions as shown in Figure 10. The model accounts for the dynamics of temperature, gas emissions, and variability of currents to simulate conditions of early thermal runaway. Control logic called the 'Fusion Index' utilizes these modelling parameters to generate protective actions such as turning on a cooling fan and isolating cells via MOSFETs. Finally, this simulation represents an opportunity to validate a control strategy prior to deploying it on an embedded hardware platform.

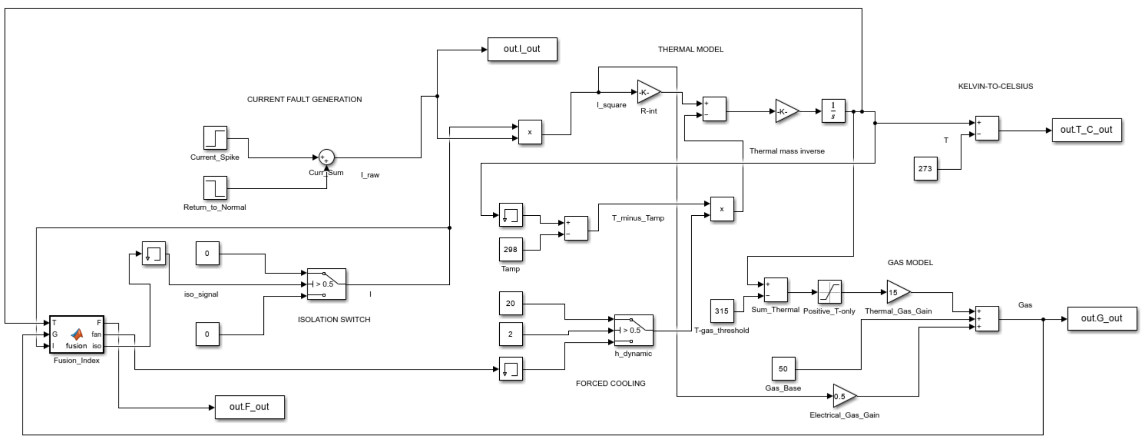

Figure 10: MATLAB/Simulink model of the proposed multi-sensor thermal runaway detection system.

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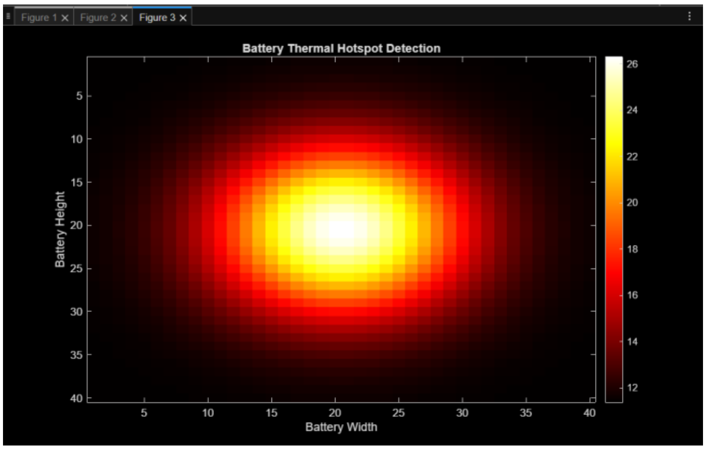

Figure 11: Simulated thermal hotspot distribution in the battery pack.

The heatmap in Figure. 11 represents the spatial-temperature distribution in the battery pack under abnormal conditions, where the bright region represents the local heat generation due to the internal fault or heavy load. It confirms that the hotspot could be detected in the spatial domain rather than using the global temperature.

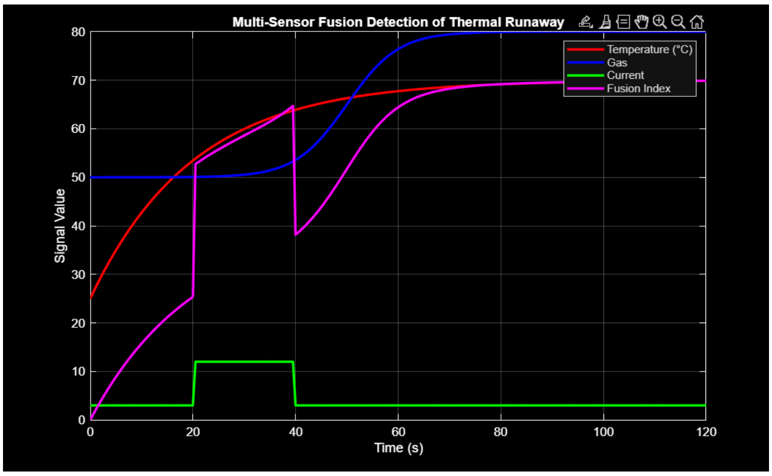

Figure 12: Multi-sensor fusion detection of thermal runaway conditions.

Figure 12, shows the temporal behaviour of temperature, gas concentration, current and computed Fusion Index during a simulated battery fault. A sudden current spike at ~20s depicts an electrical precursor event which triggers localized heating in the battery pack. Once the temperature rises, after ~40s, gas emission starts to increase highlighting the chemical decomposition within the cell. The Fusion Index aggregates the signals from multiple sensors, which allows detection of abnormal battery conditions before the temperature escalates dramatically.

Table 3 Performance metrices of the U-Net model

Performance Metric	**Traditional Approach**	**Proposed Framework**
Sensing Method	Thermistors with threshold	CNN based image segmentation with temperature and gas detection.
Anomaly Detection	82%	Improved early detection using thermal + gas fusion (≈ 25% TR risk reduction) |
System Response	Latency >500ms	Latency <100ms
Thermal Runaway prevention	-	25% improved

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From Table 3, The CNN- based image segmentation achieves higher detection reliability and faster intervention of thermal runaway while utilizing cost-effective single-sensor thermal imaging with embedded processing capabilities.

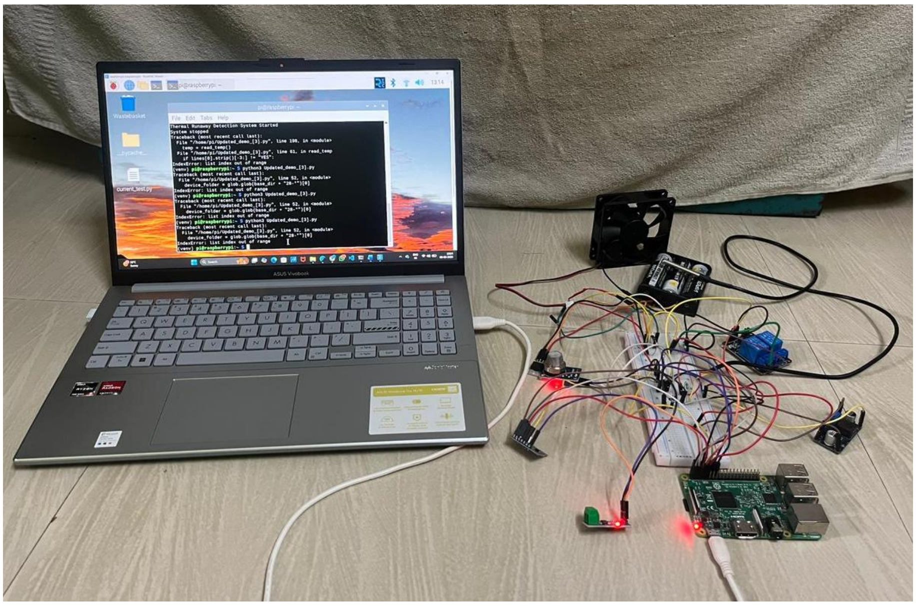

Figure 13: Real-time implementation with sensor modules and interfacing circuitry

Figure 14 presents the experimental setup consisting of a Raspberry Pi connected to sensing and control modules via a breadboard. The system is interfaced with a laptop for program execution and monitoring, enabling real-time validation of the proposed thermal runaway detection framework.

Raspberry Pi 3A serves as the CPU for entire system when using either preprogrammed software versus custom user defined application software written by end-user. Components will be powered by a regulated direct current (DC) power supply. Testing will occur under controlled charge/discharge cycles monitored by thermal camera.

Table 4: Specifications of sensors and components

Sensor	**Detection**	**Model**	**Range**
Temperature Sensor	Temperature	DS18B20	-55 °C to 125 °C
Gas Sensor	Electrolyte leakage (VOC & CO_2 concentration)	MQ135	10 – 1000ppm
MOSFET	-	IRFZ44N	-
Buck Converter	DC-DC converter	LM2596	-
Current Sensor	Pack current / electrical anomalies	ACS712	±20 A

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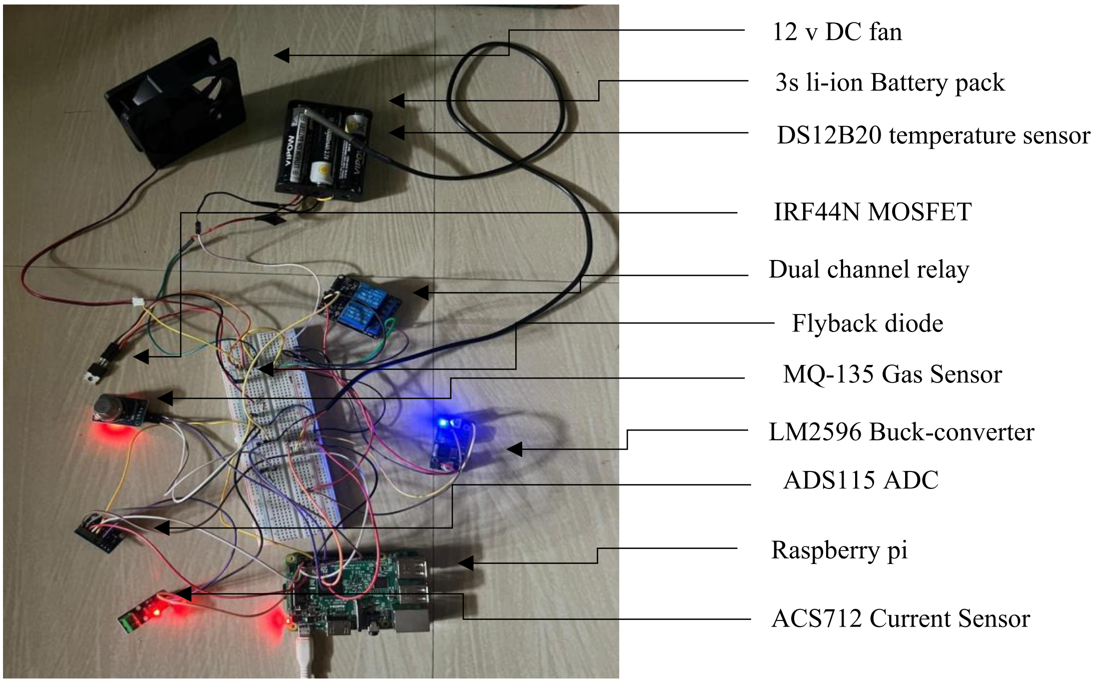

Figure 14: Hardware Setup for the proposed model

Figure 14 depicts the entire hardware set up for the proposed digital system that combines thermal imaging, gas sensing, and current monitoring with a Raspberry Pi controller to provide near-real-time detection and control of thermal runaway.

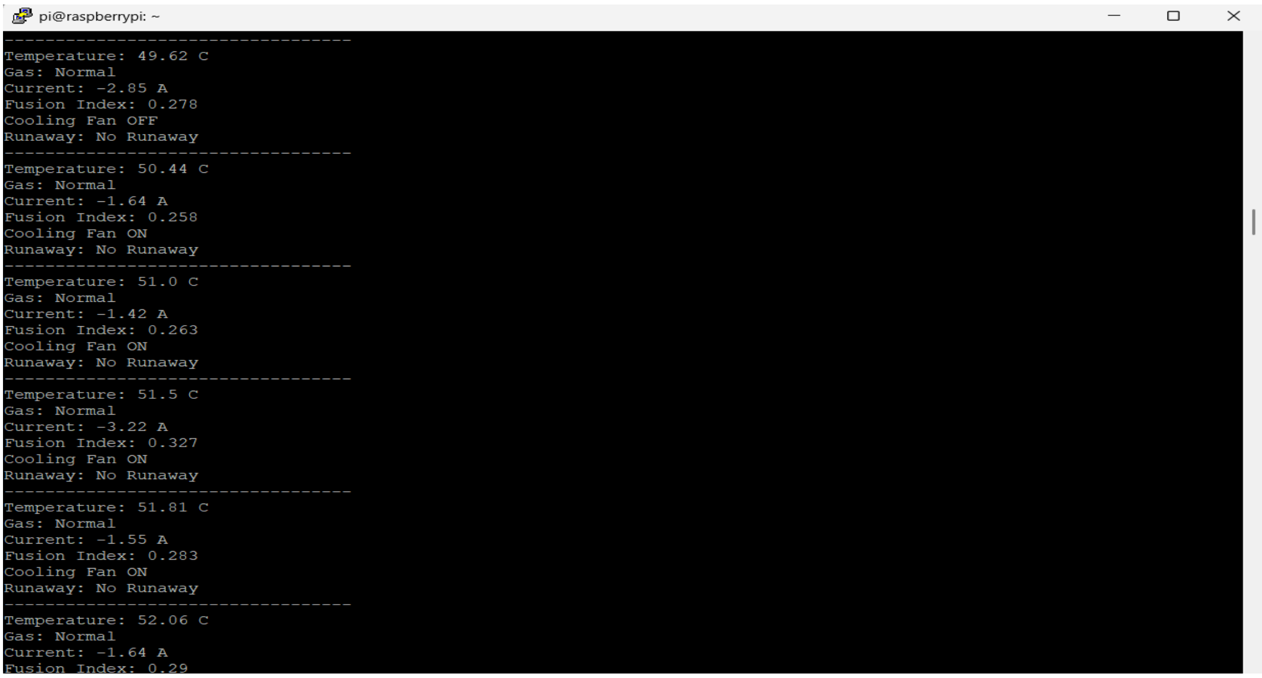

Figure 15: Output obtained from proposed model in raspberry pi

The output of our thermal runaway detection system in use with a Raspberry Pi platform is shown in Figure 15. Displays include critical parameters such as detected hotspot temperature, gas concentration, pack current and the calculated Fusion Index value. From these parameters, the system will automatically determine the battery pack operational state and perform an appropriate control action (e.g., activating cooling fans or isolating a cell with MOSFETs). The successful

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combination of the multi-sensor fusion algorithm and the embedded processing unit allows real-time monitoring and an autonomous safety response of the battery pack.

VIII. INTEGERATING CLOUD WORKFLOW

The system continuously monitors the battery pack temperature using the temperature and gas sensors (Fig. 16). The cooling fan is activated when the detected temperature rise (>50 °C). The thermal images are retrieved from the Raspberry Pi storage when the temperature rise is detected (>60 °C) and instantly processed using the quantized U-Net model. The hotspot detection, Tmax, cooling fan status and MOSFET isolation status are recorded for analysis. All the data is logged locally and uploaded to a cloud database (Firebase). This real-time monitoring allows immediate detection of faults, live thermal status, and post-event analysis. The real-time monitoring of the battery parameters occurs using the Raspberry Pi and the data is transmitted to a cloud database. This enables remote diagnostics and fleet monitoring. The parameters are transmitted to a Firebase Realtime Database: Maximum hotspot temperature (T_max), Gas concentration (G), Pack current (I), Fusion Index (F), Cooling status, Isolation status, Timestamp.

The data is uploaded in JSON format over HTTPS every 2 seconds to: Real-time monitoring of anomaly development, Historical trend analysis, Remote failure alerts, Post event analysis. The cloud integration is not involved in decision making and is purely passive, ensuring that the protective actions are independent of network availability.

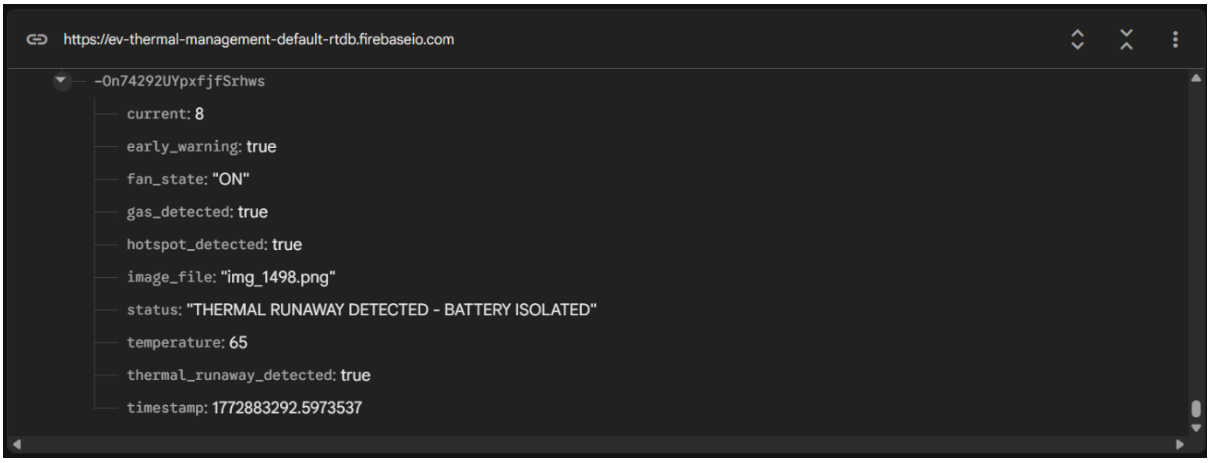

Figure 16: Firebase real-time data monitoring

The complete system, including real-time sensor measurements and Fusion Index calculations, is uploaded via secure HTTPS to a Firebase Realtime Database. A Raspberry Pi pushes different JSON packets (containing temperature, gas concentration, current magnitude, Fusion Index and actuator status flags) every 2 seconds. This allows for live cloud visualization, anomaly logging, and superimposed trend analyses without adding to the overall embedded computational burden. This cloud integration provides scalability and allows for fleet-level battery monitoring of distributed EVs.

IX. CONCLUSION

This work presents a new framework for detecting multi-modal battery Thermal Runaway. It integrates Thermal Imaging, Gas Sensor, Electrical Current Measurement and a Deep Learning (NN based) Hot Spot Detection Model to provide early warning of abnormal battery operation. The proposed Battery Management System (BMS) will conduct 2D Spatial Thermal Analyses to provide Early Warning of Localised Hot Spots. This work will use the U-Net architecture for its Convolutional Neural Network (CNN) structure to perform Thermal Analyses at the Pixel Level for Hot Spot Location. To increase the reliability of the proposed Hot Spot Detection Model, The Fusion Index algorithm will combine the Anomaly Scores from the Thermal Imaging, Gas Sensor and Electrical Current Measurement systems. A Sensor Fusion methodology will allow for the early detection of the Electrical Pre-cursors to Thermal Runaway, prior to a substantial increase in Temperature. The experimental results generated from an Electro-Thermal Digital Twin using MATLAB show that, on average, the proposed BMS can detect Abnormal Battery Operation between 30 seconds to 90 seconds earlier than a conventional BMS (based on Temperature Monitoring). The U-Net Model has been optimised for use on a Raspberry Pi 3 using TensorFlow Lite with an inference latency of < 100 ms per frame. An embedded cooling fan has been developed that will automatically activate when thermal runaway is detected by the proposed BMS.

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