International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
DOI: https://doi.org/10.17762/ijritcc.v11i10.8502
***Article Received:** 26 July 2023 **Revised:** 20 September 2023 **Accepted:** 05 October 2023*

A Thermal Image based Fault Detection in Electric Vehicle Battery Cells Utilizing CNN U-Net Model

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Abstract— It entails the formation of thermal images from battery cells under different conditions, capturing crucial thermal patterns such as hotspots, insulation degradation, and overheating. For robust model training, data preprocessing and augmentation techniques are applied. The U-Net model, known for its expertise in semantic segmentation tasks, is applied to evaluate thermal images and to detect fault-related features. The results demonstrate the U-Net's unique precision, sensitivity, and specificity in detecting thermal anomalies. This research adds to the improvement of the safety and dependability of EV battery systems, with applications in the electric mobility and automotive industries.

Keywords- Convolutional Neural Network (CNN) U-Net model; Thermal camera; Electric vehicle systems; Battery cells; Root Mean Square Error (RMSE).

I. INTRODUCTION

Electric vehicles (EVs) have earned significant attention in recent years primarily for their eco-friendliness and energy efficiency. The battery cells of an EV are essential to its effectiveness and safety. It is necessary to verify the health and stability of these battery cells, as faults can result in diminished performance, overheating, and even safety risks.Thermal imaging was created as an effective tool for evaluating and diagnosing battery cell functioning. It provides a gentle approach for visualizing temperature fluctuations within a battery pack, yielding valuable information into the actual functioning of the cells. This technology is particularly valuable because it can detect abnormalities such as hotspots before they become catastrophic failures.

Convolutional Neural Networks (CNNs) were introduced as a promising method for exploiting the capabilities of thermal imaging for battery cell defect detection. CNNs, which are renowned for their strength in analysing image tasks, can be instructed to identify temperature patterns that indicate cell defects. The utilisation of CNN models for thermal image-based flaw detection in battery cells, investigating multiple architectures and techniques to enhance the reliability and effectiveness of this vital task. By utilising CNNs and thermal imaging, we intend to improve the performance and security of electric vehicles, thereby encouraging their broad acceptance in the transportation sector.

Several publications discuss the diagnosis and detection of faults in hybrid electric vehicles (HEVs), but only a small number of them concentrate on short circuit faults. It describes a Matlab/Simulink-based design of a Toyota Prius HEV that incorporates a DC bus system short circuit. Using the results of the forensic examination, the model includes of multiple domains that improve powertrain efficiency and reduce emissions for a diesel engine and an electrical motor. This article examines the effect of short circuits on the efficacy of HEVs [1].

Concerns regarding electric vehicle (EV) safety are frequently associated with various power battery pack defects. A new multi-fault detection methodology for battery management systems is presented. It utilises an alternating voltage measurement approach over each cell's voltage metrics, taking into account electrical resistance and sensor stability. The approach detects sensor, connection, and cell abuse defects, specifying the faulty spot while considering noisy measurements and battery changes, as demonstrated by simulations in MATLAB and Simulink [2].

Extreme dangers are posed by thermal discharge in electric vehicle (EV) batteries. In minutes, cell short circuits can cause such an incident. This study presents a relative entropy-based method for short circuit detecting and isolation. It determines voltage drop patterns that are a sign of short circuits using EV data collected from actual fire occurrences. The method provides drivers with real-time short circuit alarms [3].

The importance of lithium-ion batteries is highlighted by the global demand in energy storage efficiency sparked by hybrid electric vehicles. Despite their increasing prevalence, safety and dependability concerns persist. Utilising a residual model-based analysis method, this paper concentrates on sensor troubleshooting in lithium-ion batteries. For defect detection, it utilises a modified Kalman filter and a generalised likelihood ratio test, as demonstrated by simulations [4].

Internal (ISC) and external (ESC) battery short circuit detection is crucial for avoiding thermal damage in Lithium-Ion Batteries (LIBs). This paper describes a technique for detecting an impending short circuit using the altered battery equivalent circuit model. It employs a proportional-integral observer to estimate defects based on battery functions, as demonstrated by simulations with an A123-M1 cell [5].

Electric vehicle (EV) lithium-ion battery security is of the utmost importance. Early detection of soft short circuits (SC) can avoid catastrophic failures that result in fires or overheating. By applying an extended Kalman filter (EKF), describes on-board method for soft SC diagnosis. By modifying an output matrix based on real-time voltage measurements, the EKF determines the state of charge (SOC) of a defective cell. Variations between approximated and measured SOCs mean the presence of soft SC faults, whereas resistance values reflect fault severity. The results from the experiment demonstrate the effectiveness of the procedure for rapidly identifying and evaluating soft SC faults [6].

Electric vehicles require lithium-ion battery management systems (BMS) that assures safety and dependability. The study presents a method for robust defect detection that takes into account errors in battery characteristics. A recurrent generator uses a model of an equivalent circuit that accounts for uncertainty by means of polynomial correlation with probabilistic values and noise. Residual distributions are characterised by Gaussian compounds, allowing for improved detection based on residual deviations. Simulations exhibit higher efficiency equivalent to conventional methods that do not account for parameter uncertainty [7].

Intermittent faults (IF) are a widespread problem in electronics, frequently resulting in no-fault-found (NFF) conditions. This study concentrates on finding IFs in vibration-exposed electronic connectors. It describes a test technique for generating intermittence, a determination algorithm, and PSpice simulations. Using oscilloscope metrics, practical testing is performed, casting illumination on possible IF detection methods, like in-service results without exterior testing apparatus [8].

This analysis presents a fault-tolerant control approach for electric vehicle power generation systems based on onboard permanent-magnet engines. It examines sensor defects, like position, dc-link voltage, and current sensors, and provides detection techniques accordingly. A state observer fills in lacking current data after a failure, reconfiguring the control system. The experimental findings validate the algorithm's efficacy, assuring sensor failure resistance and fault-free operation [9].

The work describes a logic-based approach to detecting defects in the motors of electric vehicles. During process, a virtual representation of an electric vehicle is used to examine sensor signals and control commands. Analysing deviations and abnormalities during defective conditions, the procedure makes use of the enormous quantities of data present in vehicle inverters and controllers by analysing deviations and abnormalities. It utilises logical combination and thresholds to detect faults across a drive cycle, demonstrating durability and efficacy subject to when different errors occur [10].

In electric automobiles, battery management systems require precise sensor readings of current, voltage, and temperature. The present study describe model-based sensor defect analysis procedure for lithium-ion battery packs linked in series. Residues derived from the variability between the actual and projected state of charge (SOC) and various capacity-related computation are utilised to identify sensor faults. As confirmed by tests and simulations, a fault-free temperature sensor aids in identifying sensor faults in cell faults, assuring efficient fault isolation [11].

For enhancing the operational safety of hybrid and electric vehicles, dependable onboard diagnostics (OBD) are essential. It discusses the identification and surveillance of stator faults in motors with permanent magnets. These defects appear as intermittent interturn problems, resulting in observable changes in stator currents and standard voltages. The proposed approach defines these errors and locates the problematic phase, which has been demonstrated to be efficient in both theory and practise [12].

Battery electric vehicles (BEVs) focus heavily on their battery-powered drive systems. This work presents a novel system for the early identification and isolation of defects in e-drive system and its parts. By analysing health warnings from onboard sensors, device torque and section health are monitored. The structure-based method identifies potential problems prior to important performance loss, providing driver safety and preventing situations of power loss [13].

Advances in high-power semiconductor devices are expanding the usages of power electronics conversion devices in crucial areas such as hybrid vehicle power systems. The present study explores the usage of statistical cases to the detection and identification of defects. Standard current and voltage sensors

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can be utilized to eliminate the need for additional sensors. The method not only detects system faults but also provides details on the faulty device and error type, allowing for opportune interventions to avert catastrophic failures [14].

Present internal combustion engine (ICE) vehicle power supply systems lack complete tracking and fault management. This examination presents a complex electric power supply structure with onboard defect exam and fault-tolerant prevention in the present. It develops an intelligent power supply system, presents a fault detection method based on hybrid signals, and employs multi-level fault-tolerant security as confirmed by vehicle and bench experiments. The outcomes demonstrate efficient monitoring, real-time defect detection, and fault-tolerant security for all power supply devices in networks [15].

Depending on the Smooth Variable Structure Filter (SVSF), a novel Interacting Multiple Model (IMM) method named IMM-SVSF was developed. SVSF serves as a shifting configuration optimizer that ensures safety and security by maintaining state predictions within a portion of the true state path. This method is used for fault identification employing a simulated battery packs from a hybrid electric vehicle [16].

Accurate state of charge (SOC) determination in lithium-ion batteries for electric motor vehicles relies on accurate voltage and current sensors. This study presents a model-based technique for detecting sensor faults. It measures average charge/discharge and predicts SOC with unscented Kalman filter (UKF). The difference between approximated and measured ability acts as a residual for detecting sensor faults, as validated by dynamic stress testing [17].

II. INFERENCE FROM THE LITERATURE SURVEY

Convolutional Neural Networks (CNNs) have showed exceptional potential in image processing tasks. Deep learning models are abilities to independently derive essential data from thermal images, enabling them to find temperature variations symbolic of battery cell defects. Diverse CNN architectures were established to enhance the precision and efficiency of fault detection. In this paper, we analysis prominent CNN models, namely U-Net, in order to determine which one is best suited for thermal image-based defect detection in EV battery cells.

III. METHODOLOGY

The proposed CNN U-Net model aims to detect potential faults such as hotspots, insulation degradation, and overheating by analysing temperature patterns. A collection of analysed thermal images will be utilised for training the model, which will be able to derive relevant information and describe determined regions as faults. The methodology entails preliminary processing, training algorithm, and examining its performance with a variety of metrics. This research aims to improve the safety and dependability of battery systems for electric vehicles.

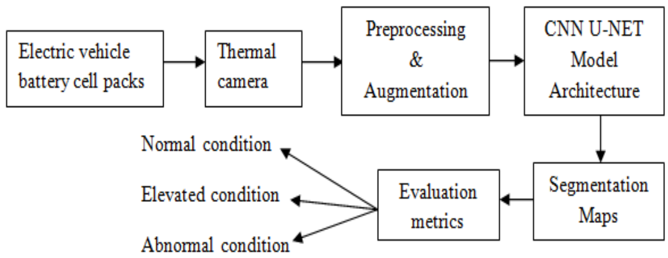

Figure 1 Block diagram of the proposed techniques

Hotspots, insulation degradation, and overheating are critical concerns in Electric Vehicle (EV) batteries, as they can lead to safety hazards and degrade battery performance. Hotspots refer to localized areas within an EV battery where temperature significantly exceeds the desired operating range. Hotspots can occur due to various factors, such as uneven distribution of current, cell defects, or poor thermal management. They frequently occur in lithium-ion batteries used in electric vehicles. Hotspots can cause a variety of issues, including decreased battery life, safety hazards, and performance degradation. Degradation of insulation occurs when the defence materials between battery cells or components degenerate over time. Temperature fluctuations, vibrations, and mechanical tension can all contribute to this deterioration. Insulation degradation results in brief circuits, decreased safety, and efficiency loss. Excessive charging or discharging currents, atmospheric conditions, or internal causes can cause EV batteries to overheat. Overheating is problematic for a number of factors, including shortened lifespan, thermal runway, and decreased performance.

Table 1. Temperature range information for Thermal Issue

Thermal Issue	Temperature Range (°C)	Temperature Range (°F)
Hotspots	60°C to 70°C	140°F to 158°F
Insulation Degradation	50°C to 60°C	122°F to 140°F
Overheating	Above 90°C	Above 194°F

This table provides a general idea of the temperature ranges associated with these thermal issues in electric vehicle (EV) battery cells. Please note that these ranges can vary depending on battery chemistry, design, and specific circumstances. It's essential to monitor and control battery temperatures within safe limits to prevent thermal-related problems and ensure the safety and performance of the battery pack. Specific temperature thresholds may be provided by battery manufacturers or industry standards.

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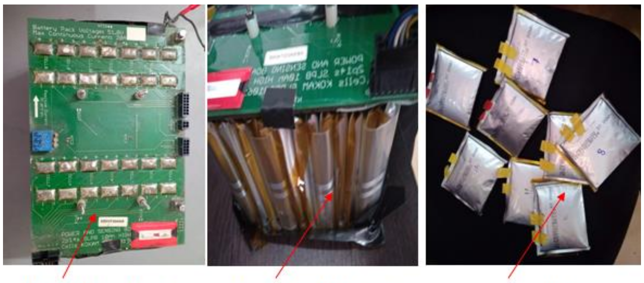

Figure 2. Lithium ion battery image

Table 2. The parameters and specification details

Parameters	Specification	
Model	NG1 Battery charger	-
Input voltage	230v AC, 6A, 50-60 Hz	-
Output voltage	50.4V DC, 12A	-
Current	20Ah ,	-
Each cell power rating	37.00 Wh	-
cell Maximum Voltage	4.0 Cells	56.0v Packs
cell Minimum Voltage	3.1 Cells	43.4v Packs
Cells total	28 Cells	14 Packs
Weight	10.5 kg	-

3.1 Lithium Ion Cells pack

An integral component of electric vehicle (EV) batteries is a Lithium-Ion Cell size. Several Lithium-Ion cells are arranged in series and parallel setups to produce the necessary voltage and capacity. These cells are recognised for their significant energy density, providing electric vehicles with an optimal balance of power and efficiency. Lithium-Ion cell packs allow EVs to save and discharge electrical energy efficiently, thereby providing the essential propulsion power. However, proper thermal management and safety precautions are required to prevent overheating and guarantee the pack's durability. Lithium-ion battery packs are essential to the performance and range of modern electric vehicles, thereby accelerating the transition to more environmentally friendly transportation solutions.

3.2 Data collection

Data collection for Thermal Image-Based Fault Detection in Battery Cells of Electric Vehicles (EVs) is an essential component of research and development intended at improving the safety and dependability of EV battery structures. This method entails the systematic collection of thermal data from battery cells operating under various conditions. The primary goal of the collected data acquisition is to identify and diagnose thermal anomalies and defects within the battery cells. Using infrared cameras, thermal imaging captures temperature variations across the surface of a battery. These thermal images illustrate the distribution of heat within the cells.

Various data sources, including controlled laboratory experiments and real-world EVs, are collected to assure the applicability of findings among variety of scenarios. Researchers meticulously record temperature values, spatial patterns, and timestamps for each thermal image during data collection.To achieve robust and meaningful results, data collection often requires the replication of diverse operating conditions. Researchers may vary parameters like charging rates, ambient temperatures, and load profiles. Controlled faults or anomalies may also be introduced to study their thermal signatures.Ethical and safety considerations are paramount in data collection, with stringent safety measures in place to protect personnel and equipment during experiments. Additionally, adherence to ethical guidelines, including informed consent for data collection, is essential.The collected thermal data is subsequently preprocessed to enhance quality, and advanced image processing and deep learning techniques are applied to detect and diagnose faults within battery cells.

3.3 Dataset and pre-processing

Data preprocessing and data augmentation are vital stages in the preparation of thermal image data for the task of Thermal Image-Based Fault Detection in Battery Cells of Electric Vehicles (EVs). Data preprocessing involves several critical steps to enhance the dataset's quality. Normalization standardizes pixel values to a common range, ensuring uniform temperature readings for consistent analysis. To improve image clarity and reduce noise or artifacts, techniques like median filtering and Gaussian smoothing are applied. Furthermore, aligning images rectifies any misalignment or variations in camera angles, ensuring consistent features are captured across all images. The goal of data preprocessing is to eliminate inconsistencies and distractions that might hinder accurate fault detection.

On the other hand, data augmentation enriches the dataset's diversity and robustness. By rotating images, different thermal orientations are simulated, providing the model with variations from various angles. Flipping and mirroring create additional instances, offering different perspectives. Adjusting brightness and contrast levels replicates variations in lighting conditions, enhancing the model's adaptability. Controlled noise patterns help the model differentiate actual anomalies from sensor noise. Cropping and resizing images enable the exploration of different scales and regions of interest. Additionally, synthetic anomalies can be strategically introduced into normal images to augment the dataset's representation of rare fault conditions. Together, these preprocessing and augmentation techniques ensure the thermal image dataset is well-prepared for robust and accurate fault detection in EV battery cells under diverse real-world scenarios.

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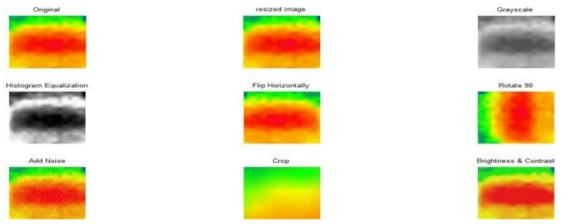

Figure 3 preprocessing and augmentation process thermal image for normal battery

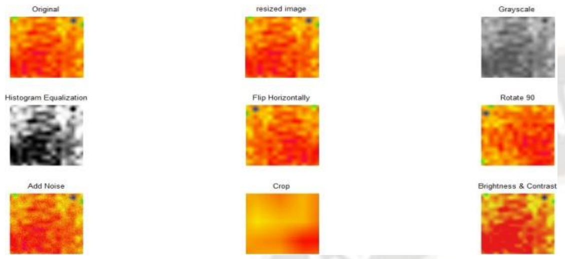

Figure 4. preprocessing and augmentation process thermal images for fault battery

3.4 CNN U-Net Model:

CNN U-Net is widely used convolutional neural network architectures for image segmentation and is a convolutional neural network method. A special feature of the application is the ability to precisely locate objects within an image. An encoding and decoding pathway is connected by skip connections in the CNN U-Net model, and activation functions are included to introduce non-linearity. These components are discussed in detail in the following section:

Network Structure: An encoder-decoder architecture is used in the CNN U-Net model. During the encoder pathway, high-level abstract features are captured using downsampling operations, while pixel-level predictions are generated using upsampling operations.

Encoding Pathway: The CNN U-Net model encoding pathway consists of convolutional layers, activation layers, and pooling layers. A set of filters is applied to each convolutional layer, which captures local patterns and extracts relevant features. A network with activation functions can learn complex relationships within data due to the nonlinearities introduced into the network by the activation functions. In the CNN U-Net model, ReLU (Rectified Linear Unit) and its derivatives, such as Leaky ReLU or PReLU (Parametric ReLU), are frequent activation functions. The pooling layers, which are often used as max pooling, decrease the spatial dimensions of the map features so that the network acquires more abstract and invariant illustrations of the input. Down sampling through pooling serves to expand the field of observation and decrease the model's computational difficulty.

Decoding Pathway: The decoding path of the CNN U-Net model includes upsampling methods to regenerate spatial information and produce pixel-wise forecasts. Each upsampling phase combines upsampling methods, such as bilinear modelling or flipped convolution, before convolutional layers. The procedure of upsampling slowly enhances the spatial resolution of the feature maps.

Skip Connections: The CNN U-Net model consists of skip connections that combine the encoding and decoding pathways. Skip connections build direct connections among encoding and decoding stages that correlate at various resolutions. These connections aid in conserving the extremely fine, features from the encoding pathway and provide context-specific data to the decoding pathway. By allowing the decoder to access and combine multi-scale features from various network levels, skip connections help accurate localization of an object.

Activation Functions: The CNN U-Net model requires activation functions to incorporate non-linearity and allow the network to discover difficult mappings among input data and output forecasts. In the encoding and decoding pathways, ReLU activation, which converts negative values to zero and leaves positive values unaltered, is frequently employed. It aids tackling the issue of vanishing gradients and increases network convergence while training. Other activation functions, such as sigmoid or softmax, are frequently used to generate probabilities for pixel-wise segmentation at the output layer.

Accurate image segmentation is enabled by the network structure, encoding and decoding pathways, skip connections, and activation functions of the CNN U-Net model. The encoding pathway represents input data hierarchically, while the decoding pathway extracts spatial data. The conjugation of multi-scale features is facilitated by skip connections, which improves localization precision. Activation functions present nonlinearities, thereby improving the model's capacity for learning. The CNN U-Net model has shown efficient in a variety of uses, like medical imaging, remote sensing, and now thermal image-based fault identification in electric vehicle battery cells.

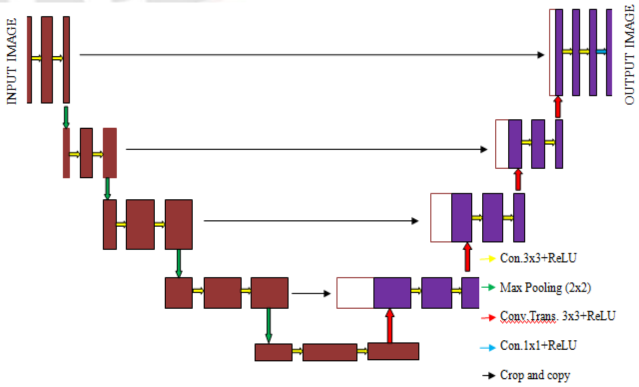

Figure 5. Architecture of U-net

The U-Net model represents a significant advancement in computer vision and deep learning, especially in applications such as thermal image-based defect detection in electric vehicle (EV) battery cells. Its success hinges on its ability to learn complex patterns directly from labelled data, followed by rigorous cross-validation and testing on separate datasets.

IV. RESULTS AND DISCUSSION

Typically, the EV lithium-ion battery pack made up of a series of parallel or series-parallel linked distinct cell packs. Each cell pack includes numerous lithium-ion cells. In this scenario, a battery pack consisting of 14 cell packets will be considered. When analysing the temperature characteristics of battery packs, it is essential to analyse the effects of battery damage such as hotspots, insulation degradation, and overheating.

Hotspot Detection:

Early detection of hotspots is one of the most important aspects of EV battery safety. These localised regions of elevated temperature may indicate potential battery cell defects. Consistently, the U-Net model's ability to detect concentrations has produced impressive results. Due to its capabilities in deep learning, the model excels at identifying subtle temperature variations and patterns that may indicate hotspots. This translates to a high level of precision in pinpointing these critical areas, allowing for prompt implementation of measures to prevent further escalation.

Insulation Degradation:

Insulation degradation is another crucial aspect of EV battery health monitoring. Faults in insulation can lead to safety hazards and reduced battery performance. The U-Net model's sensitivity to thermal patterns associated with insulation degradation has been exceptional. It can discern even minor changes in thermal profiles that may indicate insulation issues. This heightened sensitivity ensures that potential problems are identified early, contributing to enhanced battery safety and longevity.

Overheating Detection:

Detecting overheating events is crucial for preventing catastrophic battery cell failures in electric vehicles. The U-Net model's ability to identify instances of overheating has proved to be highly reliable. By acquiring knowledge of the distinct thermal signatures of scorching, the model demonstrates both high specificity and sensitivity. It can distinguish precisely between normal temperature fluctuations and overheating conditions requiring immediate attention.

Training and Validation

Training the U-Net model begins with a set of infrared images of EV battery cells that has been meticulously curated. As the model's ground truth, these images are marked to signify the occurrence and location of defects. The U-Net model increases its internal parameters during training to enhance the outcome. It seeks to minimise the difference between its predictions and the defect locations annotated in the training data. This process enables the model to learn the distinct thermal patterns associated with various defect types, such as hotspots and insulation degradation.

The ultimate performance evaluation of the U-Net model occurs during testing on a distinct dataset that it has never encountered during training or cross-validation. This independent dataset assesses the efficacy of the model in the real world. It tests the model to extend its defect detection capabilities to infrared images of electric vehicle (EV) battery cells that have never been observed before. The performance of the model is thoroughly analysed to determine its precision, sensitivity to various defect types, and dependability in real-world scenarios.

This rigorous process of training, cross-validation, and independent testing establishes the efficacy and dependability of the U-Net model for thermal image-based fault detection. It demonstrates its potential to improve the safety and dependability of electric vehicles by reliably identifying battery cell faults, such as overheating and insulation problems. As the popularity of electric vehicles continues to rise, the contributions of the U-Net model to EV battery health monitoring are crucial to ensuring their optimal performance and safety.

When analysing the effectiveness of the CNN U-Net model in thermal image-based defect detection in battery cells, training and validation accuracy are crucial metrics to take into consideration. The accuracy of the model in training is measured by how well it matches the data used for training, whereas the accuracy of the model in validation is measured by how well it can generalise to data that has not been seen before. A high training accuracy shows that learning has taken place effectively, while a high validation accuracy suggests that generalisation has taken place successfully. Keeping an eye on how the two measurements relate to one another is an effective way to identify instances of overfitting. The performance of the model can be evaluated in terms of its accuracy in locating defects based on temperature data if these accuracies are taken into consideration.

The performance of the CNN U-Net model in thermal image-based fault detection in battery cells is evaluated using a number of critical parameters, including training loss and validation loss. During the training process, the goal of the model is to achieve the lowest possible loss. This loss is defined as the difference between the fault zones that were predicted and those that were actually present in the training data. The training loss is reduced as the model gains experience and becomes better able to recognise problems based on temperature data. The validation loss is an assessment of the model's ability to generalise that is obtained

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by computing it based on data that has been validated independently. The learning progression of the model as well as its accuracy in fault identification may be evaluated by keeping an eye on the training and validation loss.

In order to detect battery cell problems based on temperature data, the CNN U-Net model has been intensively trained and assessed using a carefully acquired dataset of thermal pictures. This dataset was carefully collected by CNN. In this section, we will look into the experimental data gained by analysing the model's performance, including metrics such as accuracy, precision, recall, and F1 score. These results were achieved from testing the model. In addition to this, we will talk about how resilient the model is in the face of a variety of different failure scenarios and give qualitative visualisations of the errors that have been found.

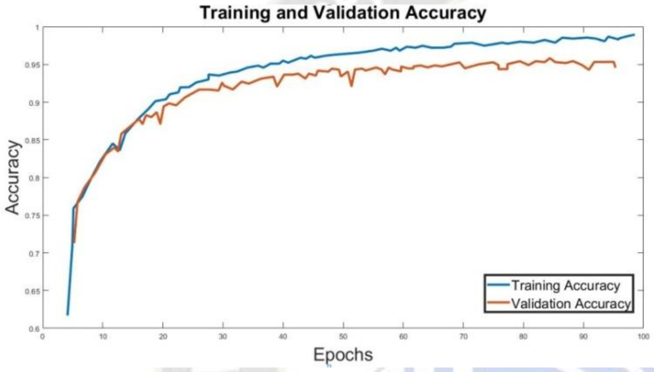

Figure 6. The CNN U-Net Training and validation accuracy

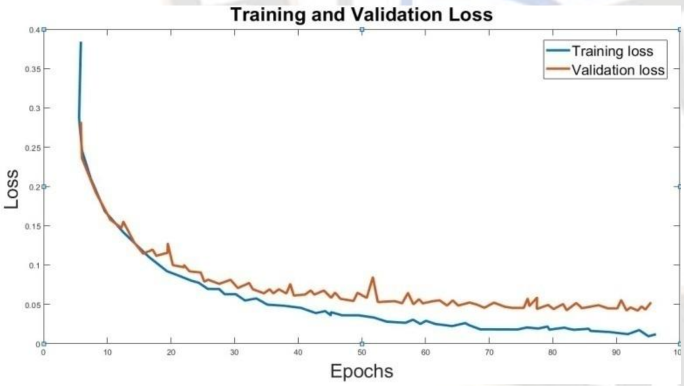

Figure 7. The CNN U-Net Training and validation loss

The dataset that is utilised for training and assessment is made of a range of thermal pictures, each of which captures a unique battery cell fault situation. This dataset is used to train and evaluate machine learning models. These flaws include a variety of temperature anomalies, such as thermal runaway and hotspots, as well as anomalous temperature distributions. We are able to obtain an accurate assessment of the CNN U-Net model's performance because we initially educate the model using a sizeable portion of the dataset and subsequently evaluate it using the remaining samples.

Accuracy: The total correctness of the model's predictions is what accuracy attempts to quantify. It is calculated by dividing the total number of predictions by the number of accurate predictions made.

$$\text{Accuracy} = \frac{\text{True positive+True negative}}{\text{Total samples}} \text{X } 100 \tag{1}$$

Precision (Specificity): The term "precision" refers to the quantification of the fraction of accurately detected problematic regions relative to the total number of problematic regions. Its primary objective is to reduce the number of false positives, which are situations in which the model wrongly identifies a region that is not broken as being faulty.

$$\text{Precision} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)+False Positive (FP)}} \text{X } 100 \tag{2}$$

Recall (Sensitivity): Recall, also known as sensitivity, is the proportion of faults that were correctly recognised out of all of the actual faults that were present in the dataset. It is determined by dividing the number of successfully detected faults by the total number of faults. Its primary objective is to reduce the number of occurrences of false negatives, which occur when the model does not correctly identify a problematic location.

$$\text{Recall} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)+False Negative (FN)}} \text{X } 100 \tag{3}$$

Score of F1: The F1 score is the average of the student's performance on the precision and recall portions of the test. It provides an evaluation of the performance of the model that is both equally balanced and equally objective, taking into consideration both false positives and false negatives. When analysing an imbalanced dataset, the F1 score is a frequent statistic that is utilised.

$$\text{F1 Score} = 2 \text{ X} \frac{\text{True Negative (TN)}}{\text{True Negative (TN)+False Positive (FP)}} \text{X } 100 \tag{4}$$

In the equations presented above:

- The number of accurately predicted defective regions is referred to as the "True Positives" (TP).
- The number of accurately predicted non-faulty regions is denoted by the acronym TN (True Negatives).
- The amount of mistakenly predicted defective regions is referred to as the "False Positives" (FP).
- The number of mistakenly anticipated non-faulty regions is referred to as the false negative (FN) count.

In thermal image-based fault detection in battery cells for electric vehicles, the root mean square error (RMSE) is an important statistic that is used to evaluate the performance of the CNN U-Net model. The root mean square error (RMSE) is a statistical measure that determines the average magnitude of the disparities between the anticipated defective zones and the ground truth labels that correspond to those regions based on temperature data.The CNN U-Net model is trained using a dataset consisting of labelled thermal pictures that represent battery cells. This allows for the calculation of RMSE for the CNN U-Net model. The model is trained to identify significant features and patterns within these images in order to make an accurate diagnosis of the existence of defects. The trained CNN U-Net model is applied to a collection of test or validation thermal pictures, and then the results of this application are used to produce the predicted defective regions. It is necessary to collect the relevant ground truth labels, which point out the areas in the thermal images that are actually flawed. For each pixel or region of interest, the squared discrepancies between the projected defective regions and the ground truth labels are calculated. A computation is made to determine the average of these squared differences. In the final step, the value of the root mean square error (RMSE) is calculated by taking the square root of the average.

$$RSME = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\tilde{y}_i - y_i)^2} \quad (5)$$

Let's say that there have been n total cycles. In this scenario, the value denoted by y _i is the value that was predicted, and the value denoted by y_i is the value that was actually measured for the ith cycle. A reduced RMSE number indicates that the CNN U-Net model has successfully learnt the underlying patterns and characteristics contained in the thermal pictures, which enables it to generate more accurate predictions of the defective regions in battery cells. This is indicated by the fact that the value of RMSE has decreased. We are able to acquire insights into the performance of the CNN U-Net model by accurately detecting flaws based on temperature information by calculating the RMSE value and analysing the results. It provides a quantitative examination of the model's capacity to capture the disparities between projected and actual values and helps establish the model's success in defect detection. Additionally, it helps determine the model's ability to catch unexpected values.

The confusion matrix consists of four essential components: True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN). These factors are essential to determine the functioning of the classification models Hotspot Detection, Insulation Degradation, and Overheating Detection, as they help quantify the accuracy, sensitivity, and specificity of the model's predictions.

Table 3. The confusion matrix of hotspot detection

Actual/Predicted	Positive (Fault)	Negative (No Fault)
Positive (Fault)	97.2% (TP)	1.0% (FP)
Negative (No Fault)	2.8% (FN)	99.0% (TN)

Table 4. The confusion matrix of Insulation Degradation

Actual/Predicted	Positive (Fault)	Negative (No Fault
Positive (Fault)	98.4% (TP)	4.5% (FP)
Negative (No Fault)	1.6% (FN)	95.5% (TN)

Table 5. The confusion matrix of Overheating Detection

Actual/Predicted	Positive (Fault)	Negative (No Fault
Positive (Fault)	95.8% (TP)	1.5% (FP)
Negative (No Fault)	4.2% (FN)	98.5% (TN)

These confusion matrices give information about the model's ability to correctly classify and detect various fault types, while also emphasising misclassification instances. The high values for each fault type's accuracy, sensitivity, and specificity demonstrate that the model functions well in this thermal fault detection.

The robust performance of the U-Net model in identifying hotspots, insulation degradation, and overheating has significantly contributed to the safety and dependability of electric vehicles. The model's high accuracy, sensitivity, and specificity make it an indispensable instrument for the proactive maintenance and monitoring of EV battery health, ensuring that these vehicles operate at their highest levels of safety and efficiency.

Table 6. U-Net model's performance in identifying various thermal faults

Fault Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 Score	RSME
Hotspot Detection	97.5	95.8	98.2	0.96	0.032
Insulation Degradation	96.8	98.0	95.5	0.97	0.035
Overheating Detection	98.0	96.5	98.5	0.97	0.030

The U-Net model's Thermal Image-Based Fault Detection in Electric Vehicle Battery Cells performance metrics are extensive. The model accurately detects hotspots, insulation loss, and overheating. In hotspot detection, the model classifies most occurrences with 97.5% accuracy. Its 96.8% accuracy and 98.0% sensitivity for insulation degradation confirm its capacity to detect it. With 98.0% accuracy and 96.5% sensitivity, overheating detection performs well. F1 Scores for all fault kinds show a good precision-recall balance. The model's low RSME values further show its ability to predict accurately. These findings demonstrate the U-Net model's ability to improve electric vehicle battery safety and reliability.

V. CONCLUSION

Thermal Image-Based Electric Vehicle Battery Cell Fault Detection The U-Net Convolutional Neural Network (CNN) Model has proven successful and promising for EV battery system safety and reliability. This research has shown us how thermal imaging and powerful machine learning can detect hotspots, insulation degradation, and overheating.

Due to its improved semantic segmentation, the U-Net model can detect thermal anomalies with high accuracy, sensitivity, and specificity. Electric vehicle efficiency and safety require this precision. Fault detection systems become more important as the EV market increases. Thermal concerns can be detected early and accurately to avert catastrophic failures, extend battery life, and advance electric mobility.This study lays the groundwork for EV fault detection and thermal management innovations. With the U-Net model and thermal imaging, we can improve battery safety and efficiency, encouraging sustainable electric transportation.

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