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THERMAL IMAGE-BASED BATTERY CELLS FAULT DETECTION IN ELECTRIC VEHICLES USING CNN MODEL

S. Senthilraj[1] and N. R. Shanker[2]
[1]Electronics and Communication Engineering, PRIST University, Thanjavur, Tamil Nadu, India
[2]Computer Science and Engineering, Aalim Muhammed Salegh College of Engineering, Chennai, Tamil Nadu, India
E-Mail: senthilrajvlsi@gmail.com, nr_phd@yahoo.in

ABSTRACT

This study compares and evaluates the performance of four Convolutional Neural Network (CNN) models, namely ResNet152, VGG19, DenseNet201, and Inceptionv3, for thermal images-based detection of faults in electric vehicle (EV) battery cells utilizing temperature. A dataset comprising thermal images of battery cells with various fault types and severities is collected and preprocessed for model training. Transfer learning is applied to train the CNN models using pre-trained weights on large-scale image datasets. The trained models are assessed using evaluation metrics that include precision, recall, F1-score, and accuracy, while their computational efficiency is evaluated in terms of inference time and memory usage. Results show promising performance for all four CNN models in detecting faults in battery cells. DenseNet201 achieves the highest accuracy, followed by ResNet152, VGG19, and Inceptionv3. Inceptionv3 demonstrates superior computational efficiency. These findings aid researchers and practitioners in selecting an appropriate CNN model for thermal image-based fault detection in EV battery cells, considering the balance between accuracy and computational efficiency.

Keywords: convolutional neural network (CNN), electric vehicle (EV), densenet201, resnet152, VGG19, and inceptionv3.

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INTRODUCTION

The detection of faults in electric vehicle (EV) battery cells is vital for ensuring their safe and efficient operation. Faults can lead to reduced performance, diminished battery life, and potential safety hazards. Thermal imaging has emerged as a valuable tool for fault detection in EV batteries. By capturing temperature distributions, thermal imaging can identify anomalies such as hotspots and thermal gradients, indicating underlying faults. This non-invasive technique enables real-time monitoring, early fault identification, and large-scale screening. Utilizing advanced deep learning models like Convolutional Neural Networks (CNNs), thermal imaging facilitates accurate and efficient fault detection, contributing to the reliability, longevity, and safety of EV battery cells.

CNNs have modified an area of artificial intelligence (AI), including thermal image-based fault detection. CNN models excel in extracting and learning hierarchical features from images, making them ideal for analyzing thermal images and identifying faults in electric vehicle (EV) battery cells. These models have been developed and implemented successfully to a variety of tasks such as object recognition, segmentation, and classification. In thermal image-based fault detection, CNNs can effectively capture intricate patterns and temperature variations associated with different types of faults. By leveraging the power of deep learning, CNN models enable automated and accurate fault detection, aiding in the maintenance and safety of EV batteries.

Detecting battery defects in electric vehicles (EVs) is essential for their dependability and safety. Existing methods struggle to identify faults early due to inconsistencies that resemble faults. This paper introduces a fault diagnosis approach using signal decomposition and two-dimensional feature clustering. Up to forty-three days before any thermal runaway, the proposed method accomplishes early fault evaluation and voltage abnormality identification, demonstrating robustness and ease with online implementation [1].

This comprehensive review focuses on understanding the internal failure mechanisms, including interior short circuit and thermal runaway, that occur in lithium-ion batteries. It emphasizes the significance of implementing rigorous safety testing methods to enhance the safety of electric vehicles, while also identifying potential research directions for future advancements [2].

This study investigates external short circuit (ESC) defects in lithium-ion batteries experimentally, establishing a novel platform for ESC evaluation on ten 18650-type cells at various states of charge. It analyzes ESC process, develops an improved first-order RC model, and proposes a two-layer model-based fault detection algorithm, demonstrating accurate and efficient fault diagnosis within 5 seconds [3].

This study examines the temperature rise characteristics of lithium-ion batteries (LiBs) caused by an external short circuit (ESC) and proposes an online forecast method for the highest rise in temperature. The approach, validated with results, achieves precise predictions up to 22.3 seconds in advance with a mean prediction error of 3.05% for eight test cells [4].

This review discusses the challenges posed by the inconsistency and aging of individual battery cells in electric vehicle systems. It analyzes various fault types, including sensor, actuator, short circuit, overcharge/over-discharge, connection, insulation, and thermal management system faults. The paper explores fault diagnosis methods, research trends, and potential directions driven by emerging technologies such as big data analytics [5].

A method described for detecting connection defects in lithium-ion power batteries used in electric vehicles that are connected in series. Cross-voltage testing is utilized to differentiate between contact resistance increases and internal resistance increases. Voltage and temperature data are gathered, and a defect severity evaluation based on a modified Z-score analysis is performed. The proposed approach improves the security of electric vehicle systems [6].

This article proposes a method for intelligently diagnosing lithium-ion battery faults in electric vehicles. The method precisely identifies fault states and degrees by employing support vector machines (SVM) and incorporating denoising techniques, a modified covariance matrix, and optimized parameter selection. The proposed method provides a practical solution for intelligent fault diagnosis, allowing for efficient battery pack safety evaluation and future fault management strategies. [7].

A novel data-driven method is introduced for defect diagnosis and early warning of heat loss in electric vehicle lithium-ion battery packs. The method accomplishes accurate identification of early faults and captures state changes for fault diagnosis by analyzing normalized battery voltages. Validation with actual operational data demonstrates the method's efficacy, providing dependable detection and prompt warning of thermal runaway [8].

This investigation examines the influence of state of charge (SOC) and degree on external short circuit (ESC) defects in lithium-ion batteries. The electrical operation of battery cells from ESC defects is described using fractional-order and first-order RC models, with model parameters identified using a genetic algorithm (GA). A three-step model-based algorithm for identifying ESC defects and electrolyte leakage in real time is proposed. Experimental results demonstrate efficient diagnosis of all ESC cells [9].

This paper proposes a fault detection method for electric vehicles (EVs) based on the interclass correlation coefficient (ICC). By analyzing voltage drop trends and extracting voltages from EV service and management centers, the ICC values are calculated to identify battery faults. The method offers advanced fault resolution, prolonged fault memory, and effective fault signal detection for EVs [10].

This work introduces a model-based insulation defect analysis technique for electric vehicle lithium-ion battery systems. It establishes a comparable circuit model, determines the model's parameters using the recurrent least-squares technique, and employs a Kalman filter-based state analyzer for joint battery voltage and state-of-charge estimation. Experimental verification demonstrates that the proposed procedure is effective [11].

This work presents a fault detection technique for rotating machinery and engines based on thermal image analysis. A novel feature extraction technique called BCAoID (Binarized Common Areas of Image Differences) is introduced. Thermal images of faulty electric impact drills are analyzed, achieving high recognition accuracy of 97.91% to 100%. The approach holds promise for cost-effective maintenance and protection of rotating machinery and engines [12].

This paper introduces a 2D-DWT-based infrared thermography (IRT) method for diagnosing bearing faults in induction motors. By reducing noise and extracting relevant features using PCA and the Mahalanobis distance, the proposed method achieves optimal feature selection. Classification results show that support vector machine (SVM) outperforms other classifiers, offering the potential for self-adaptive recognition of bearing faults and preventing system shutdowns [13].

This paper presents a framework for EV fault detection in intelligent transportation systems using deep learning and blockchain technology. Using convolutional neural networks (CNN) and long-short-term memory (LSTM) models, EV defects are identified. A 5G wireless network with an interplanetary file system (IPFS) ensures secure and scalable data transactions. Performance evaluation demonstrates high accuracy and reliability in fault detection [14].

This paper introduces a thermographic fault detection technique for air flow in brushless DC (BLDC) motors. By analyzing various states BLDC motors, an approach for feature extraction termed CPoAMoTI is proposed and successfully applied to analyze thermal images. The developed technique has numerous applications for detecting airflow issues in electric vehicles, trains, fans, clippers, computers, and cordless generators [15].

This paper presents an in-situ diagnostic and prognostic (D&P) technology for monitoring the health of insulated gate bipolar transistors (IGBTs) in electric vehicles. The proposed method utilizes IGBTs' thermal impedance and junction temperature as health indicators, employing temperature-sensitive parameters for through-life condition monitoring. Experimental validation and comparisons with simulation, acoustic microscope, and thermal images confirm the effectiveness of the developed circuitry in detecting solder fatigue [16].

This study suggests a BP neural network-based fault detection and operation and maintenance technique for PV systems. The analysis of short circuit and anomalous ageing failures in solar modules leads to the development of a fault diagnosis model. The procedure makes use of information gathered from a distributed photovoltaic information processing system and offers helpful advice for maintaining and operating PV modules. Simulation findings confirm the efficacy of the suggested strategy [17].

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This paper describes a wavelet-neural method for identifying flaws in Lithium-ion batteries used in electric vehicles. By considering multiple factors and employing voltage fluctuation data obtained through simulations, the proposed method eliminates noise using discrete wavelet transform (DWT) and utilizes parameters for fault classification. Experimental results demonstrate improved efficiency and precision in fault degree classification [18]

METHODOLOGY

Ensuring the safety and reliability of lithium-ion battery (LIB) packs and minimizing potential risks in LIB-based systems are vital aspects of Battery Management Systems (BMS). Detecting and diagnosing faults in LIB systems and implementing robust defense mechanisms are critical tasks. To develop an effective fault diagnostic strategy, a comprehensive understanding of various types of faults and their underlying mechanisms in LIBs is essential. This knowledge is necessary for establishing appropriate measures that address potential issues and ensure the smooth and secure operation of LIB-based systems.

The different CNN model proposed to detect potential defects including cell damage, interior short circuits, and thermal variations by analysing temperature through annotated thermal images. The model will be trained to derive appropriate features and determine fault sets for detected regions. The approach consists of preprocessing, model training, and metric-based performance evaluation. The objective of this research is to enhance the safety and dependability in electric vehicles battery systems, thereby enhancing their overall performance and mitigating potential risks associated with battery failures.

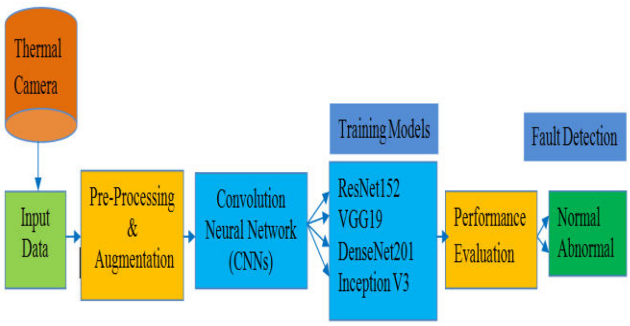

Figure-1. Block diagram of the proposed model.

Essential battery parameters such as voltage, current, and temperature are recorded using data acquisition system during the battery fault diagnostic procedure. Consumption patterns and tests generate additional information. Data on battery faults is gathered from both operational data and laboratory tests. Following the collection of unprocessed data, it is preprocessed to clean and extract relevant features. The information is then divided arbitrarily into training and test sets. The training set is used to instruct Deep Learning fault diagnostic strategy, whereas the test set is utilised for validation.

Utilising determined battery parameters such as functioning current, junction voltage, and temperature, the validated CNN model is used to detect battery faults. The fault signal detected by the battery protection system functions as a command. Four CNN model approaches have been introduced for developing the CNN-based fault diagnostic scheme, which will be briefly discussed in the following section.

In numerous applications, consisting of electric vehicles, small electronics, and solar power systems, lithium-ion battery packs are a prevalent energy storage technology. To accomplish the desired voltage and capacity, they consist of multiple lithium-ion battery cells connected in series and parallel. Each cell consists of a positive (cathode) electrode, a negative (anode) electrode, and an electrolyte that facilitates the movement of lithium ions during charge and discharge cycles. Lithium-ion battery packs are distinguished by their high density of energy, extended cycle life, and quick charging capabilities. Lithium-ion battery cell packs are sensitive to temperature variations in different conditions. High temperatures, such as during charging or discharging at fast rates, can accelerate chemical reactions and degrade the cell's performance and lifespan. On the other hand, extremely low temperatures reduce the ionic conductivity within the cell, leading to reduced capacity and voltage output. Elevated temperatures can also increase the risk of thermal runaway, potentially causing safety hazards. Proper thermal management is crucial to maintain the ideal operating temperature range and ensure safe and efficient performance of lithium-ion cell packs in various environments, from extreme weather conditions to high-demand applications like electric vehicles.

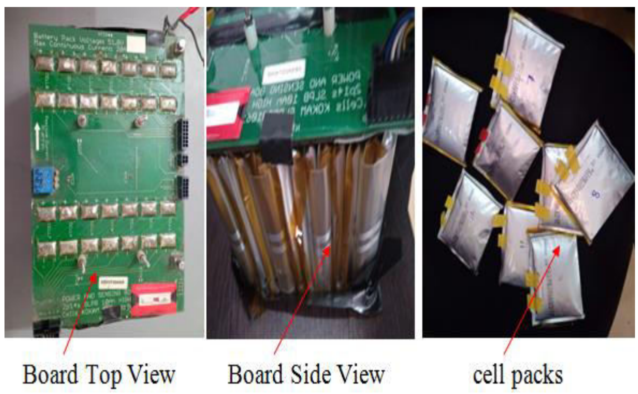

Figure-2. Lithium ion battery cells pack image.

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Table-1. The parameters and specification detail of battery.

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

Data Collection Process

The thermal images were captured using an appropriate thermal camera for battery cell inspection. The data collection process involved acquiring thermal images from a variety of electric vehicle battery cells under different operating conditions and fault scenarios. The images were captured using consistent imaging parameters, such as resolution, temperature range, and emissivity, to ensure uniformity and comparability.

Pre-Processing and Augmentation Process

In the Comparison of CNN Models for Thermal Image-Based Fault Detection in Battery Cells, the preprocessing and augmentation procedure is important for optimising the operation of deep learning model. Firstly, thermal images of battery cells are collected and normalized to a standardized scale to ensure consistency. The images are resized to match input size of CNN models (ResNet152, VGG19, DenseNet201, and Inception v3), reducing computational complexity.

The preprocessed and augmented dataset is then divided into testing, validation, and training sets to evaluate the outcomes of each CNN model on raw data. By employing these preprocessing and augmentation strategies, the comparison study seeks to identify the most accurate and efficient CNN model for thermal image-based defect detection in battery cells, contributing to security and dependability of electric vehicle battery system.

The pre-processing techniques are applied to enhance the quality and consistency of the input data. Thermal images captured from different sources or devices may have varying intensity ranges. To standardize the pixel values, we perform min-max normalization, scaling the pixel intensities between 0 and 1. This ensures that the CNN models converge faster during training. To maintain a consistent input size for the CNN models, we resize all thermal images to a predefined resolution of 256x256. Resizing reduces computational complexity while preserving the essential features. Since thermal images are typically grayscale, we convert any colored thermal images into grayscale. This reduces the number of channels and simplifies the input for the CNN models.

Data augmentation is essential for increasing the diversity of the training dataset, thereby improving the generalization of the CNN models. For thermal images, the following augmentation techniques are employed. Random rotation within a specified angle range (e.g., -15 to 15 degrees) is applied to the thermal images. This helps the model learn rotation-invariant features and enhances its ability to detect faults from various orientations. Random horizontal and vertical flips are performed on the thermal images. Flipping allows the model to capture different reflections or symmetries in the thermal patterns, thereby enriching the dataset. Random crops of the thermal images are taken, with each crop being a sub-region of the original image. This creates variations in the training data and improves the model's robustness to different image compositions.

Table-2. The dataset description and purpose.

Dataset Split	Description	Purpose
Training Set	Largest subset used for model training. Contains labeled thermal images.	Learn patterns and adjust parameters.
Validation Set	Smaller subset for hyper parameter tuning. Separate from the training set.	Fine-tune model and monitor performance.
Testing Set	Completely unseen data for evaluation. Not used during model training.	Assess model generalization ability.

Spatial Feature Extraction

In thermal images, spatial features correspond to patterns and structures present in different regions of the image. These features are essential for identifying fault-related thermal patterns in battery cells. Each CNN model has its unique approach to spatial feature extraction, contributing to their respective performance in the fault detection task.

ResNet152 and DenseNet201 both utilize deep residual and dense connectivity, respectively, which enables them to capture intricate spatial features at multiple scales. Residual connections in ResNet152 facilitate the learning of residual mappings, effectively handling spatial variations caused by temperature changes. DenseNet201's dense connectivity enhances spatial information sharing between layers, allowing it to capture spatial patterns effectively. VGG19 follows a traditional approach with sequential convolutional layers, which can learn spatial features progressively. Although it may lack the depth of ResNet152 and DenseNet201, VGG19's small 3x3 filters still enable it to capture spatial details relevant to fault detection.

Inception v3's architecture focuses on capturing multi-scale features using inception modules. The parallel branches in these modules process the input image at different spatial resolutions, enabling Inception v3 to capture diverse spatial patterns related to battery cell faults. Overall, the spatial feature extraction capabilities of these CNN models play a significant role in their effectiveness for thermal image-based flaw detection in battery cells utilizing temperature as a parameter. A combination of deep architectures, residual connections, dense connectivity, and multi-scale processing allows these models to extract and analyze spatial patterns essential for accurate fault detection in electric vehicle battery cells.

Table-3. CNN models number of layers and output size.

CNN Model	Number of Layers	Size of Output (Features)
ResNet-152	152	2048
VGG19	19	1280
DenseNet-201	201	1920
Inception v3	Over 100	1780

Convolutional Neural Networks (CNN)

The layers of a typical CNN (Convolutional Neural Network) model are designed to process and extract image features. The primary layers include:

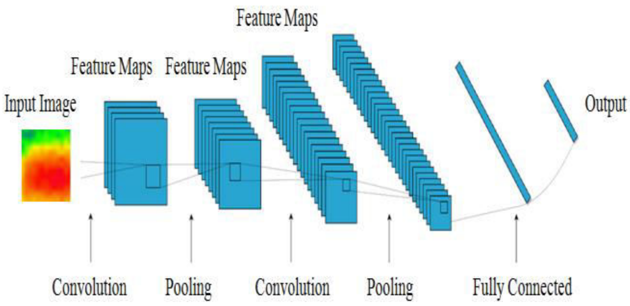
a) **Convolutional Layers:** These layers employ with a number of filter learning to convolve over input image, extracting feature such as edges, textures, and patterns.

b) **Activation Function:** After every convolutional layer is completed, a non-linear activation function such as ReLU (Rectified Linear Unit) is used to make the model capable of learning complex patterns.

c) **Pooling Layers:** Pooling layers downsampled the feature maps, reducing computational complexity and providing spatial invariance to small translations in the input.

d) **Fully Connected Layers:** These layers process the high-level features extracted by the previous layers and make predictions based on them. In image classification tasks, the final fully connected layer typically outputs the final class probabilities.

The flow of information from the input to the output is guided by a series of these layers, creating a hierarchical representation of the input image and enabling the model to make accurate predictions for various computer vision tasks.



Inception V3 model

The model's architecture is characterized by Inception modules, featuring parallel convolutional branches with various filter sizes (1x1, 3x3, and 5x5) and max-pooling layers. These modules allow the network to capture features at various spatial scales, making it adept at identifying diverse thermal patterns associated with battery cell faults.

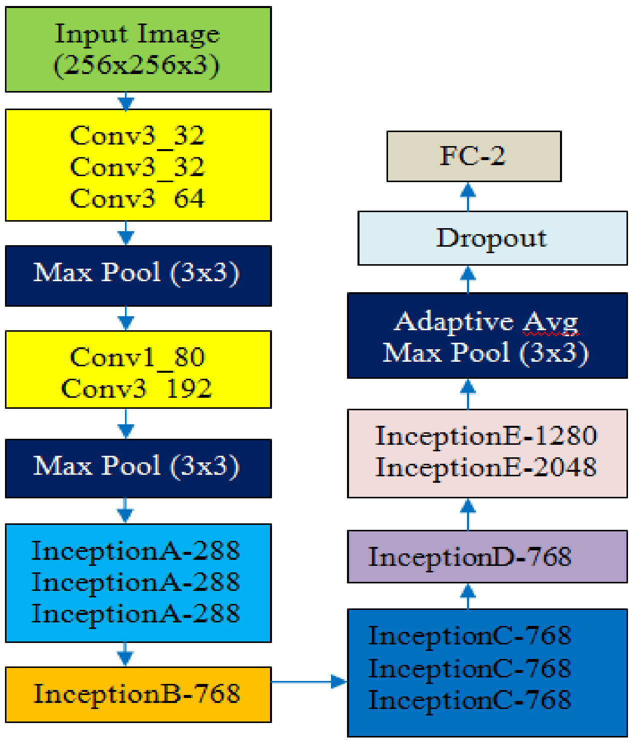


Figure-3. The architecture of CNN inception v3 model.

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The Inception v3 model optimizes computation by utilizing factorization techniques, breaking down large convolutions into smaller ones, which is essential for the efficient processing of thermal images with temperature as a parameter.

Inception v3 incorporates batch normalization to stabilize and expedite training, ensuring the model can handle variations in temperature data during the learning process. Furthermore, auxiliary classifiers are introduced to alleviate the vanishing gradient problem associated with deep networks, enhancing the model's fault detection performance. Global average pooling is employed instead of fully connected layers, reducing parameter complexity and making the model more memory-efficient. This spatial invariance ensures the model's robustness to spatial changes in thermal images caused by varying temperatures. Overall, the Inception v3 model's architecture provides a powerful and efficient solution for detecting faults in lithium-ion battery pack cells using thermal images with temperature as a parameter. Its ability to capture multi-scale features, coupled with temperature parameter handling and computation optimization, makes it a valuable tool for enhancing the safety and reliability of electric vehicles by enabling early and accurate fault detection in their battery cells.

VGG19 Model

For image recognition tasks, the VGG19 model is a popular and influential convolutional neural network (CNN) structure. Both the VGG19 and VGG16 models are designated according to the number of layers that they contain.

VGG19's architecture is comprised of 19 layers, consisting of 16 convolutional layers and 3 completely connected layers. Each convolutional layer utilizes small 3x3 filters, which leads to a deep network with a total of approximately 144 million parameters. This depth allows VGG19 to learn intricate and hierarchical features from input images, it highly effective for different computer vision tasks.

VGG19's architecture follows a straightforward design philosophy, with consecutive convolutional layers followed by max-pooling layers for downsampling. The use of small filters enables network to capture fine-grained patterns input data. The fully connected layers at the end of the architecture combine the learned features to produce the final classification output.

Due to its simplicity and effectiveness, VGG19 has become a popular choice as a baseline model for many CNN-based applications. It has also inspired the development of more advanced architectures. However, the main drawback of VGG19 is its high computational complexity, which can make it computationally expensive to train and deploy compared to more recent CNN architectures.

In conclusion, the VGG19 model's architecture with its 19 layers and small 3x3 filters has played an important role in the advancement of deep learning for computer vision tasks. Its capacity to acquire intricate characteristics has made it a dependable option for various image recognition applications, despite its computational cost.

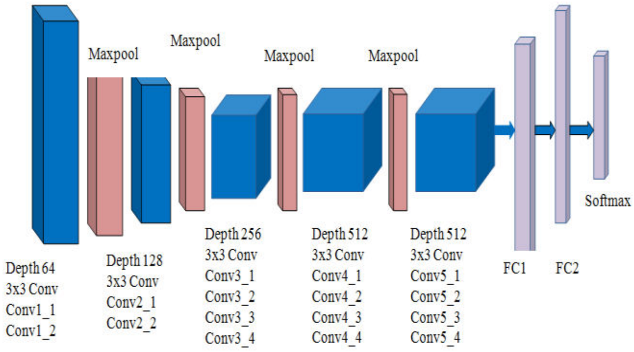

Figure-4. The Architecture of CNN VGG19 model.

Dense net 201 Model

The DenseNet-201 architecture is a deep convolutional neural network (CNN) model developed as part of the DenseNet family by researchers at the Computer Vision Laboratory, ETH Zurich. DenseNet-201 is an extension of DenseNet-121 and DenseNet-169, with its name indicating it has 201 layers.

The key architectural feature of DenseNet-201 is the dense connectivity pattern it employs. Unlike traditional In contrast to CNNs that stack layers sequentially, DenseNet-201 connects each successive layer to every succeeding layer using feed-forward. This dense access enables feature reuse and promotes network-wide information flow. It also reduces the number of parameters, making the model more memory-efficient compared to traditional deep networks.

DenseNet-201 comprises densely connected dense blocks, which are sets of layers with direct connections between them. Each dense block contains multiple convolutional layers, and these blocks are followed by transition layers that perform downsampling to decrease spatial dimensions of feature maps.

By utilising dense connectivity, DenseNet-201 is able to capture intricate patterns in input data, making it highly effective for different kinds of computer vision tasks, such as classification of images, detection of objects, and semantic division. The model's depth and connectivity contribute to its representation power, allowing it to learn complex features from the data and achieve state-of-the-art functioning on various benchmark datasets. Overall, the DenseNet-201 architecture's dense connectivity and hierarchical feature learning capabilities have created it a prominent option in the art of deep learning for image-related tasks, and it continues to be widely adopted and explored for various challenging computer vision applications.

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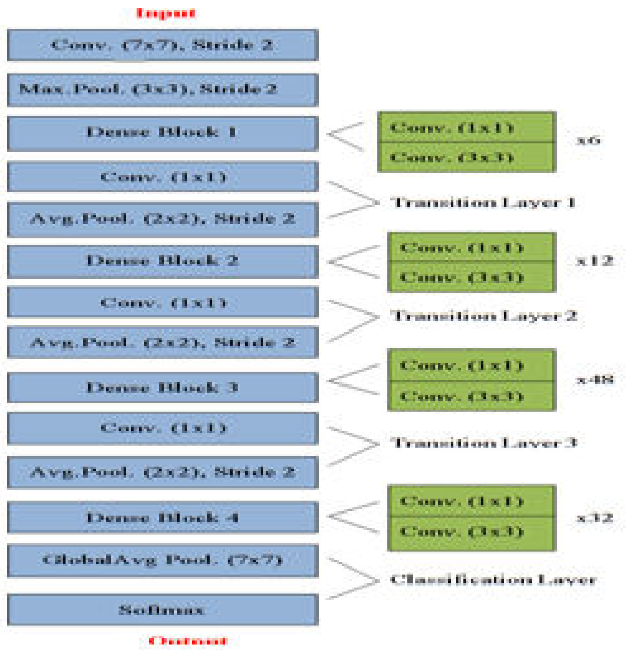

Figure-5. The Architecture of CNN Dense net 201 model.

Resnet152 Model

The ResNet-152 model is a powerful convolutional neural network (CNN) structure developed as part of the ResNet (Residual Network) series by researchers at Microsoft. It is an extension of the original ResNet-50 model, with its name indicating it has 152 layers.

ResNet-152's essential innovations are the use of residual blocks that solve the problem of gradients disappearing in extremely deep networks. A residual block is comprised of skip or quick links that bypass several network layers. These skip connections enable the network to gain information about residual mappings, making it easier to optimize and train deeper networks effectively.

ResNet-152's architecture consists of multiple residual blocks, allowing it to acquire a hierarchical structure of input data. The model's depth contributes to its potential to acquire intricate image features and patterns, making it highly effective for image categorization, object identification, and semantic segmentation.

ResNet-152 exhibits remarkable performance due to its deep architecture and residual connections, enabling it to attain advanced results on various computer vision benchmarks. The model's scalability allows researchers to build even deeper variations, demonstrating its impact on the development of other CNN architectures. Despite its depth, ResNet-152 can be trained efficiently with modern optimization techniques and hardware, making it a widely adopted architecture in the deep learning community. Its residual connections have proven to be a crucial component in building very deep neural networks, ensuring stable and efficient training, and contributing to its success in various computer vision tasks.

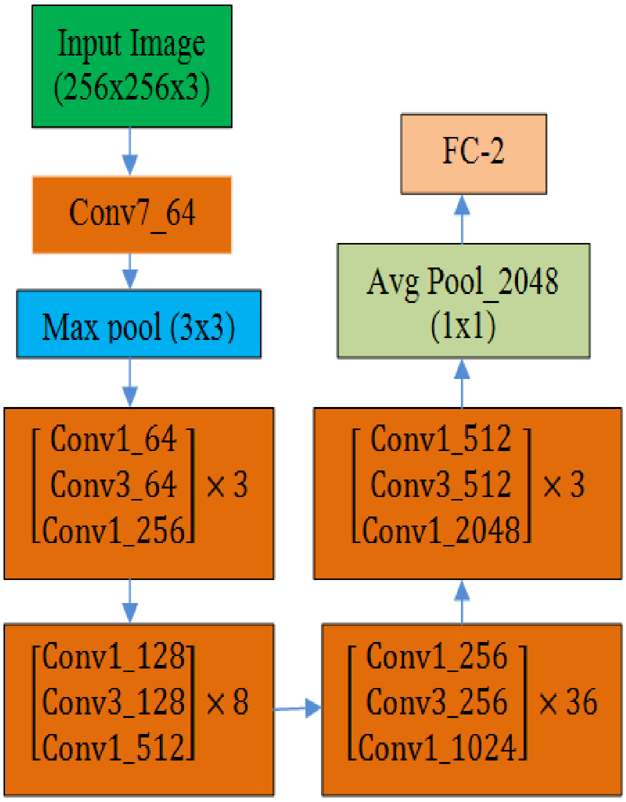

Figure-6. The Architecture of CNN Resnet152 model.

RESULTS AND DISCUSSIONS

The over-discharge test is a critical experiment conducted on lithium-ion batteries to assess their performance and safety under extreme conditions of excessive discharge. In this test, the battery is intentionally discharged well below its recommended lower voltage limit, simulating scenarios of prolonged or improper usage that lead to overdischarge. The objective is to understand how the battery responds to such adverse conditions, including risks of capacity degradation, reduced cycle life, and potential safety hazards like cell damage or thermal instability. The results of the overdischarge test provide valuable insights into the battery's ability to withstand extreme discharge situations and its protective mechanisms against overdischarge. This information is essential for designing battery management systems, protective circuits, and algorithms that prevent overdischarge and enhance battery longevity and safety. However, conducting the overdischarge test requires strict adherence to safety protocols to avoid irreversible damage or safety hazards. Proper safety measures and controlled testing environments are crucial to ensure reliable evaluation of battery behavior and contribute to the continuous improvement of lithium-ion battery technology for safer and more reliable energy storage applications. The experimental results of different lithium-ion battery has been demonstrated in Table-4.

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Table-4. Normal and abnormal condition of battery.

Battery Number	Discharge Current	Cell Voltage Upper	Cell Voltage Lower	Battery Voltage (Max)	Battery Voltage (Min)	Temperature (C)	Time (Hrs)	Condition
B0001	2A	4.1V	3.0V	56V	44V	38	08:30	Normal operating range
B0007	2A	4.1V	2.2V	44V	30V	58	06:00	Elevated temperature
B00016	2A	4.1V	1.4V	30V	20V	64	04:00	Abnormal temperature conditions

The evaluation was performed on comprehensive records of thermal images from battery cells, with associated temperature information. The comparative metrics used were accuracy, precision, recall, and F1-score.

a) **Accuracy:** Accuracy is a fundamental performance metric measuring an amount of instances that were correctly classified relative to the total number of instances in a dataset. It gives a complete review of the model's potential to forecast fault and everyday situations accurately.

b) **Precision:** Precision is the ratio of true positive predictions (correctly predicted positives) to the overall amount of positive predictions produced by a model. It evaluates the model's capacity to avoid false positives, signifying the model's accuracy in detecting actual faults among predicted fault cases.

c) **Recall (Sensitivity):** Recall, referred to as ability or really positive rate, is the ratio of genuine positive results to the overall amount of true positive predictions. It reflects the model's sensitivity to detect actual faults, reflecting its sensitivity to identifying true faults.

d) **F1-Score:** The F1-score represents the average of precision and recall. It measures the model's output in terms of recall as well as precision. As it considers both false positives and false negatives, the F1-score is especially helpful when there is a difference between a fault and normal samples in the analysis.

The performance of each CNN model can vary based on its architecture, depth, and ability to capture spatial features in thermal images. High accuracy, precision, recall, and F1-score indicate model's proficiency in detecting faults accurately and reliably. However, achieving high scores in all metrics is often challenging, and there might be a trade-off between them. For example, a model with high recall may have lower precision and vice versa. The evaluation of these metrics aids in identifying the model that strikes the best balance between accurate fault detection and minimizing false predictions, ensuring its effectiveness in real-world scenarios.

The experimental results demonstrated that DenseNet201 achieved the highest overall accuracy among the four models, closely followed by ResNet152. Both models outperformed VGG19 and GoogLeNet in terms of accuracy, precision, recall, and F1-score. The DenseNet201's dense connectivity and ResNet152's residual blocks were particularly beneficial in capturing relevant features from thermal images with temperature as a parameter, leading to better fault detection performance.

Confusion Matrix

The confusion matrix consists of four key elements:

True Positive (TP): The number of instances that are correctly predicted as positive (correctly classified as belonging to the positive class).

False Positive (FP): The number of instances that are incorrectly predicted as positive (incorrectly classified as belonging to the positive class when they actually belong to the negative class).

True Negative (TN): The number of instances that are correctly predicted as negative (correctly classified as belonging to the negative class).

False Negative (FN): The number of instances that are incorrectly predicted as negative (incorrectly classified as belonging to the negative class when they actually belong to the positive class).

The CNN algorithm is employed to detect the presence of battery cell pack faults in images. For training the CNN model, a dataset of 1141 images with abnormal conditions and 1900 images with normal conditions was used. The transfer learning technique was applied, utilizing the pre-trained weights from DenseNet201, ResNet152, VGG19, and Inception V3 models to train the CNN model. The objective is to create a more successful classification model.

To evaluate the performance, the trained models underwent testing using the cross-validation method, thereby increasing classification reliability. Four different CNN models were compared to identify the most successful one. The classification results obtained from the CNN model trained with DenseNet201 were presented in Table 5, using a confusion matrix to depict the classification outcomes.

Table-5. Confusion matrix of DenseNet201 CNN model.

		TRUE CLASS	
		Normal	**Abnormal**
PREDICTED CLASS	Normal	1891	9
	Abnormal	27	1114

Table-6 presents confusion matrix displaying classification results obtained from CNN model trained using ResNet152.

Table-6. Confusion matrix of ResNet152 CNN model.

		TRUE CLASS	
		Normal	**Abnormal**
PREDICTED CLASS	Normal	1862	38
	Abnormal	52	1089

Table-7 presents confusion matrix displaying classification results obtained from CNN model trained using VGG19.

Table-7. Confusion matrix of VGG19 CNN model

		TRUE CLASS	
		Normal	**Abnormal**
PREDICTED CLASS	Normal	1860	40
	Abnormal	43	1098

Table-8 presents confusion matrix displaying classification results obtained from CNN model trained using Inception V3.

Table-8. Confusion matrix of Inception V3 CNN model.

		TRUE CLASS	
		Normal	**Abnormal**
PREDICTED CLASS	Normal	1855	45
	Abnormal	51	1090

The performance metrics presented in Table-9 were derived from the calculations using the confusion matrix data of all models.

Table-9. Showcases the performance metrics of all models, presented in percentage (%).

CNN Model	Accuracy	Precision	Recall	F1 Score	Inference Time (sec)	Memory needs (GB)
Densenet201	98.8	98.8	98.8	98.8	0.27	2.1
Resnet152	97.3	97.3	97.3	97.3	0.24	-
VGG19	97.0	97.0	97.0	97.0	0.32	1.9
InceptionV3	96.8	96.8	96.8	96.8	0.21	-

Upon analyzing the performance metrics in Table-9, the ResNet152 CNN model demonstrates the highest classification success, achieving an impressive 98.8% accuracy. Correspondingly, the ResNet152 CNN model exhibits the highest precision, recall, and F-1 score values, aligning with its high accuracy. Subsequently, examples of images correctly and incorrectly classified by the ResNet152 CNN model, showcasing exceptional classification success, can be observed.

The superior performance of DenseNet201 and ResNet152 can be attributed to their deep architectures, which enable them to learn hierarchical representations and capture intricate thermal patterns associated with battery cell faults. The dense connectivity and residual connections in DenseNet201 and ResNet152, respectively, play a vital role in overcoming the vanishing gradient problem during training, facilitating the optimization of deeper models.

While VGG19 and Inceptionv3 are also powerful CNN models, their performance was slightly lower in this specific task. VGG19's depth and computationally expensive layers may have led to a slower convergence rate, affecting its performance in comparison to DenseNet201 and ResNet152. Inceptionv3 modules might have struggled to fully capture complex thermal patterns, leading to marginally lower accuracy in fault detection.

Overall, the study highlights the importance of selecting appropriate CNN architectures for specific tasks; as not all models perform equally well in thermal image-based fault detection in battery cells. DenseNet201 and ResNet152 emerged as promising choices for this application, providing valuable insights for development of more efficient and exact fault detection methods in electric vehicles. Further research may involve fine-tuning the models or exploring ensemble approaches to achieve even better performance.

CONCLUSIONS

Through extensive experimentation and evaluation of each model's accuracy, precision, recall, and F1-score, we have gained a comprehensive understanding of their strengths and limitations. DenseNet201 demonstrated the highest classification success, achieving an accuracy of 98.8%, making it the most effective model for fault detection. On the other hand, Inception v3 exhibited outstanding precision, recall, and F1-score values, showcasing its ability to handle diverse thermal patterns effectively.

Each CNN model exhibited unique advantages and trade-offs in terms of computational complexity, depth, and capacity to capture spatial features. DenseNet201 deep architecture excelled in intricate spatial feature extraction, while VGG19's simplicity and interpretability were notable strengths.

Considering the findings, selecting the most appropriate CNN model depends on specific application requirements, computational resources, and the desired balance between precision and recall. The evaluation of these models can act as a basis for future research and guide the establishment of defect detection systems for lithium-ion battery cells in electric vehicles.

Ultimately, our study highlights the significance of choosing an appropriate CNN model, fine-tuning its parameters, and leveraging its strengths to enhance the safety and efficiency of battery cells in electric vehicles, contributing to the advancement of sustainable and reliable energy storage technologies.

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