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Original Article

Insight on the Application of Deep Learning-Based Thermal Image Processing Methods in Electrical System Anomaly Detection and their Comparative Analysis

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Abstract *- Ensuring the reliability and safety of electrical systems necessitates constant inspections. However, manual inspections pose risks, are time-consuming, and are impractical for real-time monitoring. This paper presents a novel, non-invasive, and efficient approach for automated electrical system anomaly detection using deep learning and thermal image processing. We have proposed a Convolutional Neural Network (CNN) based framework utilizing the well-established GoogLeNet and other deep learning-based architecture to classify thermal images of electrical systems as "normal" or "abnormal." This framework achieves a high accuracy of 99% in anomaly detection, surpassing traditional methods and paving the way for real-time monitoring and early fault identification.*

Keywords *- Anomaly detection, CNN, Deep Learning, Electrical system inspection, Predictive maintenance, Thermal imaging.*

1. Introduction: Prologue to IRT Imaging

Ensuring the uninterrupted operation and safety of electrical systems is important. To achieve this, regular inspections are an absolute necessity. However, the traditional method of relying solely on manual inspections comes with significant drawbacks. Firstly, these inspections can be inherently risky to the personnel conducting them, as electrical systems can pose hazards of shock, arc flash, and other dangers [1]. Secondly, manual inspections are inherently time-consuming, requiring technicians to visit and meticulously examine each component within a system physically. This can lead to delays in identifying potential problems and hinder overall maintenance efficiency [2].

Finally, the very nature of manual inspections makes them impractical for achieving real-time monitoring of electrical systems. Continuous monitoring is crucial for catching problems early on and preventing catastrophic failures, but traditional methods simply cannot provide this level of vigilance. These limitations of manual inspections highlight the need for innovative and more efficient solutions addressed in this paper.

1.1. Emergence of Manual IRT Image Analysis Techniques

Advancements in technology offer a promising solution to the limitations of manual visual inspections. Infrared thermal (IRT) imaging has emerged as a powerful, non-invasive alternative for inspecting electrical systems. Unlike manual inspections that require physical contact, IRT uses specialized cameras to capture the temperature distribution of electrical components [3]. This thermal fingerprint can reveal hidden problems invisible to the naked eye. Hotspots, often indicative of loose connections, overloaded circuits, or failing components, become readily apparent in IRT images [4]. By detecting these thermal anomalies early on, IRT imaging offers a proactive approach to preventing electrical fires and ensuring system uptime.

Figure 1 illustrates the visual depiction of the electrical system's bus bar, while Figure 2 presents its corresponding thermal image. Notably, Figure 2 reveals the presence of conspicuous hotspots, suggestive of irregularities within the system. These anomalies, commonly attributed to loosened connections, demand prompt investigation and remedial actions to uphold operational efficiency and safety standards.

Fig. 1 Visual image

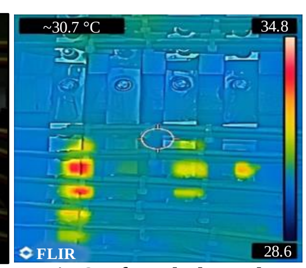

Fig. 2 Infrared Thermal (IRT) image

1.2. Limitations in Traditional Manual IRT Image Analysis Techniques

In Traditional manual IRT Techniques, engineers painstakingly identified specific characteristics like statistical properties or texture patterns that could potentially indicate anomalies. Thus, there remained a crucial hurdle in effectively analyzing the wealth of data captured in IRT images.

While skilled inspectors utilized their experience to interpret thermal patterns, this approach was inherently subjective and prone to errors. Factors like fatigue or limited experience can lead to missed anomalies or misinterpretations, potentially delaying critical maintenance actions [5]. This underscores the need for a more objective and automated approach to analyzing IRT data, paving the way for a new era of electrical systems in inspection and maintenance.

1.3. Emergence of Automation in IRT Image Analysis Technique

There aroused a critical need for an automated and reliable technique that can analyze IRT images and accurately detect abnormalities within electrical systems.

1.4. Initial Automation-Based Method Used in IRT Image Analysis Technique

The traditional automation method used for the analysis of IRT images was the method of detecting hotspots directly. Hotspot extraction from HSV images involved converting the thermal image to the HSV format and then concentrating on the hue matrix. Each pixel value in the hue matrix represents a color value, enabling engineers to segment hotspots from the image based on color indexing. At the same time, this method served as a conventional means of feature extraction.

Another technique utilized for extracting hotspots from thermal images involves leveraging the Hue Concentration values in terms of the HSV color model. In the HSV modeling, colors are represented by three components: Hue, Saturation, & and brightness value. Hue maps to the type of color (e.g., green, yellow), saturation indicates color gravity, and value determines the brightness.

By utilizing the HSV model, particularly the hue component, engineers can focus specifically on color information without being affected by variations in brightness or saturation. This approach is beneficial for various image processing tasks, including color-based object detection, image segmentation, and analysis of color patterns within an image.

Figure 3 and Figure 4 depict the RGB coordinates s-model and the HSV coordinates s-model, respectively, showcasing the transition from one color space to another for image analysis purposes. The RGB or HSV values pixel by pixel clearly depict the hotspot areas.

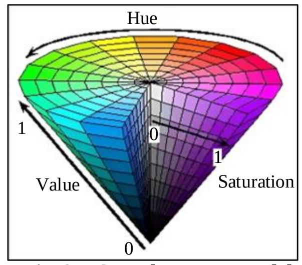

Fig. 3 RGB color space model

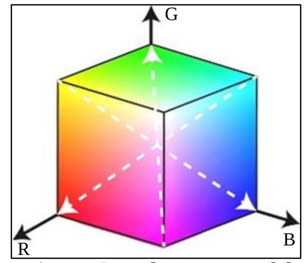

Fig. 4 HSV color space model

1.5. Limitations in the Initial Automation Based Method Used in the IRT Image Analysis Technique

HSV-related approaches are time-consuming, labor-intensive, and heavily reliant on the expertise of the engineers involved. Hand-crafted feature extraction was involved. Moreover, these methods often struggled to capture the intricate and nuanced relationships between thermal patterns and underlying electrical issues, leading to limitations in accuracy and effectiveness.

1.6. Novelty Proposed in this Research Paper

Considering all these gaps and shortfalls of both traditionally used manual and automated methods in IRT image analysis. It necessitates a solution that goes beyond the limitations of both-a solution in which machine intervention is a must. Thus A novel deep learning-CNN method has been proposed in this paper for overcoming these challenges and implementing the same for automatic anomaly detection in IRT images.

1st section of the article justifies the requirement of IRT image analysis techniques and its prologue of image processing so far. 2nd section elaborates on the Emergence of the proposed deep learning CNN method and its concepts. 3rd part of this paper reflects the research methodology implemented by us. 4th phase of the paper depicts the experimental results, and finally, 5th section concludes the proposal, leaving an insight for the researcher to work upon. It promises to be more objective and consistent than human analysis, reducing the risk of errors.

Additionally, it has the potential to be significantly faster and more scalable, enabling real-time monitoring of electrical systems. By automating the analysis process using machine learning techniques, especially with this CNN-based framework, offers several advantages. Ultimately, this research aims to pave the way for improved safety, efficiency, and predictive maintenance practices in the critical domain of electrical systems by incorporating strategies to mitigate the influence of environmental factors, enhancing the robustness of this approach. This research holds the potential to improve the effectiveness remarkably and faith-fullness of IRT-based anomaly detection in electrical systems, paving the way for improved safety, efficiency, and predictive maintenance practices.

2. Emergence of CNN

Contemporary advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have opened doors for more robust, automated and less time-consuming solutions.

Several studies have explored this potential: In the field of deep learning for IRT image analysis, relevant research is already underway. For example, Kim et al. (2021) represented a promising strategy for sustainable fault detection in electrical facilities [6]. Their method leverages object detection algorithms specifically trained on a large collection of IRT images. This training empowers the algorithms to identify specific objects within the images, potentially corresponding to electrical components. By analyzing the presence, absence, or condition of these objects, their approach aims to detect faults within the electrical system. The success of Kim et al.'s work exemplifies the potential of deep learning for automated anomaly detection in IRT images.

Building on the promise of Kim et al.'s (2021) research, Ukiwe et al. (2023) conducted a substantial recapitulations of Infrared waves dependent Thermography imaging, i.e. IRT images based electrical equipment supervisions [7]. Their review serves to underline the growing importance of IRT as a valuable tool and underscores the emerging trend of deep learning-based approaches within this field. This surge in deep learning applications signifies a growing recognition of its potential to revolutionize the way to analyze IRT data and automate anomaly detection in electrical systems.

While Kim et al. (2021) explored object detection and Ukiwe et al. (2023) highlighted the rise of deep learning, it is important to acknowledge earlier efforts that paved the way for these advancements. Chellamuthu and Sekaran (2019) employed a machine-learning approach for fault diagnosis in electrical systems using IRT images [8]. Their work involved a two-step process: first, manually extracting relevant features from the images, such as temperature variations or spatial patterns. These features were then subjected to a Support Vector based Machine (SVM) algorithm for categorization or classification, allowing them to differentiate between normal and abnormal conditions. This research, while relying on traditional machine learning techniques, demonstrates the potential of automated approaches for analyzing IRT data and lays the groundwork for the more sophisticated deep learning methods explored in recent years.

Continuing the trend towards automation, Yuan et al. (2019) took a significant step by introducing Convolutional Neural Networks (CNNs) for state detection in electrical equipment using IRT images [9]. Unlike Chellamuthu and Sekaran's (2019) method that relied on manual feature extraction, CNNs possess the remarkable capability to learn these features in automated mode from the data itself. In their study, Yuan et al. achieved high accuracy on a limited dataset, showcasing the power of CNNs for anomaly detection in IRT images. However, their work also emphasizes the need for further exploration, particularly in expanding the dataset size to enhance the generalizability and robustness of the CNN model. This paves the way for this research, which builds upon these advancements by proposing a CNN-based framework for anomaly detection in IRT images and addressing the limitations of dataset size.

Despite the promising advancements in IRT-based anomaly detection, several challenges remain. As highlighted by studies like Ukiwe et al. (2023) [7] and Chellamuthu and Sekaran (2019) [8], limitations exist in both traditional machine learning and deep learning approaches. All these approaches leverage the immense capability of CNNs to learn complex patterns from large datasets of thermal images.

2.1. Challenges Posed by Deep Learning-Based CNN

2.1.1. Feature Extraction Challenges

Extracting meaningful features from Infrared Thermography (IRT) images poses a significant challenge due to various inherent characteristics. One such challenge arises from the tendency of temperature data to cluster around the center of the images, which can obscure subtle variations and anomalies present in the peripheral areas. Additionally, IRT images often exhibit low contrast, further complicating the identification and extraction of relevant features. These complexities compound the difficulties in performing tasks such as image segmentation and feature engineering, which are crucial for anomaly detection.

Moreover, traditional machine learning methods face limitations in handling these challenges, as they often require large training datasets and may struggle with generalizing to unseen data. Furthermore, these methods heavily rely on hand-crafted features, which may not encompass the full spectrum of anomalies present in the data, thus diminishing their effectiveness. Figure 5 illustrates this contrast by showcasing an original thermal image alongside a contrast-enhanced thermal image, highlighting the challenges posed by low contrast in feature extraction and analysis processes.

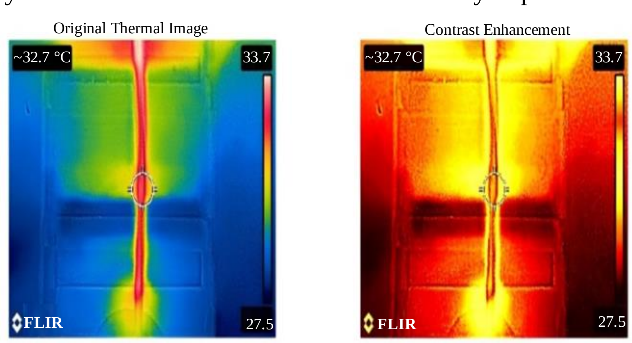

Fig. 5 Original thermal image vs Contrast thermal image

2.1.2. Environmental Sensitivity

Infrared Thermography (IRT) measurements, while valuable for anomaly detection, are vulnerable to a range of environmental factors that can distort the data. Factors such as ambient temperature fluctuations, humidity levels, wind speed, and solar radiation exposure all contribute to introducing noise and inconsistencies into the thermal images captured. These environmental variables can obscure genuine anomalies within the data and affect the accuracy and reliability of anomaly detection algorithms. Researchers face a continual challenge in mitigating the influence of these external factors to develop robust IRT-based anomaly detection systems capable of providing accurate assessments.

Figure 6 provides a visual representation of this challenge, depicting a comparison between a noisy thermal image and a filtered thermal image, highlighting the impact of noise reduction techniques in enhancing the clarity and reliability of the data for more effective anomaly detection. These limitations underscore the need for innovative solutions that can overcome the feature extraction challenges and environmental sensitivity issues inherent to IRT-based anomaly detection in electrical systems.

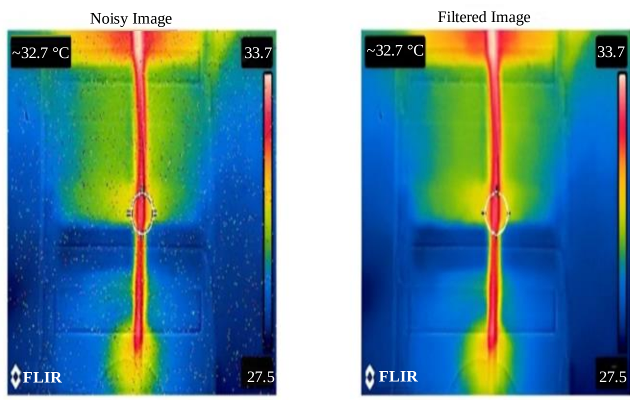

Fig. 6 Noisy thermal image vs. Filtered thermal image obtained from laboratory setup

As highlighted by Ukiwe et al. (2023) [7], the inherent characteristics of IRT images, such as the over-centralized temperature distribution and low-contrast nature, often pose significant challenges in traditional feature engineering processes. Deep learning circumvents this hurdle by automatically learning the most discriminative features from the data, potentially leading to more robust and generalizable anomaly detection models.

2.2. Related Existing Work

Extensive research has been conducted on anomaly detection in electrical systems using infrared thermography (IRT) images. This section reviews relevant studies, highlighting existing approaches, limitations, and potential areas for advancement.

2.2.1. Traditional Machine Learning

Several studies have explored techniques like Support Vector Machines (SVMs) and feature extraction algorithms for IRT anomaly detection [6-8]. While these methods offer a foundation for automation, they often rely on hand-crafted features, which can be labour-intensive to design and may not capture the full complexity of IRT data.

2.2.2. Object Detection Methods

Recent works have investigated the application of object detection algorithms like Faster R-CNN and YOLOv3, Machine Learning for identifying anomalies in IRT images [6]. While promising, these methods might require large training datasets and potentially struggle with the specific challenges of IRT images, such as low-intensity contrast and over-centralized temperature distribution. Faster RCNN & Yolo V3 uses CNN; accuracies are reduced and affected by Environmental sensitivity and feature extraction. Novel deep learning-based methods like simple deep learning, Ras-net, and Google paper have applied deep learning-based methodologies like Simple Deep learning, Google net and Ras-net to improve accuracy and training time reductions, overcoming the previously discussed limitations of CNN.

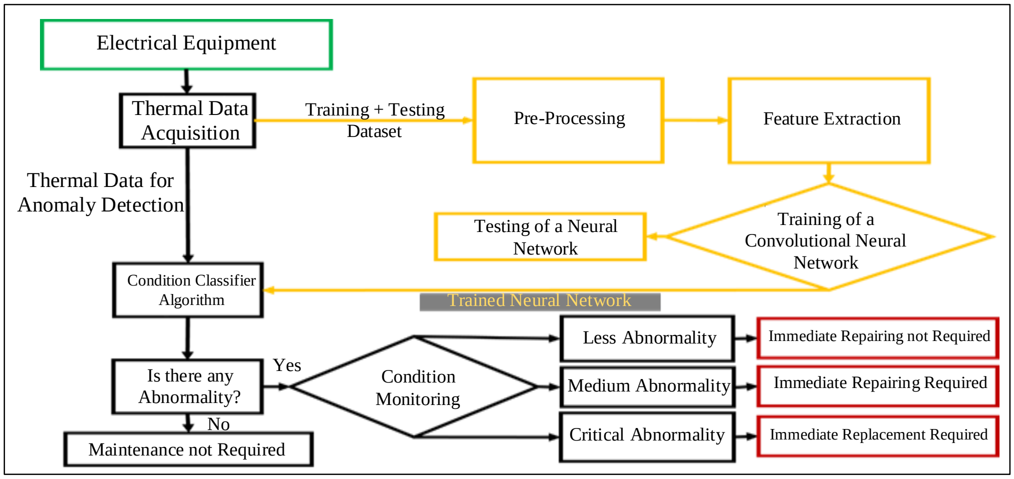

Fig. 7 Process flow diagram of the proposed abnormality detection system start, stage 1 (CNN training phase), stage 2 (Classification phase), stop

3. Research Methodology

Figure 7 presents a comprehensive flow diagram outlining the key stages of the concept at large. This portion provides a detailed overview of the research technique employed to develop and evaluate the proposed deep learning-based framework for IRT anomaly detection in electrical systems, through the same.

3.1. Data Acquisition

IRT images are gathered from various sources, encompassing diverse electrical components like transformers, wires and solar panels. These images depict both normal and abnormal conditions, ensuring a balanced dataset for model training.

3.1.1. Selection of Electrical Equipment

This study focuses on the development of a deep learning framework for anomaly detection in electrical systems using Infrared Thermography (IRT) images. Three prominent electrical components were chosen for analysis:

Current-Carrying Conductors

These conductors are essential for transmitting electrical current within a system and are susceptible to overheating due to high resistance or loose connections, potentially leading to safety hazards.

Transformer Porcelain Insulators

These insulators provide electrical isolation between various components within a transformer and can develop cracks or delamination due to ageing or environmental factors, compromising their insulating properties and posing a risk of electrical breakdown.

Solar Panels

Solar panels are subject to various potential defects, such as hot spots caused by micro-cracks or faulty connections, which can significantly impact their energy conversion efficiency. These diverse components represent commonly encountered electrical equipment with varying failure modes, allowing for a comprehensive evaluation of the proposed framework's generalizability.

3.1.2. Setup for IRT Image Acquisition of Selected Equipment

For each chosen electrical component type, a dataset of 100 to 100.0 IRT images must be captured, with 50% of images depicting normal conditions and 50% representing abnormal conditions. The image acquisition process involves the following steps:

3.2. Image Preprocessing

Format of captured images should be saved in JPEG format for efficient storage and subsequent processing. Figure 8, Figure 10, and Figure 12 showcase the sum of sample normal or Non IRT images of various electrical system components like current-carrying conductors, Transformer insulators, and solar panels. Figure 9, Figure 11, and Figure 13 are the thermal image samples in abnormal conditions, corresponding to the Electrical Conductor, Transformer Insulator, and Solar Panel, respectively, used in experimentation. These images provide a visual representation of the anomalies which the proposed technique aims to detect within IRT images of electrical components.

3.2.1. Transfer and Storage

Images were transferred to a computer for further processing and analysis. Essential preprocessing steps are applied to the acquired IRT images to enhance their quality, consistency, and suitability for model training.

These steps aim to standardize image dimensions: All images are resized to a uniform resolution to ensure.consistent input size for the deep learning model. This facilitates efficient processing and reduces computational complexity during training.

Fig. 8 Live current-wire

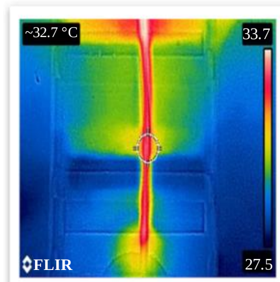

Fig. 9 Transformer

Fig. 10 Solar panel

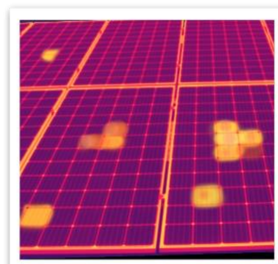

Fig. 11 Test-thermal image of wire

Fig. 12 Thermal image of insulator

Fig. 13 Test-thermal image of panel

3.3. Feature Extraction

It includes the following processing stages on IRT images.

3.3.1. Normalize Pixel Values

Pixel values within the images are often scaled to a limit of 0-1 or -1 to 1) to refine the convergence factor as well as stabilize the training process. This normalization step helps mitigate the impact of varying pixel intensity levels across different images.

3.3.2. Data Augmentation (Optional)

To artificially expand the dataset and enhance model generalizability, data augmentation techniques may be employed. This involves introducing controlled variations to the existing images, such as random cropping, flipping, or adding noise. These variations create new “virtual” examples that the model can learn from, improving its ability to handle unseen data during prediction.

3.4. Model Development and Training

This section details the process of developing and training the deep learning model for IRT anomaly detection

3.4.1. Model Selection and Architecture

GoogLeNet, a well-established CNN architecture known for its performance in image classification tasks, was chosen as the basis for the proposed framework.

3.4.2. Training Configuration

This subsection describes the essential hyperparameters and settings used for training the deep learning model in Table 1:

Table 1. Training configuration

Epoch	6
Iteration	252
Frequency	42 Iteration per epoch
Hardware System	Single C.P.U.
Learning-Rate-Schedule	Constant
Learning-Rate	0.0003

Minibatch Size

This parameter defines the number of images processed by the model during each training iteration. Choosing an appropriate minibatch size balances computational efficiency and gradient estimation accuracy.

Number of Epochs

An epoch idealizes one full pass through the total dataset used for training. The epoch’s number reflects the number of times the learning model iterates through the total training data and its influence on the learning process.

Learning Rate

This value controls the magnitude of updates applied to the weights of the model and biases amidst training. A suitable learning rate helps the model converge effectively and avoid getting stuck in local minima.

Validation Parameters

These parameters specify the frequency and data source used for validation during training. Supervising the Behaviour of the model with respect to its performance parameters on a dedicated validating set helps prevent overfitting and ensures generalizability to unseen data. Figure 14 depicts the training progress of the Convolutional Neural Network (CNN) model implemented in MATLAB software. This plot typically visualizes two key metrics: training accuracy and training loss across training epochs.

Training Accuracy

This metric reflects the percentage of true projections made by the model on training data during each epoch. Ideally, the training accuracy should increase steadily as the model learns and refines its parameter labels during the training process. Lower training loss signifies the model’s increasing capability to learn and fit the data of training. The specific values chosen for these hyperparameters were carefully selected based on the following:

Network Architecture

The chosen GoogLeNet architecture has inherent characteristics that inform appropriate hyperparameter selection.

Training Loss

This metric represents the divergence between the model’s projected outputs and ground truth.

Dataset Size and Complexity

The size and complexity of the IRT dataset influence the optimal hyperparameter settings.

Network Architecture

The chosen GoogLeNet architecture has inherent characteristics that inform appropriate hyperparameter selection.

Desired Training Time and Accuracy

Balancing training speed and achieving the desired accuracy involves careful selection of hyperparameters.

3.4.3. Training Process

The pre-trained GoogLeNet model was employed as a starting point for the training process. This practice, known as transfer learning, leverages existing knowledge acquired from a vast dataset and adapts it to the specific critical task of IRT anomaly detection.

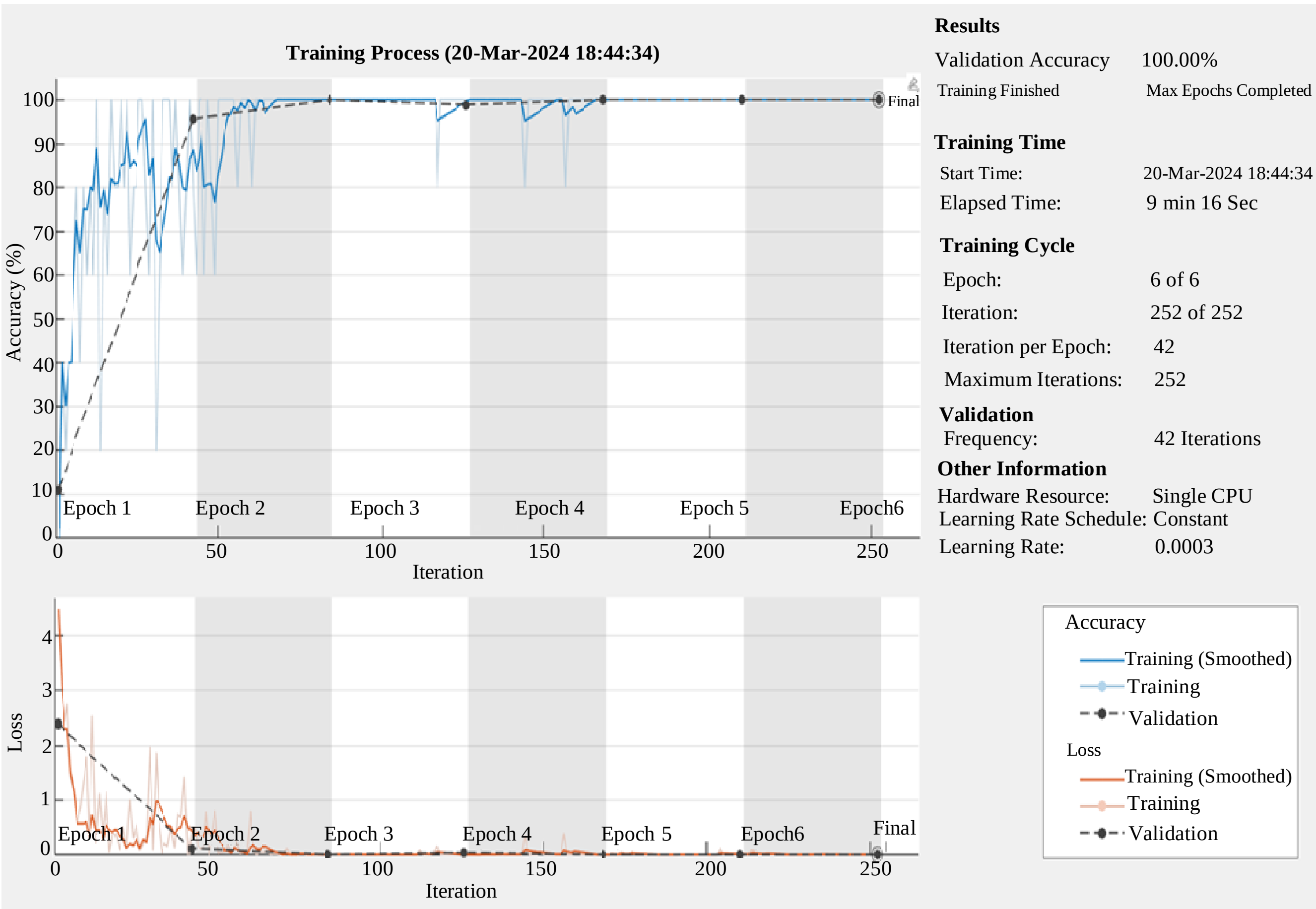

Fig. 14 Plot of CNN training progress in MATLAB software

The training process involves the following steps:

Fine-Tuning

The pre-trained model's final layers, specifically those responsible for classification, are fine-tuned on the prepared IRT dataset. This fine-tuning process adjusts the weights and biases of these layers to learn the specific patterns and features relevant to the anomaly detection task.

Optimization

An appropriate optimization algorithm, such as Stochastic Gradient Descent (SGD), is used to upgrade the model's parameters, including weights and biases, while training. This optimization process targets to alleviate the loss function, which computes the model's prediction error on the training data.

Hyperparameter Tuning

Hyperparameters, such as the learning rate and batch size, are crucial for effective training. These hyperparameters are carefully selected or tuned using techniques like grid search or random search to achieve optimal model performance. Upon completion, the trained model was saved for further analysis and evaluation.

3.4.4. Performance Evaluation

Following the training process, the model's performance was rigorously evaluated on an unseen validation set. This set consisted of 90 IRT images (15 per category: normal and abnormal) not used during training. This evaluation aims to assess the model's capability to standardize unseen data and avoid overfitting the training data.

3.5. Model Testing

The trained model, loaded from the "Retrained_GooglenetCNN.mat" file, was used to predict labels (normal or abnormal) for the validation set images. These predicted labels were stored for further analysis.

3.5.1. Performance Metrics

The evaluation process involved calculating various performance metrics to quantify the model's effectiveness:

Accuracy

This metric represents the overall proportion of correctly classified images across both normal and abnormal categories. It is evaluated as the ratio of the sum of TP and TN to the total number of test images:

$$Accuracy = \frac{(TP+TN)}{Total\ Images}$$

Precision

This metric quantifies the proportion of correctly recognized anomalies among the images predicted as abnormal by the model. It is evaluated mathematically by ratio of TP to the sum of TP and FP:

$$Precision = \frac{TP}{(TP+FP)}$$

Recall

This metric reflects the model's capability to detect all real-time anomalies within the test set. It is evaluated as the ratio of TP to the sum of TP and False Negatives (FN):

$$Recall = \frac{TP}{(TP+FN)}$$

F1-Score

This parameter reflects a harmonic mean of both achieving precision and recalling rate, offering a proportionated view of the model's performance. It is realized as:

$$F1 - Score = \frac{2 * (\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})}$$

These metrics provide crucial insights into the model's strengths and weaknesses, enabling a comprehensive and objective evaluation of its suitability for IRT anomaly detection.

3.5.2. Confusion Matrix

A confusion matrix is employed to visualize the model's performance by presenting the distribution of correct and incorrect predictions across different categories.

True-Positives (TP): These indicate correctly classified abnormal images.

True-Negatives (TN): These indicate correctly classified normal images.

False-Positives (FP): These indicate normal images incorrectly classified as abnormal.

False-Negatives (FN): These indicate abnormal images incorrectly classified as normal.

Table 2 presents a confusion matrix of a simple deep learning method, one of the result tables obtained during the comparative analysis of our proposed methods, which is a valuable tool for evaluating the performance of a classification model. The model classifies thermal images of electrical system components as either "normal" or "abnormal." The confusion matrix organizes the results of this classification process into a table format.

Understanding the Confusion Matrix

Rows: The row reflects the actual ground truth or class/category labels of images ("Normal" and "Abnormal").

Columns: The column reflects classes or categories predicted by the model. i.e. "Normal" and "Abnormal".

Table 2. Confusion matrix for simple deep learning

Abnormal Current	**0 0.0%**	**0 0.0%**	**00 0.0%**	**0 0.0%**	**0 0.0%**	**0 0.0%**	**Nan% Nan%**
Abnormal Insulator	**0 0.0%**	**0 0.0%**	**0 0.0%**	**0 0.0%**	**0 0.0%**	**0 0.0%**	**Nan% Nan%**
Abnormal Solar Panel	**0 0.0%**	**0 0.0%**	**0 0.0%**	**0 0.0%**	**0 0.0%**	**0 0.0%**	**Nan% Nan%**
Normal Current	**0 0.0%**	**0 0.0%**	**0 0.0%**	**0 0.0%**	**0 0.0%**	**0 0.0%**	**Nan% Nan%**
Normal Insulator	**0 0.0%**	**0 0.0%**	**0 0.0%**	**0 0.0%**	**25 33.3%**	**50 66.7%**	**33.3% 66.7%**
Normal Solar Panel	**0 0.0%**	**0 0.0%**	**0 0.0%**	**0 0.0%**	**0 0.0%**	**0 0.0%**	**Nan% Nan%**
	Nan% Nan%	**Nan% Nan%**	**Nan% Nan%**	**Nan% Nan%**	**Nan% Nan%**	**Nan% Nan%**	**33.3% 66.7%**
	Abnormal Current	**Abnormal Insulator**	**Abnormal Solar Panel**	**Normal Current**	**Normal Insulator**	**Normal Solar Panel**	

Accuracy:33.33%, Precision:66.67%, Recall:16.67%, F1 Score:10.00%

Diagonal Elements

Ideally, the highest values should appear on the diagonal elements (e.g., "True Normal" classified as "Predicted Normal" and "True Abnormal" classified as "Predicted Abnormal"). These values represent correct classifications.

Off-Diagonal Elements

Off-diagonal elements indicate errors made by the model. For example, a value in the "True Normal" row and "Predicted Abnormal" column signifies an image with a normal condition being incorrectly classified as abnormal (false positive). Conversely, a value in the "True Abnormal" row and "Predicted Normal" column represents an abnormal image being misclassified as normal (false negative).

Benefits of Confusion Matrix

Visualization of Classification Performance**:** The confusion matrix provides a clear visual representation of the model's ability to classify both normal and abnormal images correctly.

Identification of Errors: By analyzing the off-diagonal elements, researchers can identify the types of errors the model makes (false positives or false negatives) and prioritize potential areas for improvement.

3.6. Anomaly Detection and Classification

This section describes the final stage of the research, where the trained neural network is utilized to detect and classify anomalies within unseen IRT images of electrical system components.

3.6.1. Image Classification Process

The anomaly detection process leverages a custom MATLAB function named test Network. This function takes the path to the target IRT image as input and performs the following actions:

Load Trained Model

The function loads the pre-trained GoogLeNet model, fine-tuned on the prepared dataset, from the saved file ('Retrained_GooglenetCNN.mat').

Image Preprocessing

The input image is loaded and resized to match the expected input dimensions of the GoogLeNet architecture (224x224 pixels).

Classification and Probability Prediction

The resized image is fed into the loaded network, and the model predicts a label (normal or abnormal) and associated probability score.

Visualization and Output

The predicted label and its corresponding probability score are displayed. Additionally, the original image is visualized with the predicted label and probability overlaid as the title using the imshow and title functions.

The main program section calls the test Network function, providing the specific path to the IRT image under analysis. This structure allows for reusability, enabling the application of the function to various images by simply modifying the input image path.

3.6.2. Anomaly Classification Criteria

The classification of an IRT image as normal or abnormal is determined by considering both the predicted label and the associated probability score:

Normal

Images classified as "normal" with a probability score exceeding 0.9 are considered normal, indicating a high confidence level in the absence of anomalies.

Abnormal

Images classified as "abnormal" with a probability score exceeding 0.9 are considered abnormal, signifying a high confidence level in the presence of anomalies.

Uncertain

Images with a probability score below 0.9 are categorized as uncertain, requiring further investigation due to insufficient confidence in the automated classification. This classification scheme prioritizes high-confidence predictions while ensuring potential anomalies are not overlooked due to low probability scores.

3.6.3. Anomaly Severity Levels

For the identified abnormal images, the severity of the anomaly is assessed based on the following factors:

Probability Score

Higher probability scores indicate a greater degree of abnormality.

Defect Characteristics

The size, location, and type of the detected defect also contribute to the severity assessment. For instance, a larger, centrally located defect would be considered more severe compared to a smaller, peripheral one. Based on this combined evaluation, the anomaly severity is categorized into three levels:

Less Abnormal

Images with a probability score between 0.9 and 0.95, exhibiting small or peripheral defects, are classified as less abnormal.

Medium Abnormal

Images with a probability score between 0.95 and 0.99, presenting moderate or central defects, are classified as medium abnormal.

Critically Abnormal

Images with a probability score exceeding 0.99, indicating large or multiple defects, are classified as critically abnormal. The assigned severity level informs the appropriate maintenance or replacement actions for the corresponding electrical system component.

Less Abnormal

These components may be scheduled for repair or replacement shortly.

Medium Abnormal

Prompt repair or replacement of these components is recommended.

Critically Abnormal

Immediate repair or replacement of these components is crucial. Figures 15 to 20: Examples of IRT Image Classification by the Deep Learning Model. These figures showcase examples of IRT images and their corresponding classifications by the trained deep-learning model.

Each figure is labelled as either "Normal Condition Detected" or "Abnormal Condition Detected" based on the model's predictions.

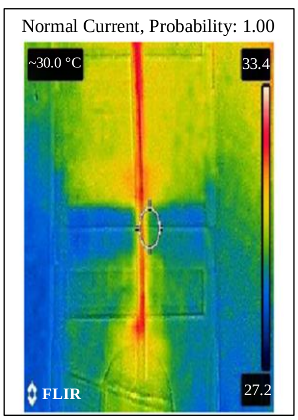

Fig. 15 Normal condition (Current)

Fig. 16 Abnormal condition (Current)

Fig. 17 Normal condition (Insulator)

Fig. 18 Abnormal condition (Insulator)

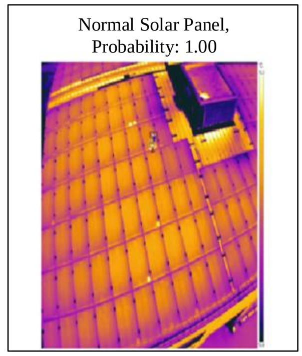

Fig. 19 Normal condition (Solar panel)

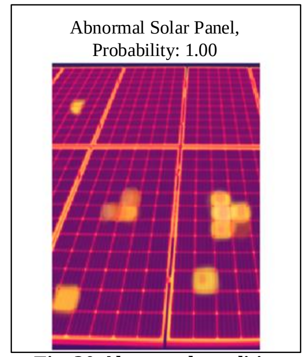

Fig. 20 Abnormal condition (Solar panel)

4. Experimental Results

4.1. Experimental Setup

4.1.1. Imaging Tool Used

A FLIR C2 infrared camera with a resolution of 80 x 60 pixels, a thermal sensitivity of 0.10°C, and a temperature range of -10°C to 150°C was utilized for image capture. Figure 21 depicts the FLIR-C2 thermal camera utilized to capture thermal images throughout the research.

4.1.2. Sample Test System in the Laboratory

Figures 22 and 23 provide visual context for the experimental setup carried out in the laboratory for considering electrical conductors of variable lamp loads to provide varying currents from 0 to 50 Amps as one of the test components. Figure 24 depicts the real-time IRT image captured by said Thermal Camera.

4.1.3. Dataset Preparation

The experiments utilized a dataset of 300 IRT images encompassing various electrical system components, including current conductors, transformer insulators, and solar panels.

Fig. 21 Flir thermal Camera

Fig. 22 Laboratory setup

Each image was meticulously labelled as "normal" or "abnormal" based on the presence or absence of defects. This IRT-image dataset was strategically proportionated into a training set of 70%, remaining 30% for validation purposes. The training set facilitated the training of the GoogLeNet CNN model, while the validation set served to assess its performance.

Model Training and Evaluation Tools Used

The GoogLeNet CNN model was trained using MATLAB software, employing the hyperparameters and configuration outlined in Section 3.3. Following training, the model was evaluated on the validation set, classifying images and generating predicted labels and probabilities were implemented. These predictions were then compared against the ground truth labels and probabilities to assess the model's accuracy and reliability.

Fig. 23 Laboratory setup for high current testing

Fig. 24 Flir camera based thermal

4.2. Performance Evaluation Metrics and Comparison

The evaluation of the proposed technique's performance primarily relied on confusion matrices and the accuracy metric. A confusion matrix visualizes the distribution of correct and incorrect predictions across different categories or classes.

Accuracy, expressed as the proportion of correct predictions among all predictions, reflects the overall model performance. Both the confusion matrix and accuracy were calculated using the MATLAB code. Furthermore, the proposed technique was compared against established methods, namely Faster R-CNN and YOLOv3, which also leverage CNN architectures for anomaly detection in IRT images.

4.3. Results and Discussion

The experimental results attained by the proposed technique and existing methods for anomaly detection are presented in Tables 2, 3, and 4. Table 2, already addressed in the previous section of the paper, reflects the confusion matrix for machine learning methods like simple deep learning methods, implemented.

Table 3 shows the confusion matrix for GoogleNet-based deep learning method. Moreover, Table 4 delineates the experimental findings for the anomaly detection techniques under critical observation. It encapsulates a comparative analysis of performance metrics for Support Vector Machine (SVM), Simple Deep Learning, and the advanced GoogLeNet & RasNet50 CNN architectures. The table evaluates these machine learning paradigms against criteria like accuracy, precision, recall, F1-score, and duration of model training.

Table 3. Confusion matrix for Google net

Abnormal Current	15					
Abnormal Insulator		15				
Abnormal Solar Panel			15			
Normal Current				15		
Normal Insulator					15	
Normal Solar Panel						15
	Abnormal Current	**Abnormal Insulator**	**Abnormal Solar Panel**	**Normal Current**	**Normal Insulator**	**Normal Solar Panel**

Figures 25 to 29 reflect the comparative statistics of each performance parameter of all the machine learning paradigms implemented for electrical system maintenance and anomaly detection. This superior performance underscores the potential and effectiveness of the claimed technique for real-world applications related to electrical system maintenance and their anomaly detection.

Table. 4 Comparison of various machine learning and deep learning techniques implemented for electrical system anomaly detection

No.	Machine Learning Architecture	Accuracy	Precision	Recall	F1-Score	Time Required to Train Model
1	Support Vector Machine (SVM)	91%	95.80%	94.40%	98.10%	2 min 30 sec
2	Simple Deep Learning	33.33%	6.66%	16.66%	10%	45 Sec
3	GoogLeNet (CNN)	99.8%	99.9%	99.9%	99.9%	16 min 56 sec
4	RasNet-50 (CNN)	99.8%	99.9%	99.9%	99.9%	1 min 40 sec

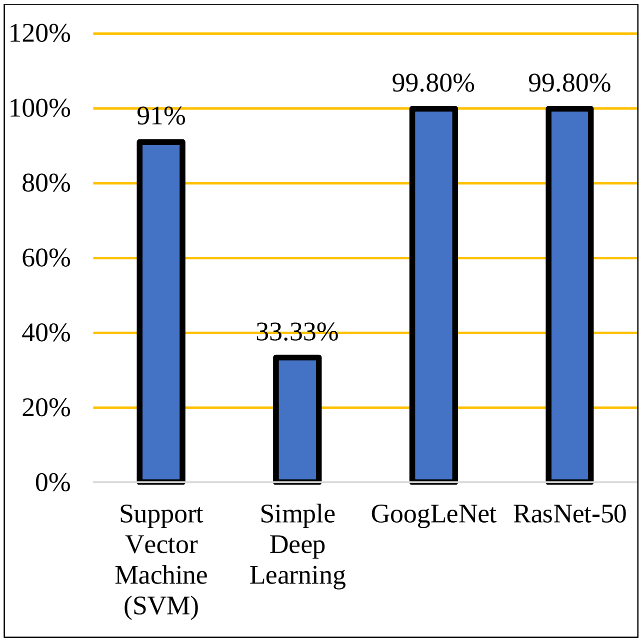

Fig. 25 Prediction accuracy

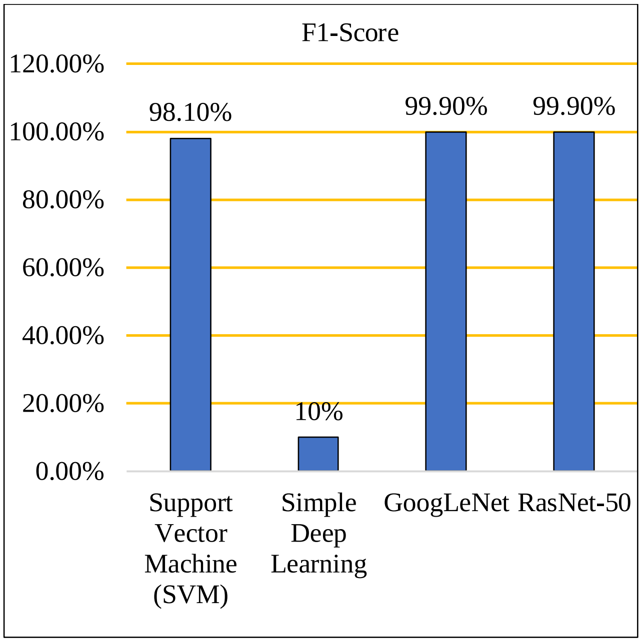

Fig. 27 Normal condition (F1-score)

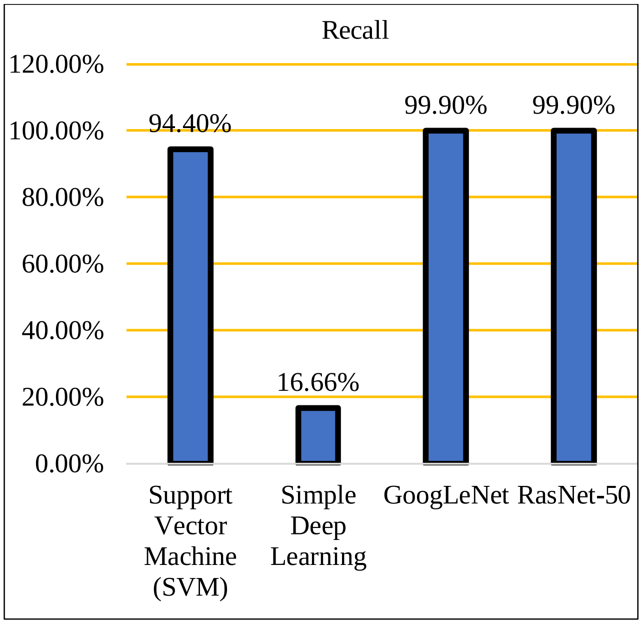

Fig. 26 Normal condition (recall)

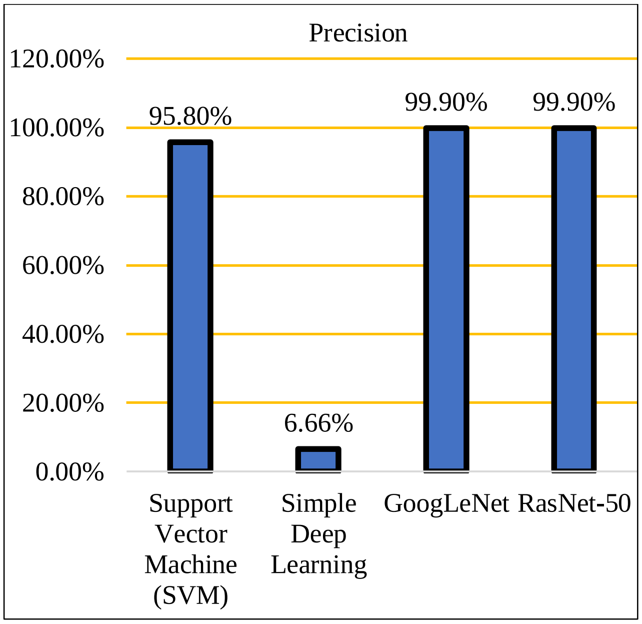

Fig. 28 Normal condition (precision)

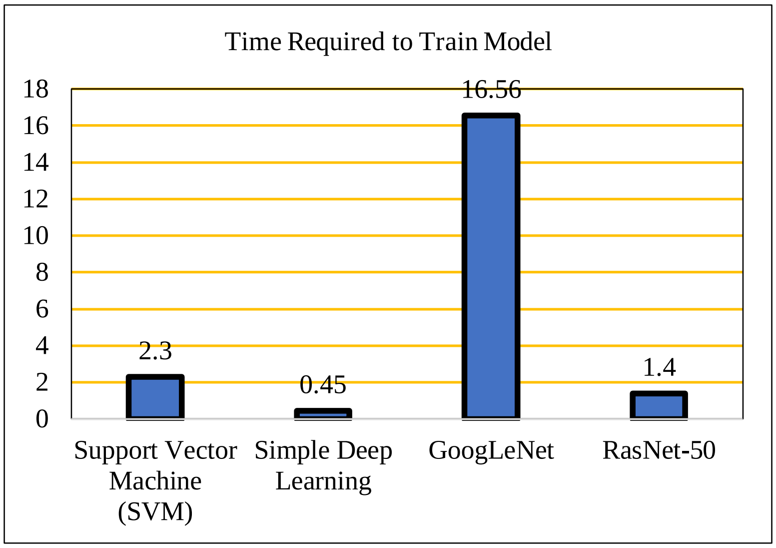

Fig. 29 Normal condition (time required to train model)

5. Future Work and Conclusion

5.1. Recommendations for Future Research or Practice

Based on the limitations of the study, some recommendations for future research or practice are suggested. Future research should collect and use a larger and more diverse dataset of IRT images covering different types of electrical system components, defects, and conditions obtained from real-world or field experiments.

Future research should also investigate and control the effects of external factors on the IRT images and the neural network classification, and optimize the parameters and settings of the IRT camera and the neural network model accordingly. Future research should also compare the proposed technique with other types of CNN models or architectures and explore the possibility of combining or hybridizing them to enhance the performance or robustness of the abnormality detection.

Future practice should apply the proposed technique to other types of electrical system components and integrate it with other methods or techniques, such as fault diagnosis, to provide a comprehensive solution for electrical system maintenance and management.

5.2. Conclusion

The data illustrates that the GoogLeNet & ResNet50 CNN methodologies significantly outperform traditional SVM (91%) and traditional deep learning techniques (33.33%) with an impressive accuracy of 99.8%. This stark contrast in performance highlights not only the robustness of the CNN-based approaches but also their applicability in practical scenarios such as electrical system maintenance and anomaly detection. Moreover, the training time analysis offers insights into the efficiency of these models, with ResNet-50 demonstrating a remarkable balance between high accuracy and reduced training time attributed to its optimized network complexity.

The findings of this study may have significant implications for the field of electrical engineering and the related literature, as they demonstrate the potential and effectiveness of incorporating deep learning and IRT for abnormality detection in electrical system components, which can improve the performance and safety of the system, and prevent fire hazards or power outages.

Ethical Approval

This research did not involve human participants or animals. The results were obtained through simulations and repeated testing to ensure the final values were reliable.

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Author-Contributions

PC: Conceptualization, Software, Investigation, Writing - Original Draft Preparation. SP and NV: Methodology, Investigation, Writing, Reviewing and Editing, Approval of Thermal Imaging Camera Usage, MS: For Laboratory setup and resource availability and simulation guidance.

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