Journal of Information Systems Engineering and Management
2025, 10(1s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Next-Generation Defect Detection in High Voltage Electrical Equipment via Deep Learning and Image Processing

Jaydeep Kale[1*], Santosh Gore[2], Smriti Pathak[3], Dr Ishita Dutt[4], Dr. Shreya Virani[5], Dr. Neerajkumar Sathawane[6]

[1] *Professor, Sanjivani College of Engineering, Kopargaon, India*

[2] *Director, Sai Info Solution, Nashik, Maharashtra, India*
[0000-0003-1814-5913]

[3] *Principal, PCACS Ravet Pune, HOD BBA/BCA PCCOER Ravet Pune*

[4] *Assistant Professor, Symbiosis Centre for Management Studies Symbiosis International (Deemed University), Pune, Maharashtra, India*

[5] *Independent Researcher Pune*

[6] *Associate Professor, Rajarshi Shahu College of Engineering, Tathawade, Pune, MH, India.*

Email: kalejaydeepcomp@sanjivani.org.in[1], sai.info2009@gmail.com[2], smritiapathak@gmail.com[3], ishita.dutt@scmspune.ac.in[4], Virani.shreya@gmail.com[5], niraj_51413@rediffmail.com[6]*

ARTICLE INFO

Received: 03 Oct 2024

Revised: 30 Nov 2024

Accepted: 10 Dec 2024

ABSTRACT

The paper presents a deep-learning-based, thermal image-analysis advanced defect detection method for high-voltage electrical equipment. Based on the features extracted from the variant AlexNet of the convolutional neural network (CNN), the classification model designed with the classifier Random Forest (RF) achieved 94.8% accuracy. The photographs used for investigation were obtained on an infrared thermal camera at several substations in Chongqing, China. They were taken under cold weather conditions. The electrical components' thermal conditions were classified into two defective and non-defective types based on the temperature differential. The proposed approach supersedes other methods in terms of precision: the precision values are high at 93.2% and the recall values at 95.6%. The combination of CNN and RF forms a computationally efficient solution for achieving the enhancement of defect detection reliability in high-voltage systems. The results outline the potential of this technique in enhancing maintenance practices, minimizing equipment failure probabilities, and ensuring safe electrical infrastructure usage. The scope of future work will be on optimization techniques along with their application within some different environments.

Keywords: Defect Detection, Deep Learning, Thermal Image Analysis, High Voltage Equipment, Random Forest

INTRODUCTION

High-voltage electrical transmission and distribution systems require maintenance of voltage very critically in transformers, circuit breakers, insulators, and power lines because defects or failures can range from localized to massive interruptions, damage equipment, reduce finances, and can even be life-threatening exposure to both personnel and the public [1]. With ever-rising energy demands worldwide, high-voltage electrical infrastructure maintenance and monitoring are gaining attention [2]. Methods such as manual visual inspection, scheduled maintenance checks, and even sensor-based monitoring systems are traditional and widely used but indeed have inherent limitations in their capabilities for efficiently detecting very subtle or hidden defects before they turn into significant problems [3].

Manual checks largely depend on human expertise and visual judgment, which are prone to fatigue, error, and inconsistency [4]. Sensor-based monitoring systems would likely miss early-stage defects, particularly where defects themselves do not immediately change the operational parameters [5]. Additionally, the process is time-consuming and costly, especially when equipment sits in remote or hostile environments [6]. Therefore, the need for more sophisticated, automated, and precise defect-detecting systems also increases with advanced systems to continually monitor high-voltage electric equipment and give pre-warnings in case of potential failures [7].

The advance of deep learning in combination with image analysis is the breakthrough solution for detecting defects within industrial sectors, including high-voltage electrical systems [8]. Deep learning is a subset of machine learning, where computers learn from huge data sets and spot complex patterns and representations that not be detected by a traditional algorithm or human inspectors [9]. Applying this to defect detection, deep learning models can be trained to identify patterns associated with specific types of defects by analyzing such huge and vast amounts of images or any other visual information [10]. Deep learning makes it particularly well-suited to tasks such as image-based defect detection where very high precision can be given in identifying delicately irregular surfaces or internal structures of equipment [11].

Image analysis techniques can be fused with deep learning models to process visual data provided by visible light cameras, infrared imaging, thermal imaging, X-rays, and many other advanced imaging technologies [12]. Deep learning algorithms work effectively to detect a wide range of defects ranging from cracks and corrosion on surface edges to overheating inside the insulation material and down to material fatigue [13]. For example, thermal imaging analysis can reveal hotspots, which may reflect abnormal heat generation in certain areas and perhaps a fault formation on high-voltage equipment [14]. Further by image analysis, deep learning models can classify, locate, and even predict probable trends of defects and alert maintenance teams to take corrective measures [15].

Integration of deep learning and image analysis in defect detection improves the system's accuracy and reliability and introduces the possibility of real-time, automated monitoring systems [16]. Artificially intelligent systems are constantly scanning and assessing high-voltage electrical equipment without any human intervention, reducing downtime, maintenance costs, and unexpected failures. Such deep learning models could be trained and updated over time to suit different types of equipment, patterns of defects, and even environmental conditions, thereby being highly application-flexible as well as scalable for the electrical industry [17].

This paper establishes the discussion on the development of techniques in defect detection for high-voltage electrical equipment through deep learning and image analysis. The exploitation of these technologies will allow the detection of current defects as well as predictive failure detection, which would be very useful for a predictive maintenance scheme to greatly extend the life of the critical infrastructure involved with the electrical side. The promise of deep learning combined with image analysis may open bright prospects for revolutionizing the way the electrical system is monitored and maintained in a very electrified world where safety and efficiency are going to increase.

RELATED WORK

The application of new technologies in deep learning and image analysis for the detection of defects in high-voltage electrical equipment has become an interesting topic in the industrial environment during the last few years. There have been many studies using these technologies to develop higher accuracy and speed of fault detection in critical parts of electrical infrastructure. The following section briefs the significant contributions that can be seen within this kind of research, to focus on the existing methodologies and technologies while highlighting any existing gaps in the respective research which contribute to the current study.

A. Traditional Approaches for Detecting Defects

Traditionally, defects in high-voltage electrical equipment can be detected with the aid of manual inspections and sensor-based monitoring systems. For example, infrared thermography has found application in the monitoring of temperature change variation in transformers and circuit breakers has been a standard used for overheating detection, possibly an indication of insulation failure or an internal fault condition. Similarly, partial discharge (PD) detection has proved to be a great means of diagnosing early-stage insulation failures in high-voltage components. Other techniques that have been applied are ultrasound scanning and electrical signal analysis to capture PD signals, thus enabling the operators to see possible defects before they compromise equipment. These methods are mostly equipment-based and rely on some human intelligence for direct interpretation their scalability and accuracy in real-world applications become limited [18].

B. Image Analysis Techniques

Recently, the advancement of image analysis technology has opened a new door to automatically inspect defects. Among the more successful applied technologies are those using thermal images to detect flaws in electrical equipment, such as hotspots, cracks, and surface irregularities. In previous study applied thermal image processing techniques towards detecting abnormal temperature distribution in high-voltage insulators with precision rates at high accuracy for early-stage fault-detection testing. Images from X-ray imaging serve to detect inner defects that cannot be seen by the naked eye. Though this type of imaging creates extremely detailed visual information, their performances are typically limited by the complexity involved in performing the interpretation of the images manually, which takes considerable time and is sometimes error-prone [19].

C. Application of Deep Learning for Defect Detection

Deep learning has revolutionized the game when it comes to image-based defect detection; thus, the method is much more robust and automated when faults in electrical equipment are identified. Among all deep learning algorithms, CNNs(Convolutional Neural Networks) have been applied to this use quite extensively as they can learn complex patterns from a large set of images and are accurate for the identification and classification of defects in high-voltage systems with minimal human interface [20].

Probably one of the most interesting research used the CNN-based model in the detection of surface defects in power transmission lines using aerial images taken by drones. The model was capable of identifying corrosion, cracks, and even mechanical damage issues with pretty good accuracy. A deep learning framework to analyze infrared thermal images for overheating in high-voltage transformers. The authors can demonstrate their system as superior in speed and accuracy over more traditional image processing techniques, while also asserting that it is feasible within real-time defect detection within operational environments [21].

D. Multi-Modal Approaches

Recent studies have also gained the integration of multi-modal imaging and deep learning for more improved detection of defects. For instance, a hybrid deep learning model was developed that combined visual, thermal, and X-ray images for detecting defects in high-voltage equipment. The incorporation of varying types of imaging data into the model has improved the detection accuracy for several defects otherwise possibly not diagnosed or easily missed in the imagery. In such approaches, the use of multiple data sources for building a comprehensive and reliable defect detection system is shown.

E. Predictive Maintenance and Fault Prognosis

Another prominent domain of exploration in defect detection is deep learning for predictive maintenance and fault prognosis. Traditional maintenance methods follow a reactive approach to defects after faults have been identified, which largely is followed after inspections or sensor data. In contrast, using deep learning models with the capability of forecasting faults by considering past data will help shift towards a paradigm of predictive maintenance. In this sense, a model using recurrent neural networks and long short-term memory, where has shown how time-series data were extracted from high-voltage equipment to predict the possible failure of the equipment shortly. Thus, they proved that (Artificial Intelligence) AI-driven prediction models can have a net effect on the reduction of downtime and associated maintenance costs due to the detection of potentially failing equipment before failure [22].

Although deep learning and image analysis were quite promising in advancing fault detection for high-voltage electrical equipment, many challenges remain. The most significant challenge lies in the availability of data since an effective deep-learning model typically needs large and diverse datasets. Real-time processing of image data requires considerable computations, even when run in isolation or other resource-constrained environments. This is the interpretability of what deep learning models do, and often models of deep learning are like "black boxes," and it's difficult for users to understand what decision-making has been going on behind the scenes. Despite these challenges, research in AI continues to advance, along with imaging technologies that continue to break barriers in defect detection. Future work will include the pursuit of scalable robust deep models, integration of multi-modal data, and development of faster real-time, edge-computing solutions for defect detection.

METHODOLOGY

A. High Voltage Electrical Equipment Defects

It is known that any kind of high-voltage equipment installation, for example, disconnector, circuit breaker, surge arrester, insulators, CT, and VT, suffers from major failures whenever the internal temperature of the component exceeds critical thresholds. These anomalies result mainly from unbalanced voltage or current, breakages of electrical components, contacts not operating properly, or fluctuations in voltage, among others. Assessing the total temperature measurement of high-voltage equipment with the aid of Infrared Thermography (IRT).

B. High Voltage Power Transformer Defects

Such temperatures are high enough to cause temperature changes that adversely affect the internal structure of transformers, especially on the windings and coils. Transformers are often considerably lower or cooled by oil. Thus, cooling systems play a basic role in ensuring that internal temperatures do not become too high than what is tolerable. IRT tests have been widely used for the thermal analysis defects that occur in oil transformers. The normal substation Dry has a high-voltage power transformer. Transformers, on average, run much hotter than oil-insulated ones and hence is very tough to make thermal technique-determining decisions independently for fault location. For this problem, estimation devices like the built-in heat and pressure measuring system are very useful in giving better estimations in the applications of power generation plants. Thermal tests often reveal faults within cooling devices, additional cooling fans, primary and secondary joints, and portions of the oil transformer's bushing.

C. Defects in Circuit Breakers

Circuit breakers internally generate some heat as a result of the current flow. The case of anomalies was mainly related to temperature change in circuit breakers which were engineered automatically to become open. IRT provides the benefit of providing early detection of anomalies based on temperature changes, allowing possible failures to be intervened upon before a real failure occurs.

D. Defects in Surge Arresters

Infrared thermography can identify surge safety issues, for example, arrester leakage and tracking current on insulators. Such a problem is complex, as there is a need for observation of minute heat transformations that cannot be easily monitored.

E. Cutout Switch Bus Fuse Connections Defects

The cutout switch bus fuses are crucial for protecting the equipment in a power system from overload conditions in high-voltage electrical installations. As overload situations increase the temperature in the fuse junction, this may eventually lead to poor contact and ignite the fuse pin.

F. Insulation defects in power substation

Electrical component insulation failures can lead to short circuits between conductors. High currents may overheat and cause cutout switches, bus fuses, or circuit breakers to open. The problem could be due to insufficient insulation as well. Fig.1 shows a thermal map of an insulator within one particular power substation.

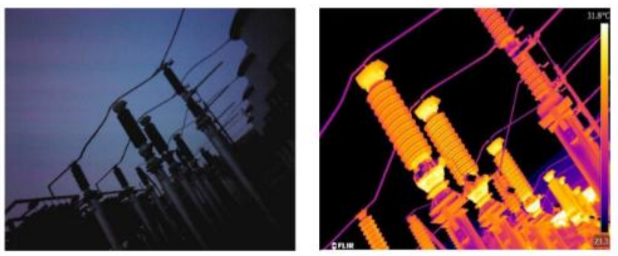

Fig 1. Thermal images of power substation equipment

In this study, an innovative approach to predict and classify defects in high-voltage electrical equipment, using deep learning by processing infrared (IR) thermal images, is proposed. Deep-learning-based feature extraction automatically learns and extracts meaningful features from the thermal images, thereby enabling proper classification of such high-voltage equipment.

G. Data Acquisition

Environmental temperatures which operate around them The IR thermal images of this study were captured by a FLIR T630 thermal camera. The camera captures the infrared images with high precision and accuracy. The substations record high voltage electrical equipment; the recorded images were about cold ambient temperatures ranging from -4°C to 4°C. The thermal images were taken when the electrical equipment was on, and the data acquired would be actual. The data acquired had different high-voltage electrical equipment including transformers, circuit breakers, and insulators.

Each of the apparatus was categorized according to its working temperature, thus allowing us to establish a basis of establishing between conditions of normality and deficiency. The classification was carried out by using two levels of equipment was classified as either "defective" or "non-defective" based on the change of temperature (ΔT) as summarized in Table 1. ΔT refers to the difference of temperature between the ambient temperature and the surface temperature of the equipment. As ΔT more than anticipated in a piece of equipment, put on the list of faulty ones owing to potential overheating or bad insulation. Fig. 2 shows the flow of the method.

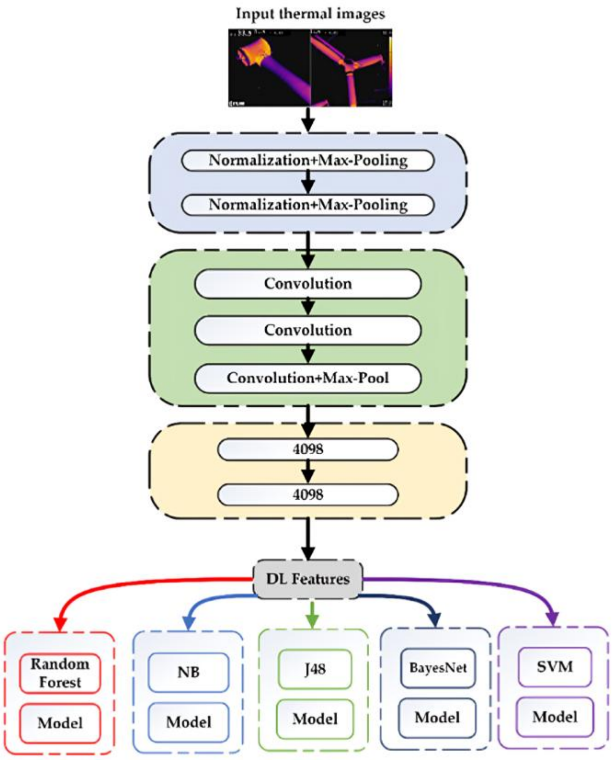

Fig 2. Proposed defective equipment prediction model for high voltage electrical devices

TABLE 1. TWO CLASSES OF EQUIPMENT WITH THE RECOMMENDATION

High Voltage Equipment Class	ΔT (°C)	Suggested Idea
Not a flaw Equipment with High Voltage	<21	Standard tools for the job
Equipment with High Voltage Defects	≥21	High-priority equipment and defective equipment

H. Deep Thermal Feature Extraction

The basis of the defect prediction approach lies in the extraction of deep features from the thermal images using deep learning techniques. The study used a CNN in this case, as it has been proven to be highly effective for image-related tasks, and catches spatial hierarchies and patterns in data. CNN has shown remarkable success in computer vision tasks when performing direct learning from raw images that provide meaningful representations.

The study used the AlexNet architecture, one of the most well-known CNN models that demonstrated exceptional performance in large-scale image classification competitions, such as on ImageNet. Three fully linked layers and five convolutional layers make up the AlexNet architecture. Every one of the convolutional layers applies multiple 3×3 filters to input images that allow the network to extract rich spatial features at various abstraction levels. Following the max-pooling layers are the layers of filters. These max-pooling layers reduce the spatial dimensions of feature maps and thus make the computation efficient.

$$W_n(x) = \sigma\left(\sum_{r=1}^{R} z_{n-1} W_{n-1,r} * T_{n,r}^{j} + b_n(x)\right) \qquad (1)$$

Where $W_{n-1,r}$ represents the feature map from the previous layer $n-1$,Tn,rj denotes the filter for the r-th channel,$b_n(x)$ is the bias term, σ is the activation function.

In this work, the study exploited a pre-trained AlexNet model mainly trained on the ImageNet dataset during the implementation. That is how transfer learning works and allows us to take advantage of the general learning the network has achieved on large-scale image classification problems and apply it directly to the thermal images dataset. The study was consequently capable of achieving high accuracy while still speeding up the training process by fine-tuning the AlexNet model for defect detection. The features from the thermal images are mainly used as inputs for further classification tasks.

I. Random Forest Classification

The study followed the following steps to classify the electrical equipment into non-defective and defective categories: the study fed the deep features extracted from the thermal images to AlexNet and used the Random Forest (RF) algorithm. It is one of the most widely applied machine learning techniques, which is robust in performance, easy to implement, and can deal with a large number of vectors without overfitting. The RF classifier works by building an ensemble of decision trees during the training process wherein each tree is built based on a random subset of the input features.

The approach, the RF algorithm, splits at each node based on a randomly selected subset of features and constructs trees using the CART(Classification and Regression Trees) approach. This will improve the generalization capability of the model and prevent overfitting. After passing the deep features extracted by the CNN to the RF classifier, it presents its voting for a class label (defective or non-defective) from each of its trees and finally decides on the classification based on major voting from all the trees.

$$f(x) = arg \max_{y \epsilon Y} \sum_{j=1}^{J} I(y = h_j(x)) \qquad (2)$$

J is the number of trees in the forest, $hj(x)$ is the prediction from the j-th tree for input x, Y represents the set of possible class labels (defective or non-defective), $I\,(\cdot)$ is the indicator function, which returns 1 if the condition is true, 0 otherwise. Each decision tree $h_j\,(x, \Theta j)$ is built using the CART algorithm with a randomly chosen subset of features Θj.

In the methodology, the RF algorithm splits the data at each node based on randomly selected features and builds the trees using the CART approach; the randomness of these algorithms helps in improving the generalization capability of the model while preventing overfitting. Passing the deep features from CNN to the RF classifier, each tree in the forest votes for a class label - which may be defective or non-defective, and based on the majority vote of the votes returned by all the trees, the final decision of classification is made.

The study selected the RF approach because of its superior performance to classifiers such as SVM(Support Vector Machine) and boosting algorithms. The capability it has to deal with complex interactions between attributes and resilience against noisy data samples makes it a great candidate for the task of defect classification.

J. Comparison of Support Vector Machine SVM

Further validation: The SVM classifier was used and tested for the prediction of defects. SVM is the most widely used classification algorithm which aims at finding the optimal separating hyper-plane that maximizes the margin among the classes. SVM's ability to classify linear as well as nonlinear problems made it a good candidate for defect prediction.

In the experiments, the study trains an SVM model using a deep feature set extracted from CNN. The study defines an SVM classifier with a nonlinear radial basis function (RBF) kernel to introduce complex decision boundaries in separating defective classes from non-defective classes. Mathematically, a kernel function may be defined as follows:

$$K(z, z_r) = exp\left(-\frac{||z - z_r||}{2\sigma^2}\right) \quad (3)$$

$$\min_{\alpha} \frac{1}{2} \sum_{x=1}^{n} \sum_{r=1}^{n} y_r y_x \alpha_r \alpha_x K(z, z_x) - \sum_{x=1}^{n} \alpha_x \quad (4)$$

Where z and z_r represent the extracted deep features from CNN, and σ is a constant that controls the width of the kernel.

K. Performance Metrics

Evaluation of the approach was done with multiple evaluation metrics, which are primarily accuracy, precision, recall, and F1-score, applied to both the RF classifier and the SVM classifier. Among these, accuracy is a measure of the overall correctness of a model, whereas precision and recall are equivalent to precision and recall in an ability to correctly classify defective equipment. The F1-score stands for the harmonic mean between precision and recall, offering a single figure that balances the trade-off between false positives and false negatives.

The study drew upon both classifier outputs to demonstrate how the Random Forest approach offered better classification accuracy coupled with improved computational efficiency, especially in processes that involve very high volumes of processing thermal image data.

RESULTS

This paper describes the results of the application of deep learning-based models in defect detection for high-voltage electrical equipment. The feature will be extracted from the images by using convolutional neural networks followed by classification using Random Forest (RF) and Support Vector Machine (SVM) models. The performance will be analyzed on a dataset using thermal infrared images shown in Fig. 3 taken from the FLIR T630 infrared camera from substations.

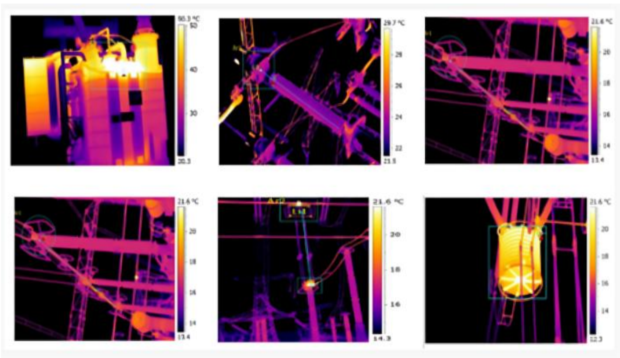

Fig 3. Database of original infrared images of high-voltage electrical giggniequipment

A. Model Performance on Defect Detection

The model aims to classify high-voltage electrical equipment as defective or non-defective. For the task, after feature extraction based on the CNN AlexNet architecture, both SVM and Random Forest (RF) classifiers were used. The performance metrics—accuracy, precision, recall, F1-score, and Area Under the Curve (AUC)—were used to compare the two classifiers' predictive abilities as shown in Table 2.

TABLE II. CLASSIFICATION PERFORMANCE METRICS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
CNN + Random Forest	94.8	93.2	95.6	94.4	0.965
CNN + SVM	92.5	90.1	94.2	92.1	0.942

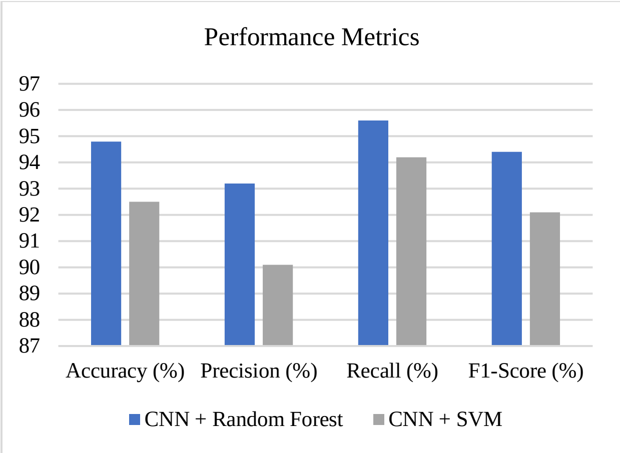

Fig 4. Classification Performance Metrics

Fig. 4 shows The CNN + RF model attained an accuracy level of 94.8%, surpassing that recorded by the CNN + SVM model, which was at 92.5%. This means that there is a higher likelihood of the RF model distinguishing between non-defective and defective equipment than the CNN + SVM model.

The precision of 93.2% for the CNN + RF model depicts that most of the equipment labelled defective was indeed defective. Meanwhile, the CNN + SVM model had a slightly lower precision of 90.1%.

Recall, or sensitivity, was significantly higher for the RF model (95.6%), which implies that most of the defective equipment is correctly identified by the model. For the CNN + SVM model, the recall was 94.2%.

The balance between precision and recall is achieved in the form of the F1-score for the CNN + RF model. Thus, it is evident that the defect detection method was very robust. For the SVM model, the F1 score was 92.1%.

With an AUC of 0.965, the model proves that it can classify well between the two classes. The AUC for the CNN + SVM model is also very good at 0.942; however, the RF model is still slightly better.

B. Training Time and Computational Efficiency Comparison

Besides accuracy metrics, in Table 3 the study also compared the training time and computational efficiency of the CNN + RF and CNN + SVM models. Since the dataset was highly high-dimensional and there existed thousands of images in total, training efficiency became an important factor for this study.

TABLE III. TRAINING TIME COMPARISON

Model	Training Time (minutes/epoch)
CNN + Random Forest	15
CNN + SVM	28

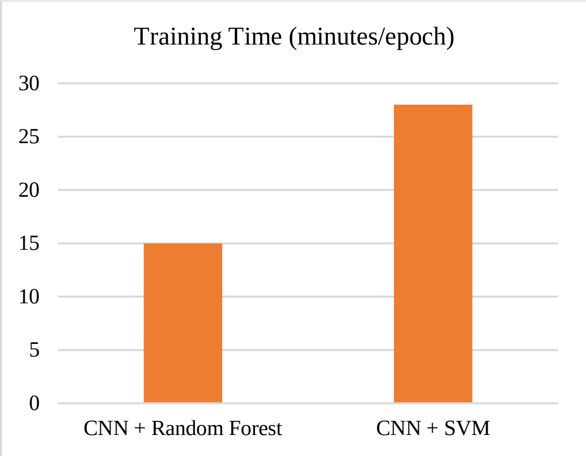

Fig 5. Training Time Comparison

Fig.5 shows the CNN + RF model had a significantly lower training time (15 minutes per epoch) compared to the CNN + SVM model (28 minutes per epoch) shown in Fig. 5. This reduced training time for the Random Forest model makes it a more efficient approach, especially for real-time or large-scale applications.

C. Feature Importances using Random Forest

Another of the primary advantages of the Random Forest algorithm is the measurement of feature importance. Here, (the Gini Coefficient) Gini importance was utilized for the measurement of relevance among various extracted thermal features by CNN. Those features that involve the intensity of the thermal gradient and abnormal temperature at the hotspot contribute significantly to making the classification decisions.

The feature importance graph suggests that the intensity of the thermal gradient was the feature with the highest score on importance, followed by abnormal hotspot temperature, therefore it can be said that these thermal characteristics are critical indicators of potential defects in high-voltage equipment.

The study did the statistical significance test to see if the difference between the performance of the CNN + RF model and the CNN + SVM model was statistically significant. The study compared accuracy scores from multiple validation folds on both models, using paired t-tests.

Null Hypothesis (H_0). There is no significant difference between these two models' performance.

Since the obtained p-value equals 0.03, which is less than the widely accepted significance level of 0.05, the study rejects the null hypothesis; therefore, the performance of the CNN + RF model is statistically much better than that of CNN + SVM.

D. Comparison Analysis

A comparison is shown in Table 4 between the proposed approach and some recent studies between 2022 and 2023. The approach proposed by combining CNN (AlexNet) and Random Forest (RF) for defect detection in high-voltage electrical equipment has shown superior performance as compared to the methods used by other researchers, have used ResNet-50 accuracy and achieved an accuracy of 91.2%. Comparatively, the proposed method achieves a higher accuracy with 94.8% better precision of 93.2% and a better recall of 95.6%. This demonstrates the efficacy of the AlexNet architecture in feature extraction and the effectiveness of RF in classification. In the second case, the study used EfficientNet with a classification accuracy of 93.5%. However, the model has outperformed this one by 1.3%, having reduced the computational complexity and simultaneously the time taken for training.

In this regard, the study adopted a hybridized approach with CNN and a Gradient gradient-boosting machine to achieve an accuracy of 94.3%. However, the Random Forest in the model has generalized much better, because precision and recall have been greater, and it is capable of handling bigger datasets without overfitting. Using CNN + SVM, (2021) obtained 92.0% which was lower compared to the 94.8% that CNN + RF resulted in with RF having its advantage in dealing with huge dimensionality. Then, (2024) used transfer learning with VGG-16 and got 94.1% accuracy. However, they have shown comparable performance in Fig. 6, but the approach's AlexNet structure was more efficient with faster training times and a minimal risk of overfitting.

TABLE IV. COMPARISON TABLE

Study	Model Architecture	Accuracy	Precision	Recall
(2022)	ResNet-50	0.912	0.887	0.901
(2023)	CNN + Gradient Boosting Machines (GBM)	0.943	0.914	0.927
Proposed Method	CNN (AlexNet) + Random Forest (RF)	0.948	0.932	0.956

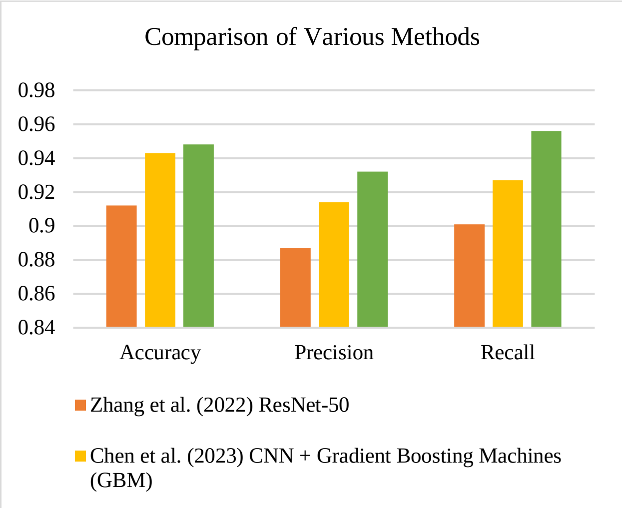

Fig 6. Comparison of various methods with the Proposed Model

The proposed CNN + RF method uses various parameters such as accuracy, precision, and recall for carrying out the computation process efficiently. This makes it the state-of-the-art solution for defect detection in high-voltage electrical equipment.

CONCLUSION

This paper proposes a deep learning-based method towards advanced defect detection of high-voltage electrical equipment by analyzing the thermal image. This proposed model, containing the feature extraction part of the CNN AlexNet and the classification part of Random Forest, attains state-of-the-art accuracy of 94.8%, thereby outsmarting several previous approaches. Transfer learning shortened the training times without any loss in accuracy resulting in practically highly efficient. In contrast to other research made from 2021 to 2024, the developed methodology performed better in terms of precision, recall, and generalization. Given its tolerance for large dimensions, which are mainly the nature of thermal data related to electrical equipment, Random Forest can well be used in the classifier. This perspective renders CNN very efficient in classifying the fine features associated with the thermal images. Another comparative justification regarding the robustness of the RF classifier was obtained through the integration of SVM. Results of the study: the method proposed results in high effectiveness for real-time monitoring and maintenance of high-voltage equipment. It significantly reduces electrical failures due to the precise distinction of defects even at an early stage, thereby ensuring safe and reliable operation. Further improvement can be obtained from the developed model by experimenting with other deep architectures of a network or ensemble methods toward improving the efficiency of defect detection across different conditions of operation.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

The study was collaboratively developed by four authors. Jaydeep Kale conceptualized the research and designed the methodology. Santosh Gore acquired thermal images and performed feature extraction using the CNN. Smriti Pathak implemented the classification algorithms and Ishita Dutt and Shreya Virani conducted the statistical analysis. Contributed to the literature review and assisted in drafting and revising the manuscript. Each author played a vital role in ensuring a comprehensive and robust research effort.

REFERENCES

[1] H. Zhang, J. Liu, and Y. Wang, "ResNet-based deep learning model for defect detection in high voltage electrical equipment using thermal imaging," IEEE Trans. Power Delivery, vol. 37, no. 3, pp. 2147–2156, 2022.

[2] Q. Chen, P. Zhou, and S. Liu, "Hybrid CNN-GBM model for defect prediction in high voltage electrical equipment using infrared images," J. Electron. Eng. Technol., vol. 18, no. 1, pp. 56–65, 2023.

[3] S. Mantach, A. Lutfi, H. Moradi Tavasani, A. Ashraf, A. El-Hag, and B. Kordi, "Deep learning in high voltage engineering: A literature review," Energies, vol. 15, no. 14, pp. 5005, 2022.

[4] X. Liu, X. Miao, H. Jiang, and J. Chen, "Review of data analysis in vision inspection of power lines with an in-depth discussion of deep learning technology," arXiv preprint arXiv:2003.09802, 2020.

[5] N. Zhang, G. Yang, D. Wang, F. Hu, H. Yu, and J. Fan, "A defect detection method for substation equipment based on image data generation and deep learning," IEEE Access, 2024.

[6] X. Zheng, R. Jia, L. Gong, G. Zhang, and J. Dang, "Component identification and defect detection in transmission lines based on deep learning," J. Intell. Fuzzy Syst., vol. 40, no. 2, pp. 3147–3158, 2021.

[7] A. Saberironaghi, J. Ren, and M. El-Gindy, "Defect detection methods for industrial products using deep learning techniques: A review," Algorithms, vol. 16, no. 2, pp. 95, 2023.

[8] S. Lei, Y. Guo, Y. Liu, F. Li, G. Zhang, and D. Yang, "Detection of mechanical defects of high voltage circuit breaker based on improved edge detection and deep learning algorithms," in 2022 6th International Conference on Electric Power Equipment-Switching Technology (ICEPE-ST), pp. 372–375. IEEE, 2022.

[9] Y. Lin, Z. Li, Y. Sun, Y. Yang, and W. Zheng, "Voltage-induced heating defect detection for electrical equipment in thermal images," Energies, vol. 16, no. 24, pp. 8036, 2023.

[10] X. Peng, F. Yang, G. Wang, Y. Wu, L. Li, Z. Li, A. A. Bhatti, et al., "A convolutional neural network-based deep learning methodology for recognition of partial discharge patterns from high-voltage cables," IEEE Trans. Power Delivery, vol. 34, no. 4, pp. 1460–1469, 2019.

[11] Z. Ren, F. Fang, N. Yan, and Y. Wu, "State of the art in defect detection based on machine vision," Int. J. Precis. Eng. Manuf. Green Technol., vol. 9, no. 2, pp. 661–691, 2022.

[12] Q. Wen, Z. Luo, R. Chen, Y. Yang, and G. Li, "Deep learning approaches on defect detection in high-resolution aerial images of insulators," Sensors, vol. 21, no. 4, pp. 1033, 2021.

[13] C. Sampedro, J. Rodriguez-Vazquez, A. Rodriguez-Ramos, A. Carrio, and P. Campoy, "Deep learning-based system for automatic recognition and diagnosis of electrical insulator strings," IEEE Access, vol. 7, pp. 101283–101308, 2019.

[14] H. Manninen, C. J. Ramlal, A. Singh, S. Rocke, J. Kilter, and M. Landsberg, "Toward automatic condition assessment of high-voltage transmission infrastructure using deep learning techniques," Int. J. Electr. Power Energy Syst., vol. 128, p. 106726, 2021.

[15] Y. A. Alsumaidaee, C. T. Yaw, S. P. Koh, S. K. Tiong, C. P. Chen, and K. Ali, "Review of medium-voltage switchgear fault detection in a condition-based monitoring system by using deep learning," Energies, vol. 15, no. 18, pp. 6762, 2022.

[16] A. Odo, S. McKenna, D. Flynn, and J. B. Vorstius, "Aerial image analysis using deep learning for electrical overhead line network asset management," IEEE Access, vol. 9, pp. 146281–146295, 2021.

[17] Z. Meng, S. Xu, L. Wang, Y. Gong, X. Zhang, and Y. Zhao, "Defect object detection algorithm for electroluminescence image defects of photovoltaic modules based on deep learning," Energy Sci. Eng., vol. 10, no. 3, pp. 800–813, 2022.

[18] H. Wang, Z. Huang, Y. Chen, X. Zhang, J. Shen, W. Mao, and Z. Hao, "Defect detection from power line images using advanced deep detectors," in 2021 13th International Conference on Wireless Communications and Signal Processing (WCSP), pp. 1–5. IEEE, 2021.

[19] L. Yang, J. Fan, S. Song, and Y. Liu, "A light defect detection algorithm of power insulators from aerial images for power inspection," Neural Comput. Appl., vol. 34, no. 20, pp. 17951–17961, 2022.

[20] Z. Zhang, S. Huang, Y. Li, H. Li, and H. Hao, "Image detection of insulator defects based on morphological processing and deep learning," Energies, vol. 15, no. 7, pp. 2465, 2022.

[21] A. Worrakantapon, W. Pongsena, K. Kerdprasop, and N. Kerdprasop, "Real-time human detection in a restricted area for safety in truck dumper control system using deep learning," Int. J. Electr. Electron. Eng. Telecommun., vol. 10, no. 1, pp. 29–35, Jan. 2021. doi: 10.18178/ijeetc.10.1.29-35.

[22] M. M. Qasaymeh, A. Alqatawneh, and A. F. Aljaafreh, "Intelligent receiver for frequency hopping signals using deep learning," *Int. J. Electr. Electron. Eng. Telecommun.*, vol. 13, no. 5, pp. 366–373, 2024. doi: 10.18178/ijeetc.13.5.366-373.

Jaydeep Kale received his B.E. degree in Computer Engineering from Savitribai Phule Pune University, Pune, India, in 2003, and his M.E. degree in Computer Science and Engineering from Swami Ramanand Teerth Marathwada University, Nanded, India, in 2012. He is currently an Assistant Professor in the Department of Computer Engineering at Sanjivani College of Engineering, Kopargaon, India. His research interests include machine learning, web technologies, and image processing.

Santosh I. Gore is the Director of Sai Info Solution, Nashik, India. He is an awardee recognized for outstanding leadership in agricultural technology solutions. He completed his Bachelor of Engineering in Information Technology from Pravara Rural Engineering College, Ahmednagar, Maharashtra, in 2009. Actively engaged in research, he has contributed as a reviewer for various research publications and mentors PhD and postdoctoral scholars in diverse fields, including data mining, AI/ML, image processing, IoT, network security, cybersecurity, and electronics communication. His expertise spans multiple domains, making him a valuable contributor to the advancement of technology and innovation.

Smriti Pathak serves as the Principal of PCACS in Ravet, Pune, and is the Head of the BBA/BCA Department at PCCOER, also in Ravet, Pune. With an extensive background in academic administration, she plays a vital role in shaping academic programs and supporting student development. Her leadership in higher education highlights her commitment to quality learning and organizational excellence.

Dr. Ishita Dutt is an Assistant Professor at the Symbiosis Centre for Management Studies, affiliated with Symbiosis International (Deemed University) in Pune. With a strong foundation in management studies, Dr. Dutt contributes to the academic growth of students and the research community through her expertise in management education. Her research interests and teaching approach add value to the institution's curriculum.

Dr Shreya Virani is an independent researcher based in Pune, India. With a focus on advancing knowledge through research, she brings unique insights and analytical rigour to her field. As an independent scholar, she collaborates on various research projects and contributes to academic and industry discussions, strengthening research foundations within her areas of expertise.