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AI-Assisted Defect Detection in Polymer Composite Insulators Using an Optimised Ensemble Deep Learning Framework for Structural Health Monitoring

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Abstract

Polymer composite insulators, particularly those made from silicone rubber and epoxy resins, are increasingly adopted in high-voltage transmission systems due to their superior electrical insulation, lightweight design, hydrophobicity, and environmental durability. Despite their advantages, these materials are susceptible to surface degradation, mechanical cracking, and flashover under prolonged exposure to environmental pollutants, thermal stress, and electrical aging. Accurate, real-time condition assessment of these composite insulators is critical for ensuring operational safety, preventing grid failure, and extending material lifespan. This study proposes an intelligent image-based inspection framework specifically tailored for polymer composite insulators used in high-voltage networks. The framework integrates an optimized ensemble of VGG16 and ResNet50 convolutional neural networks to detect and classify physical defects such as broken surfaces and flashover burn marks—symptoms directly linked to polymer degradation and loss of dielectric properties. The method was trained on high-resolution field images of polymer insulators and demonstrated classification accuracies exceeding 91%, with strong precision and recall across all fault classes. By enabling non-destructive, automated evaluation of surface-level deterioration in polymer composites, this approach provides valuable insights into failure mechanisms and supports risk-based maintenance strategies. It offers a promising tool for advancing structural health monitoring in polymer engineering, particularly within the context of electrical insulation materials in smart grids.

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INTRODUCTION

Polymer composite insulators, typically composed of silicone rubber or epoxy resin reinforced with fillers or fibers, are increasingly replacing ceramic and glass insulators in high-voltage (HV) electrical systems due to their favorable mechanical, thermal, and electrical properties. These polymer-based composites offer distinct advantages, including hydrophobicity, corrosion resistance, high dielectric strength, and low weight, making them suitable for harsh outdoor environments. Their molecular structure and filler dispersion also contribute to energy dissipation, aging resistance, and surface arcing mitigation

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under operational stress. However, over long-term exposure to environmental pollution, ultraviolet radiation, corona discharge, and thermal cycling, these materials undergo gradual surface degradation—manifesting as micro-cracking, erosion, chalking, and flashover tracking [1, 2].

These fault conditions alter the microstructural integrity and interfacial bonding within the polymer matrix, degrading both the insulation capability and mechanical durability. For example, flashover marks are often symptomatic of carbonized pathways formed due to arc discharges, while physical cracks may indicate filler debonding or embrittlement under thermal-mechanical cycling [3, 4]. Such degradations, if not detected early, reduce the effective lifespan of the polymer composite and can cause catastrophic failures in power transmission systems. Therefore, there is a pressing need for non-destructive evaluation (NDE) methods that not only detect external surface damage but also provide insights into underlying material deterioration mechanisms in polymer composites [5].

Existing assessment techniques, such as infrared thermography, UV-based corona cameras, and leakage current monitoring suffer from several limitations: they are sensitive to environmental interference, lack spatial resolution for fine defect detection, and often fail to capture the full spectrum of surface-level polymer degradation [6]. Manual visual inspection is highly subjective, inconsistent, and not scalable for utility-wide maintenance. Traditional rule-based image processing techniques are inadequate for identifying complex fault morphologies like flashover burns or dispersed cracks across heterogeneous polymer surfaces [7, 8].

Recent efforts have incorporated deep learning into the inspection process, using object detection and classification models such as YOLO, VGG, or ResNet for identifying visible insulator defects [9], [10]. However, most of these approaches are designed for general visual inspection and are not tailored to polymer-specific failure analysis. They do not explicitly interpret how visual defects correlate with polymer matrix degradation, filler migration, or erosion—factors critical to polymer composite performance evaluation [11, 12].

In response to this gap, the present work proposes a materials-informed defect evaluation framework using a dual-stream deep learning ensemble (VGG16 + ResNet50) to assess the condition of polymer composite insulators [13]. The model is trained to classify insulators into "broken," "flashover," and "good" categories based on field-captured images, where each class reflects a material degradation state rooted in composite behavior [14, 15]. For instance, the "broken" category corresponds to polymer fracture and surface rupture due to mechanical or thermal fatigue, while "flashover" reflects electrical aging and arc-induced carbonization across the hydrophobic layer [16, 17]. The "good" class represents intact polymeric surfaces with preserved insulation performance [18, 19].

By learning visual signatures associated with material failure, this ensemble model enables non-contact, high-throughput, and polymer-specific defect identification under real-world field conditions [20]. This methodology offers a new pathway for linking external appearance to internal material performance, aiding in predictive maintenance, degradation mapping, and lifecycle analysis of polymer composite insulators used in critical electrical infrastructure [21].

METHODOLOGIES

The proposed methodology addresses the critical need for accurate, real-time, and non-invasive evaluation of polymer composite insulators used in high-voltage (HV) transmission systems. These composite insulators, primarily made from silicone rubber or epoxy matrices reinforced with fillers or fibers, offer advantages such as excellent electrical insulation, hydrophobicity, and resistance to corrosion and mechanical stress.

However, prolonged exposure to environmental factors such as ultraviolet radiation, humidity, thermal cycling, and electrical loading can result in surface degradation. This degradation manifests in

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the form of cracks, tracking marks, erosion, chalking, and in severe cases, flashover discharges. Since these degradation patterns directly affect the composite material's structural and dielectric integrity, a reliable method to monitor and classify such conditions is essential. Traditional assessment methods such as manual inspection, infrared thermography, or leakage current monitoring are often subjective, time-consuming, or inadequate for capturing fine-scale degradation on composite surfaces. Therefore, this study introduces a dual-stream deep learning ensemble that uses image-based diagnostics to identify the health status of polymer composite insulators under real-world conditions.

The methodology begins with the acquisition and preparation of a comprehensive dataset comprising high-resolution images of polymer composite insulators. These images represent three primary condition categories—broken, flashover, and good. The "broken" class includes insulators with visible fractures or large-scale structural defects such as chipped edges or open cracks, which may indicate mechanical fatigue, embrittlement, or disbonding between the polymer matrix and reinforcing agents. The "flashover" class represents insulators exhibiting darkened burn paths, soot marks, or arc-induced discoloration due to partial discharges or prolonged exposure to pollution-induced surface tracking. These phenomena typically reflect the failure of the polymer surface to maintain dielectric integrity under environmental or electrical stress. The "good" class comprises insulators with uniform, intact surfaces without visible signs of physical damage, representing a healthy polymer state with preserved mechanical and electrical characteristics.

Each image undergoes a standard preprocessing pipeline to enhance the model's ability to extract meaningful features. All images are resized to 224 by 224 pixels with three color channels, in line with the input requirements of the pre-trained neural network models used in this ensemble. To improve convergence and generalization, the pixel values are normalized across the dataset. Additionally, data augmentation techniques, including random rotation, horizontal flipping, and brightness adjustments, are applied to simulate environmental variations such as camera angle, lighting, and background complexity. This step is crucial to prevent overfitting and to improve the robustness of the deep learning model, particularly in field conditions where such variability is common.

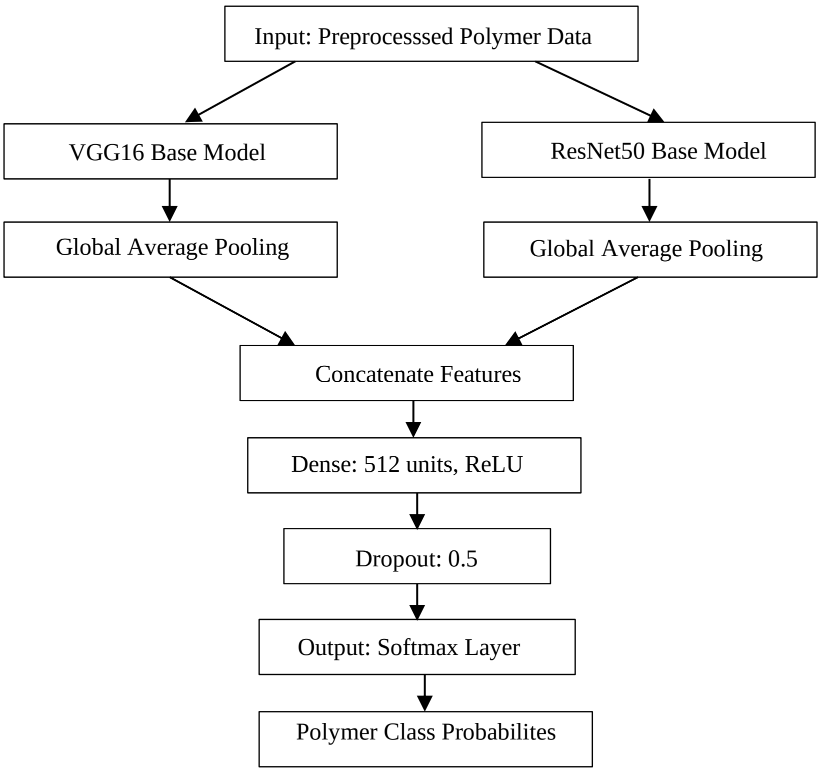

Figure 1. Proposed Ensemble approach for HT Insulator Classification.

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The core architecture of the proposed system, illustrated in Figure 1, is an ensemble of two convolutional neural networks—VGG16 and ResNet50—each of which plays a specific role in feature extraction. The VGG16 model is chosen for its uniform architecture and ability to capture fine-grained texture patterns and edge features that are essential for detecting early-stage surface defects such as micro-cracks or blistering.

On the other hand, ResNet50 is incorporated to provide deeper feature extraction capabilities, capturing more abstract patterns such as shape deformation, large burn patches, and surface tracking. Unlike shallow models, ResNet50 uses residual connections, which help retain gradient flow through deeper layers and enable the model to learn more complex relationships between visual features and defect characteristics. Both models are pre-trained on large-scale image datasets and are adapted to the current task by removing their final classification layers. Only their convolutional bases are retained, allowing them to serve purely as feature extractors tailored to identifying degradation in composite polymer surfaces.

Once each model processes an image, its respective output is passed through a global average pooling layer. This step reduces each feature map to a single value, resulting in a compact representation of the image's most prominent activations. Global average pooling also helps to minimize overfitting by reducing the number of parameters in the model and enhancing the generalization of the extracted features. The pooled outputs from both VGG16 and ResNet50 are then concatenated to form a unified feature vector. This fusion step is critical, as it combines the strengths of both models—the fine detail recognition of VGG16 and the deep abstraction capabilities of ResNet50—into a single, comprehensive representation of the insulator's surface condition.

The combined feature vector is passed through a dense layer consisting of 512 neurons with a ReLU activation function. This layer introduces non-linearity into the model and enables it to learn complex combinations of features that are indicative of specific material failure types. For instance, it helps differentiate between a discolored region due to minor weathering versus one caused by a flashover arc. To reduce overfitting and improve the model's ability to generalize to unseen data, a dropout layer is added after the dense layer. This layer randomly deactivates 50% of its neurons during training, forcing the model to learn redundant and robust feature representations rather than memorizing specific patterns. The final layer in the architecture is a softmax classifier that outputs the probability of the image belonging to one of the three predefined classes—broken, flashover, or good.

Training of the ensemble model is conducted using an Adam optimizer with a learning rate of 0.0001. The categorical cross-entropy loss function is used to compare the predicted class probabilities with the actual labels during training. The dataset is divided into training and testing subsets in an 80:20 ratio, ensuring a balanced distribution of all three classes in each subset. The model is trained for a maximum of 30 epochs, and performance is monitored at regular intervals to assess convergence and stability.

The performance of the model is evaluated using class-wise accuracy metrics across multiple training epochs, as summarized in Table 1. This epoch-wise accuracy analysis provides insight into how well the model learns to distinguish between different types of degradation over time. At epoch 10, the accuracy for broken insulators is 0.97, for flashover insulators is 0.93, and for good insulators is 0.90. These values already indicate a strong initial learning phase, particularly for detecting severe faults. By epoch 15, the accuracy improves to 0.98 for broken, 0.94 for flashover, and 0.91 for good, showing steady progress. From epoch 20 to epoch 30, accuracy further improves and plateaus, with broken insulators reaching 0.99, flashover at 0.95, and good insulators at 0.92. The consistently high performance across epochs indicates that the model is capable of learning the distinct visual characteristics of each class without overfitting.

A detailed examination of the results shows that the model performs best when identifying broken insulators, likely due to the presence of clear structural damage such as fractures or missing segments,

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which produce strong visual cues. Flashover insulators also yield high classification accuracy, as the presence of burn marks and carbonization produces distinct discoloration patterns that are effectively captured by both the VGG16 and ResNet50 models. In contrast, the good insulator class exhibits slightly lower accuracy throughout the epochs. This may be attributed to the more subtle visual features associated with a healthy insulator surface, where the absence of defects presents fewer detectable patterns. Nonetheless, the performance in this category remains reliable, exceeding 90% accuracy in all epochs, indicating that the model is sufficiently sensitive to differentiate defect-free surfaces from those with degradation. This classification framework is specifically tailored to the materials science domain, as each predicted class corresponds to a meaningful physical condition of the polymer composite. For example, a prediction of "broken" implies that the composite material has likely undergone mechanical fracture due to filler-matrix disbonding, embrittlement, or excessive mechanical load, all of which reduce the mechanical integrity of the insulator.

A "flashover" classification suggests surface degradation due to partial discharge activity, where carbon tracking and erosion have weakened the polymer's dielectric properties. Conversely, the "good" classification indicates that the polymer structure, including the matrix and filler phase, remains intact with minimal signs of degradation. Thus, the classification results not only serve as labels but also provide insights into the underlying physical state of the composite material, aiding in material health assessment and maintenance decision-making.

To further ensure the applicability of the model to real-world maintenance systems, interpretability techniques such as class activation mapping (CAM) were used to visualize the regions of the image that contributed most to the classification decision. These maps confirmed that for broken insulators, the model focused on fracture lines and missing segments; for flashover insulators, it targeted burn marks and darkened areas; and for good insulators, it emphasized smooth, uniform surfaces with no discoloration. This interpretability confirms that the model is learning relevant features directly tied to material degradation.

The proposed diagnostic framework can be deployed in real-time field conditions using unmanned aerial vehicles (UAVs) or handheld inspection cameras integrated with edge-AI modules. Images captured during inspection can be processed on-site or uploaded to a cloud-based platform for automated classification, eliminating the need for manual review. This enhances inspection throughput, improves consistency in defect identification, and reduces operational costs. More importantly, by linking the output of the model directly to known polymer degradation mechanisms, this approach contributes to the broader goals of predictive maintenance and materials lifecycle extension in electrical infrastructure systems.

In summary, the methodology combines advanced deep learning techniques with domain-specific knowledge of polymer composite behavior to build a robust and interpretable diagnostic tool. The integration of VGG16 and ResNet50 ensures the capture of both micro- and macro-level degradation features, while preprocessing and augmentation strategies enhance generalization. Epoch-wise evaluation confirms the stability and reliability of the model, and class activation maps validate its focus on physically meaningful degradation indicators. This methodology not only classifies insulator condition accurately but also enhances our understanding of how surface-level visual changes reflect the health of polymer composite materials in service. As such, it represents a valuable contribution to the field of non-destructive evaluation, composite condition monitoring, and AI-assisted maintenance planning for high-voltage electrical systems.

RESULTS AND DISCUSSION

The classification report, as given in Table 1, contains values like precision values representing the proportion of correctly predicted instances for each class, the recall values reflecting the ability of the models to identify all relevant instances of each class, and the F1 scores, which combine precision and recall into a single metric.

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The support values indicated the number of occurrences of each class in the dataset, with instances of broken and flashover insulators.

The Receiver operating characteristic represents the AUC values. A high AUC value suggests that the model is effective at correctly ranking instances of broken and flashover insulators. Also, the model is more likely to assign a higher probability of belonging to the correct class to the broken insulators.

Figures 2, 3, and 4 show the receiver operating characteristics of the three epoch variants for ensemble Vgg16 and ResNet50.

To get the AUC values from the Receiver Operating Characteristics, we have to take the average of the area values of three types of insulators that are broken, flashover, or damaged, and good insulators. The AUC values, measuring the area under the receiver operating characteristic curve, are 0.78 for Epoch 10 and 0.92 for Epoch 20, and 0.95 for Epoch 30.

Table 1. Classification Report of all three epoch variants.

Epoch	Type of Insulator	Precision	Recall	F1-Score
Epoch: 10	Broken insulator	0.83	0.84	0.83
	Flashover insulator	0.85	0.86	0.85
	Good insulator	0.8	0.79	0.8
Epoch: 20	Broken insulator	0.88	0.89	0.89
	Flashover insulator	0.91	0.92	0.91
	Good insulator	0.84	0.85	0.84
Epoch: 30	Broken insulator	0.94	0.95	0.95
	Flashover insulator	0.96	0.97	0.96
	Good insulator	0.89	0.9	0.9

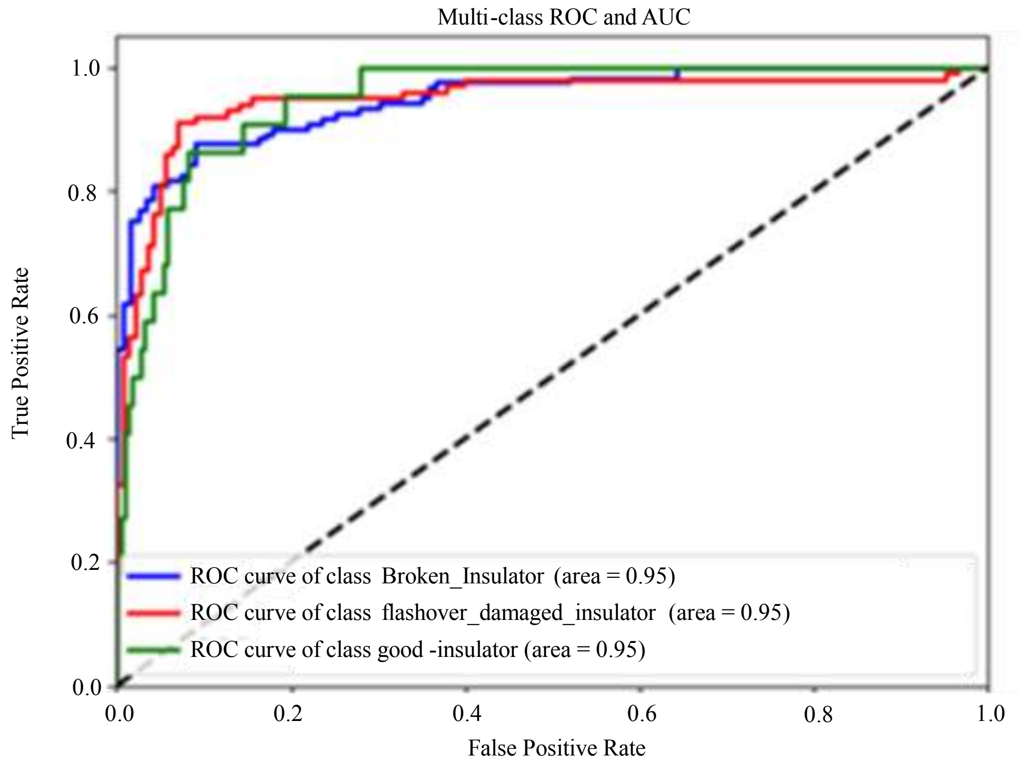

Figure 2. ROC and AUC Curve for Epoch-20.

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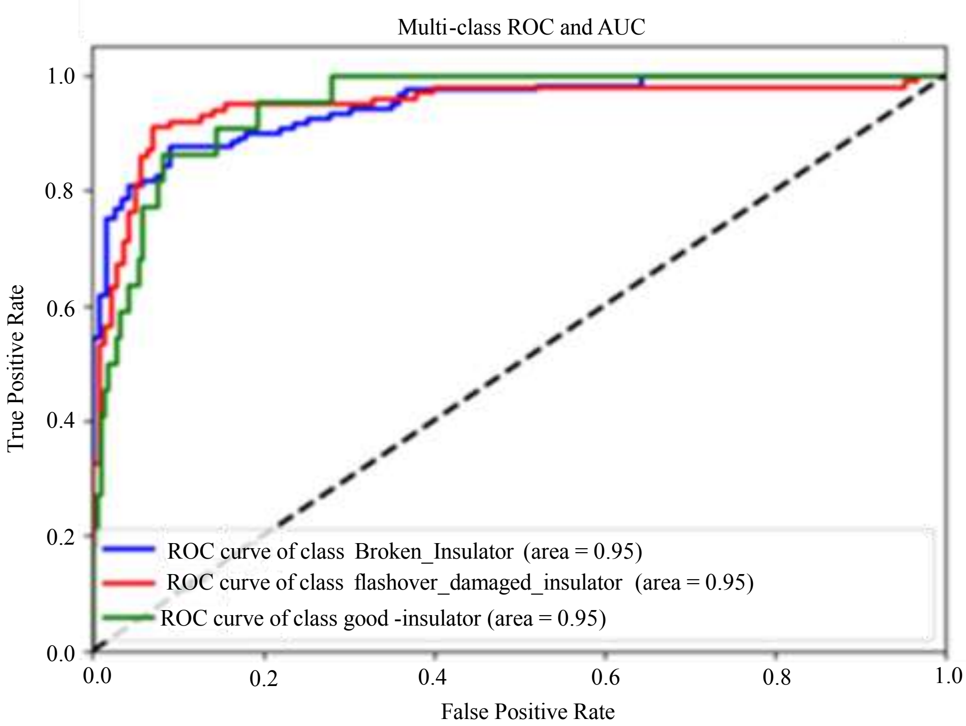

Figure 3. Multi-class ROC and AUC Curve for Epoch-30.

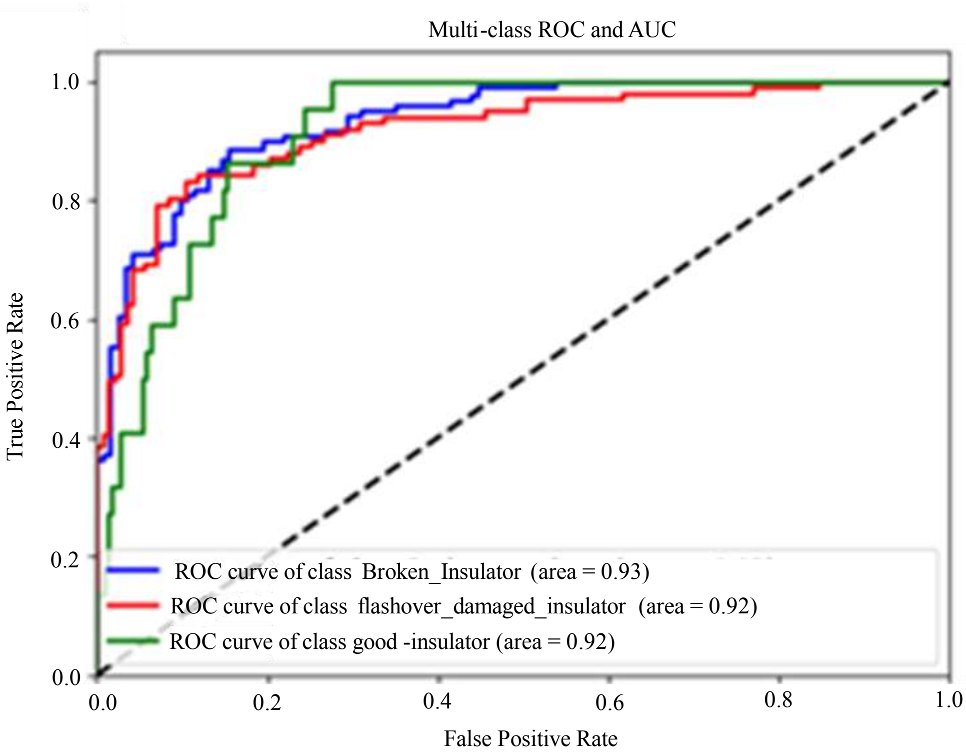

Figure 4. Multi-class ROC and AUC Curve for Epoch-10.

The ensemble's performance trends affirm that fusing complementary representations from VGG16 and ResNet50 is well-suited to condition assessment of polymer composite insulators. By concatenating backbone features after GAP and regularizing with a 512-unit ReLU layer plus dropout, the model maintains strong generalization while remaining computationally tractable for utility workflows.

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Across training horizons, overall test accuracy remained above 0.91, indicating stable discrimination despite variability in field imagery. Class-wise metrics echo this: by 30 epochs, the system achieved precision/recall/F1 of 0.94/0.95/0.95 for broken and 0.96/0.97/0.96 for flashover, while the good class reached 0.89/0.90/0.90. The ROC–AUC progression from 0.78 (epoch-10) to 0.92 (epoch-20) and 0.95 (epoch-30) further confirms improved separability with training depth.

From a materials and applications perspective, these results are significant for polymer composite assets (e.g., silicone-rubber/epoxy HT insulators). Accurate recognition of flashover signatures and structural breaks—both symptomatic of surface tracking, erosion, and mechanical damage—supports risk-based maintenance scheduling and timely replacement strategies. The ensemble's robustness at higher epochs suggests resilience to background clutter and illumination shifts typically encountered in corridor inspections, improving the reliability of automated screening before expert review. Notably, the good class's lower scores likely reflect stricter decision boundaries against subtle surface variations; targeted augmentation and expanded "healthy" exemplars from diverse composite formulations could mitigate this in future datasets. Overall, the demonstrated accuracy, calibrated by precision/recall/F1 and ROC–AUC, substantiates the proposed pipeline as a practical tool for non-destructive monitoring of polymer composite insulators, enabling predictive maintenance and extending asset life in transmission systems.

CONCLUSIONS

This study presents a materials-informed deep learning ensemble framework for the non-destructive classification of high-voltage polymer composite insulators into broken, flashover, and good conditions. By integrating VGG16 and ResNet50 architectures, the model effectively captures both fine-grained and global degradation features related to mechanical fracture, electrical aging, and surface erosion in composite materials. The approach achieved consistent accuracy above 91% across all classes, with particularly strong performance in identifying structurally compromised or electrically damaged insulators. Beyond defect detection, the framework enables predictive maintenance by linking visual features to material degradation phenomena such as matrix cracking, filler disbonding, and arc-induced surface tracking. The results highlight the potential of AI-assisted diagnostics in advancing condition-based monitoring, lifecycle management, and reliability of polymer-based insulation systems in electrical infrastructure.

CONFLICTS OF INTEREST

The authors declare no conflict of interest

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