Application of Computer Vision Technology in Defect Detection of Electrical Engineering Equipment and Strategies for Improving Recognition Accuracy

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ABSTRACT Addressing the limitations of traditional electrical equipment defect detection methods, including low efficiency, high missed detection rates, strong subjectivity, and insufficient real-time performance, this paper investigates the application of computer vision technology and corresponding strategies for improving recognition accuracy. Reliable defect identification is essential for ensuring the operational safety and electromagnetic reliability of modern power equipment and intelligent electromagnetic infrastructures. First, based on image processing, deep learning, and pattern recognition theories, a computer vision framework for electrical equipment defect detection is established, covering image acquisition, preprocessing, feature extraction, and defect classification. Second, through field investigations and experimental analysis, the visual characteristics of typical defects in transformers, circuit breakers, and insulators are systematically analyzed, while key challenges including complex environmental interference, limited small-sample recognition capability, and inadequate feature extraction are identified. Finally, an experimental platform is constructed using three representative categories of electrical engineering equipment, and comparative experiments are conducted to evaluate multiple optimization strategies. The results demonstrate that the proposed approach effectively improves defect recognition performance and provides a practical solution for intelligent electromagnetic equipment inspection, condition monitoring, and reliability enhancement in advanced power systems.

INDEX TERMS computer vision, electrical engineering equipment, defect detection, recognition accuracy, electromagnetic equipment diagnostics

I. INTRODUCTION

A. RESEARCH BACKGROUND

ELECTRICAL engineering equipment serves as the core infrastructure for the safe and stable operation of power systems, with its health status directly determining the reliability and safety of power supply, which is especially critical for maintaining the continuous, high-energy demands of manufacturing processes. As China's power systems rapidly advance toward ultra-high voltage and intelligent technologies, the number of critical devices such as transformers, circuit breakers, and insulators has significantly increased [1]. Concurrently, operating environments have grown increasingly complex, markedly elevating the risk of failures caused by equipment defects [2]. According to statistics from the National Energy Administration, equipment defects accounted for 42.3% of power system failures in China during 2022. Among these, large-scale blackouts caused by defects in equipment rated at 35kV and above increased by 18.7% year-on-year [3].

B. CURRENT RESEARCH STATUS AT HOME AND ABROAD

Traditional research on electrical equipment defect detection has primarily focused on optimizing individual detection methods. Internationally, Siemens optimized the application parameters of ultrasonic detection technology for internal transformer defect detection, achieving a detection resolution of 0.1mm [4]. ABB Group developed a circuit breaker defect diagnosis system based on partial discharge detection, effectively identifying insulation aging defects [5]. Domestically, the State Grid research team improved infrared thermal imaging detection technology, enabling precise localization of equipment heating defects through temperature field analysis [6]. The East China Electric Power Design

Institute proposed a mechanical defect detection method based on vibration signal analysis, enhancing the timeliness of mechanical fault identification [7].

C. RESEARCH CONTENT

Analysis of Electrical Equipment Defect Types and Visual Features: Categorizing core defect types in typical equipment like transformers, circuit breakers, and insulators, and extracting visual features (shape, color, texture, grayscale) for each defect category.

Construction of Computer Vision Defect Detection Technology Framework: Building an end-to-end technical framework—"image acquisition → preprocessing → feature extraction → defect recognition → result output"—based on image processing and deep learning theories.

Identification of Key Technical Bottlenecks in Defect Detection: Through experimental analysis, pinpoint core issues affecting recognition accuracy, such as complex environmental interference, small-sample defects, and imprecise feature extraction.

Design and Validation of Accuracy Improvement Strategies: Develop optimization strategies across three dimensions—image preprocessing, model refinement, and data fusion—and experimentally validate their effectiveness.

II. THEORETICAL FOUNDATIONS

A. CORE THEORIES OF COMPUTER VISION TECHNOLOGY

1) Image Processing Technology

Image processing forms the foundation of computer vision-based defect detection, comprising three core stages: image preprocessing, feature extraction, and image segmentation.

Image Preprocessing: Enhances image quality through denoising, enhancement, and geometric correction to provide clear data for subsequent processing. Common algorithms include Gaussian filtering, median filtering, adaptive histogram equalization (AHE), and Retinex enhancement [8,9].

Feature Extraction: Extracts key defect-representative information from preprocessed images, including shape features (area, perimeter, circularity), color features (RGB mean, HSV histogram), and texture features (grayscale co-occurrence matrix, LBP features) [10-12].

Image Segmentation: Isolating defect regions from the background. Common algorithms include threshold segmentation, edge detection, region growing, and semantic segmentation. Among these, deep learning-based semantic segmentation algorithms (e.g., Mask R-CNN) demonstrate superior segmentation performance in complex scenarios [13-15].

2) Deep Learning Theory

Deep learning provides core technological support for automatic feature extraction and precise defect recognition. Common models include:

Convolutional Neural Networks (CNNs): Automatically extract and classify image features through convolutional, pooling, and fully connected layers, suitable for defect classification tasks. Representative models include LeNet, AlexNet, and ResNet [16].

Object Detection Models: Simultaneously locate and classify defects, suitable for multi-defect detection in complex backgrounds. Representative models include Faster R-CNN, YOLO series, and SSD [17].

Few-shot learning models: Designed for defect detection scenarios with limited samples, these models enhance generalization capabilities through meta-learning and transfer learning. Representative models include Prototypical Network and Matching Network [18].

B. THEORETICAL FOUNDATIONS OF ELECTRICAL EQUIPMENT DEFECT DETECTION

The formation of defects in electrical equipment is closely related to operational environments, material properties, and maintenance standards:

Electrical defects: Caused by factors like insulation aging, partial discharge, and overvoltage, e.g., insulator flashover, transformer insulating oil degradation [19].

Mechanical defects: Resulting from component wear, loosening, deformation, etc., e.g., circuit breaker operating mechanism jamming, poor contact in disconnect switches [20].

Thermal defects: Resulting from excessive contact resistance or abnormal loads causing equipment overheating, such as joint overheating or winding heating [21-23].

Different defect types exhibit distinct formation mechanisms and visual characteristics, providing identification criteria for computer vision-based detection.

C. KEY TECHNOLOGY INTEGRATION LOGIC

The integration of computer vision technology with electrical equipment defect detection follows a logical chain: "Data - Features - Models - Decision":

Data Layer: Acquires multi-source heterogeneous image data (including visible light texture data and infrared thermal distribution data) of equipment through image capture devices, covering samples from diverse environments and defect types.

Feature Layer: Combines traditional image processing with deep learning techniques to achieve precise extraction of defect features, balancing robustness and discriminative power.

Model Layer: Selects appropriate deep learning models based on defect types and inspection scenarios to achieve precise defect recognition and classification.

Decision Layer: Generates defect severity assessments and maintenance recommendations based on model outputs, integrated with equipment operational data and historical defect records [24,25].

III. ANALYSIS OF ELECTRICAL EQUIPMENT DEFECT TYPES AND VISUAL FEATURES

A. CORE DEFECT TYPES IN TYPICAL ELECTRICAL EQUIPMENT

1) Transformer Defect Types

As core equipment in power systems, transformers exhibit primary defect categories including:

Insulation-related defects: insulator flashover, bushing cracks, moisture-induced insulation oil degradation, etc.;

Thermal defects: winding overheating, joint overheating, multi-point grounding core heating, etc.;

Mechanical defects: tank deformation, radiator blockage, tap changer contact failure, etc. [26]

2) Circuit Breaker Defect Types

Circuit breakers perform control and protection functions in power systems. Primary defect types include:

Insulation-related defects: arc-extinguishing chamber insulation aging, porcelain sleeve damage, moisture ingress in insulating rods, etc.

Mechanical defects: operating mechanism sticking, link deformation, contact wear, etc.

Thermal defects: contact overheating, terminal heating, etc. [27]

3) Insulator Defect Types

Insulators ensure equipment insulation and mechanical fixation. Primary defect types include:

Mechanical defects: Insulator breakage, string detachment, steel foot corrosion, etc.

Electrical defects: Insulator contamination, flashover marks, insulation layer aging/peeling, etc.

Installation defects: Insulator tilt, hardware loosening, etc. [28]

B. VISUAL FEATURE EXTRACTION AND ANALYSIS OF DEFECTS

High-definition cameras captured image samples of various defects (12,000 samples in total, including 3,000 normal samples and 9,000 defective samples). Image processing techniques were employed to extract visual features of defects, yielding the following results:

Thermal defects: In visible light images, these defects appear in high-temperature color tones such as red and yellow; in infrared images, they manifest as high-brightness areas.

Insulation degradation defects: After aging, the insulator's insulation layer turns grayish-white or yellowish-brown, forming a stark contrast with the normal insulator's bluish-gray color.

Corrosion defects: Corroded steel feet and fittings exhibit reddish-brown or dark red hues, with color intensity positively correlated with corrosion severity [29,30].

Contamination Defects: Contaminated insulator surfaces exhibit uneven textures with dispersed grayscale values, distinctly differing from the uniform texture of normal surfaces.

Crack Defects: Cracked areas show lower grayscale values than surrounding normal regions, forming noticeable grayscale gradients.

Damage Defects: Damaged areas exhibit high grayscale contrast with normal regions and texture continuity fracture in defect areas (manifested as sudden changes in grayscale values and discontinuous edge contours).

For ceramics, glass, and other insulators with no obvious color change, accurate identification of aging defects is achieved through the multimodal fusion method of 'visible light images capturing texture/crack features + infrared images capturing local temperature rise caused by insulation aging'.

C. DEFECT SAMPLE DATASET CONSTRUCTION

To support model training and validation, the Electrical Engineering Equipment Defect Image Dataset (EEED-2024) was constructed. Specific dataset details are as follows:

Sample Size: 12,000 images, comprising 8,400 training images (70%), 2,400 validation images (20%), and 1,200 test images (10%).

Defect Type Coverage: 3 equipment categories and 12 core defect types, with 500–1,000 samples per defect type.

Environmental Diversity: Samples represent five typical conditions: normal lighting, strong lighting, low lighting, rainy/snowy weather, and occlusion.

Data Annotation: Defect regions annotated using LabelImg in Pascal VOC format, including defect category and bounding box coordinates, refer to Table 1 for details.

TABLE 1. Defect Type Sample Distribution

Defect Type	Sample Size	Training Set (70%)	Validation Set (20%)	Test Set (10%)
Insulator Flashover	750	525	150	75
Bushing Crack	800	560	160	80
Insulating Oil Degradation	650	455	130	65
Winding Overheating	700	490	140	70
Joint Overheating	850	595	170	85
Tank Deformation	500	350	100	50
Arc Extinguishing Chamber Insulation Aging	750	525	150	75
Porcelain Sleeve Damage	600	420	120	60
Operating Mechanism Jamming	550	385	110	55
Insulator Contamination	900	630	180	90
Steel Foot Corrosion	850	595	170	85
Installation Tilt	900	630	180	90
Total (Defective Samples)	9000	6300	1800	900

IV. COMPUTER VISION DEFECT DETECTION FRAMEWORK AND BOTTLENECK IDENTIFICATION

Based on computer vision and deep learning theories, a defect detection technology framework for electrical engineering equipment was constructed. This framework comprises five core modules:

Designing a three-stage preprocessing workflow: "Noise Reduction - Image Enhancement - Geometric Correction":

Noise Reduction: Selecting tailored algorithms for different noise types—Gaussian filtering for Gaussian noise, median filtering for salt-and-pepper noise, and adaptive Wiener filtering for complex noise.

Image Enhancement: Employing the Retinex algorithm to address uneven illumination, and utilizing Adaptive Histogram Equalization (AHE) to enhance contrast between defects and background.

Geometric Correction: Applying perspective transformation to correct image distortion, and employing image registration techniques to eliminate feature shifts caused by variations in acquisition angles.

Hybrid feature extraction scheme combining "traditional features + deep learning features":

Traditional feature extraction: Texture features extracted via grayscale co-occurrence matrices, shape features via morphological operations, and color features via color space transformations.

Deep learning feature extraction: Feature extractor built using a CNN network (ResNet50) to automatically learn deep semantic features of defects, avoiding the subjectivity and limitations of manual feature extraction.

Selecting Adaptive Models Based on Defect Type and Detection Scenario: Single Defect Detection: Utilizes a CNN classification model (ResNet50) for defect type recognition.

Multi-Defect Detection: Employs an object detection model (YOLOv7) for defect localization and classification.

Small-Sample Defect Detection: Combines transfer learning with a Prototypical Network model to enhance recognition capabilities for defects with limited training data.

V. DESIGN OF ACCURACY IMPROVEMENT STRATEGIES

To address the aforementioned technical bottlenecks, strategies for enhancing defect detection accuracy in electrical equipment are designed across three dimensions: image preprocessing optimization, deep learning model refinement, and multimodal data fusion.

A. IMAGE PREPROCESSING OPTIMIZATION STRATEGY

Adaptive noise suppression is achieved through an improved bilateral filtering algorithm: by integrating local grayscale information with spatial distance, the filter kernel parameters are dynamically adjusted to remove noise while preserving defect details. The core algorithmic formula is as follows:

$$
\begin{aligned}
B(x,y) = C(x,y)^{-1} &\sum_{(i,j)\in S} f(i,j) \\
&\cdot \exp\left(-\frac{(x-i)^2+(y-j)^2}{2\sigma_d^2}\right) \\
&\cdot \exp\left(-\frac{\|f(x,y)-f(i,j)\|^2}{2\sigma_r^2}\right)
\end{aligned}
$$

Where $B(x,y)$ is the filtered pixel value, $f(x,y)$ is the original pixel value, σ_d is the spatial domain standard deviation, and σ_r is the grayscale domain standard deviation. Adaptive thresholding dynamically adjusts σ_d and σ_r values.

Lighting balance is achieved using a multi-scale Retinex algorithm: by decomposing the image into reflection and illumination components, the illumination component undergoes adaptive adjustment to address image quality issues caused by strong or weak lighting. The algorithmic workflow includes: multi-scale image decomposition, illumination component estimation, reflection component enhancement, and image reconstruction. This effectively suppresses glare and shadows while enhancing image contrast.

B. DEEP LEARNING MODEL IMPROVEMENT STRATEGIES

1) Attention Mechanism-Enhanced CNN Model

Building upon the ResNet50 architecture, we integrate channel attention (SENet) and spatial attention (CBAM) mechanisms to construct a dual-attention-enhanced CNN model, thereby strengthening defect feature extraction capabilities:

Channel Attention Mechanism: Adaptively adjusts weights across feature channels to amplify focus on critical defect-detection channels while suppressing interference from irrelevant channels;

Spatial Attention Mechanism: Focuses on the spatial region containing defects to enhance the extraction accuracy of local defect features;

Model Structure Optimization: Attention modules are added to stages 3 and 4 of ResNet50, forming a "Convolution-Attention-Pooling" feature extraction unit to improve the discriminative power of deep semantic features.

2) Transfer Learning and Meta-Learning Fusion Approach for Few-Example Defect Detection

Transfer Learning: Based on a pre-trained YOLOv7 model on the ImageNet dataset, freeze the backbone network parameters and train only the classification and detection heads. Leverage the pre-trained model's general feature extraction capabilities to improve feature learning efficiency for small-sample defects;

Meta-Learning: Integrates Prototypical Networks with MAML (Model-Agnostic Meta-Learning) to establish a meta-learning training framework. Through "task-level" training, the model learns universal feature representations across defect types, accelerating adaptation to small-sample defects.

Data Augmentation: Employing techniques such as random cropping, rotation, flipping, noise injection, and MixUp to expand training data for small-sample defects, mitigating sample scarcity issues.

3) Multi-Scale Adaptive Defect Detection Model

To address the identification needs of defects at different scales (e.g., large fractures and microscopic cracks), the detection head structure of the YOLOv7 model is enhanced:

Added a small-scale detection branch: Incorporated an additional detection branch with 16x downsampling at the model's output layer to enhance detection accuracy for small defects.

Adaptive anchor clustering: Utilized the K-Means clustering algorithm based on defect bounding box information from the dataset to generate anchors tailored to different defect scales, improving the model's localization precision.

Feature fusion optimization: Employed PANet (Path Aggregation Network) to enhance feature fusion across scales. Through top-down and bottom-up feature propagation, this improved the model's ability to identify multi-scale defects.

C. MULTIMODAL DATA FUSION STRATEGY

1) Visible Light and Infrared Image Fusion Detection

Leveraged the detailed texture information from visible light images and the thermal feature information from infrared images to construct a multimodal fusion detection model:

Data-Layer Fusion: Employing a wavelet-based image fusion algorithm, pixel-level information from visible and infrared images is integrated to generate a fused image combining both detailed texture and thermal characteristics.

Feature-Layer Fusion: Texture and shape features are extracted from visible images, while thermal distribution features are extracted from infrared images. These are fused through feature concatenation and attention-weighted integration to form a multidimensional feature vector.

To achieve pixel-level fusion, multimodal image registration and calibration must first be completed, following the process below:

Hardware Calibration: Use Zhang Zhengyou's calibration method for intrinsic parameter calibration of visible light cameras and infrared thermal imagers to obtain parameters such as focal length and principal point coordinates; complete extrinsic parameter calibration through a chessboard calibration board to establish the spatial position conversion relationship.

Image Preprocessing: Interpolate and upscale infrared images to a unified resolution of 1920×1080 pixels, consistent with visible light images.

Feature Matching and Geometric Correction: Use the SIFT algorithm to extract key feature points, eliminate mismatched points via the RANSAC algorithm, and solve the homography matrix to achieve geometric correction of infrared images, ensuring spatial alignment of defect areas.

Registration Effect Verification: After registration, the overlap rate of defect areas between the two types of images reaches over 95%, and the average gradient value of pixel-level fusion is 28% higher than that of unregistered fusion.

D. CROSS-SOURCE DATA COMPLEMENTARITY AND FEATURE CALIBRATION

Integrate cross-source data including drone-captured images, fixed camera surveillance footage, and handheld device images to establish a data complementarity mechanism:

Cross-Source Data Alignment: Employ image registration techniques to spatially align images from different sources and angles, ensuring consistency in defect features;

Feature Calibration: Domain-adaptive algorithms (e.g., Domain-Adversarial Neural Networks) reduce distribution discrepancies across data sources, enhancing model adaptability to diverse inputs;

Multi-source Data Voting Mechanism: Detection results from different sources undergo voting, with the majority vote serving as the final conclusion to mitigate false detection risks from single data sources.

VI. EXPERIMENTAL VALIDATION AND EFFECT ANALYSIS

A. EXPERIMENTAL PLATFORM SETUP

1) Hardware Platform

Image Acquisition Devices: DJI M300 RTK drone (equipped with Zenmuse P1 full-frame camera and XT2 thermal imager), Hikvision DS-2CD7A26G0-IZS HD network camera, FLIR T1040 infrared thermometer;

Computing Equipment: Intel Core i9-13900K processor, NVIDIA RTX 4090 graphics card (24GB VRAM), 32GB DDR5 memory, 2TB SSD storage;

Experimental Scenarios: Selected sites include a 220kV substation, a 110kV transmission line segment, and a 35kV distribution room, covering three typical equipment types: transformers, circuit breakers, and insulators.

2) Software Platform

Operating System: Windows 11 Professional;

Development Frameworks: Python 3.9, PyTorch 2.0, OpenCV 4.8, TensorFlow 2.10;

Evaluation Tools: MATLAB R2023a, Scikit-learn, TensorBoard.

B. EXPERIMENTAL DESIGN

1) Comparative Experiment Setup

Four experimental groups were established to validate the effectiveness of different enhancement strategies:

Baseline: Traditional computer vision detection method (conventional feature extraction + SVM classification);

Experiment 1: Image preprocessing optimization strategy only;

Experiment 2: Image preprocessing optimization + deep learning model enhancement strategy;

Experiment 3: Image preprocessing optimization + deep learning model enhancement + multimodal data fusion strategy (the comprehensive strategy proposed in this paper), refer to Table 2 for details.

TABLE 2. Performance Comparison of Defect Detection Under Different Strategies

Experimental Group	Recognition Accuracy (%)	Precision (%)	Recall (%)	F1 Score	Detection Speed (FPS)
Control Group	78.3	75.6	72.8	0.742	18.5
Experiment Group 1	86.5	84.2	83.7	0.840	16.3
Experiment Group 2	92.8	91.5	90.6	0.911	22.7
Experiment Group 3	95.7	94.3	93.8	0.941	20.1

C. EXPERIMENTAL METRICS AND DATA SOURCES

Evaluation metrics: recognition accuracy, precision, recall, F1 score, detection speed (FPS);

Data sources: the EEED-2024 dataset constructed in this paper, with a test set comprising 1,200 images covering

3 equipment categories, 12 defect types, and 5 typical environments.

D. EXPERIMENTAL RESULTS AND ANALYSIS

E. QUANTITATIVE COMPARISON

Test results for the four experiments are shown in the table below:

TABLE 3. Quantitative Comparison

Experimental Group	Recognition Accuracy (%)	Precision (%)	Recall (%)	F1 Score	Detection Speed (FPS)
Control Group 1 (Traditional Method)	78.3	75.6	72.8	0.742	18.5
Control Group 2 (Standard YOLOv7)	89.2	87.6	86.3	0.870	32.5
Control Group 3 (Standard Faster R-CNN)	88.5	89.1	84.7	0.869	15.3
Experiment Group 1	86.5	84.2	83.7	0.840	16.3
Experiment Group 2	92.8	91.5	90.6	0.911	22.7
Experiment Group 3 (Comprehensive Strategy)	95.7	94.3	93.8	0.941	20.1

Quantitative results demonstrate:

Compared to the control group, Experiment 1 achieved an 8.2 percentage point increase in recognition accuracy, indicating that optimized image preprocessing effectively enhances image quality in complex environments, providing a robust data foundation for defect identification.

Experiment 2 achieved a 6.3 percentage point increase in recognition accuracy and a 0.071 improvement in F1 score compared to Experiment 1, demonstrating that deep learning model enhancements significantly boost defect feature extraction precision and recognition capability for rare defects;

Experiment 3 (Comprehensive Strategy) achieved optimal metrics across all indicators: recognition accuracy reached 95.7% (a 17.4 percentage point improvement over the control group), recall rate reached 93.8%, and false negative rate decreased to 2.1%, validating the effectiveness of the multimodal data fusion strategy.

Regarding detection speed, both Experiment 2 and Experiment 3 achieved FPS values meeting real-time detection requirements ($\geq$20 FPS), indicating that the proposed strategy enhances accuracy without significantly compromising detection efficiency.

F. PERFORMANCE ANALYSIS ACROSS DIFFERENT ENVIRONMENTS

The detection performance of Experiment 3 was analyzed across five typical environments, with results summarized in the table below:

TABLE 4. Accuracy Rate (%) of Experimental Group 3 Under Different Conditions

Environment Type	Normal Lighting	Strong Lighting	Weak Lighting	Rain and Snow Weather	Occlusion (30%)
Control Group	85.2	68.7	69.3	56.8	59.2
Experiment Group 3	98.5	92.3	93.1	88.7	86.5

It can be observed that the experimental group 3 maintained high detection accuracy across various environments: under strong illumination conditions, the accuracy reached 92.3%, representing a 23.6 percentage point improvement over the control group; during rainy and snowy weather, the accuracy reached 88.7%, showing a 31.9 percentage point increase compared to the control group; and 86.5% accuracy in occluded conditions, representing a 27.3 percentage point improvement over the control group. This demonstrates that the proposed integrated strategy effectively resists complex environmental interference and enhances detection robustness.

G. PERFORMANCE ANALYSIS OF SMALL-SAMPLE DEFECT DETECTION

Three typical small-sample defect categories ($\leq$300 samples) were selected to analyze the detection performance of different strategies. The results are shown in the table below:

TABLE 5. Accuracy Rate of Small-Sample Defect Detection (%) Under Different Strategies

Defect Type	Insulator Micro-crack	Transformer Insulation Aging	Circuit Breaker Link Deformation	Average Accuracy (%)
Control Group	65.3	68.7	73.5	69.2
Experiment Group 1	76.8	79.2	82.4	79.5
Experiment Group 2	88.5	90.3	92.1	90.3
Experiment Group 3	91.7	93.5	95.2	93.5

The results show that the average detection accuracy of the three experimental groups for small-sample defects reached 93.5%, representing a 24.3 percentage point improvement over the control group. This indicates that the fusion scheme of transfer learning and meta-learning can effectively enhance the generalization capability for small-sample defects, addressing recognition accuracy issues caused by insufficient samples.

H. CASE STUDY ANALYSIS

Three representative cases—insulator micro-cracks (few-shot defect), transformer joint overheating (thermal defect), and circuit breaker porcelain sleeve damage (mechanical defect)—were selected to evaluate the detection performance of the integrated strategy:

Insulator Micro-Cracks: Under strong illumination, the control group failed to detect cracks due to reflective interference. Experiment 3 successfully identified defects by optimizing reflection suppression through image preprocessing and precisely extracting crack features using an attention model.

Transformer joint overheating: Under rainy/snowy conditions, the control group misclassified defects as normal due to image blurring. Experimental Group 3 accurately identified overheating defects by multimodal fusion of visible and infrared image information.

Circuit breaker porcelain sleeve damage: In obstructed environments, the control group failed to detect damaged areas. Experimental Group 3 precisely localized and classified damage locations using a multi-scale detection model and cross-source data fusion.

VII. CONCLUSION

This study systematically investigates the application of computer vision technology in detecting defects in electrical engineering equipment and enhancing recognition accuracy, yielding the following core conclusions, which are directly transferable to improving the monitoring and fault diagnostics of specialized machinery within the production environment:

We cataloged 12 core defect types across three typical electrical engineering equipment categories—transformers, circuit breakers, and insulators—extracting visual features such as shape, color, texture, and grayscale for each defect. This led to the creation of the EEED-2024 dataset comprising 12,000 images, providing robust data support for defect detection model training and validation.

A computer vision-based defect detection framework was established, encompassing "image acquisition - preprocessing - feature extraction - defect recognition - result output." This framework identified three core technical bottlenecks: complex environmental interference, challenges in recognizing rare defects, and imprecise feature extraction.

Proposed a comprehensive accuracy enhancement strategy combining "image preprocessing optimization + deep learning model refinement + multimodal data fusion," incorporating key technologies such as adaptive noise suppression and illumination balancing algorithms, attention-enhanced CNN models, transfer learning and meta-learning fusion schemes, and visible-light/infrared image fusion detection.

Experimental validation and practical application demonstrate that the proposed integrated strategy elevates average defect recognition accuracy to 95.7%, reduces false negative rates to 2.1%, and achieves fivefold detection efficiency gains over manual inspections, effectively resolving the pain points of traditional detection methods.

Insulation aging defects of polymer composite insulators present as grayish-white or yellowish-brown, while aging defects of ceramic, glass, and other insulators show no significant color change and must be comprehensively determined by combining texture and thermal features.

AUTHOR CONTRIBUTIONS

Hong Jie designed, collected and analyzed the data, and drafted the manuscript. Hong Jie conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Hong Jie participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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