A Comprehensive Approach to Fault Diagnosis of Electrical Equipment Based on Color Images

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Abstract: Electrical equipment plays a critical role in industrial electrical systems, where unexpected mechanical failures during operation can lead to severe consequences, such as disruptions in technological processes, reduced quality and quantity of produced goods, and the occurrence of emergency situations. To ensure the reliable operation of these systems, it is essential to conduct regular inspections and maintenance of electrical equipment using modern computer technologies for the timely detection of faults. To address this issue, a comprehensive approach is proposed, based on the processing of color images obtained from thermal imaging devices, black-and-white graphs generated from sensor data stored in Excel format, as well as simple color photographs. The core of the image, graph, and photograph processing (recognition) lies in artificial intelligence technologies, specifically convolutional neural networks (CNNs). The developed CNN outputs a class number corresponding to the current state of the equipment. Additionally, an algorithm for a comprehensive approach to fault detection in electrical equipment using CNNs is proposed. The results obtained allow for a reduction in the number of unplanned failures by providing early warnings about the development of faults and potential equipment failures..

1 INTRODUCTION

With the rapid development of various industrial sectors, fault diagnosis of electrical equipment is becoming increasingly significant to ensure the safe operation of equipment and production processes. This equipment is prone to frequent premature failures due to potential damage, wear and tear, climatic conditions, and other external and internal environmental factors, making regular inspections and maintenance of electrical equipment (EE) necessary (Shao, Xia, Han, Zhang, Wan, 2020; Cheng, Zixuan, Mingsong, 2021; Kolodenkova, Vereshchagina, 2023).

As traditional periodic inspections can no longer meet the safety requirements of EE operation due to the increasing complexity of these systems, achieving automatic fault recognition now relies heavily on computer technologies and image recognition techniques, particularly those using thermal imaging devices. The advantage of using such devices is the ability to conduct rapid inspections without direct contact with the object.

There is a significant body of work by both international and Russian researchers dedicated to assessing the technical condition of EE using convolutional neural networks (CNNs) (Alvarado-Hernandez, Zamudio-Ramirez, Jaen-Cuellar, Osornio-Rios, Donderis-Quiles, Antonino-Daviu, 2022; Zhen, Zhenbao, Vong, Pecht, 2019; Mingshu, Haiting, Xipeng, 2021).

For instance, the study by Alvarado-Hernandez et al. (2022) discusses the structure and development of an intelligent sensor based on infrared thermography for diagnosing faults in related elements of an induction motor (such as rolling bearings and gearboxes). Significant statistical features are extracted using principal component analysis, which leads to preliminary classification, facilitating the final fault classification with a feedforward backpropagation neural network, ensuring accurate fault categorization.

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In the work by Zhen et al. (2019), a fault detection method based on infrared thermography (IRT) is examined for rotating machinery. First, images of the rotating equipment in various states are captured using IRT, and then two popular feature extraction methods from IRT images—bag-of-visual-words and CNN—are sequentially tested. The extracted features are classified to achieve automatic fault diagnosis.

Mingshu, Haiting, and Xipeng (2021) investigate the diagnosis of thermal faults in electrical equipment at substations based on image fusion. They propose an algorithm for the registration and fusion of infrared images of substation electrical equipment. A model based on mask R-CNN for image segmentation and recognition was developed for these images.

Despite the extensive research in this field, the issue of diagnosing EE faults through thermal imaging remains unresolved. This is because the developed approaches and methods have practical limitations, as they are often tailored to specific equipment.

In light of this, the authors propose a comprehensive approach to EE fault diagnosis, which integrates color images and photographs, as well as black-and-white graphs obtained through various methods, to identify faults in EE under a multitude of factors using convolutional neural networks (CNNs).

2 CHALLENGES IN FAULT RECOGNITION OF ELECTRICAL EQUIPMENT BASED ON IMAGES

For the recognition and identification of color images, Convolutional Neural Networks (CNNs) are most commonly used, as they provide partial robustness to changes in scale, shifts, displacements, rotations, and other distortions (Pekhota, Galushko, Gromyko, 2021; Cheng-Jian, Chun-Hui, Frank, 2023; Bengio, 2009). However, their application presents several challenges, despite their advantages:

1. Requirement for Large Data Sets: This issue arises during CNN training when the amount of available data (labeled data) is limited.

2. Interpretability: This problem is due to the complex mechanisms underlying CNNs, making it difficult to interpret their operations.

3. Computational Complexity: CNNs require significant computational resources for training, particularly powerful processors and preferably GPUs (Graphical Processing Units).

4. High Sensitivity to Changes: This issue can occur if factors affecting the image (lighting, background, viewing angle, weather conditions such as wind, rain, etc.) were not represented in the training data set.

5. Noise Suppression: This problem arises if the image was obtained through digitization. Sources of noise can include imperfect image-capturing equipment (e.g., video cameras) as well as poor shooting conditions (e.g., nighttime photography). Noise suppression is employed to enhance visual perception (e.g., image compression).

6. Overfitting and Robustness: To address these issues, researchers propose data augmentation techniques, which can generate a large number of training data sets.

7. Training CNNs: Training large CNNs can be time-consuming. As a solution, researchers suggest using parallel computing and optimizing model architectures.

Therefore, when diagnosing electrical equipment using thermal imaging, it is crucial to minimize the influence of factors that could introduce errors or inaccuracies in the readings.

3 ALGORITHM OF A COMPREHENSIVE APPROACH

Infrared thermographic imaging is well-suited for detecting faults in electrical equipment, as it allows for diagnostics while the equipment remains in continuous operation. By capturing and analyzing temperature data distributed across the equipment's surface, it is possible to identify localized areas where faults are present and assess the severity of the damage. If the thermal image cannot be fully evaluated by personnel, it can still be used to determine the need for further diagnostics of the equipment.

The idea behind the approach to fault detection in electrical equipment using Convolutional Neural Networks (CNNs) lies in the comprehensive processing of color images, black-and-white graphs, and standard color photographs, as well as the design and training of CNNs. The recognized data must be used to classify the technical condition of the electrical equipment.

Figure 1 presents an algorithm for the comprehensive approach to fault detection in electrical equipment using CNNs, consisting of 7 steps.

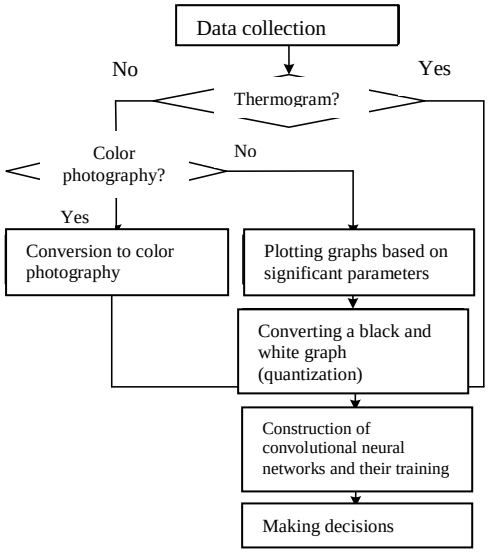

Figure 1. Algorithm of a Comprehensive Approach for Fault Detection in Electrical Equipment Using Convolutional Neural Networks (CNNs).

Step 1: Data Collection

Data can be acquired in the form of color images (thermograms) obtained using a thermal imaging device, black-and-white graphs that characterize changes in various parameters over time based on sensor data stored in Excel format, and standard color photographs. It is important to note that graphs constructed from the electrical equipment's parameter values are used in cases where thermograms or color photographs are unavailable or of poor quality.

Step 2: If the input is a thermogram, proceed to Step 7; otherwise, proceed to Step 3.

Step 3: If the input is a color photograph, proceed to Step 4; otherwise, proceed to Step 5.

Step 4: Convert the color photograph to a black-and-white image.

This conversion is performed using the Niblack method (Saxena, 2019), as it is relatively simple and provides the highest speed for image binarization. The threshold value for the point with coordinates

(*m*,) is calculated using the following formula::

$$t(m,n) = \mu(m,n) + k \cdot \sigma(m,n)$$

where μ(m,n) is the mean,

σ(m,n) is the standard deviation within the local neighborhood of the considered image point, and

k is a parameter that determines the portion of the object's boundary to be considered as part of the object.

This method, due to its simplicity, enables the highest speed of image binarization. It is most commonly used in practice for the rapid filtering of high-contrast images where there are minimal highly noisy regions with smooth brightness transitions.

It should be noted that there are numerous methods for converting color images to black-and-white (Fedorov, 2018; Israfilov, 2017). Each method has its own advantages and disadvantages. Therefore, before selecting and applying a method, it is advisable to consider the specific domain as well as the image quality.

Step 5: Plotting Graphs Based on Parameter Values

Step 6: Quantization of Black-and-White Graphs (Pekhota, Galushko, Gromyko, 2021). In this step, image quantization is used, where the continuous dynamic range of brightness values is divided into several discrete levels using the Lloyd-Max quantizer:

$$x(i_1,i_2) = \frac{1}{4\pi^2}\int_{-\pi}^{\pi}\int_{-\pi}^{\pi}\frac{1}{\Delta t_1 \Delta t_2}\sum_{k_1}\sum_{k_2} X_{\text{Н}}\left(\frac{\omega_1 + 2\pi k_1}{\Delta t_1}, \frac{\omega_2 + 2\pi k_2}{\Delta t_2}\right)\cdot \exp(j\omega_1 i_1 + j\omega_2 i_2)d\omega_1 d\omega_2$$

,

where $\Delta t1$ and $\Delta t2$ are the vertical and horizontal steps or discretization intervals, respectively;

$k1$ and k2 represent the segment numbers;

Xn is the two-dimensional continuous frequency spectrum;

$\omega 1$ and $\omega 2$ are the normalized frequencies, and

j=1

The quantization process also takes into account the mean square quantization error, calculated using the following formula:

$$E\{\varepsilon^2\} = E\{x^2\} - \sum_{j=1}^{L} r_j^2 \int_{d_j}^{d_{j+1}} w(x)dx,$$

where x is the continuous variable,

dj and dj+1 are the boundary thresholds determined by the dynamic range of brightness;

r is the finite set,

L is the number of levels, and

w is the probability density.

Step 7: CNN Construction and Training

The training of CNNs is carried out using a database of thermograms and graphs based on the parameter values of the electrical equipment.

The convolutional neural network for thermogram recognition is essential for identifying critical or abnormal temperatures, which can be detected in real-time without contact while the equipment is in operation.

The convolutional neural network for simple color photograph recognition is necessary for detecting the contours of equipment parts with temperatures exceeding permissible limits.

The convolutional neural network for black-and-white graph recognition is crucial for identifying faults in the electrical equipment.

Step 8: Decision Making

Each CNN outputs a class number corresponding to the current state of the electrical equipment:

Class 1: The equipment is fully operational.

Class 2: The equipment is operational with minor deviations.

Depending on the class, a list of recommended actions is provided to prevent equipment failure.

4 RESULTS

The research results were obtained during the diagnosis of an asynchronous motor model AIR63A4U1 based on thermograms. The development of the CNN was conducted using the TensorFlow library in the Python programming language. The thermogram database was populated with images captured using a Testo 875-1i thermal imager, which has a thermal sensitivity (NETD) of < 0.05°C at 30°C and an operating temperature range from –15°C to 40°C. Thermal imaging was performed during the spring, summer, and autumn seasons under various climatic conditions (temperature fluctuations, heating). The thermogram database contains 136 images in .bmt format, which include both the real image and the thermogram, with a resolution of 640 x 480 pixels.

When measuring with the thermal imager, the threshold temperature values are set both automatically (continuous automatic adjustment based on current minimum/maximum values) and manually. All temperature measurements below or above the threshold value are displayed in the same color as the threshold value.

Since the number of images representing equipment in good technical condition is much greater than those with faults, the error rate alone cannot objectively evaluate the quality of the CNN. Therefore, its accuracy was assessed as follows:: $P = TP / (TP + FP)$, where TP (*True Positive*) – is the correct identification of a functioning condition as functional, and FP (*False Positive*) – is the incorrect identification of a functioning condition as faulty.

The CNN achieved an accuracy of 96.2%. The equipment was determined to be operational, albeit with minor deviations. Analysis of the thermograms revealed an elevated temperature on the motor housing, which is indicative of winding overheating. Consequently, the following measures were recommended:

Analyze the voltage unbalance coefficient in the zero-sequence component.

Analyze the voltage unbalance coefficient in the negative-sequence component.

Analyze the voltage asymmetry.

5 CONCLUSION

The study proposes an approach for identifying faults in electrical equipment based on the comprehensive processing of input data (thermograms, graphs, photographs). This approach enables faster decision-making regarding the technical condition of the equipment, improves the accuracy of image classification, and reduces the influence of human factors. Additionally, for color images, the varying thermal conductivity of materials (e.g., steel for the housing, copper for the windings, etc.) is taken into account.

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