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Enhancing Transformer Fault Identification Through PCA-SVM Approach

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Abstract. As a key component of the power system, the health of the transformer directly affects the stability and security of the entire power grid. Therefore, accurate identification and classification of transformer fault types is important for the prevention of large-scale power outages. This study aims to improve the accuracy and efficiency of transformer fault diagnosis by combining principal component analysis (PCA) and support vector machine (SVM). Firstly, thermal imaging maps of transformers under multiple types of fault states are collected using infrared thermography, and after image preprocessing, dimensionality reduction is carried out using the PCA method to extract the most representative feature vectors as inputs, reducing computational complexity and eliminating noise interference. A multiclassification SVM-based fault classification model is constructed, which employs a radial basis function (RBF) kernel to improve the nonlinear processing capability of the classifier. Results of the study show that the feature input optimized by PCA can significantly improve the performance of the SVM classifier. The experimental results show that the accuracy of the method on the transformer fault dataset reaches more than 95%, which is significantly better than the traditional single classification method. The method not only can effectively improve the accuracy of fault detection, but also has good generalization ability and fast processing speed, providing a reliable technical means for transformer condition monitoring and fault warning.

Keywords: transformer, Principal Component Analysis (PCA), Support Vector Machine (SVM), multiple classification, fault classification

1 Introduction

As an indispensable part of the power system, the transformer undertakes the key task of power transmission and distribution. Its operation status is directly related to the stability and safety of the whole power grid, so the fault diagnosis of transformer plays a vital role in preventing power system accidents and guaranteeing the continuity and reliability of power supply. Transformers may fail due to insulation aging, oil deterioration, etc. Failure to detect in time may cause fire, explosion, and other serious accidents, resulting in huge economic losses and casualties. With the development of the power system, the size of the transformer increases, the structure is complex, and the traditional periodic inspection and maintenance methods have been difficult to meet the requirements of modern power systems for high efficiency and high reliability [1]. Advanced fault diagnosis technology with the help of big data, cloud computing, Internet of Things and other modern information technology helps real-time monitoring and intelligent analysis, providing more powerful technical support for fault diagnosis. Advanced fault diagnosis technology is crucial to the safe, stable, and economic operation of the power system, which can prevent faults, improve efficiency and the scientific nature of maintenance strategies, and bring significant social and economic benefits.

The contributions of this manuscript are to:

1) Integrate of thermal imaging technology with machine learning for transformer fault detection.

2) Utilize Principal Component Analysis (PCA) to extract features and reduce the dimensionality of raw thermal imaging data, eliminating noise and redundant information from the data.

3) Employ feature extraction and train a Support Vector Machine (SVM) algorithm, achieving commendable performance.

The structure of this paper is arranged as follows:

Setion 2 critiques existing methods, and provides a detailed literature review to contextualize the study.

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Setion 3 is the research methodology. The PCA-SVM methodology used in this study is described in detail. The data preprocessing steps will be explained, detailing how to use PCA for feature reduction and extraction of key information. The SVM classifier will be constructed and the suitable kernel function and parameter optimization strategy will be selected.

Section 4 are presented the experimental design and result analysis. It includes the experimental setup, description of the dataset, definition of evaluation indexes, and detailed analysis of the experimental results. In addition, the effects of different kernel functions and model parameters on classification performance will be compared and the results will be discussed.

Section 5 is the conclusion and outlook. The main findings of this study are summarized to highlight the advantages of the PCA-SVM method in improving the accuracy and efficiency of transformer fault diagnosis. Meanwhile, suggestions for future research directions are presented.

2 Related Work

External short circuit is one of the most common faults in transformers [2]. In the power system, the diagnosis of transformer faults mainly rely on artificial experience and equipment detection means, this method often exists in the diagnosis of low efficiency, false judgement rate and other problems. Scholars have been working hard by developing various monitoring techniques and low-cost rapid diagnostic tools. To achieve the diagnosis of this fault, Low Voltage Impulse (LVI) [3], Frequency Response Analysis (FRA) [4], Sweeping Frequency Impedance (SFI) [5], and Dissolved Gas Analysis (DGA) [6] have been applied to provide, to some extent, reliable monitoring techniques and low-cost rapid diagnostic tools for transformer fault diagnosis. These methods need to be in a power failure situation for offline inspection, and the DGA method requires the installation of specific sensors or complex equipment to collect and analyse transformer oil gases over a long period of time, which does not allow for rapid diagnosis. Some monitoring techniques may require expensive equipment and specialised operators, which may increase operating costs for small and medium-sized utilities. This is not only inefficient, but may miss the best time to make repairs, leading to wider faults.

With the development of information technology, especially the application of big data analytics and machine learning algorithms to learn patterns from historical and real-time data and predict failure trends, the accuracy and efficiency of troubleshooting has been significantly improved, resulting in optimized maintenance schedules and a reduction in unnecessary maintenance work.

Liu et al presents a transformer condition assessment method that utilizes fault feature extraction to achieve dynamic evaluation of the transformer's status and progressively enhance the accuracy of equipment fault diagnosis. The approach involves screening numerous indicators, employing regression techniques to identify those indicative of faults, and conducting the analysis without reliance on external factors [7].

Zhang et al. introduces a multi-sensor, multi-directional optical image integrated monitoring method aimed at enhancing the efficiency of transformer fault diagnosis and surveillance within power systems. The technique is designed to facilitate fault detection in unmanned remote adaptive transformers. It employs a DBNI model, which demonstrates superior diagnostic precision over traditional BP neural networks, single DBN without data fusion, and SVM methods [8].

Shiling investigates the performance of two optimization classification algorithms PSO-GRNN and PSO-SVM for fault diagnosis in oil-immersed transformers. The findings reveal that while the PSO-GRNN classifier offers relatively consistent accuracy, it tends to be more time-consuming for fault classification. The validity of these optimized classification methods is substantiated through simulation results presented, which also compares their respective performances, offering insights and approaches for enhancing fault classification techniques in oil-immersed transformers [9].

Fang et al. address the issue of reduced accuracy in power distribution transformer fault diagnosis caused by an imbalance in the number of cases across different fault categories within machine learning-based diagnostic methods. Their work offers valuable insights and references for enhancing the precision of power distribution transformer fault detection [10].

Bai et al. introduce a power transformer evaluation method that combines principal component analysis with gray correlation analysis to accurately pinpoint faults and enhance the diagnostic process's accuracy and stability. The application of this method in a case study demonstrates its effectiveness and objectivity for transformer fault diagnosis, offering innovative perspectives for transformer assessment techniques [11].

Jiang et al. leverage the synergistic benefits of two approaches by utilizing the PCA algorithm for dimensionality reduction in MMC fault diagnosis. The outcomes indicate that this method significantly enhances both the speed and accuracy of fault detection. The study serves as a reference for the practical implementation of the PCA-SVM method within MMC fault diagnosis engineering [12].

Liu et al. present a transformer fault diagnosis technique that incorporates an enhanced version of particle swarm optimization, known as IPSO, coupled with a multigrained cascade forest algorithm, or gcForest. The resulting IPSO-gcForest model significantly elevates the precision of fault detection in transformers, confirming the method's viability and efficacy [13].

Zhang et al. address the challenges of transformer fault diagnosis within power systems by proposing a method that employs a genetic algorithm to optimize a BP neural network. This approach constructs the BP neural network architecture upon the foundation of the conventional three-ratio fault diagnostic technique [14].

Zhang et al. explore the application of an enhanced PNN for transformer fault diagnosis, aiming to overcome the limitations in accuracy and efficiency that plague existing methods, as well as their excessive dependency on manual processes. The practicality and efficacy of their proposed technique are demonstrated through a case study using real-world data [15].

Xv et al. conduct research on transformer fault diagnosis utilizing an enhanced deep belief network framework. To augment the precision of fault detection, they develop a sophisticated model dubbed SMOTE-RF-IHPO-DBN. This model integrates random forest techniques for data dimensionality reduction, enabling the extraction of critical information and enhancing operational efficiency [16].

Li et al. proposes a transformer fault diagnosis method based on the optimization of kernel parameters and weight parameters of a kernel extreme learning machine (KELM) [17]. Traditional shallow machine learning algorithms cannot effectively explore the relationship between the fault data of oil immersed transformers, resulting in low fault diagnosis accuracy. Li et al., propose a transformer fault diagnosis method based on Multi-class AdaBoost Algorithms in response to this problem [18].

Fault detection as described above is mainly achieved through parameters such as electrical signals, sounds, oil samples and temperatures. Electrical signal analysis can detect some fault characteristics but may not cover all types of faults. In addition, electrical signals are affected by a variety of factors and may require specialized knowledge to be interpreted accurately. While Dissolved Gas in Oil Analysis (DGOA) can provide information about the internal condition of a transformer, this method is usually carried out offline and results are not instantly available, which may delay the detection and treatment of faults. Sound analysis often relies on operator experience and judgement and can be subjective. It may be difficult to pinpoint the exact location of the fault by these methods, and sometimes further inspection or the use of other diagnostic tools is required to assist in confirmation. On the eve of a transformer failure, it is accompanied by an increase in its own temperature, and infrared thermography is the best detection technology to find thermal defects in transformers, providing infrared safety detection for thermal defects, equipment status, and safe operation monitoring of transformers. Infrared thermography can also identify hot spots inside the transformer, discover potential equipment failures in time, and provide a basis for equipment repair and maintenance.

Although machine learning provides powerful tools for data analysis, they rely on large amounts of training data. Access to large amounts of labelled fault data is a challenge during application. In addition, the ability of models to generalize and adapt to emerging fault patterns is one of the limitations of current techniques. In order to meet the urgent need for transformer fault diagnosis technology in the power industry. The development of an intelligent fault diagnosis system that can provide real-time monitoring and highly accurate prediction is of great significance to improve the reliability of power systems and reduce potential economic losses. The aim of this paper is to explore an advanced method that combines principal component analysis (PCA) and support vector machine (SVM) to improve the accuracy and efficiency of transformer fault diagnosis. By utilizing PCA for feature extraction, the data dimensionality can be effectively reduced and noise and redundant information can be removed, thereby highlighting fault-related features. Subsequently, by utilizing the powerful classification capability of SVM, a multi-classification model can be constructed to identify and differentiate between different fault types, providing a reliable tool for the power industry to achieve continuous monitoring and timely maintenance of transformer condition to ensure the stability and security of power supply.

3 Methodology

The proposed transformer diagnostic system integrates thermal imaging technology, principal component analysis methodology and multi-classification SVM classification algorithm to provide a comprehensive solution for transformer fault diagnosis as shown in Fig. 1. This research aims to provide transformer maintenance personnel with actionable insights using a thermal imaging camera in combination with the PCA-SVM algorithm, providing a reliable technological tool for condition monitoring and fault warning of transformers.

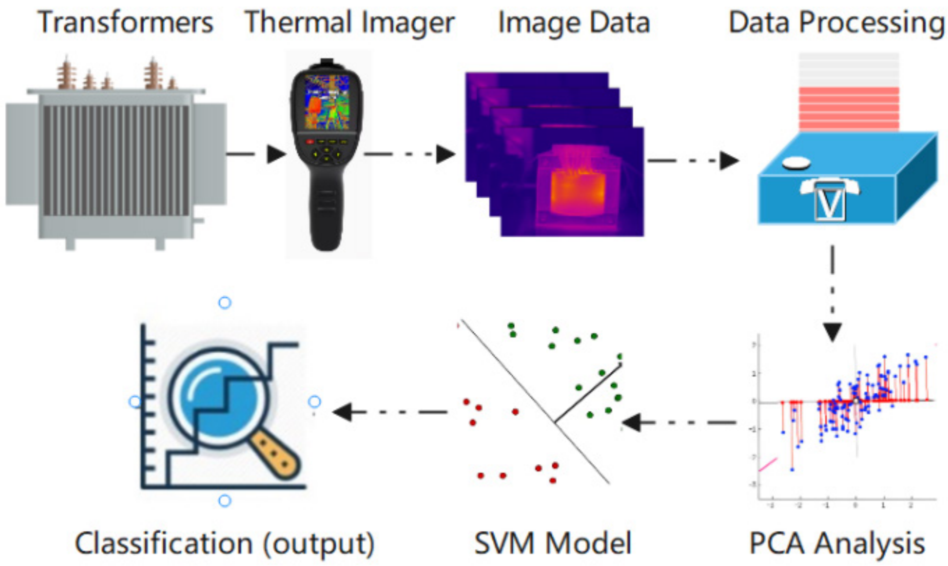

Fig. 1. Architecture of transformer fault identification system

3.1 Data Acquisition

In order to collect data from the transformer, thermography is used. Thermal imaging is a non-contact temperature measurement method that generates a thermal image by detecting infrared radiation emitted by an object. The principle behind this technology lies in the fact that all objects emit electromagnetic radiation of different wavelengths, often referred to as infrared, depending on their temperature. Thermal imaging equipment captures the electromagnetic radiation and converts it into an electrical signal that is eventually presented on a display in grey levels or pseudo-colour, resulting in a thermal image that represents the temperature distribution on the surface of the object. Thermal imaging provides an efficient, accurate, and safe means of data acquisition for transformers. By scanning a transformer with thermal imaging, potential hot spots or faulty areas can be quickly identified, which is critical for preventive maintenance and troubleshooting. In addition, due to its long-range monitoring capability and stealthiness, thermography is also ideally suited for periodic inspections and maintenance of electrical utilities.

In order to obtain the data for the experiment, nine different operating states of the transformer were set up, with one in normal operation and the other eight in different fault states. The eight fault states were simulated by eight different short circuit defects in the common core winding. A Dali-tech T8 TIC thermal imaging camera is used to collect the data. The Dali-tech T8 TIC thermal imaging camera has a resolution of 384*288, an accuracy of 2° or 2%, a temperature measurement range of -20°-+650°, and an imaging frequency of 50/60Hz. The transformer used for the experiment is a single-phase transformer with a power of 1Kw, an operating voltage of 220V, and an operating current of 1.5A, and the frequency is 50-60Hz. The acquired thermal imaging images of the transformer were labelled as 9 types, respectively 1-9. It is obvious from the acquired images that the faulty state can be detected by direct observation of the thermal imaging camera compared to the normal state, but it is not possible to detect the faulty state, i.e., it is difficult to detect the defective state by using the human naked eye transformer with a healthy state transformer [19].

3.2 Principal Component Analysis (PCA)

Principal component analysis converts data from a set of potentially correlated variables to a set of linearly uncorrelated variables through orthogonal transformation, and the converted variables are called principal components, which can replace the original larger number of variables with a smaller number of variables [20].

Reads all image files under the specified path, converts them to images of 28x28 pixel size, and store the image data along with the corresponding labels. This data is processed for dimensionality reduction using PCA. First centering After that the covariance matrix is derived and the coefficients, eigenvalues and contributions of each principal component are calculated and the eigenvalues are selected. Assumed that the mean of a given m-dimensional data sample X is $\overline{X}$, the variance of the de-mean is S, and $cov(x, y)$ is the covariance of the features x and y, the

$$\overline{X} = \frac{1}{m}\sum_{i=1}^{m} X_i \quad \textbf{(1)}$$

$$S = \frac{1}{m-1}\sum_{i=1}^{m}\left(X_i - \overline{X}\right)^2 \quad \textbf{(2)}$$

$$\mathrm{cov}(x, y) = \frac{1}{m-1}\sum_{i=1}^{m}\left(x_i - \overline{x}\right)\left(y_i - \overline{y}\right) \quad \textbf{(3)}$$

Thus, the covariance matrix with m samples of n features is found to be:

$$cov = \frac{1}{m}X^T X = \begin{bmatrix} Cov11 & Cov12 & \dots & Cov1n \\ Cov21 & Cov22 & \dots & Cov2n \\ \dots & \dots & \dots & \dots \\ Covm1 & Covm2 & \dots & Covmn \end{bmatrix} \quad \textbf{(4)}$$

The n eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_n$ and the n eigenvectors $T_1, T_2, \dots, T_n$ are found based on the covariance matrix, and there is then the i-th principal component Y_i as:

$$Y_i = X.T_i,\ 1 \le i \le n \quad \textbf{(5)}$$

Based on the principal component contribution and cumulative contribution, the contribution of the kth principal component is found:

$$\varphi_k = \frac{\lambda_k}{\Sigma_{i=1}^{n}\lambda_i} \quad \textbf{(6)}$$

The cumulative contribution of the first p principal components of the sample is:

$$\Psi_p = \frac{\Sigma_{k=1}^{p}\lambda_k}{\Sigma_{k=1}^{n}\lambda_k} = \sum_{k=1}^{p}\varphi_k \quad \textbf{(7)}$$

The smallest q value that satisfies the following equation is selected as the new feature. According to Jolliffe's theoretical work, it is common practice in PCA to retain components that explain the vast majority of the variation in the data. In general, selecting eigenvalues with a cumulative contribution of 95 per cent can be considered to cover the most important structural information in the data. This criterion is widely accepted and applied in many fields.

$$\frac{\Sigma_{i=1}^{q}\lambda_i}{\Sigma_{i=1}^{n}\lambda_i} \geq 0.95 \quad \textbf{(8)}$$

The image of thermal imaging is 240*320 in size and after resizing to 28*28, finally 2352 data are obtained. This data is processed for dimensionality reduction using PCA. And then 4 eigenvalues are obtained.

3.3 Support Vector Machines (SVM)

The principle of Support Vector Machine (SVM) is to create a hyperplane in a N-dimensional space that optimally separates the data into two classes. In the case of linearly separable data, SVM finds the hyperplane that maximizes the margin between the two classes. The margin is the distance between the hyperplane and the nearest point from each class, which are called support vectors. For data that is not linearly separable, SVM uses a kernel trick to map the data into a higher-dimensional space where it becomes separable [21].

The optimization problem for SVM can be formulated as follows:

$$\text{minimize}\frac{1}{2}\|\mathbf{w}\|^2 \quad \textbf{(9)}$$

$$\text{Subject to } y_i\,(\mathbf{w}^T\,\mathbf{x}_i + b) \geq 1,\ i = 1,\ \ldots,\ n \quad \textbf{(10)}$$

where:

- $\mathbf{w}$ is the normal vector to the hyperplane, defining its orientation.
- b is the bias term, representing the distance of the hyperplane from the origin along the normal vector .
- $\mathbf{x}_i$ are the feature vectors of the training samples.
- y_i are the class labels, which take values of either -1 or 1.
- n is the number of training samples.
- $\|\mathbf{w}\|^2$ is the L2 norm of $\mathbf{w}$, which is minimized to find the optimal hyperplane.

The constraints $y_i\,(\mathbf{w}^T\,\mathbf{x}_i + b) \geq 1$ ensure that all samples are correctly classified and lie on one side of the margin or the other.

To solve this optimization problem, we use Lagrange multipliers, which lead to the dual form of the problem:

$$\text{maximize } \Sigma_{i=1}^{n}\ \alpha_i - \frac{1}{2}\Sigma_{i=1}^{n}\ \Sigma_{j=1}^{n}\ \alpha_i\alpha_j y_i y_j \mathbf{w}_i^T\mathbf{x}_j \quad \textbf{(11)}$$

$$\text{subject to } \Sigma_{i=1}^{n}\ \alpha_i y_i = 0,\ \alpha_i \geq 0,\ i = 1,\ldots,n \quad \textbf{(12)}$$

where:

- α_i are the Lagrange multipliers, which are greater than or equal to zero.
- The first term in the objective function represents the sum of the Lagrange multipliers times the corresponding class labels.
- The second term represents the inner product of the feature vectors weighted by the Lagrange multipliers and class labels.

The solution to this problem gives us the optimal hyperplane parameters $\mathbf{w}$ and b, which can be used for classification of new data points.

For non-linearly separable data, SVM uses a kernel function to transform the data into a higher-dimensional space where it becomes linearly separable. The most common kernel functions include the linear kernel, polynomial kernel, and radial basis function (RBF) kernel. The optimization problem then involves replacing the dot product $\mathbf{w}_i^T\mathbf{x}_j$ with the kernel function $K(\mathbf{x}_i,\ \mathbf{x}_j)$.

SVM has numerous applications in various fields, including image and pattern recognition, text and hypertext categorization, bioinformatics, and others. Its ability to handle high-dimensional data and provide a robust solution makes it a popular choice for many classification tasks [21].

4 Analysis of the Results of the Experiment

4.1 Description of the Data Set

The dataset contains 180 samples with a total of 9 different operating states, one of which is the normal state and the other 8 different fault states, which are shown in Fig. 2.

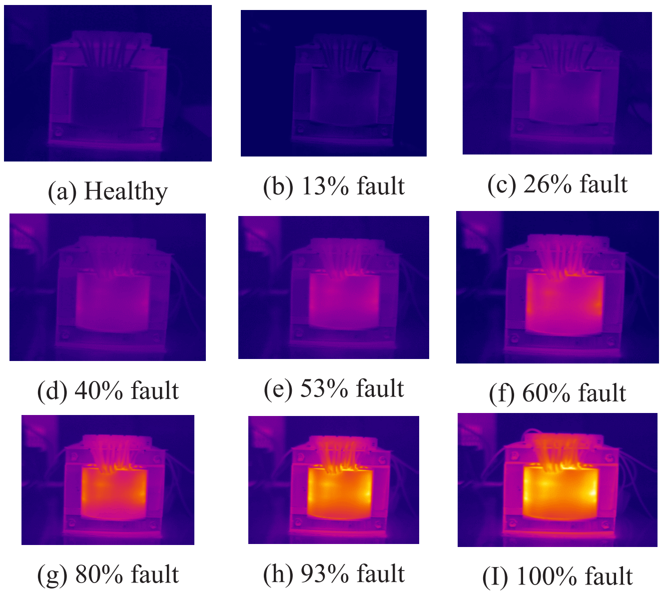

Fig. 2. 9 different operating states of transformer

where the percentages correspond to different numbers of short-circuit rounds. 13%, 26%, 40%, 53%, 66%, 80%, 93% and 100% corresponds to 80, 160, 240, 320, 400, 480, 560 and 600 short circuit rounds respectively, along with its corresponding fault's class labels 1-9.

There are 20 samples for each working state. Fifteen of the captured images are used as a training set and five as a test set. Considering that a smaller image size can reduce the computational load, increasing the speed of model training and prediction, it also helps to emphasize key features, thus improving the model's generalization capability. All the images are resized to 28*28, PCA analyses and sent to the SVM model for training and testing, and the final output of transformer diagnostic results are used for performance metrics for result analysis. The configuration of the computer used for the experiment is Intel Core i7 processor, 16GB RAM, Win11 operating system. We used Matlab 2014 as the programming language and relied on the PCA and SVM implementations in the function library.

4.2 Definition of Evaluation Indicators

The selection of evaluation indicators is crucial to quantify the performance of the model, the evaluation indicators used in this paper and their definitions are as follows.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

$$Precision = \frac{TP}{TP + FP} \tag{14}$$

$$Recall = \frac{TP}{TP + FN} \tag{15}$$

$$F1\ Score = 2 * \frac{Precision \times Recall}{Precision + Recall} \tag{16}$$

Where, TP (True Positives): true cases, i.e., the number of samples correctly predicted as positive classes. TN (True Negatives): True Negatives, i.e., the number of samples correctly predicted to be in the negative category. FP (False Positives): False Positive examples, i.e., the number of samples incorrectly predicted to be in the positive category. FN (False Negatives): False Negatives, i.e., the number of samples incorrectly predicted to be in the negative category.

4.3 Analysis of Experimental Results

The main objective of this paper is to evaluate and demonstrate the performance of the PCA-SVM method in transformer fault diagnosis. Therefore, a comparison with three other algorithms, namely K-Nearest Neighbour (KNN), Support Vector Machines (SVM), Random Forest (RF), etc., is carried out with the aim of comparing the accuracy and stability of each technique and evaluating their efficiency. The results of the performance tests are shown in Table 1.

Table 1. Performance test results of the five tested algorithms

Algorithms	Accuracy	Precision	Recall	F1 Score
PCA-SVM	0.9778	0.9815	0.9778	0.9776
SVM	0.9111	0.9506	0.9111	0.9158
KNN	0.9333	0.9497	0.9333	0.9313
RF	0.9333	0.9497	0.9333	0.9313

Based on the data in the table, we can elaborate from four aspects.

Accuracy: Accuracy measures the proportion of samples that are correctly classified by an algorithm. In this table, PCA-SVM has the highest accuracy rate at 0.9778, while SVM, KNN, and RF have accuracy rates of 0.9111, 0.9333, and 0.9333, respectively. Therefore, PCA-SVM performs the best in terms of accuracy, improving by approximately 0.0667 over SVM, and about 0.0222 over both KNN and RF.

Precision: Precision measures the proportion of positive predictions that are correct. In this table, PCA-SVM has a precision of 0.9815, SVM has a precision of 0.9506, and both KNN and RF have a precision of 0.9497. Thus, PCA-SVM performs the best in terms of precision, improving by approximately 0.0315 over SVM, and about 0.0094 over both KNN and RF.

Recall: Recall measures the proportion of actual positives that are correctly identified by an algorithm. In this table, PCA-SVM has a recall of 0.9778, SVM has a recall of 0.9111, and both KNN and RF have a recall of 0.9333. Hence, PCA-SVM performs the best in terms of recall, improving by approximately 0.0667 over SVM, and about 0.0222 over both KNN and RF.

F1 Score: The F1 score is a measure that considers both precision and recall to balance the relationship between them. In this table, PCA-SVM has an F1 score of 0.9776, SVM has an F1 score of 0.9158, and both KNN and RF have an F1 score of 0.9313. Therefore, PCA-SVM performs the best in terms of F1 score, improving by approximately 0.0628 over SVM, and about 0.0538 over both KNN and RF.

In summary, PCA-SVM performs the best in accuracy, precision, recall, and F1 score, showing improvements of about 0.0667, 0.0315, 0.0667, and 0.0628, respectively, compared to the other algorithms. Therefore, it can be considered that PCA-SVM is the best algorithm.

To visualize the classification effect of the tested algorithms, confusion matrices were plotted and are shown in Fig. 3 to Fig. 6.

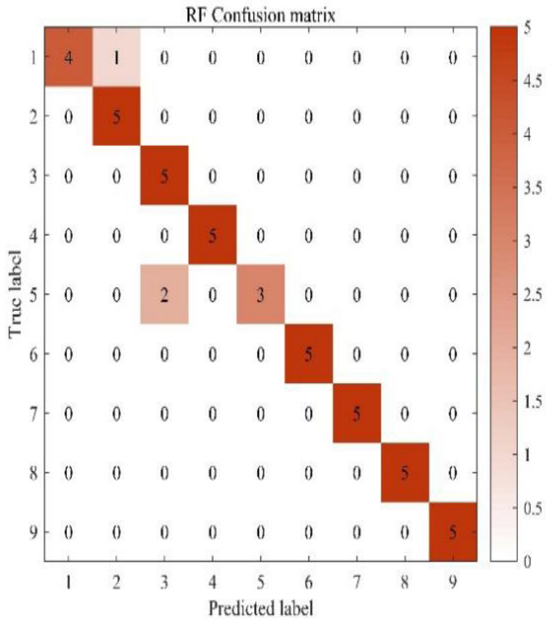

Fig. 3. Confusion matrix diagram of RF

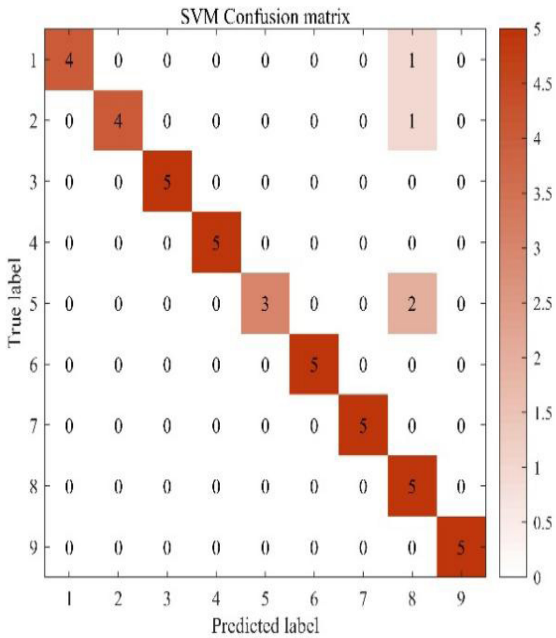

Fig. 4. Confusion matrix diagram of SVM

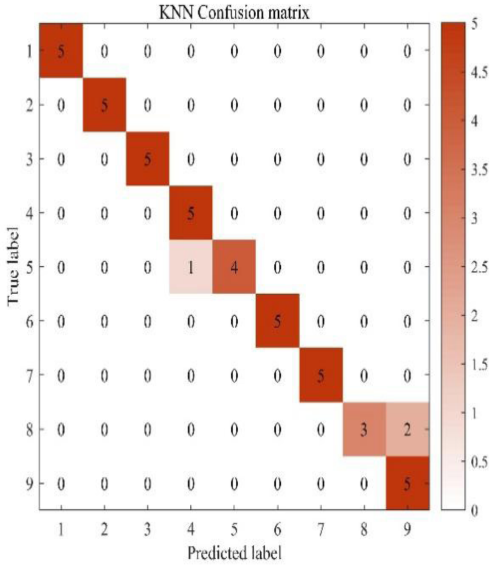

Fig. 5. Confusion matrix diagram of KNN

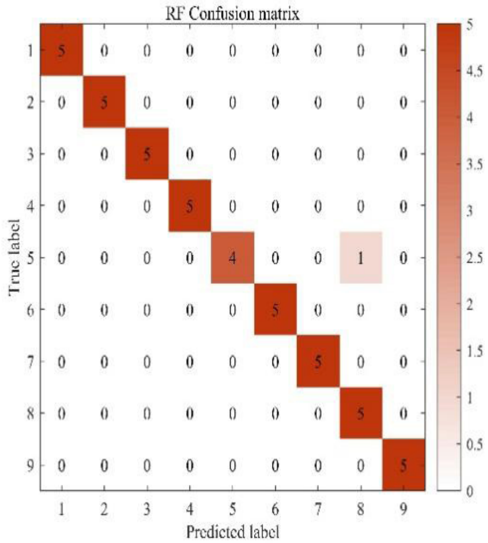

Fig. 6. Confusion matrix diagram of PCA-SVM

As can be seen in Fig. 3, errors were made in the predictions for categories 1 and 5, with two of category 1 being incorrectly classified as category 2, while one of category 5 was incorrectly classified as category 3, giving a number of errors of three. In Fig. 4, on the other hand, has three predictions with errors, in categories 1, 2 and 5, with a number of errors of four. Predictions were incorrect in Fig. 5 for categories 5 and 8 with a number of errors of three. Only category 5 in Fig. 6 has 1 prediction error. It is clear from the number of errors that PCA-SVM predicts best.

5 Conclusion

In this study, key features are successfully extracted from the raw data and the data dimensionality is reduced by applying the PCA method, while retaining enough information for effective fault diagnosis. Highly accurate diagnosis of transformer faults was achieved by utilizing SVM as a classifier in combination with the reduced dimensionality features from PCA. In addition, the study employed thermal imaging to collect transformer data, which provides non-contact, long-distance monitoring capability that facilitates continuous monitoring without disrupting system operation. These results demonstrate the high efficiency and accuracy of the PCA-SVM approach in handling complex power system data.

The application of the PCA-SVM methodology significantly improves the efficiency and accuracy of transformer fault detection, which is essential for timely prevention and repair of faults, reducing outage time, and ensuring power system reliability. Accurate fault diagnosis helps O&M personnel to quickly pinpoint problems, thereby reducing unnecessary maintenance work and associated costs. In addition, it helps to ensure the continuity and security of power supply, which is positive for promoting China-style modernization and achieving the "double carbon" goal.

In order to further improve the accuracy and efficiency of transformer fault diagnosis, this study proposes several future research directions. Firstly, by optimizing the parameters of PCA and SVM, the applicability and robustness of the algorithms in different working conditions and transformer types can be improved. Secondly, a wider range of data collection and processing can be achieved by combining big data analytics and smart technologies using cloud computing and the Internet of Things (IoT). In addition, deep learning methods, such as CNN or RNN, are explored to better handle nonlinear features and complex pattern recognition problems. Meanwhile, develop a PCA-SVM-based online monitoring system to continuously track transformer status and provide early warnings. Finally, a comprehensive diagnosis and management platform is constructed to integrate multi-source sensor data and decision support systems to improve the efficiency and intelligence of maintenance. These directions aim to promote transformer fault diagnosis technology to a higher level of automation and intelligence.

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