Proposing a Novel Method in Diagnosing Power Transformer Failures Based on the Analysis of Morphological Components

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ABSTRACT:
Power transformers are very important in electrical energy distribution systems. In establishing a power plant and even in distribution networks, the cost of power transformers is significant. Any damage or failure in transformers can cause irreparable and heavy losses. Therefore, this equipment is always important in periodic visits. In periodic visits, various parameters of this equipment are checked. One of the ways used in periodic visits is to use infrared images to evaluate the health of this equipment. However, the analysis of these images by human experts is always error-prone and expensive. In this article, a new method is proposed in machine vision to diagnose transformer faults. In the proposed method, infrared images are pre-processed and then features based on multi-resolution transformations such as morphological component analysis, wavelet transform and bandlet transform are extracted and dimension reduced with the help of independent component analysis. The given one-dimensional features are classified using random forest classification, support vector machine and k-nearest neighbor. The classification accuracy obtained in the random forest bin class as the best classifier in fault detection is equal to 98.81%, as well as 91.51% sensitivity and 84.54% negative news rate, as well as 91.86% negative news rate compared to other the numbers showed their superiority. In the F criterion, this value has reached 0.99, which shows the efficiency of the proposed method.

KEYWORDS: Transformer, Failure, Analysis of Morphological Components, Image Processing.

1. INTORADUCTION

As the heart of a substation, the power transformer acts as an important link for voltage conversion and energy delivery. Survey results show that most of the power transformers around the world were installed in the 1980s and many of them are reaching the end of their life. The failure rate of these transformers has been continuously increasing in recent years, especially in power companies with poor maintenance and asset management methods, causing the loss of this valuable equipment [١]. Any change and failure in the transformer causes unwanted heat in this equipment. Hot spots in electrical equipment, especially power transformers, often occur as a result of looseness, oxidation and corrosion of connections, asymmetry of phases, and insulation failure of coils. All these things can be done by using thermal or infrared IR imaging equipment to measure the temperature of equipment such as energy distribution overhead lines, cables, transformers and fuses, cables, electrical panel equipment and all electrical distribution network equipment, including substations. Determined ground [٢].Diagnosing transformer failure is done online with the help of infrared image. These images are sensitive to the heat caused by various errors in the transformer. The performance of these cameras is limited by the level of

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image processing used. In other words, in infrared imaging in thermal cameras, the proposed method is important in detecting failures in image processing[3-6]. With the development and spread of substation inspection robots and smart substations in distribution networks, a large number of infrared fault images need to be analyzed. The infrared image transformer fault detection method can automatically identify and analyze the collected infrared images, which can reduce the maintenance costs of transformers and the dependence on technicians. and reduce manpower. Therefore, it is important to develop an infrared image recognition method to help deal with large amounts of infrared image data. In the early stage, the detection based on infrared or infrared thermal was very limited by thermography and the level of computer calculations. Researchers focused on removing image noise with filter algorithms including Gaussian filter, adaptive median filter, median filter, etc. Also, the image segmentation technique, including object segmentation or fault region segmentation, is performed simultaneously, represented by threshold segmentation by the OTSU method[7-9].Gray histogram methods [۱۰], K-means [10,11], similarity of adjacent regions, growth algorithm based on area and morphological opening and closing operations [۱۲], edge detection [۱۳] and PCNN (pulse coupled neural network) pulse) [۱۴] is presented. In [۱۵], a new non-contact and non-intrusive method for monitoring electrical transformers and detecting their defects based on infrared thermography imaging techniques (IRT) imaging techniques is adopted. In [۱۶], a method based on deep learning is proposed in transformer failure detection. In this paper, in addition to accuracy-based analysis, an in-depth evaluation is presented to show the most suitable architecture in thermal image classification. [۱۷]proposes a fault detection model that includes adaptive synthetic oversampling (ADASYN), reconstructed data method, and an improved Mask Region convolutional neural network (CDCN). In [۱۸], by building an object recognition system with a Convolutional Neural Network (CNN) frame, the Bush frame can be accurately extracted. To detect the fault area of bushings and the background, a pulse connected neural network based on simple linear iterative clustering is proposed to improve the fault area segmentation performance. In [۱۹] a new interpretation of transformer failure analysis is proposed including new image features based on image processing technique. In [۲۰], it has been proposed to detect faults in the power network using Gabor filters. In this method, the investigated image passes through a filter bank, then the output of the filter is thresholded. By combining the output of different filters, a suitable pattern of the defect can be obtained. In [۲۱], in order to solve the key problem of automatic fault detection technology of power equipment, projected transformation has been introduced to extract the features of the thermal image in the system, using the characteristics of the equipment in this design. In [۲۲]. they have proposed GLCM based equipment fault detection. In [۲۳], a new transformer failure interpretation approach has been proposed to detect winding short circuit fault in transformer, radial deformation and bushing faults using polar diagram and have introduced digital image processing in which various unique image features of a polar plot are extracted using geometric dimensions, invariant moments. In [۲۴], an online technique is introduced to detect internal faults in a power transformer by constructing a voltage-current (V-I) location diagram to provide the current status of the transformer's health status. However, the above methods are only applicable for images with a relatively simple background. For those infrared images with complex background, the main image segmentation methods have strong limitations. In order to overcome these complications, multi-resolution transformation methods are proposed[25]. Wavelet transform is one of the important mathematical multi-resolution transforms, which obtains a time-scale representation of the digital signal using digital filtering techniques [۲۶]. In this transformation, it will be calculated by changing the scale of the analysis window, changing the location of the window in time, multiplying it by the signal and integrating it in all times. In the discrete case, filters of different cutoff frequencies are used to decompose the signal at different scales[27-29]. The signal is passed through a series of high-pass filters to analyze high frequencies and through a series of low-pass filters to analyze low frequencies. The degree of signal resolution, which is a measure of the amount of detail in the signal, is varied by filtering operations and scaled by upsampling and Subsampling (downsampling)[۳۰].Bandelet are one of the multi-resolution transforms that have been developed to overcome the challenges and shortcomings of the wavelet transform. Bandelet calculates a geometric flow of an image to better extract smooth edge information. Bandelet decomposition is applied to the orthogonal wavelet coefficients or wavelet filter bank of an image and is calculated by geometric orthogonal transformation through orthogonal filters. As a result of this process, a different transformation is obtained from each geometric direction and they can be processed to find the optimal set of filters with the best basic algorithm. The characteristics of wavelets can be manipulated by selecting low-pass and high-pass square mirror filters [31].Morphological component analysis (MCA) can decompose an image into two components[32]. The advantages of MCA include completeness and effectiveness. (1) Completeness: In multiscale transformation, transformation bases are built to reveal salient features of an image. (2) Effectiveness: The sparse representation uses a complete dictionary with more columns than rows and models the image of the 1-D representation as a linear combination of columns (atoms) [33].The stability and reliability of a power system depends in many ways on the condition and health of power transformers[29]. As one of the most expensive and important elements, the power transformer is a very necessary element whose failure and damage may cause the power system to be interrupted. Therefore, it seems that transformers should be constantly inspected and reviewed in order to apply preventive repairs. In addition to the cost and the need for experienced manpower, visual inspection for power transformers is not very accurate and is always associated with errors. For this purpose, using methods based on image processing can be helpful[34]. Thermal or infrared IR cameras that work with infrared technology are an efficient way to provide preventive maintenance in power transformers and failure detection along with efficient image processing methods. It seems that it is necessary to propose a new and efficient method in diagnosing the failure of power transformers[35]. Therefore, in this research, a method based on the morphological component analysis will be presented in order to detect faults in power transformers. In the proposed method, taking advantage of the morphological diversity of images and the advantages of MCA, the component (carton, texture, and edge) is considered as a feature and will be entered into a classification for failure detection. The innovations of this research can be stated as follows:

- Improving the accuracy of transformer failure detection based on the analysis of morphological components

In the following, this article is divided as follows. In the second part, the principles of image processing in detecting defects in infrared images are presented. In the third part, the suggestion method will be presented. In the fourth part, the evaluation of the proposed method will be done. Finally, the conclusion of the article will be presented in the fifth section.

2. MATERIAL AND METHOD

The passage of electric current through various circuits and components in a device, devices and electrical equipment is always associated with heat production, it seems that by measuring the temperature and preparing thermal photographs of electrical components and equipment, it is a reliable guide in determining the weak points that may be in The future will lead to major connections. Hot spots in electrical equipment are often caused by not being strong, oxidation or corrosion of connections, as well as asymmetry of phases or insulation failure of coils. By using IR infrared image recording equipment in measuring the temperature of equipment such as power transmission lines, high voltage substations, transformers, switches, fuses, cables and all control equipment and electrical panels, it reveals them before they lead to destructive events. It was solved in the electrical system [36].Unique information is extracted from infrared images related to electric energy distribution network equipment and used to show the performance status of this equipment in electric energy distribution smart networks. In addition to morphological features that can be observed, features such as wavelet features and statistical features are also effective in diagnosis. The method of analyzing infrared images in electrical energy distribution network equipment based on machine vision and image processing, data pre-processing, dimension extraction and reduction, classification and application are discussed[37].

2.1. Wavelet Transform

Wavelet transformation is one of the mathematical transformations in multi-precision domains. This conversion is a desirable strategy for establishing an optimal balance between time accuracy and frequency accuracy [38]. At higher frequencies, the wavelet transform gains time-domain information at the cost of losing frequency-related information. While at lower frequencies, it gains frequency information at the expense of temporal information loss. As the Fourier transform is defined based on an integral, the wavelet transform can also be defined based on an integral as follows:

$$W_{X(S,U)} = \int_{-\infty}^{+\infty} X(t)\Psi_{s,u}(t)dt \quad (1)$$

In the above integral, the input signal x(t) is related to the wavelet by means of the transfer parameter u and the coherence parameter s. This transform transforms a signal into coefficients that represent time-frequency information [39]. These coefficients have more time accuracy at high frequencies and more frequency accuracy at low frequencies. The homogeneity parameter enables the wavelet to exchange information in frequency events [۴۰].

The DWT method overcomes the drawbacks and weaknesses of the fast Fourier transform (FFT)[41]. Signal analysis based on FFT works well when its frequency spectrum is not dependent on time, in other words, it is statistically stationary, but many signals are non-stationary in nature. Time-frequency representation of time series signals is an attractive way to capture frequency information at low frequencies and time information at high frequencies. The DWT method is one of the techniques based on multi-resolution analysis [28]. For the signal X(t), the wavelet transform is defined as follows:

$$WT_X\left(j, k\right) = \frac{1}{\sqrt{a_0^j}} \int x(t)\, \Psi^* \left(\frac{t-ka_0^j b_0}{a_0^j}\right) dt \tag{2}$$

In equation (2), x(t) and Ψ are the initial signal and the wavelet transform function, respectively, and also the transmission parameter and$a_0^j\, is$ the scale parameter. where j represents the wavelength. Usually $a_0 = 2$, so scales are sampled during a binary sequence. The sample time domain is specified using Kb_0. At each level of analysis, approximation coefficients CA and detail coefficients CD are created by passing the X(n) signal through the high-pass H and low-pass L filters [29]. Approximation coefficients and detail coefficients are obtained by the following equations [37]:

$$CA_j = \sum_{n=-\infty}^{\infty} X_{j-1}\,(n) l(n-2k) \tag{3}$$
$$CD_j(k) = \sum_{n=-\infty}^{\infty} X(n) l(n-2k) \tag{4}$$

Wavelet transform may not be the best choice for edge detection in natural images. This observation is based on the fact that wavelets are blind to the smoothness of edges commonly found in images. Therefore, there should be a new multi-resolution approach that is more flexible and efficient in capturing edge smoothness of images, should be used in edge detection and image segmentation applications.

The bandlet approach is a multi-resolution approach in the field of curve transformation. Their reasoning is as follows:

• This approach successfully removes noise, because the noise is not part of the structural information of the image, and the curve transform does not generate coefficients for the noise.

• But the transformation of the curve is defined in polar coordinates, which makes it difficult to translate it into Cartesian coordinates.

For segmentation in an image and especially for finding image edges for infrared images in transformers, they have limitations in determining wavelet base defects, because they are not well adapted to detect highly anisotropic elements such as alignments in an image. Bandlet transform performs better than wavelet transform in displaying salient image features such as edges, lines, curves and contours due to its anisotropy and directionality properties. Therefore, it is suitable for multi-scale edge-based color image enhancement.

Bandlet (Contourlet) conversion consists of two steps:

Subband decomposition and directional transformation .

A Laplacian pyramid (LP) is first used to capture point discontinuities in the subband decomposition step, then directional filter banks are used to link point discontinuities to linear structures. The overall result is an expansion of the image using basic elements such as contour segments and curves in the image and is named bandlet transform. Figure 1 shows the bandlet conversion flow diagram. The image is first decomposed into subbands by LP transformation, and then, each detail image is analyzed by directional filter banks (DFB).

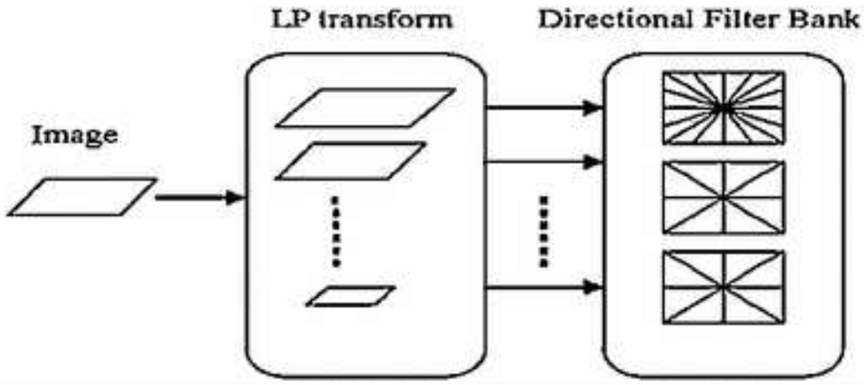

Fig. 1. Bandlet conversion performance.

In this section, the image separation method based on MCA Morphological component decomposition is described. The first related issue is the dimensions of the original data set, especially in far-infrared images with low and even appropriate spectral resolution such as hyperspectral data, and in order to reduce the dimensions of the data, this issue is very important. Dimensionality reduction of remote image classification can be done using all the original image information.
MCA-based image segmentation is a method that allows us to separate features in an image when these features present different morphological aspects. For an image $y \in R^N$، where N is the number of pixels in y, and a given texture feature, the task is to find the most sparse solution to the problem as follows:

$$x = argmin\|x\|_1 \\ subject\ to: y = Ax \tag{5}$$

where $x \in R^K$ denotes the sparse MC coefficients, $A \in R^{N\times K}$ denotes the associated dictionary, and K denotes the number of atoms in the dictionary (usually K>N). which is a portable convex constrained optimization problem and can reduce the computational complexity by linear programming. In image texture separation, we often use MCA to decompose an image into texture and content components. In the work presented in [۲۹], MCA-based decomposition is used to classify hyperspectral images, where the obtained results were very promising. For a given image y with N pixels, the goal of MCA is to split it into two components: a smoothness component y_s and a texture component y_t, respectively. These components represent the original image under a linear combination as follows. where n is the remainder in the image approximation.

$$y = y_s + y_t + n \tag{6}$$

3. PROPOSED METHOD

The main goal of this research is to detect transformer failures in infrared images using MCA principal components analysis. After improving the image quality with the help of pre-processing methods, MCA principal component analysis will be applied to the image. To classify and identify the failure, the relevant features of the cartoon texture and edge will be used for classification. The general block diagram of the proposed method is shown in Fig. 2.

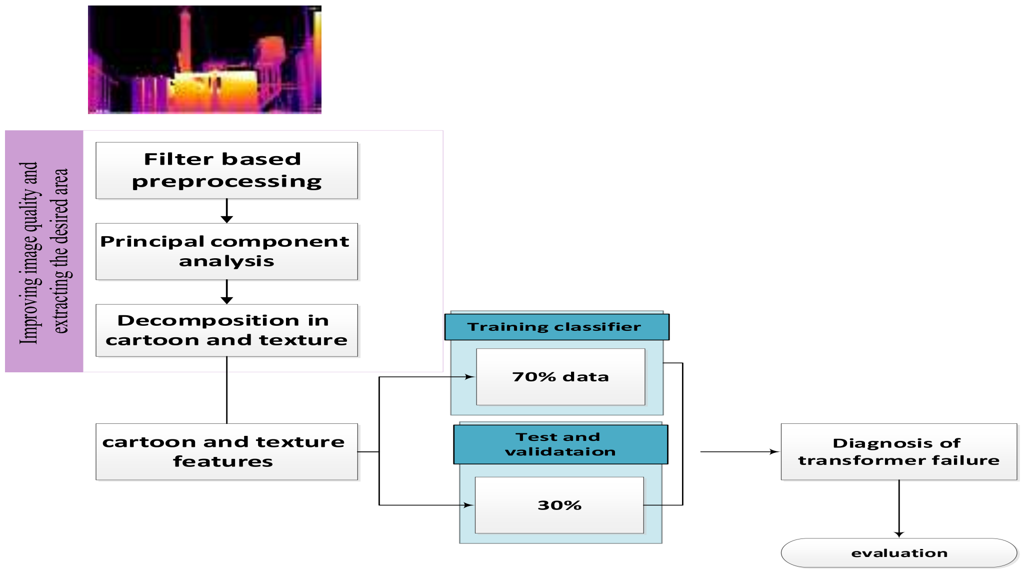

Fig. 2. Block diagram of the proposed method.

The first step: improving the quality of the infrared image

Infrared images consist of a gray color spectrum that lies between white and black. Sometimes, due to the low contrast in the image, it is very difficult to distinguish the difference between adjacent pixels that have very close colors. Since the defect in an equipment discussed in this research may be similar to the rest of the parts, it is necessary to improve the quality of the image in such a way that it becomes easier to detect this defect in the transformer [۴۲].Bidirectional filtering is used as an edge preservation tool in image enhancement applications [4]. Along with a low-pass spatial kernel (which helps with smoothing), it uses a kernel to prevent smoothing near the edges. As a result, the filter is able to smooth homogeneous areas and preserve sharp edges at the same time. It was shown that spatial and domain kernels are typically Gaussian, which can be improved by adjusting the width and center of the Gaussian domain kernel at each pixel, and the enhancement capacity of the two-way filter.

Fig. 3. (a) The original image and (b) the improved rendering based on filtering in the proposed method.

The second step: applying MCA principal components analysis

Morphological component analysis (MCA) is a new method that allows us to separate features in an image when these features present different morphological aspects. We show that MCA can be very useful for decomposing images into textures, edges and piecewise smooth (cartoon)or for feature extraction applications. To classify the defects in the infrared images using the neural network method or any other classifier in machine learning, first the features based on the morphological component analysis (MCA) are extracted from the infrared image and by them the neural network or another classifier. It is taught in machine learning.

In the framework of thin representation, a dictionary $U = [\emptyset_1, \dots, \emptyset_T]$ is viewed as an N×T matrix. When T > N or even T >>N, the dictionary is too complete and is built by merging several dictionaries. An image $x \in R^N$ (an image with N pixels can be expressed as a lexically ordered 1-D vector) as a linear combination of elementary atoms M(M < T) of the dictionary, according to the model equation has been made

$$min_{\alpha \in R^m} \|\alpha\|_0 \quad s.t. \ x = \emptyset\alpha. \tag{7}$$

$$x = \emptyset\alpha = \sum_{i \epsilon I_m} \alpha[i]\emptyset_i \tag{8}$$

where a[i] is the representation coefficients of x. IM is a subset of [۴۳] and Card(IM) = M. ui represents U atoms. Obviously, from Eq. (7), x has a large number of candidate representations. It is the thinnest purpose of representation. Therefore, the sparse representation problem requires the following minimization solution.

$$min_{\alpha \in R^m} \|\alpha\|_1 \quad s.t. \ x = \emptyset\alpha. \tag{9}$$

The complexity of the problem is formulated in equation (9). grows exponentially with the number of dictionary columns because the problem is non-convex. To reduce the complexity, the non-convex l0 scattering criterion is replaced by the l1-norm [38]. Therefore, equation (9) becomes a portable convex optimization problem that can be solved by the base tracking (BP) basis pursuit [39].
In order to extract cartoon and texture features in MCA, the infrared images are systematically decomposed into texture and cartoon parts. The coefficients created in the texture and cartoon layers are tight enough to be used for the feature. If α_C and α_T represent the thin representation of texture and cartoon images respectively, the feature vector resulting from each visualization is $\left[\alpha_c \ \ \alpha_T\right]$. BCR simplification based on block coordinates is used to calculate α_C and α_T pseudo-digram blocks.

Bandlet features

The bandlet transform, which is a combination of the previous two transforms, allows us to analyze the image with different block sizes. The work process is that first, the image is decomposed into a set of wavelet bands and the analysis of each band will be by Reglet transformation. The size of the blocks can be changed in each level. In fact, it is a two-dimensional transformation that cannot be separated into one-dimensional transformations parallel to the coordinate axes. A bandlet transform is presented to optimally represent two-dimensional discontinuities. In this research, 2 levels of Corlott transformation are used. Figure (4) shows the filter banks resulting from bandlet transformation.

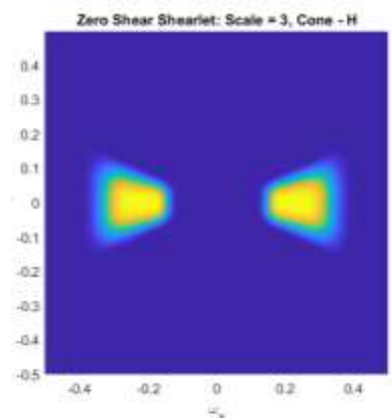

Fig. 4. Bandlet filterbanks

Fourth step: error detection

In order to reduce the dimension and remove duplicate information, principal component analysis has been used in this research. The classification model is responsible for separating and categorizing based on a series of input data, and as a result, it finally achieves the goal of detecting failure in the desired equipment. Common machine learning algorithms including K nearest neighbor (KNN), decision tree and random forest, support vector machine (SVM), Artificial neural network (ANN) have been used in this research [۴۴].

4. RESULTS

In this research, the proposed method will be evaluated with multiple evaluation criteria. The system for simulating the proposed method has hardware with 7 cores (Core™ (i7 CPU)) and a working frequency of 2.60GHz. The RAM available in this system is 16 GB. The Windows operating system installed on this device is version 11. The simulations were carried out in the used MATLAB 2020b software. The criteria of accuracy, sensitivity, positive predictive value and negative predictive value were used. Relationships are defined as follows. Necessary explanations regarding the values used in relations (10) to (12) have been stated[45].

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (10)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (11)$$

$$Specificity = \frac{TP}{TP+FN} \quad (12)$$

In above equation True Negative :TN, False Negative :FN, True Positive :TP, False Positive :FP.

The desired criteria in the evaluation of the proposed method have been checked separately on the collected database. In order to determine the best parameters in the classification and faults and breakdowns in transformers, several tests were conducted on the SVM and K nearest neighbor KNN support vector machine classifications, as well as the random forest. Based on the tests, the best parameters have been announced as follows:

- In SVM window Radial based function RBF
- In the KNN classification, Euclidean metric criteria and neighborhood radius 3
- 1000 trees in the forest

In the whole classification process, 70% of the data is used for training and 30% for testing.

4.1. Research database

Saman Niro Sepahan Company is one of the active companies in the field of troubleshooting and fault detection in power networks, which uses Thermovision thermal cameras to identify faults. The image database used in this research is images collected by Saman Niro Sepahan Technical and Engineering Company. The used camera model is Trotec AC080V made in Germany. The number of images in this research is 300 images of different equipments including transformers, insulators, arresters and other equipments.

4.2. Quality evaluation

An example of qualitative fault diagnosis is shown in this article. Figure 5 shows the main image of the evaluated database. The results of Figure 6 show that the proposed method has achieved acceptable results. The quality of this method can be discussed from two perspectives. First, the algorithms based on morphological component analysis are among the most powerful zoning methods and have many defects in improving zoning. Second, the use of pre-processing methods has been able to reduce the system error to a great extent.

4.3. Quantitative assessment

Table 2 shows the fault results in transformer equipment without dimension reduction and with features based on wavelet transformation. As can be seen from Table 2, the detection results are not very promising and it seems that to improve the results, a suitable dimension reduction method and a suitable feature descriptor are needed in order to avoid overfitting and improve the results. The results of Table 1 show the superiority of the KNN classification method in the defect in the transformer equipment in the state without dimension reduction.

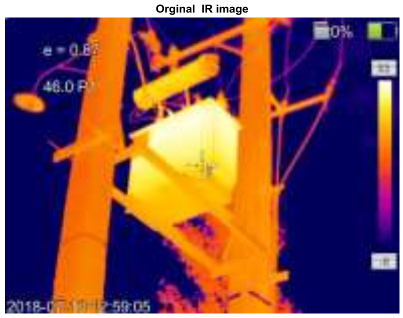

Fig. 5. The main image of existence in the database.

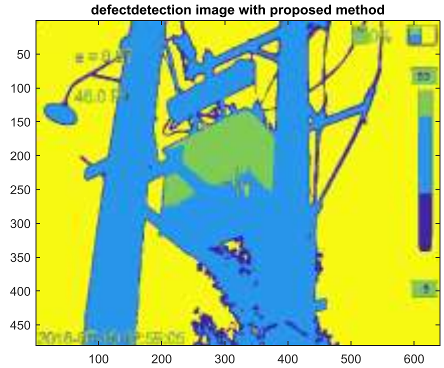

Fig. 6. Zoning and error detection in the proposed method.

The results of PCA classification

Support vector machine, random forest and K-nearest neighbor classifiers were used to classify the infrared image data in the database. For classification, first pre-processing was done on the desired database images. After feature extraction with the help of the proposed method, the next step of reduction was done with the help of PCA, then the classification was done with the help of the introduced classes. Table 2 shows the results of this classification. As can be seen from the results of Table 3, the results obtained are in a similar range. However, the KNN classifier has been able to perform as the best classifier with the best calculated accuracy value as well as lower sensitivity, higher accuracy, and although lower recall rate. The random forest classifier as well as the SVM classifier have similar results, and in any case, the accuracy of the results has not reached 90%.

The results of the classification of the proposed method

The given dimensionality reduction features are classified using the proposed method based on main morphological components as well as multi-resolution analysis with KNN classifier and SVM support vector machine as well as random forest classifier. The results of the proposed method in Table 4 show the results of this classification.

Table 1. Simulation results without dimension reduction

Evaluation criteria	**K nearest neighbor(%)**	**Support vector machine (%)**	**Random forest(%)**
Precision	75.26	68.13	71.76
Sensitivity	71.38	66.75	72.72
Accuracy	72.33	63.75	70.27
Recall	67.21	71.89	69.43
Criterion F	87.01	80.01	74.00

Table 2. The results of the simulation with dimension reduction with the help of PCA.

Evaluation criteria	**K nearest neighbor(%)**	**Support vector machine(%)**	**Random forest (%)**
Precision	86.26	79.13	75.64
Sensitivity	81.38	80.57	66.72
Accuracy	89.33	83.75	76.26
Recall	77.21	85.89	75.43
Criterion F	87.25	80.80	74.02

Table 3. Simulation results along with dimension reduction in the proposed method.

Evaluation criteria	**K nearest neighbor(%)**	**Support vector machine(%)**	**Random forest (%)**
Precision	95.81	94.10	98.18
Sensitivity	91.51	85.37	86.25
Accuracy	84.54	81.14	63.38
Recall	91.25	90.87	97.87
Criterion F	94.28	91.23	99.25

As it is clear from the results of Table 4, the RF classifier with K nearest neighbor has been able to get better results. It should be noted that the accuracy and sensitivity values obtained and the recall rate are also acceptable results. As it can be seen from the graph, the combination of the extracted features has led to better results, and this proves the important sub-hypothesis of this research, including the improvement of results in classifications by reducing the dimension with the help of the proposed method. This superiority is still perceptible in all the criteria used. The F criterion is also included in these evaluations. In this case, the random forest classifier has been able to obtain the best result with 0.99 in the accuracy criterion as well as the F criterion with one hundred features.

4.4. Comparison with other studies

The proposed method in this article is compared with other related researches in fault diagnosis in transformer equipment. These methods include RNN recurrent neural networks [32] and deep learning [33]. In recent years, methods based on deep learning are among the most common methods and of course with good efficiency. Various researches have used methods based on deep learning. Although these methods are acceptable and highly accurate, they require a large database for simulation. The desired methods for comparison have been simulated on the database of this research. Therefore, a correct comparison and correct evaluation has been made. The results of the comparison of the proposed method with the desired researches are shown in table (5). As can be seen from the results of this table, the proposed method has better accuracy than other methods based on deep learning. The database used in all these researches is the database collected in this research by Saman Niro Sepahan Company.

Table 4. Comparison of the proposed method with other articles.

The presented model	Research	Average accuracy
2 D-CNN	[۳۲]	94.10
RNN	[۳۳]	95.91
Proposed	-	99.00

5. CONCLUSION

In this research, the relationship between In this article, the proposed method for detecting defects in transformer equipment was evaluated in infrared images. In the proposed method, several features in the time domain including morphological features (edge and cartoon), multi-resolution features based on wavelet transform with Dabich's filter bank were also extracted. A method based on PCA principal component analysis was introduced. The feature vector matrix was classified by support vector machine, random forest and k nearest neighbor classifiers. The parameters of recall rate, precision, accuracy, specificity and f-criterion are evaluated in three categories: SVM, KNN and RF. The RF classification has the best result with numerical values higher than 99% in the proposed method in feature selection based on the PCA algorithm.

REFERENCES

[1] X. Ouyang, Q. Zhou, H. Shang, Y. Zheng, S. Pan, and J. Luo, “Towards a Comprehensive Evaluation on the Online Methods for Monitoring Transformer Turn-to-Turn Faults,” *IEEE Transactions on Industrial Electronics*, 2022.

[2] L. Raeisian, H. Niazmand, E. Ebrahimnia-Bajestan, and P. Werle, “Thermal management of a distribution transformer: An optimization study of the cooling system using CFD and response surface methodology,” *International Journal of Electrical Power & Energy Systems,* vol. 104, pp. 443-455, 2019.

[3] E. Karimi, and A. Ebrahimi, “Considering risk of cascading line outages in transmission expansion planning by benefit/cost analysis,” *International Journal of Electrical Power & Energy Systems,* vol. 78, pp. 480-488, 2016.

[4] E. Karimi, A. Ebrahimi, and M. R. Tavakoli, “How optimal PMU placement can mitigate cascading outages blackouts?,” *International Transactions on Electrical Energy Systems,* vol. 29, no. 6, pp. e12015, 2019.

[5] E. Karimi, and A. Ebrahimi, “Probabilistic transmission expansion planning considering risk of cascading transmission line failures,” *International Transactions on Electrical Energy Systems,* vol. 25, no. 10, pp. 2547-2561, 2015.

[6] M. Emadi, Z. Jafarian Dehkordi, and M. Iranpour Mobarakeh, “Improving the Accuracy of Brain Tumor Identification in Magnetic Resonanceaging using Super-pixel and Fast Primal Dual Algorithm,” *International Journal of Engineering,* vol. 36, no. 3, pp. 505-512, 2023.

[7] F. B. Zade, and M. Emadi, “The Improvement of Breast Cancer Diagnosis Rate in Magnetic Resonance Imaging (MRI) using Fusion of Super Pixels and Fuzzy Connectedness,” *Majlesi Journal of Telecommunication Devices,* vol. 10, no. 4, pp. 137-145, 2021.

[8] S. A. M. Mobarakeh, and M. Emadi, “Improvement of the Identification Rate using Finger Veins based on the Enhanced Maximum Curvature Method using Morphological Operators,” *Majlesi Journal of Telecommunication Devices,* vol. 11, no. 1, pp. 1-8, 2022.

[9] M. Soleimani, and J. Coykendall, "Divisors and Factorization Type."

[10] R. S. Marques, A. Conci, M. G. Perez, V. H. Andaluz, and T. M. Mejia, “An approach for automatic segmentation of thermal imaging in Computer Aided Diagnosis,” *IEEE Latin America Transactions,* vol. 14, no. 4, pp. 1856-1865, 2016.

[11] N. Liu, J. Zhang, and X. Wu, “Asset analysis of risk assessment for iec 61850-based power control systems—part i: methodology,” *IEEE Transactions on Power Delivery,* vol. 26, no. 2, pp. 869-875, 2010.

[12] A.-V. Vo, L. Truong-Hong, D. F. Laefer, and M. Bertolotto, “Octree-based region growing for point cloud segmentation,” *ISPRS Journal of Photogrammetry and Remote Sensing,* vol. 104, pp. 88-100, 2015.

[13] A. Aslam, E. Khan, and M. S. Beg, “Improved edge detection algorithm for brain tumor segmentation,” *Procedia Computer Science,* vol. 58, pp. 430-437, 2015.

[14] D. Zhou, and Y. Shao, “Region growing for image segmentation using an extended PCNN model,” *IET Image Processing,* vol. 12, no. 5, pp. 729-737, 2018.

[15] A. Mahami, T. Bettahar, C. Rahmoune, F. Amrane, M. Touati, and D. Benazzouz, "A New Transformer Condition Monitoring Based on Infrared Thermography Imaging and Machine Learning," *Advanced Computational Techniques for Renewable Energy Systems,* pp. 408-418: Springer, 2023.

[16] G. Sakallı, and H. Koyuncu, “Identification of asynchronous motor and transformer situations in thermal images by utilizing transfer learning-based deep learning architectures,” *Measurement,* vol. 207, pp. 112380, 2023.

[17] Z. Li, Y. He, Z. Xing, and J. Duan, “Transformer fault diagnosis based on improved deep coupled dense convolutional neural network,” *Electric Power Systems Research,* vol. 209, pp. 107969, 2022.

[18] J. Jiang, Y. Bie, J. Li, X. Yang, G. Ma, Y. Lu, and C. Zhang, “Fault diagnosis of the bushing infrared images based on mask R- CNN and improved PCNN joint algorithm,” *High voltage,* vol. 6, no. 1, pp. 116-124, 2021.

[19] L. Zhou, J. Jiang, X. Zhou, Z. Wu, T. Lin, and D. Wang, “Detection of transformer winding faults using FRA and image features,” *IET Electric Power Applications,* vol. 14, no. 6, pp. 972-980, 2020.

[20] L. Zhu-Mao, L. Qing, J. Tao, L. Yong-Xin, H. Yu, and B. Yang, "Research on thermal fault detection technology of power equipment based on infrared image analysis." pp. 2567-2571.

[21] S. Anoop, K. Ilango, A. Dhieep, C. Thomas, J. Jose, A. Kumar, and P. Ajith, "Thermal stress monitoring and pre-fault detection system in power transformers using fibre optic technology." pp. 886-891.

[22] H. Shen, L. Zhu, X. Hong, and W. Chang, "ROI extraction method of infrared thermal image based on GLCM characteristic imitate gradient." pp. 192-205.

[23] O. Aljohani, and A. Abu-Siada, “Application of digital image processing to detect transformer bushing faults and oil degradation using FRA polar plot signature,” *IEEE Transactions on Dielectrics and Electrical Insulation,* vol. 24, no. 1, pp. 428-436, 2017.

[24] A. Abu-Siada, and S. Islam, "Image processing-based on-line technique to detect power transformer winding faults." pp. 5549-5554.

[25] M. Soltani, M. Bahadori, and M. Soleimani, “Optimal Predictive Maintenance and Spare Part Inventory Policies for a Degrading System Subjected to Imperfect Actions,” *Available at SSRN 4558570,* 2023.

[26] A. Mahami, C. Rahmoune, M. Zair, T. Bettahar, and D. Benazzouz, “Automated Transformer fault diagnosis using infrared thermography imaging, GIST and machine learning technique,” *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering,* vol. 236, no. 4, pp. 1747-1757, 2022.

[27] S. Aryanmehr, M. Karimi, and F. Z. Boroujeni, "CVBL IRIS Gender Classification Database Image Processing and Biometric Research, Computer Vision and Biometric Laboratory (CVBL)." pp. 433-438.

[28] M. Emadi, M. Karimi, and F. Davoudi, "A Review on Examination Methods of Types of Working Memory and Cerebral Cortex in EEG Signals," *Majlesi Journal of Telecommunication Devices,* vol. 12, no. 3, 2023.

[29] M. Harouni, M. Karimi, A. Nasr, H. Mahmoudi, and Z. Arab Najafabadi, "Health Monitoring Methods in Heart Diseases Based on Data Mining Approach: A Directional Review," *Prognostic Models in Healthcare: AI and Statistical Approaches*, pp. 115-159: Springer, 2022.

[30] M. Aqil, A. Jbari, and A. Bourouhou, "ECG signal denoising by discrete wavelet transform," *International Journal of Online and Biomedical Engineering (iJOE),* vol. 13, no. 09, pp. 51-68, 2017.

[31] A. R. Khan, F. Doosti, M. Karimi, M. Harouni, U. Tariq, S. M. Fati, and S. Ali Bahaj, "Authentication through gender classification from iris images using support vector machine," *Microscopy research and technique,* vol. 84, no. 11, pp. 2666-2676, 2021.

[32] M. Karimi, M. Harouni, and S. Rafieipour, "Automated medical image analysis in digital mammography," *Artificial intelligence and internet of things*, pp. 85-116: CRC Press, 2021.

[33] M. Harouni, M. Karimi, and S. Rafieipour, "Precise segmentation techniques in various medical images," *Artificial Intelligence and Internet of Things*, pp. 117-166, 2021.

[34] M. Soleimani, F. Mahmudi, and M. H. Naderi, "On the Maximal Graph of a Commutative Ring," *Mathematics Interdisciplinary Research,* 2021.

[35] M. Soleimani, and A. S. Mirshahzadeh, "Multi-class Classification of Imbalanced Intelligent Data using Deep Neural Network," *EAI Endorsed Transactions on AI and Robotics,* vol. 2, 2023.

[36] M. Soleimani, F. Mahmudi, and M. Naderi, "Some results on the maximal graph of commutative rings," *Advanced Studies: Euro-Tbilisi Mathematical Journal,* vol. 16, no. supp1, pp. 21-26, 2023.

[37] A. Rehman, M. Harouni, F. Zogh, T. Saba, M. Karimi, and G. Jeon, "Detection of Lung Tumors in CT Scan Images using Convolutional Neural Networks," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 2023.

[38] M. Karimi, M. Harouni, A. Nasr, and N. Tavakoli, "Automatic lung infection segmentation of covid-19 in CT scan images," *Intelligent Computing Applications for COVID-19*, pp. 235-253: CRC Press, 2021.

[39] A. Raftarai, R. R. Mahounaki, M. Harouni, M. Karimi, and S. K. Olghoran, "Predictive models of hospital readmission rate using the improved AdaBoost in COVID-19," *Intelligent Computing Applications for COVID-19*, pp. 67-86: CRC Press, 2021.

[40] V. Seena, and J. Yomas, "A review on feature extraction and denoising of ECG signal using wavelet transform." pp. 1-6.

[41] A. Rehman, M. Harouni, M. Karimi, T. Saba, S. A. Bahaj, and M. J. Awan, "Microscopic retinal blood vessels detection and segmentation using support vector machine and K- nearest neighbors," *Microscopy research and technique,* vol. 85, no. 5, pp. 1899-1914, 2022.

[42] L. Xie, Z. Li, Y. Zhou, Y. He, and J. Zhu, "Computational diagnostic techniques for electrocardiogram signal analysis," *Sensors,* vol. 20, no. 21, pp. 6318, 2020.

[43] K. Zhang12, Y. Huang, C. Song, H. Wu, L. Wang, and S. M. Intelligence, "Kinship verification with deep convolutional neural networks," 2015.

[44] T. G. Jan, and S. M. Khan, "A Systematic Review of Research Dimensions Towards Dyslexia Screening Using Machine Learning," *Journal of The Institution of Engineers (India): Series B,* pp. 1-12, 2023.

[45] M. Soleimani, A. Harooni, N. Erfani, A. R. Khan, T. Saba, and S. A. Bahaj, "Classification of cancer types based on microRNA expression using a hybrid radial basis function and particle swarm optimization algorithm," *Microscopy Research and Technique,* 2024.