Use of machine learning techniques for classification of thermographic images

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***Abstract* — The possibilities for using machine learning techniques in the classification of thermographic images for the purposes of technical diagnostics are examined in the paper. A program for extracting the statistical characteristics of thermographic images has been developed. A machine learning model for classification of thermographic images of induction motors has been trained and tested.**

Keywords — thermal images, machine learning techniques, diagnostics, image classification

I. Introduction

The early detection and determination of the type of fault occurring in electrical systems is vital for modern industry, as power outages or production processes interruption can have a serious impact on social and economic activities carried out in an organization. To ensure the continuity of power supply and the reliability of the electrical equipment used in industrial processes, regular timely inspections must be carried out. Traditional preventive maintenance plays an important role in preventing accidents, ensuring the safety of electrical systems and the reliability of equipment operation, but it cannot fully meet the needs, leading to sudden failures. This feature leads to the increasing application of modern approaches such as technical monitoring and online diagnostic systems.

Thermal imaging is an ideal technology for temperature monitoring, as it allows fully display of the thermal field of a machine or its components, without physical interaction (non-destructive) and provides results in a very short period of time. In this context, the thermal imaging technique shows very good results when used as a method for online diagnostics, detecting faults such as: defective connections between conductors or between conductors and switchgear or other equipment, incorrect selection or design of switchgear and equipment, overload of individual elements of the electrical equipment, defects in cables, insulators and electrical machines [3].

Despite the impressive development of the application of thermal imaging for the diagnostics of rotating electrical machines, some important questions remain that pose the future challenges to research in this area. One of them is based on the lack of objective temperature thresholds, allowing the detection of various defects or anomalies that can be applied to any motor and in any operating condition. Typically, industrial plants develop their own thresholds, adapted for each machine, which are derived from their own experience in this field. This increases the dependence of this technique on the expert opinion of the examiner and makes its application more subjective. In addition, the lack of knowledge about the thermal field patterns associated with each specific failure is also a serious limitation that can be overcome over time.

In order to achieve a certain degree of automation of the process of processing and analysis of thermographic images of induction motors, procedures (algorithms) are developed to identify the thermal field distributions of serviceable motors and motors with different types of faults. The use of these algorithms in combination with a suitable mathematical model allows to distinguish anomalies such as: damage to the cooling system, damage to the bearing units, damage to the windings and others. The base structure of a system for automated analysis and classification of thermal images is shown in Fig.1. In some cases, computer vision techniques are used to extract the region of interest, and in others, this is done by manual selection. The final analysis, after the extraction of the potential problem regions, can be carried out by a specialist, by thermal comparison or AI algorithms [1, 2].

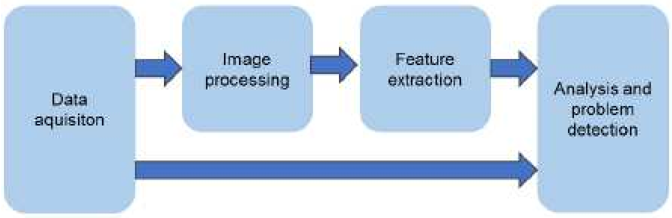

Fig. 1. Structure of a system for automated analysis of thermal images

Some of the processing algorithms use the statistical indicators obtained for the part of the image corresponding to the studied object, to distinguish the individual states of the machine, as well as to quantify the size or severity of the damage. The improvement of these algorithms and models is developing in the direction of using the information about the technical condition, which can be obtained from the thermal transients occurring in the machine.

II. Machine learning techniques

Taking into account the great complexity of the physical processes (mathematical models) arising from the imaging of thermographic images on the one hand, and the significant set of operational and human factors influencing the measurement results on the other hand, it is clear that the use of the classical programing approach for compiling mathematical models and algorithms for image classification is impractical. This requires the use of machine learning and deep learning techniques, which have already become extremely widespread in the modern world.

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The application of machine learning techniques in the classification of thermographic images is appropriate, as machine learning algorithms build a mathematical model based on sample data known as "training set", which allows predictions or decisions to be made without the need of complex mathematical models.

Machine learning techniques use different methods and models to train computers to perform tasks for which there is no completely satisfactory algorithm. The choice of a specific model and method for its training depends mainly on the nature of the problem to be solved, the number of input parameters and the number of potential output states [7].

The classic k-nearest neighbors (k-NN) model and various modifications of the support vector machine (SVM) model have been widely used in the classification of images.

A. K-nearest neighbors model

At the heart of this model is an important assumption, called the compactness hypothesis which states that if the measure of object similarity is introduced successfully enough, then similar objects are much more likely to lie in the same class than in different ones. In this case, the boundary between the classes has a fairly simple shape and the classes form compactly localized regions in the object space.

The k-nearest neighbors (k-NN) algorithm is a nonparametric model used to classify and recognize images. k-NN is a model that uses a local approximation of the generalized vector of input parameters in multidimensional space to assign input data to a given class.

When this model is used for image classification the number of nearest neighbor points *k* is usually bigger than one. The number of nearest neighbors *k* is a user-defined constant and the newly introduced generalized vector of input parameters (query or test point) is classified by assigning it to the class that is most common among *k* nearest neighbors to the test point already known points.

The number of nearest neighbor points k is one of the parameters which can increase the accuracy of classification. The optimal value of the number of considered neighboring points depends on the data. In general, larger values of k reduce the effect of noise on classification, but make the boundaries between classes less clear. Depending on the number and type of adjacent points considered, k-NN models are classified into the following groups:

- ***Nearest neighbor model*** (*k =1*). The classified vector x belongs to the class y_i, to which the nearest object of the training data belongs x_i;
- ***k Nearest neighbors model*** (*k >1*). To increase the reliability of the classification, the classified vector belongs to the class y_i, to which most of its neighbors belong - k closest to it points from the training data x_i;
- ***Weighted k nearest neighbors model***. In this model, the classified vector is assigned to the class that gains the greatest total weight among the k closest points of the training data. x_i.

In the case of a large number of the considered neighboring points *k>5*, in order to increase the accuracy of classification, additional indicators are introduced, through which weight coefficients are determined for the individual nearest neighboring points. Frequently used indicator is the distance between the test point and the specific neighboring point *d*. In this case, the weighting factor for the ith neighbor point is determined by the dependence

$$w_i = 1/d_i\,. \tag{1}$$

Regardless of the number of adjacent points considered, the k-NN classification model can be described by the following equation:

$$a\,(j) = \arg\max_{y\in Y} \sum_{i=1}^{m} [x_{i;j} = y]\, w(i,j)\,. \tag{2}$$

where: $w(i, j)$ is the weight function, which evaluates the degree of importance of the ith adjacent point for the classification of the input vector *j*.

B. Suport vector machine model

Suport vector machine (SVM) models are a set of supervised training algorithms used for classification and regression. The classical SVM algorithm is a non-probabilistic, binary linear classifier, which limits its practical application for the classification of thermographic images. However, there are improved modifications of this model, allowing its conversion to a nonlinear classifier (kernel method), as well as algorithms for obtaining probabilistic estimates based on SVM (Platt scaling) [5].

Generally speaking, the Support vector machine model is based on the construction of a hyper-plane or multiple hyper-planes in multidimensional space that can be used to classify or regress the input data. Each hyperplane can be described by a set of points x that satisfies the condition:

$$\vec{\omega}.x - b = 0\,, \tag{3}$$

where: $\vec{\omega}$ is the normal vector of the hyper-plane;

b - the distance of the hyper-plane passing through the boundary points of one group of elements and the separating hyper-plane.

The parameter $b / \vec{\omega}$ determines the relative margin width between the separating hyper-plane and the boundary hyper-planes. In the case of linearly separable data classes, this parameter is unchanged (hard margin), while in the cases when the data are not linearly separable this parameter is variable.

For the use of the SVM model in the classification of thermographic images for the purposes of technical diagnostics, it is necessary to recur to the application of a multi-class nonlinear classifier with a soft margin. The classification model is presented with the following equation:

$$a\,(i) = \min\left[\frac{1}{n}\sum_{i=1}^{n}\max(0, 1 - y_i(\vec{\omega}.x_i - b)) + \lambda \| \omega \|^2\right], \tag{4}$$

where λ is a parameter that is determined by the balance between increasing the relative width of the margin and ensuring the correct classification of the individual points.

III. Image Processing

The application of machine learning for the classification of thermographic images requires the latter to be processed in order to form the vector of input data. The methodology for performing the processing is discussed in detail in [6].

A program in the Matlab R2019b software environment has been developed to perform the processing of thermographic images. The program allows the input data to be set in the form of thermographic images with different pseudo-color representations of the thermal field or CSV files containing the temperature matrix. Regardless of the type of input data, they are converted to a grayscale image. The grayscale image of an induction motor that is used in the training set is shown in Fig.2.

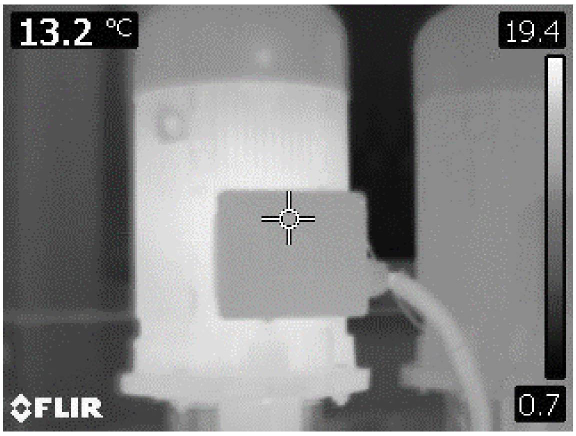

Fig. 2. Gray scale image of an induction motor

After image conversion, the histogram-based statistical features (mathematical expectation, variance, standard deviation, skewness, kurtosis and entropy) are calculated..

The next step in the processing is the segmentation of the resulting grayscale image. For this purpose, the value of the threshold intensity against which the image is converted into binary is calculated. The Otsu method is used to determine the value of the threshold intensity.

The resulting segmented image is visualized in the user interface, where the operator selects the region of interest (ROI). The selection of ROI is shown in Fig. 3.

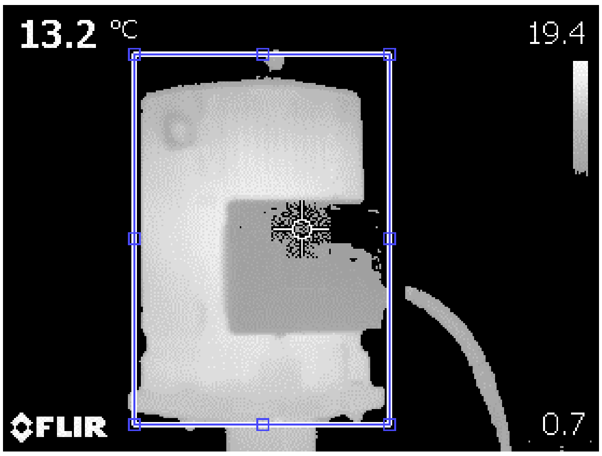

Fig. 3. Selection of the region of interest in the segmented image

The choice to manually enter the region of interest is imposed by the peculiarities of the processed images - the presence of more than one element whose intensity values are above the threshold value used for segmentation.

The processing continues with the determination of the features of the gray-scale co-occurrence matrix (contrast, correlation, energy and homogeneity) and the component-based features of intensity (minimum and maximum intensity, mean intensity, variance and standard deviation for ROI) [4].

Table 1 shows the values of the individual parameters forming the vector of the input data.

TABLE I. Input Parameters

Histogram-based statistical features		
№	**Feature**	**Value**
1	Mean	126,9424
2	Variance	4008
3	Standard deviation	63,3087
4	Skewness	-0,122
5	Kurtosis	2,0914
6	Entropy	0,0362
Features of the gray scale co-occurrence matrix		
7	Contrast	4922,1
8	Correlation	-0,0023
9	Energy	0,000040195
10	Homogeneity	0,0483
Component-based features of intensity		
11	Maximum intensity	254
12	Minimum intensity	4
13	Average intensity	181,6767
14	Variance	2254
15	Standard deviation	47,4761

This procedure is repeated for all selected images, and the resulting vectors are recorded in tabular form to be used for training, testing, and validation of machine learning models.

IV. Results from Thermal Image Classification by Machine Learning Models

Based on the obtained statistical characteristics, two machine learning models (kNN and SVM) for classification of thermographic images were developed and trained. Each of the models is trained to distinguish three states of the induction motor presented in the thermographic image - serviceable (good), fault in the cooling system, and fault in the bearings.

With the kNN model, the approach of the weighted nearest neighboring points is chosen. The number of the nearest neighboring points needed to assign the inputs to a given class is $k = 3$.

The SVM model is a multiclass linear classifier with a soft margin, as the number of hyper-planes for the realized classification model is $K = Y(Y-1)/2 = 3$.

The statistical characteristics of a training set of 100 thermographic images of induction motors were used for the training of both models. In order to expand the recognizing capabilities of the models, the training set includes thermographic images of induction motors with different design, shaft location, and operating environment. The training set also contains images in which the engine is not oriented on one of the axes of the field of view or is incompletely covered by the field of view.

To evaluate the performance of the two models, a classification of the same set of sixty test images was made. The testing set contains 40 images of serviceable motors, 10 images of motors with ventilation problems, and 10 images of motors with bearing faults.

When processing the test image set using the kNN classification model, a result was obtained in which 47 images were classified as serviceable (good), 11 images were classified as bearing fault and 2 were classified as a ventilation problem. The relative error in predicting the condition of the motors of the kNN model is 35.33%. The inaccuracies in the interpretation of the test set of images are represented by the confusion matrix shown in Fig.4. From the confusion matrix, it is clear that the developed kNN model is not able to successfully distinguish the characteristics corresponding to the problems with motor ventilation.

Fig. 4. Confusion matrix for classification with the k-NN model

Fig. 5. Confusion matrix for classification with the SVM model

When processing the test image set using the SVM classification model, a result was obtained in which 42 images were classified as good, 11 images were classified as bearings fault, and 7 were classified as a ventilation problem. The relative error in predicting the condition of the motors with the SVM model is 16.7%. The inaccuracies in the interpretation of the test set of images are represented by the confusion matrix shown in Fig.5.

The results from the image classification with the SVM model show that this model achieves better accuracy in classifying images into a given class. The SVM model successfully recognizes and distinguishes the characteristics corresponding to the various technical conditions.

V. Conclusion

The application of machine learning techniques in the processing and classification of thermographic images significantly facilitates these processes, leading to a reduction in their duration and labor absorption.

The proposed image processing methodology and classification model can be successfully applied to other types of electrical equipment. All that is needed is to retrain the fault detection model.

An increase in the accuracy of prediction of the considered technical states can be achieved by analyzing the relevance of individual statistical characteristics and reducing the number of input parameters.

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References

[1] Y. Olivatti, C. Penteado, B. P. T. Aquino Jr, R. Maia, Analysis of artificial intelligence techniques applied to thermographic inspection for automatic detection of electrical problems, 2018 IEEE International Smart Cities Conference (ISC2), 2018, DOI: 10.1109/ISC2.2018.8656724.

[2] Z. Jia, Z. Liu, C. Vong, M. Pecht, A Rotating Machinery Fault Diagnosis Method Based on Feature Learning of Thermal Images, IEEE Access Vol. 7, pp 12348-12359, 2019, DOI: 10.1109/ACCESS.2019.2893331.

[3] M. S. Jadin, K. H. Ghazali, S. Taib, Thermal condition monitoring of electrical installations based on infrared image analysis, 2013 Saudi International Electronics, Communications and Photonics Conference, 2013, DOI 10.1109/SIECPC.2013.6550790.

[4] A.S.N. Huda, S. Taib, Suitable features selection for monitoring thermal condition of electrical equipment using infrared thermography, Infrared Physics & Technology vol. 61, 2013, pp 184-191, DOI 10.1016/j.infrared.2013.04.012.

[5] Z. Hui, H. Fuzhen, An Intelligent Fault Diagnosis Method for Electrical Equipment Using Infrared Images, Proceedings of the 34th Chinese Control Conference, 2015.

[6] Y. Lozanov, S. Tzvetkova, A methodology for processing of thermographic images for diagnostics of electrical equipment, 2019 11th Electrical Engineering Faculty Conference (BulEF).

[7] I. Ullah, F. Yang, R. Khan, L. Liu, H. Yang, B. Gao, Predictive Maintenance of Power Substation Equipment by Infrared Thermography Using a Machine-Learning Approach, Energies 2017, 10, 1987; doi:10.3390/en10121