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MONITORING AND DIAGNOSTICS OF ELECTROMECHANICAL SYSTEMS BASED ON MACHINE LEARNING

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Abstract. Induction motors, widely used in electromechanical equipment of mining enterprises, are susceptible to failure due to frequent starts, overloads, and wear, leading to accidents and economic losses. Induction motors are one of the main sources of kinetic energy in industry and agriculture. Motor failure leads to shutdown of the technological process and reduced efficiency, requiring regular monitoring. Traditional diagnostic methods based on the analysis of individual signals and classic machine learning with manual feature selection are insufficiently reliable under variable operating conditions and are highly susceptible to human factor. This paper proposes an approach to diagnosing induction motor faults based on a deep residual network using signal analysis, deep and transfer learning, and information fusion. Various three-phase current input strategies are implemented, and a model capable of automatically extracting informative deep features from the current signal is constructed. The experimental results confirm that the proposed deep learning-based model provides higher diagnostic accuracy compared to traditional machine learning algorithms.

Keywords: motor fault diagnosis, deep residual network, information fusion theory, machine learning, induction motors

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МОНИТОРИНГ И ДИАГНОСТИКА ЭЛЕКТРОМЕХАНИЧЕСКИХ СИСТЕМ НА ОСНОВЕ МАШИННОГО ОБУЧЕНИЯ

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Аннотация. Асинхронные двигатели, широко применяемые в электромеханическом оборудовании горных предприятий, подвержены отказам из-за частых пусков, перегрузок и износа, что ведет к авариям и экономическим потерям. Асинхронные двигатели являются одним из основных источников кинетической энергии в промышленности и сельском хозяйстве. Отказ двигателя приводит к остановке технологического процесса и снижению эффективности, поэтому его состояние требует регулярного контроля. Традиционные методы диагностики, основанные на анализе отдельных сигналов и классическом машинном обучении с ручным выбором признаков, недостаточно надежны в переменных условиях эксплуатации и сильно зависят от человеческого фактора. В статье предлагается подход к диагностике неисправностей асинхронных двигателей на основе глубокой остаточной сети с использованием методов анализа сигналов, глубокого и трансферного обучения, а также слияния информации. Реализованы различные стратегии ввода трехфазного тока и построена модель, способная автоматически извлекать информативные глубинные признаки из токового сигнала. Экспериментальные результаты подтверждают, что предложенная модель на основе глубокого обучения обеспечивает более высокую точность диагностики по сравнению с традиционными алгоритмами машинного обучения.

Ключевые слова: диагностика неисправностей двигателя, глубокая остаточная сеть, теория слияния информации, машинное обучение, асинхронные двигатели

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Introduction

Induction motors are one of the main sources of kinetic energy in industry and agriculture. The failure of the engine leads to a shutdown of the process and a decrease in efficiency; therefore, its condition requires regular monitoring.

Traditionally, performance is assessed by routine inspections and threshold methods of signal analysis, which often leads to "blind" maintenance and late detection of defects. The development of sensor technologies and computing tools makes it possible to implement online diagnostics based on recorded current and other signals, and the use of intelligent algorithms increases the accuracy and stability of diagnostics compared to simple threshold approaches [1]. Motor fault diagnosis technologies can be divided into four groups: based on signals, mechanical theory, models and digital modeling [2–4].

Algorithms based on signals and traditional machine learning are developed by improving the methods of signal detection and processing, but require manual selection of features and a large volume of data [5–7]. Modeling-based approaches use physically justified models of the motor and make it possible to obtain responses in terms of current, vibration, and acoustic parameters that reflect its condition [8–10]. Deep learning, which has become one of the main directions in the processing of technical data, is being actively studied and used in the tasks of diagnosing electric motors [11–13]. At the same time, existing intelligent algorithms remain sensitive to cross-domain differences and imbalanced samples. In this regard, this paper discusses a method for diagnosing and classifying induction motor states based on deep learning, focused on improving accuracy under various operating conditions with a limited amount of training samples.

Materials and methods

Types of engine faults

If the engine starts and stops frequently, the rotor rods may break due to uneven force [14]. Load changes and voltage drops can also affect the service life, which will lead to rotor failure (Fig. 1).

When a fault occurs, the characteristic frequency expression of the rotor is as follows:

$$f_{bb} = \left(1 \pm 2ks\right) f_1, \tag{1}$$

where s is the sliding speed; f_1 is the power frequency; k is a positive integer.

Air gap between rotor and motor stator is unevenly distributed (Fig. 2).

The simplified expression of the frequency of the fault characteristic is as follows:

$$f_{ag} = f_1 \pm m f_r, \tag{2}$$

where m is a positive integer, m is the rotor speed, and the expression has the form:

$$f_r = \frac{\left(1 - s\right) f_1}{p}, \tag{3}$$

where p is the number of pairs of poles of the magnetic field of the motor.

One type of the stator failure is the stator turn-to-turn failure – a common fault in induction motors [15]. It consists of damage to the insulation between two or more adjacent turns of the stator winding, which leads to a current leakage.

When this fault occurs, the stator current waveform is distorted, and harmonic components appear [16–18]. The specific expression of the harmonic component characteristic of the fault is as follows:

$$f_{st} = \left[\frac{n}{p}\left(1 - s\right) \pm z\right] f_1 = n f_r \pm z f_1, \tag{4}$$

where $z = 1, 2, 3,\ldots,(2p - 1)$; $n = 1, 3, 5,\ldots$

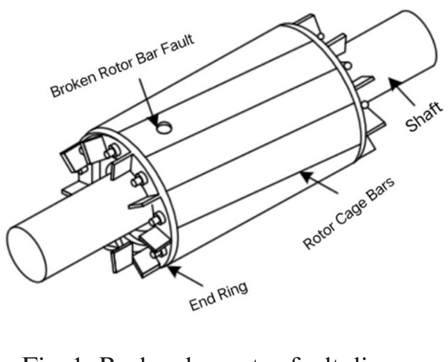

Fig. 1. Broken bar rotor fault diagram

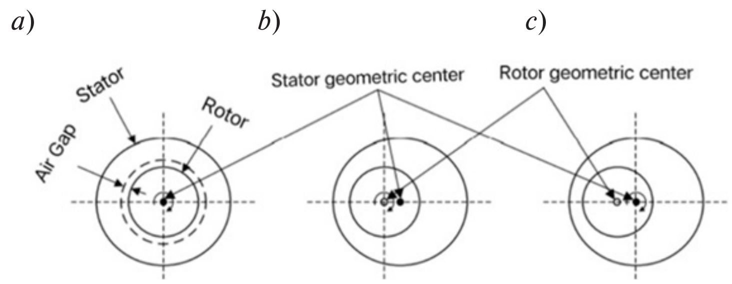

Fig. 2. Air gap eccentricity fault diagram: normal state (*a*), static eccentricity (*b*), dynamic eccentricity (*c*)

Bearings often operate under undesirable conditions, such as prolonged operation, overload, corrosion, and wear, which can easily lead to the failure of various parts of the bearing. At this time, the motor undergoes abnormal vibrations, causing changes in the magnetic field, thereby generating harmonics in the stator current.

Faults in different parts of the bearing will generate vibration information at specific frequencies, and their vibration characteristics differ from one another [19].

Failure of internal ring f_{bi}:

$$f_{bi} = \frac{Nn}{120}\left(1 + \frac{d}{D}\cos\alpha\right). \tag{5}$$

Destruction of the outer ring f_{bo}:

$$f_{bo} = \frac{Nn}{120}\left(1 - \frac{d}{D}\cos\alpha\right). \tag{6}$$

Failure of rolling elements f_{br}:

$$f_{br} = \frac{n}{120}\left(1 - \frac{d}{D}\cos\alpha\right). \tag{7}$$

Cell breakdown f_{bc}:

$$f_{bc} = \frac{Dn}{120d}\left[1 - \left(\frac{d}{D}\right)^2 \cos^2\alpha\right]. \tag{8}$$

Traditional current signal analysis method

A fast Fourier transform (FFT) analysis of the stator current spectrum is used to identify frequency features. Based on the measured three-phase current, a spectrum is constructed, in which components appear at frequencies corresponding to the types of faults described in the previous section.

Next, a standard sequence of coordinate transformations is applied. First, the Clarke transform is performed, which converts the three-phase stator current into a two-phase orthogonal signal i_α, i_β. Then, using the Park transform, this signal is converted into a synchronously rotating coordinate system *d-q* with an electric angle θ, determined by rotor position. In the *d-q* coordinates, components i_d, i_q and their spectral components at diagnostic frequencies are analyzed, and they are used in the traditional model as fault features.

Convolutional neural networks

Deep learning refers to neural network machine learning methods and is distinguished by the fact that it automatically extracts complex features from data without manual specification. One of the main options is a convolutional neural network (CNN) – a sequence of convolutional and pooling layers followed by fully connected layers. In this article, a CNN is used to extract informative features from the current signals of an induction motor and then diagnose its faults.

CNNs share parameters and employ local receptive field strategies to reduce computation time. Initially, they were used in the field of motor fault diagnostics, either to extract and recognize features, or directly as a classifier. The most typical CNN is LeNet-5 [20].

In addition to the classical LeNet, other convolutional network architectures have been developed, such as AlexNet, VGG, and ResNet, which differ in depth and organization of layers. In this paper, a ResNet network was chosen as the basic model, using residual blocks (skip connections) for sustainable training of deep structures and reducing the risk of overfitting. Such a network includes a series of convolutional layers, multi-level residual modules, and an output fully coupled layer performing motor state classification.

There are eight residual modules in the entire network, and their structure is shown in Fig. 3.

The residual block design is divided into a non-downsampling module and a downsampling module, depending on whether a convolution step change is used. With input X and output Y, the block actually learns the residual mapping (Y–X), which reduces the problem of gradient disappearance with increasing network depth and helps preserve information about the input data.

Residual blocks use batch normalization (BN), which normalizes layer outputs over a small group of training examples. This accelerates convergence, reduces the spread of activation values and increases the network's resistance to changing the distribution of input data.

Engine fault diagnosis system based on deep residual mains

In the diagnosis of electric motors, methods of information fusion are widely used, where data from several sensors or different representations of the same signal are combined. This approach allows expanding the set of failure features and obtaining more reliable classification compared to the analysis of a single data source. A distinction is made between fusion at the data level, feature level, and decision level. This paper uses fusion at the feature level: informative characteristics are extracted from the initial signals, after which they are combined and sent to the classifier input.

Traditional information fusion systems in motor diagnostics usually use shallow networks and do not allow obtaining deep signal features. Here, a deep ResNet-based residual network is applied, that extracts features from current signals and performs classification using a Softmax output layer.

The shapes of stator currents for different types of faults (rotor rod failure, air gap eccentricity, stator turn-to-turn short circuit, bearing defects etc.) differ in amplitude, phase, and waveform structure.

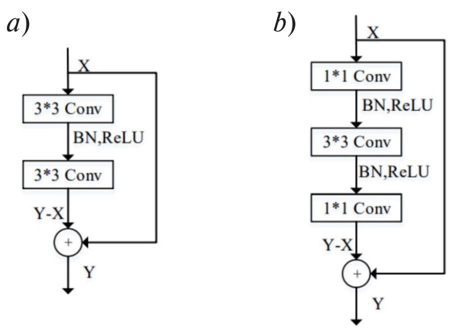

Fig. 3. Residual module architecture (*a*), residual module architecture downsampling (*b*)

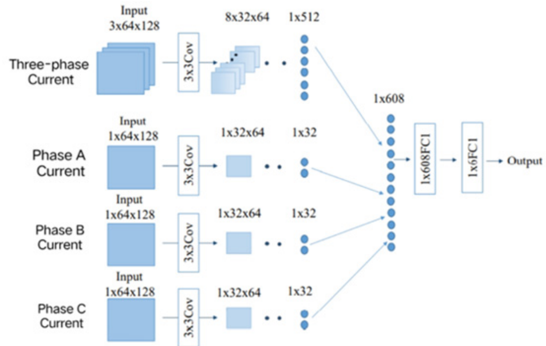

Fig. 4. Third strategy: three-phase current + single-phase current

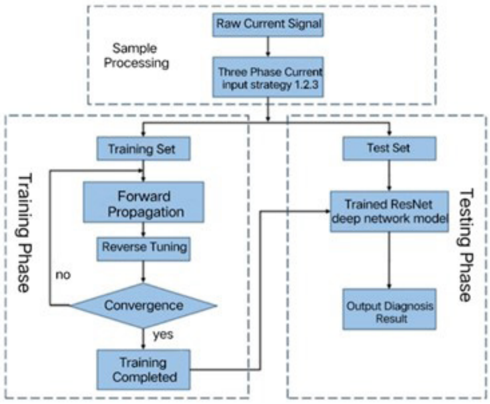

Fig. 5. ResNet deep learning motor fault diagnostic flowchart

These differences are reflected in both time and frequency domains and can be used as features for deep network training.

To assess the effect of the signal representation method, three strategies for introducing three-phase current into the network are considered. In the first strategy, the three-phase current is used as a three-channel input of a single convolutional branch of the network. In the second strategy, phase A, B and C currents are fed to three separate network branches, after which the extracted features are combined. In the third, combined strategy, the three-phase current and the sum of the A+B+C phases are processed by three-channel and single-channel branches, respectively, and then the features are fused in a fully connected layer (the structure is shown in Fig. 4).

The ResNet-based deep learning algorithm for fault diagnosis includes three main stages (Fig. 5). At the first stage, pre-processing and normalization of recorded current signals are performed, and training and test samples are formed for the selected input strategy. At the second stage, ResNet is trained on a training set using a loss function based on the classification results. At the third stage, the trained model is tested on independent data, and the motor state is determined from the output of the Softmax layer and the diagnostic accuracy is evaluated.

Results and discussions

In order to analyze the diagnostic effect of the above diagnostic model, three-phase normal motor stator currents, stator turn-to-turn short circuit, rotor failure, air gap eccentricity, imbalance and bearing failure are collected during stable operation, and 8192 consecutive sampling points are taken as one sample of current signals. 200 samples of three-phase stator currents are collected for each state at 1200, 1500 and 1800 rpm, and 100 samples are randomly selected to construct a training set. 100 samples are randomly selected to construct a training sample, and the remaining 100 samples are used as a test sample, in which the categories of samples are presented in Table 1.

Rotor rod break, air gap eccentricity, stator turn-to-turn short circuit, bearing defects etc.

Table 1

Description of the experimental sample of the tag

Motor status	Training set	Test kit	Category
Normal	100	100	0
Rotor rod failure	100	100	1
Air gap eccentricity	100	100	2
Stator turn-to-turn short circuit	100	100	3
Power supply imbalance fault	100	100	4
Bearing failure	100	100	5

To verify the efficiency of the proposed algorithms, a three-speed fault classification model is used and three series of experiments are performed:

1. Traditional machine learning: 71 statistical features are extracted from the training and test datasets and fed into an SVM classifier to obtain the results.
2. Deep learning: the diagnostic performance of different current input strategies is compared, the network is trained on processed samples, the results of deep and classical models are compared under three-phase and single-phase current input conditions.
3. Variable modes of operation: 1500 → 1800, 1800 → 2100, and 1500 → 2100 rpm: the results of diagnostics of traditional and deep learning are compared, while the proposed algorithm uses a three-phase current input strategy.

Experimental analysis of a machine learning model

To analyze the capabilities of machine learning to recognize the state of motor failure, 71 statistical features were selected in the article, each feature was fed into SVM for classification after normalization, and, finally, an accuracy indicator was obtained (Table 2).

Table 2

Motor fault diagnosis results based on traditional machine learning

Speed	1500 rpm	1800 rpm	2100 rpm
Diagnostic accuracy	92.17%	92.67%	93.83%

As shown in Table 2, when using traditional machine learning for classification, the diagnostic accuracy depends on the rotation speed, and its values are 92.17% and 93.83%. at 1500 rpm and 2100 rpm, respectively.

When using machine learning for classification, there is a large number of errors in diagnosing motor imbalance faults, errors in diagnosing air gap eccentricity, and errors in diagnosing stator turn-to-turn short circuit for individual samples, while for all other states they can be distinguished directly.

Experimental analysis of deep learning models

Implementing deep learning in the context of motor fault diagnosis does not require signal processing. Feature extraction and other operations may be performed directly on the original current samples as training and test sets for deep learning.

In the training phase, the training sets are used as input to a deep learning network, and the diagnostic results of the current network for the training set are verified by minimizing the loss function. The test phase iteratively calculates the loss function for the test set and determines the accuracy of fault diagnosis for the test set. When the training set losses converge, it means that the network for testing is trained, and the diagnostic accuracy for the test set is the final diagnostic accuracy. Using the example of a speed of 2100 rpm, the parameters and weights of the ResNet deep network model are initialized, a training set at a speed of 2100 rpm is used to train the model, and a test set at the same speed is fed to the network for prediction and diagnosis. The curves of the loss function during the training and testing phases and the accuracy of the model diagnostics are shown in Fig. 6.

As shown in Fig. 6, the training set loss function begins to converge at the 31st iteration, the network loss is close to 0, and the training set validation effect reaches 100%. While the network losses of the test set tend to be stable and the diagnostic accuracy reaches 95.17% after a small fluctuation, i.e., the accuracy of the selected model of diagnosing motor faults based on ResNet deep learning for faults at 2100 rpm reaches 95.17%. Under these conditions, the final classification results from the confusion matrix are shown in Fig. 7. The horizontal coordinate is the real mark of the sample, and the vertical coordinate is the predicted mark.

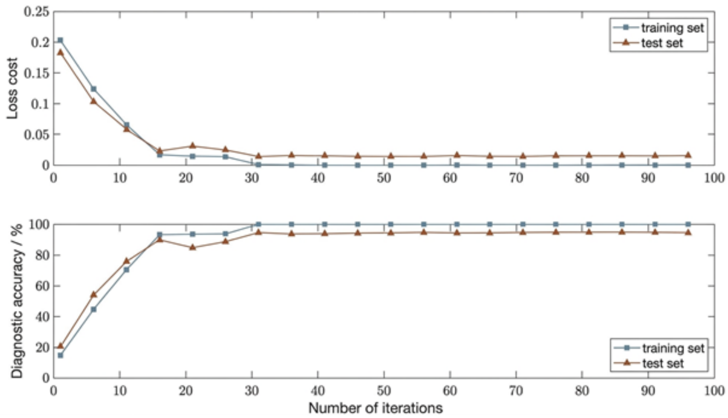

Fig. 6. ResNet deep network model at 2100 rpm

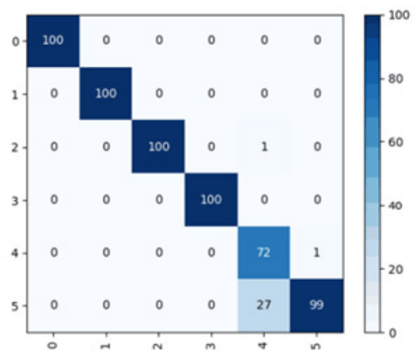

Fig. 7. ResNet deep network model results confusion matrix at 2100 rpm

As shown in Fig. 7, the deep learning model is able to fully identify four motor states: normal, open-circuit faul, eccentricity fault and turn-to-turn short circuit. For bearing failure, very few misclassified examples were observed, and for stator winding imbalance faults, only 72 out of 100 examples were classified correctly, with 27 examples were misdiagnosed as bearing failures.

In deep learning, evaluation metrics for multi-classification fault diagnosis models include micro-averaging (Micro-F1) and macro-averaging (Macro-F1), as well as accuracy and the confusion matrix. In the former case, the Micro-F1 value is calculated based on the total accuracy and metrics across all categories, and in the latter case, the Macro-F1 value is obtained by averaging the F1-Score values for each category. Taking the diagnosis at 2100 rpm as an example, the precision P and the recall R for each category should be calculated first, and the formula is as follows:

$$P = \frac{TP}{TP + FP}; \tag{9}$$

$$R = \frac{TP}{TP + FN}, \tag{10}$$

where TP is true positive, meaning “predicted positive, actual positive”; FP is false positive, meaning “predicted positive, actual negative”; FN is false negative, meaning “predicted negative, actual positive”.

The value of F1-Score can be calculated from precision and recall, and the formula is as follows:

$$F_1 = \frac{2}{\frac{1}{P} + \frac{1}{R}} = \frac{2 * P * R}{P + R}. \tag{11}$$

It can be seen that the Micro-F1 is calculated taking into account the number of each category in the sample, which is suitable for imbalanced samples, and also affects classes with a large sample size; while Macro-F1 accounts for each category equally and is influenced by precision and recall rates for different categories. From the above equation, Micro-F1 and Macro-F1 can be calculated as shown in Table 3.

Table 3

Deep learning model score at 2100 rpm

Failure category	TP	FP	FN	P	R	F1
0	100	0	0	100%	100%	1
1	100	0	0	100%	100%	1
2	100	1	0	99%	100%	0.995
3	100	0	0	100%	100%	1
4	72	1	28	99%	72%	0.8324
5	99	27	1	79%	99%	0.8761
General indicators	571	29	29	95%	95%	–

The Micro-F1 and Macro-F1 values of the diagnostic model for this rotation speed are 0.9517 and 0.9506, respectively, which exceeds 0.95, indicating that the constructed deep learning model has excellent performance in multi-classification of motor faults and strong generalizability.

Diagnostic results for different current injection strategies

A diagnostic system with different current input strategies is used to diagnose motor faults at three speeds: 1500 rpm, 1800 rpm and 2100 rpm, and the accuracy of the results is shown in Table 4.

Table 4

Diagnostic results of motor faults based on deep learning at different values of input current

Current input strategy	1500 rpm	1800 rpm	2100 rpm
Three-phase current	94.17%	95.00%	95.17%
Single-phase current (A/B/C)	92.50%	95.50%	94.50%
Three-phase current + single-phase current (A/B/C)	94.67%	95.33%	95.83%

As shown in Table 4, the diagnostic effect of the diagnostic network at 2100 rpm is generally better than under the other two conditions, indicating that motor fault features are more apparent at 2100 rpm. When comparing circuits with different current strategies, the diagnostic accuracy when using three-phase currents and single-phase currents as input for different deep learning networks is higher than when using single-phase currents as input, but the difference in diagnostic results of the first two is small. The diagnostic result of 95.83% is achieved at 2100 rpm, which corresponds to the real requirements for fault diagnosis, and the specific diagnostic results are given in Table 5, which indicates the number of samples with correct prediction results from 100 samples for each condition.

Table 5

Diagnostic results for different current injection strategies at 2100 rpm

Fault type	Three-phase current	Single-phase current (A/B/C)	Three-phase current + single-phase current (A/B/C)
0	100	100	100
1	100	100	100
2	100	99	100
3	100	100	100
4	72	71	76
5	99	97	99
Medium accuracy	95.17%	94.50%	95.83%

As can be seen from Table 5, all current input strategies better differentiate the normal state of the motor, rotor rod failure and stator turn-to-turn short circuit, while for other faults, three-phase and single-phase currents can be fully differentiated in diagnosing air gap eccentricity faults and bearing failures by feeding them into a deep learning network, respectively, and in the case of stator windings, misdiagnosis still occurs, even though the rate of fault diagnosis has improved. For the stator winding, even though the fault diagnosis rate has improved, there are still misdiagnoses, and for the fault winding imbalance in the best diagnostic result of 100 samples, there are 24 misdiagnosed samples, of which 22 samples are predicted as bearing faults.

Comparison of diagnostic outcomes between machine learning and deep learning

For the diagnostic process of machine learning, extraction of the original signal features and extraction of the Park fusion current features correspond to the deep feature extraction of the single-phase and three-phase current in the third deep learning current input strategy, and therefore the results in this state can be used to directly compare the fault diagnosis results of machine learning and deep learning for motor faults. The results of the comparison are shown in Table 6.

Table 6

Comparison of diagnostic results between traditional machine learning and deep learning model

	1500 rpm	1800 rpm	2100 rpm
Traditional machine learning	92.17%	92.67%	93.83%
Deep learning	95.17%	96.33%	96.83%

As shown in Table 6, the effects of traditional machine learning and deep learning are similar for the three speeds, and the diagnostic accuracy increases as it approaches the rated speed. The diagnostic accuracy of both traditional machine learning and deep learning is lowest at 1500 rpm, while the diagnostic accuracy of deep learning is higher than that of traditional machine learning for all speeds. For traditional machine learning, effective features must be selected manually, and diagnostic accuracy is easily dependent on the selected features, but the deep ResNet model can avoid this disadvantage. Thus, the deep ResNet network has potential for practical application in the diagnosis of numerous faults in electrical machines.

Conclusion

Induction motors are used in various industries and their safe operation affects the stability of the entire system. However, due to frequent starts and stops, as well as long-term use, the probability of faults increases; therefore, diagnosing failures and determining the state of induction motors is of great importance. With the development of diagnostic technologies, AI methods are being increasingly used in the field of equipment diagnostics. This article considers an induction motor with a squirrel-cage rotor as an object of research, the current state of motor fault diagnosis and the problems it faces are analyzed, and the method for recognizing the state of an induction motor under variable operating conditions based on deep learning methods and information fusion of current signals is investigated.

The article provides an analysis of causes of various faults and characteristic frequencies of faults in motors. On the basis of FFT and Park conversion, the manifestation of faults in current signals is considered. A stand with a real induction motor was built, current signals were collected in six different states. Deep learning theory is then generalized, and ResNet-based deep network is considered as the primary tool for motor state classification, utilizing the fact that several residual modules allow reduced network learning complexity and improved feature extraction.

It is evident that conventional signal analysis and machine learning methodologies require expert knowledge to extract a variety of statistical features that describe fault information. In this regard, this paper proposes a method for diagnosing faults in electric motors based on a deep residual network. It is shown that three-phase current carries different diagnostic information; therefore, several three-phase current input strategies have been developed. These strategies are used in combination with a deep ResNet network for deep feature extraction and state classification. Based on the deep ResNet network, a model for diagnosing motor faults is built, which combines the processing of three-phase current and its single-phase combination. The results of the experiments show that the diagnostic accuracy of entering three-phase and single-phase current data into the ResNet multi-branch deep learning network, which performs feature extraction and fusion, outperforms alternative strategies. The accuracy of diagnostics at three speeds is 94.67%, 95.33% and 95.83%, respectively, which confirms the effectiveness of using deep learning for fault diagnosis of induction motors.

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