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DETERMINING THE EFFICIENCY OF VIBRATION SIGNAL PROCESSING METHODS FOR PREDICTIVE DIAGNOSTICS OF ELECTRIC MOTORS

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The object of this study is the vibration signals received from engines with existing defects. The problem that was solved within the framework of this work arises from the need to construct an accurate and reliable system of prognostic diagnostics, capable of automatically recognizing malfunctions in electric motors, despite the influence of external noises, complex operating conditions, and the similarity of characteristics of signals of various types of defects.

The essence of the results is the devised methodology, which includes several stages of vibration signal processing and the use of a convolutional neural network (CNN) for the identification and classification of engine states. At the first stage, the signal is processed in the time domain, in which its main characteristics are analyzed. The signal is then transformed into the frequency domain using a Fast Fourier Transform (FFT) to extract its spectral components. To obtain a more informative representation of the signal, the short-time Fourier transform (STFT) is applied, which makes it possible to obtain a time-frequency characteristic in the form of a spectrogram. The resulting spectrograms represent a vibration signal in a form suitable for processing by a convolutional neural network, which performs their further analysis.

The use of CNN as the main analysis tool allowed us to achieve high results in the classification of engine states. According to the results of experiments, the model showed 100 % accuracy in detecting various types of engine malfunctions, including the most difficult to diagnose conditions. This high level of accuracy is due to the neural network's ability to efficiently process spectrograms and detect hidden patterns in the data. In addition, the application of STFT ensured the preservation of critical time-frequency information that is not available for use with only conventional FFT.

The main advantage of the proposed approach is its versatility and adaptability to different types of engines and malfunctions. The methodology can be used under industrial conditions for automated monitoring of equipment condition. This makes it possible to accidentally detect malfunctions, prevent emergencies, reduce maintenance costs, and increase the overall reliability of the equipment. The proposed approach is particularly useful in applications in which high diagnostic accuracy and fast response to engine state changes are required

Keywords: predictive maintenance, machine learning, vibration analysis, frequency analysis, neural networks

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1. Introduction

Electric motors are a key element of modern industrial systems; they perform a variety of tasks by converting electrical energy into mechanical energy. The reliability of these devices is the basis for the stable functioning of equipment at enterprises and the continuous production process.

Timely control and diagnostics of the state of electric motors are important to avoid malfunctions. Serviceable equipment works continuously and efficiently, reducing the likelihood of emergencies. In cases where attention to the technical condition of engines is not sufficient, even minor malfunctions, such as worn parts, can lead to serious consequences, including stopping the entire production. This, in turn, causes financial losses and additional costs to eliminate problems. In addition, the performance and energy efficiency of electric motors are closely dependent on their technical condition. Equipment in good condition consumes less electricity, which helps businesses reduce operating costs and minimize negative impact on the environment. Thus, early detection of defects, even as small as minor bearing wear, is critical to maintaining the stability of production systems.

Innovative monitoring and analytics technologies open up new opportunities for increasing the reliability of electric motors. With the help of automatic diagnostic systems, potential problems can be quickly detected before they progress to the stage of a serious malfunction. This makes it possible to take timely measures to eliminate defects, extend the life of the equipment, and ensure its stable operation. Therefore, research related to the use of predictive diagnostics is extremely relevant. The results of such studies are of great practical importance as they help optimize the operation of equipment, increase its productivity, and reduce maintenance costs.

2. Literature review and problem statement

The rapid development of scientific and technical progress leads to an increase in the complexity of both individual machine components and the relationships between them. Because of this, any element of the system can become a potential point of failure. Even a minor malfunction often causes large-scale problems in the operation of the equipment. That is why monitoring the technical condition of machines is an extremely urgent task [1]. Among various methods of diagnostics of rotating equipment, the following parameters stand out: analysis of vibrations, electrical and acoustic characteristics, as well as temperature, pressure, etc.

Vibration analysis is one of the most effective approaches for detecting faults in electric motors [2]. Since even a fully functional engine produces vibrations, they are a natural manifestation of periodic processes occurring in the machine, such as the operation of shafts, gears, or electromagnetic fields. However, vibration signals contain both important information and extraneous noise, which complicates their interpretation. Only thanks to a competent analysis of vibrations, one can get accurate data about the technical condition of the machine.

The diagnostic process usually consists of four main stages: data collection, processing, feature extraction, and classification. For a reliable assessment of the condition of the engine, it is necessary to collect data in real time. However, long-term measurement is often required to obtain a complete array of information. In this regard, there is a need for methods that can quickly and efficiently process large amounts of data with minimal use of resources. In this context, machine learning (ML) methods are the optimal solution. They build mathematical models based on training data, which makes it possible to make predictions or make decisions without clear algorithmic instructions. ML methods can be supervised or unsupervised. The main difference between these two approaches is the use of labeled datasets. Simply put, supervised learning uses labeled inputs and outputs, while an unsupervised learning algorithm does not.

One of the studies proposed an intelligent method for detecting anomalies in electric motors based on vibration signals in combination with artificial intelligence algorithms [3]. An unsupervised learning model was built for two different types of engines in the same category: a new experimental engine and an old industrial engine. The model's anomaly detection performance for both engine types was studied in detail, and the results showed that it has the highest anomaly detection ability for standardized engine conditions using the displayed functions. However, only data from normal engine conditions were used due to the lack of information on fault conditions.

Paper [4] presents a solution using vibration signal features such as mean, variance, skewness, kurtosis, median, range, etc., to train the model, similar to many other studies. For the data preprocessing step, this paper reports an approach called Median-Based Outlier Detection (MOD). This approach is used to detect outliers. Outliers are data samples whose characteristics are influenced by external factors rather than defects. This data is excluded from the training process to improve the model. However, this paper did not consider the classification of similar defect types with different defect sizes.

Study [5] examines the use of machine learning algorithms to identify faults in asynchronous motor bearings based on the analysis of vibration signals collected at different sampling rates. The authors compare the accuracy of fault diagnosis using different algorithms, such as support vector method (SVM), decision trees, Multilayered perceptron (MLP), and Long short-term memory (LSTM) networks. The research is aimed at cost optimization by choosing the appropriate sampling frequency, which achieves the necessary diagnostic accuracy with minimal equipment and data processing costs. Neural networks, especially MLPs, have been shown to be sensitive to data volume, and their accuracy drops significantly when using signals with low sampling rates. Also, a low frequency reduces the volume of data and facilitates their processing, but it leads to the loss of information about high-frequency components, which can make it difficult to detect some types of malfunctions.

Work [6] gives an overview of vibration data visualization methods for diagnosing malfunctions of rotating machines. The authors consider various approaches for converting one-dimensional temporal vibration signals into two-dimensional images, which involves their use in diagnostics using deep learning methods, including convolutional neural networks (CNNs). Focus is on time, frequency, and time-frequency domains of signal processing, with descriptions of each, such as RGB visualization, spectrogram, and plot repetition. The use of visualization makes it possible to obtain important characteristics that may be difficult to access with conventional vibration analysis. The main disadvantage is noise. Noise can distort the visualization of signals, making accurate diagnosis difficult.

In [7], a method for diagnosing malfunctions of rotating machines using images obtained from vibration signals is considered. A complex Morlet transform is applied to obtain the characteristics of the signals, which are then converted into color images for analysis using neural networks. The main disadvantage is the small number of samples for testing, as well as the interpretation of images can be difficult and require additional processing methods.

Work [8] proposes an innovative approach to the diagnosis of malfunctions of centrifugal pumps, combining wavelet coherence analysis and deep learning methods. In this approach, researchers use wavelet transforms to analyze time series of vibration data. Wavelets help break down signals into manageable components, making it easier to detect different types of faults, such as mechanical or hydraulic. The obtained data is used to train a neural network that classifies the state of the pump. Here, deep learning is a key element that enables efficient processing of complex and multi-level data. Despite high diagnostic accuracy, deep learning methods can be difficult to interpret. In addition, high qualifications are required for setting up and maintaining such systems, which can be a barrier to their implementation at small and medium-sized enterprises.

After analyzing the works that consider detection of equipment defects using Convolutional Neural Networks (CNNs), it can be concluded that there are very few studies that investigate the use of CNN in different fault states of rotating machines. Most of the experiments are focused only on the detection of bearing malfunctions [9, 10]. This emphasizes the need for comprehensive research focused on the integrated analysis of electric motor faults using machine learning methods, in particular convolutional neural networks (CNNs).

3. The aim and objectives of the study

The purpose of our study is to determine the possibility of detecting and classifying electric motor faults by using vibration signal processing methods in combination with machine learning methods. This will make it possible to increase the reliability of electric motors, as well as to minimize their maintenance costs.

To achieve the goal, the following tasks were set:

– to perform an analysis of the vibration signal in the time domain;

– to analyze the vibration signal in the frequency domain using the fast Fourier transform (FFT);

– to simulate a convolutional neural network using the short-time Fourier transform.

4. The study materials and methods

The object of our research is the vibration signals of electric motors, which characterize the dynamic behavior of the motor and contain information about possible malfunctions. Special attention is paid to signal processing methods in the time and frequency domains and their integration with machine learning methods.

The main hypothesis of the study assumes that the combination of analysis of vibration signals in the time and frequency domains using a convolutional neural network (CNN) makes it possible to improve the accuracy of detection and classification of electric motor faults.

All data were taken from a test bench consisting of an induction motor and two accelerometers. Accelerometers measure the vibration signal in the y and x directions. With this bench, studies can be carried out for various operating modes, namely: normal, bent shaft, broken rod, displacement, mechanical weakening, bearing failure and unbalance. The first accelerometer is attached to the motor using a threaded base. The second is also fixed by a threaded base installed in the bearing housing.

In the time domain, the vibration signal may not carry enough information and may look almost the same for all types of defects but in the frequency domain it has a characteristic distribution. These signals are classified as stationary when their statistical properties do not change over time and non-stationary when their statistical properties change over time. Thus, the classification of the signal type is crucial in determining which processing technique can and should be used. Thus, correct signal classification helps in successful analysis and diagnosis.

In this study, all signals are stationary, so Fast Fourier Transform (FFT) will be used for processing. For a non-stationary signal, other methods such as wavelet or Hilbert-Huang transform would have to be used. The FFT input signal is inherently reduced. This reduction is modeled as multiplying the signal by a rectangular window function. However, in the spectral domain, this type of windowing causes an effect called spectral leakage [11]. To reduce this effect, one can use a different type of window; in this case, a Blackman window, characterized by equation (1) [5, 6]:

$$\omega(n) = 0.42 - 0.50\cos\left(\frac{2\pi n}{N-1}\right) + \\ +0.08\cos\left(\frac{4\pi n}{N-1}\right), \\ n = 0,1,2,\ldots,N. \tag{1}$$

To diagnose the technical condition of the engine, it is necessary to have both data for normal operation and information about its operation in the presence of defects.

Vibration signals are closely related to the operation of rotating elements, including gears, rotors, shafts, bearings, and couplings. The ability to detect faults based on these signals depends on various factors, such as the speed of rotation, the level of noise and vibration, the position of the sensors, as well as the characteristics of the loads, and other operating conditions of the equipment. All mechanical defects cause changes in vibration characteristics that differ markedly from the signals of a healthy machine. This allows diagnostics and identification of malfunctions by analyzing the received vibration data. For example, unbalance, mechanical weakening, offset deformation of the shaft can be identified by the fundamental frequency of rotation and its harmonics. Other defects, such as gears, belts, and bearings, are detected by a characteristic defect frequency that varies according to the geometrical characteristics of the element and the operation of the machine.

Many studies have already been conducted on the issue of bearing malfunction detection, and all defects are already known [12]. The characteristic equations for the frequency of the ball passing through the outer ring are shown in equation (2). The failure of the inner ring is shown in equation (3). In addition, the fundamental frequency is highlighted in equation (4), and the frequency of rotation of the ball (roller) is shown in equation (5):

$$BPFO = 0.50 n\pi f_r\left(1-\frac{d}{D}\cos\varphi\right), \tag{2}$$

$$BPFI = 0.50 n\pi f_r\left(1+\frac{d}{D}\cos\varphi\right), \tag{3}$$

$$FTF = 0.50 f_r\left(1-\frac{d}{D}\cos\varphi\right), \tag{4}$$

$$BSF(RSF) = \frac{D}{2d}\left(1-\frac{d}{D}\cos\varphi\right)^2, \tag{5}$$

where f_r is the rotation frequency, d is the diameter of the ball, D is the pitch diameter, n is the number of rolling elements, φ is the contact angle of the ball.

One can use two approaches to diagnose the equipment, including the engine. The first approach is to examine the engine without defects. Thanks to the monitoring of the vibration signal, its changes can be detected and further compared with the signal for a healthy engine. However, this approach is resource-intensive and has limitations, as it is impossible to cover all possible types of faults. Therefore, the second option is used, in which defects are created artificially, and then a comparison is made with the signal from a working engine. This makes it possible to work with each defect separately and study them in more detail. In this study, it is the second approach that is considered.

Since the vibration signal is always noisy by default, and it is also affected by external vibrations, it is necessary to pay attention to filtering. Based on the Nyquist-Shannon theorem, a low-pass filter with a sampling frequency divided by two is used to minimize noise and smooth the data. To increase the contrast of the spectrum, the Blackman-Harris window is additionally used.

The entire process is based on the received vibration signal (acceleration) during a fixed time in an electric motor operating under different conditions. A discrete fast Fourier transform was applied to the received signal to represent the signal in the frequency domain.

Convolutional neural networks (CNNs) belong to the category of feed-forward networks. One of the key advantages of CNNs is the ability to learn efficiently on smaller amounts of data compared to other neural architectures [13].

The main difficulty in working with CNN is the specific requirements for input data; to be more specific, the input signal must be in image format. In general, an image can be characterized by three parameters – *a*, *b*, *c*, where *a* and *b* are the size of the image, or rather the size of the matrix used to represent the image, and *c* is responsible for the three-color image channel. Instead of simply converting the vibration signal into an image, one can use a so-called "time-frequency map" generated using a short-time Fourier transform (STFT). After preparing the input data, one can start working with CNN, namely start training it.

Choosing the right settings for CNN is critical. Choosing the best parameters directly affects the learning process. Main parameters:

– learning rate: this is a very important parameter that affects the choice of weights and the convergence of errors. To improve the performance of CNN, it is important to choose an appropriate learning rate for the data;

– packet size: since the data size is quite large, it is divided into small sets, so-called packets, for CNN training. Choosing the right packet size makes CNN more reliable and accurate;

– epoch: responsible for the number of times the network works with a sample of data for training.To implement our study, a sequential method of analyzing vibration signals of an electric motor was used, which includes the following stages:

1. Collection of input vibration data. The signals were recorded using high-sensitivity transducers installed on an electric motor operating under different modes and types of faults. Data were collected in the form of time series representing the amplitude of vibrations over time.

2. Analysis of signals in the time domain. At the first stage, the time signals were visualized in the form of graphs, which allowed for preliminary analysis. The main attention is paid to amplitude bursts, pulses, or changes in the general dynamics of the signal. Such an analysis made it possible to make initial assumptions about the types of malfunctions.

3. Analysis of signals in the frequency domain. For a deeper understanding of the signal structure and the selection of hidden characteristics, the method of fast Fourier transformation was applied. The signals were transformed into spectra, where the main attention was paid to the frequency components characteristic of various faults.

4. Application of the short-time Fourier transform. To analyze the time-frequency structure of signals and prepare data for a convolutional neural network, short-time Fourier transformation was applied. It made it possible to obtain spectrograms – images reflecting the change in the frequency content of the signal over time. This step provided a more detailed view of the signal dynamics and made the data suitable for neural network processing.

5. Training and tuning of a convolutional neural network. At the final stage, spectrograms were used as input data for a convolutional neural network. The network was trained to classify the state of the engine (normal or with different types of faults). To increase the accuracy of the model, the hyperparameters of the network were adjusted.

The applied experimental data processing procedure was devised taking into account the specificity of vibration signals and the requirements for predictive diagnostics. The use of a sequential approach – from the analysis in the time domain to the frequency domain and further to the frequency-time domain – made it possible to cover the diagnostic information contained in the signal as fully as possible. Each stage has been justified:

– time analysis provides operational information about gross anomalies;

– frequency analysis makes it possible to identify features related to specific malfunctions (transition to the frequency domain is performed by applying fast Fourier transformation);

– the short-time Fourier transform combines time and frequency information, providing accurate input data for the neural network;

– the use of convolutional neural is justified by the complexity of vibration signals and the need for automatic classification, which conventional methods cannot provide with the same efficiency.

Thus, the chosen methods of research and data analysis are correct and justified, as they provide a high level of diagnostic accuracy and effectively use the capabilities of modern signal processing and deep learning technologies.

5. Results of an electric motor diagnostics study

5. 1. Detection and diagnosis of malfunctions using the analysis of the vibration signal in the time domain

Fig. 1 shows the acceleration signal in the time domain for all operating modes of the electric motor. The signals were obtained from a working electric motor (Fig. 1, *a*), as well as from electric motors with existing defects (Fig. 1, *b–h*).

Analysis in the time domain is the simplest and fastest type of vibration signal analysis. All fault signals shown in Fig. 1, *b–h* have minor visual deviations, making it difficult to assess and identify defects.

5. 2. Detection and diagnosis of malfunctions using vibration signal analysis in the frequency domain

To obtain more useful information, it is necessary to translate the signal into the frequency domain, for this purpose, an FFT was used. Next, the results of converting the signal into the frequency domain are shown. Fig. 2–7 show the acceleration signal in the frequency domain for all engine operating modes. The red line is responsible for a signal with a defect, the green line is a signal for a motor without defects. For a visual perception of the situation, the fault signals were plotted together with the engine signal without defects.

Since the bearing defect is located on the outer ring, it will be defined as RPM×BPFO (*Ball Pass Frequency Outer*) [14, 15]. From the technical documentation of the engine, the BPFO value of the bearing was taken; it is equal to 3.7 Hz. Using formula (2) and the maximum amplitude values, we check whether they actually correspond to a fault defect on the outer race of the bearing:

$$BPFO_1 = \frac{P_2 - P_1}{\vartheta} = \frac{3.266 - 3.085}{48.7} = 3.7166, \tag{6}$$

$$BPFO_1 = \frac{P_3 - P_2}{\vartheta} = \frac{3.447 - 3.266}{48.7} = 3.7166, \tag{7}$$

where P_1 – marked 1st point, P_2 – marked 2nd point, P_3 – marked 3rd point, ϑ – motor rotation frequency (Hz).

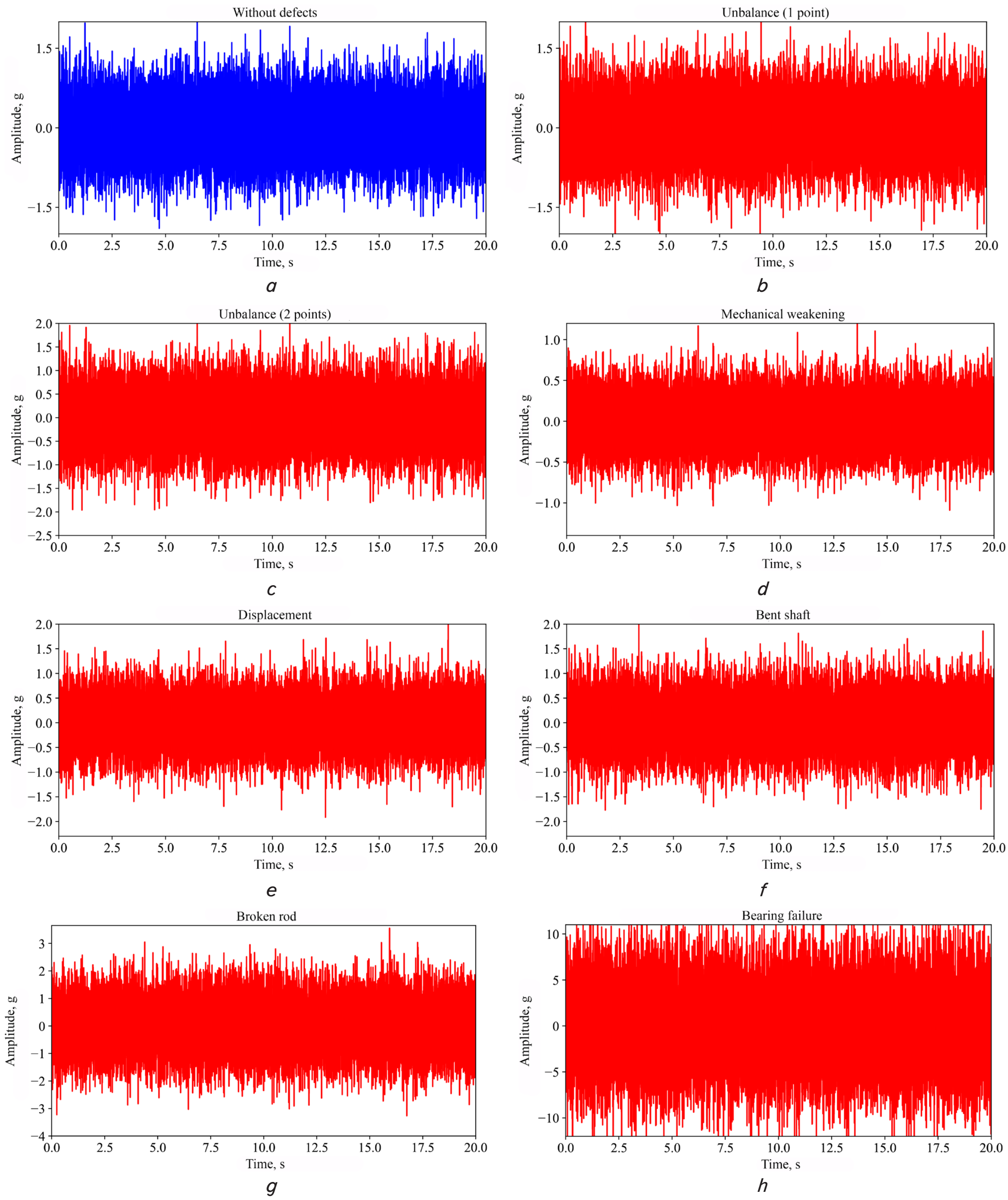


Fig. 1. Signals in the time domain: *a* – without defects; *b, c* – unbalance; *d* – mechanical weakening; *e* – displacement; *f* – bent shaft; *g* – broken rod; *h* – bearing failure

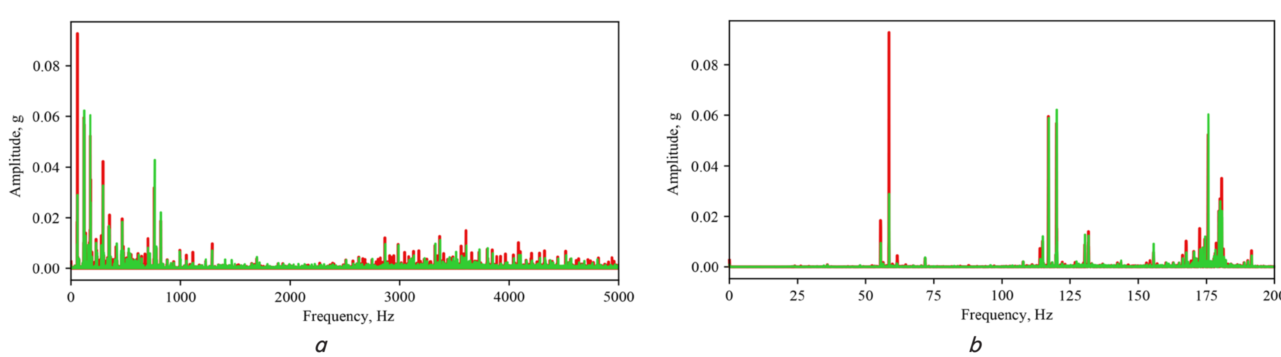
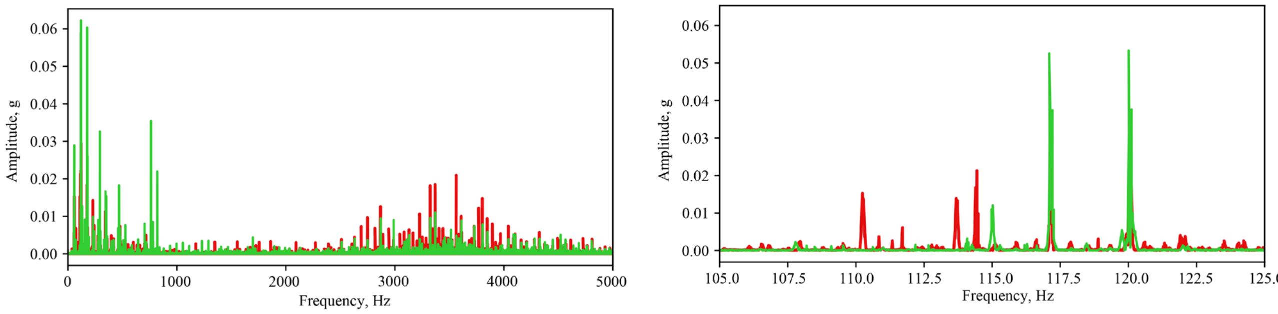
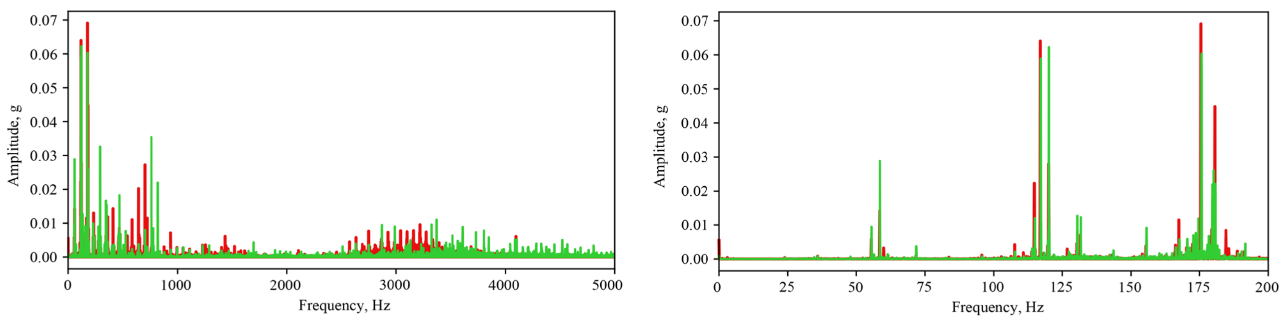


Fig. 2. Signals in the frequency domain for an engine with unbalance: *a* – full spectrum; *b* – enlarged scale in the defect zone



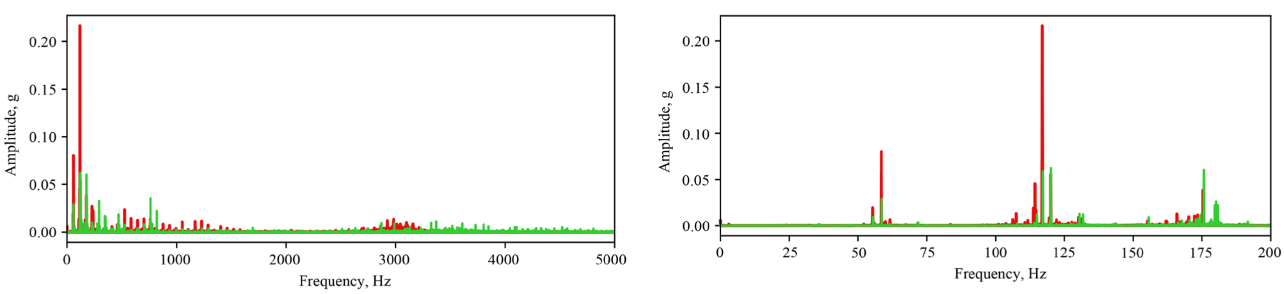
a *b*

Fig. 3. Signals in the frequency domain for an engine with mechanical weakening:
a — full spectrum; *b* — enlarged scale in the defect zone



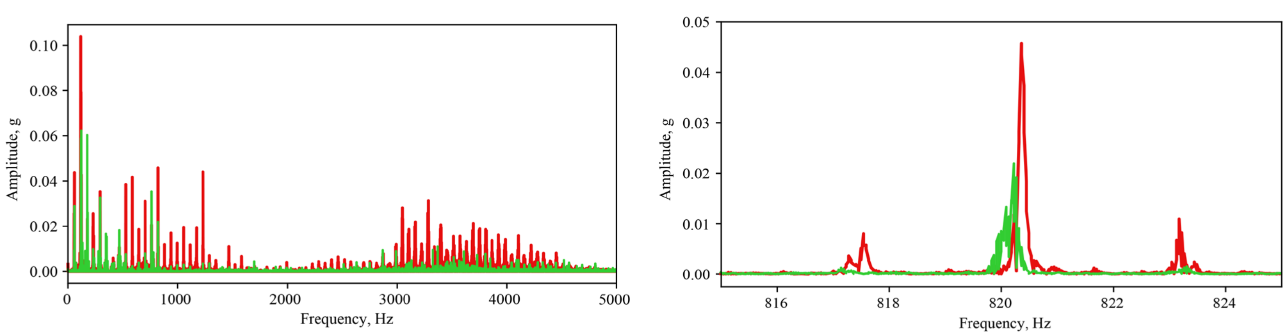
a *b*

Fig. 4. Signals in the frequency domain for a displacement engine:
a — full spectrum; *b* — enlarged scale in the defect zone



a *b*

Fig. 5. Signals in the frequency domain for an engine with a bent shaft:
a — full spectrum; *b* — enlarged scale in the defect zone



a *b*

Fig. 6. Signals in the frequency domain for an engine with a broken rod:
a — full spectrum; *b* — enlarged scale in the defect zone

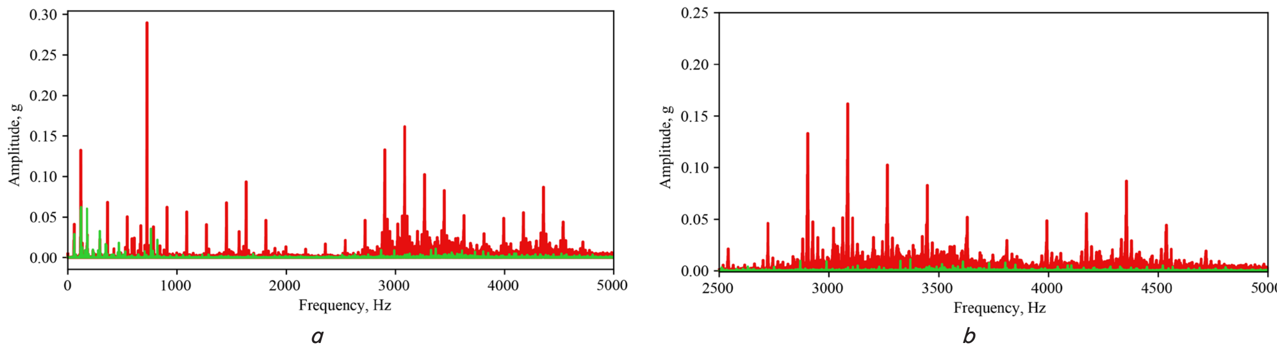


Fig. 7. Signals in the frequency domain for an engine with a bearing defect: *a* – full spectrum; *b* – enlarged scale in the defect zone

5. 3. Detection and diagnosis of faults using a convolutional neural network and short-time Fourier transform

The following parameters were used for the short-time Fourier transform: the length of each segment is 1024, the Blackman-Harris window, and the overlap is 15 %. In this case, each signal was divided into 40 parts, and STFT was performed for each part. Finally, to reduce the number of computations and speed up CNN training, the image is compressed to 128×128 size. Fig. 8 shows the result of using STFT for each operating mode.

All data were divided into data for training and for testing. These data are randomly selected. For each of the operating modes, 150 samples are used for training and 45 for testing.

Fig. 9 shows the results of the first attempt to train the model. The green line shows the training results, and the red line shows the test results.

Fig. 10 shows the results of the next learning process with other parameters.

In order to understand which parameters provide the highest accuracy, several runs were conducted. Thus, the optimal parameters were determined experimentally: a learning rate of 0.00225 and a packet size of 23.

Fig. 11 shows the relationship between accuracy and number of epochs. Fig. 12 demonstrates the loss function at different number of epochs.

In order to make the feature selection process clearer, an additional analysis was performed, namely, the output of the first layer of CNN for all modes of operation was displayed (Fig. 13, 14).

Fig. 15 shows the error matrix for CNN.

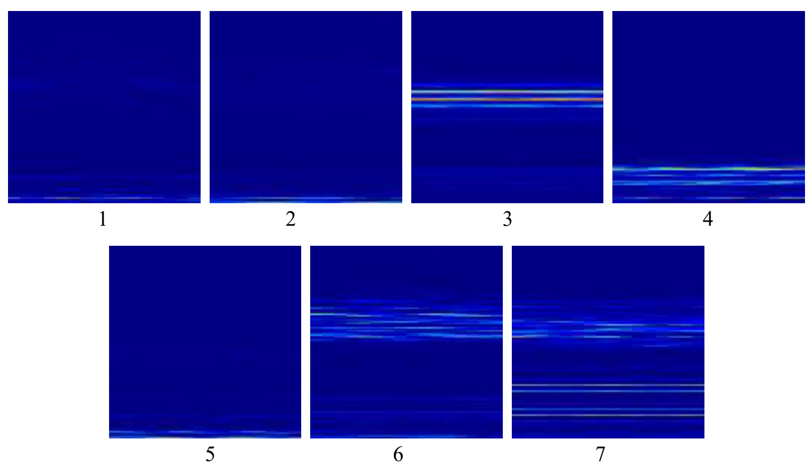


Fig. 8. The result of STFT conversion for all operating modes: 1 – without defects; 2 – unbalance; 3 – mechanical weakening; 4 – displacement; 5 – bent shaft; 6 – broken rod; 7 – bearing failure

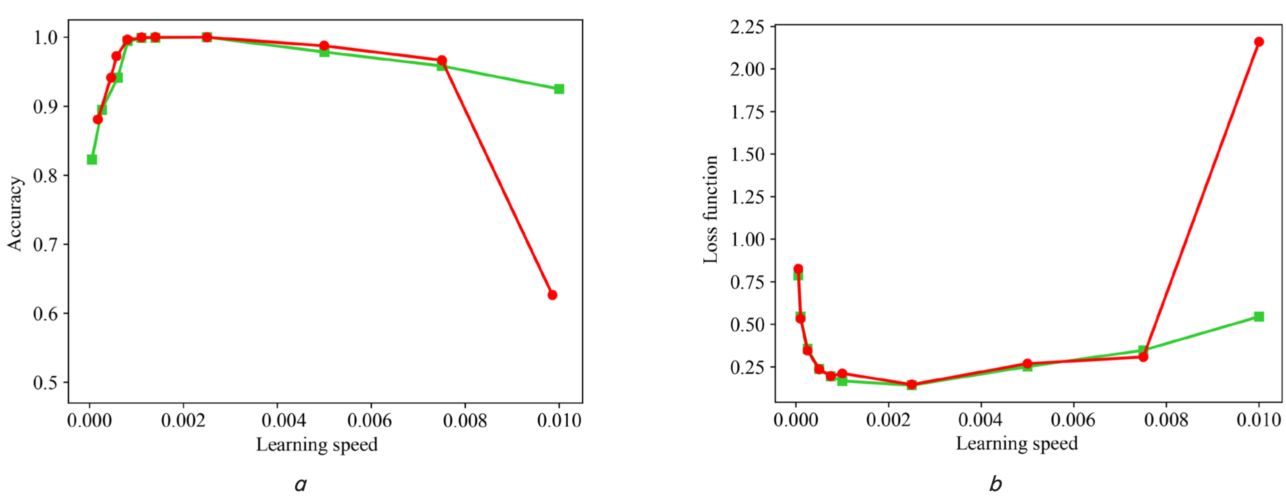
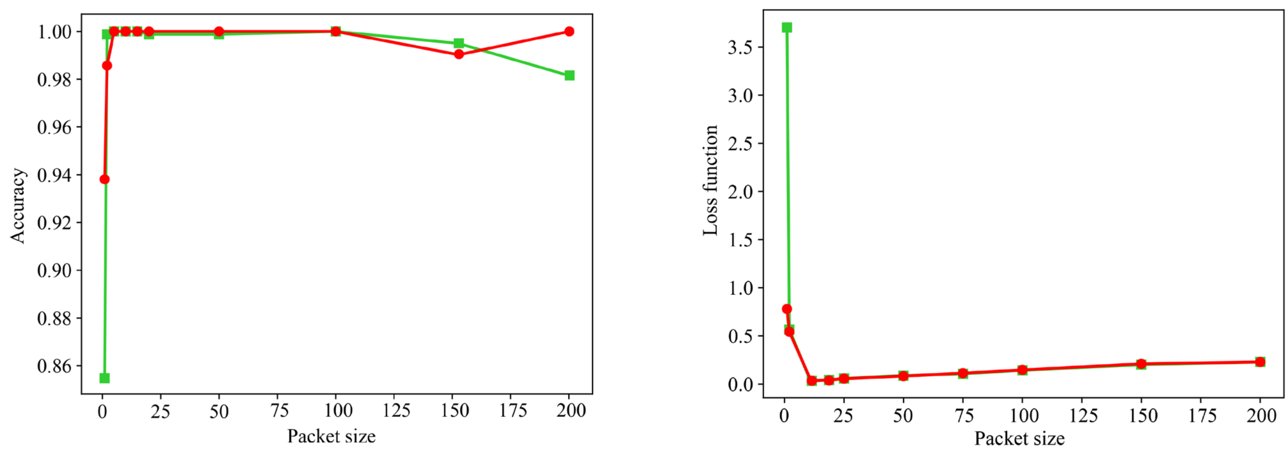


Fig. 9. The result of model training: *a* – accuracy at different learning speeds; *b* – loss function at different learning rates



a *b*

Fig. 10. The result of model training:
a — accuracy at different packet sizes; *b* — loss function for different packet sizes

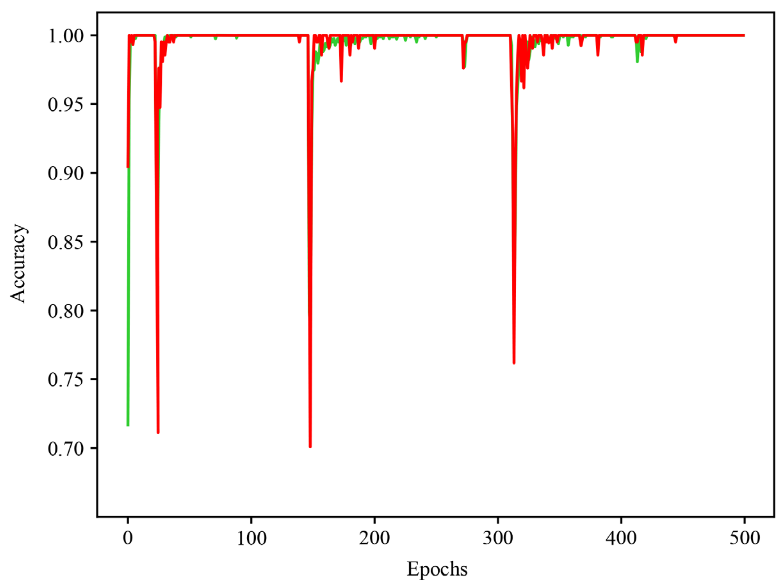


Fig. 11. Dependence of accuracy on the number of epochs

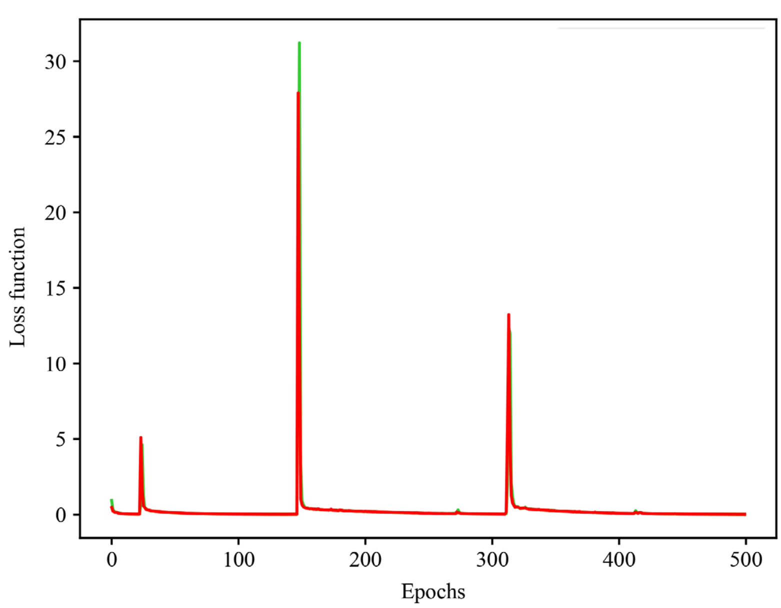


Fig. 12. Loss function at different number of epochs

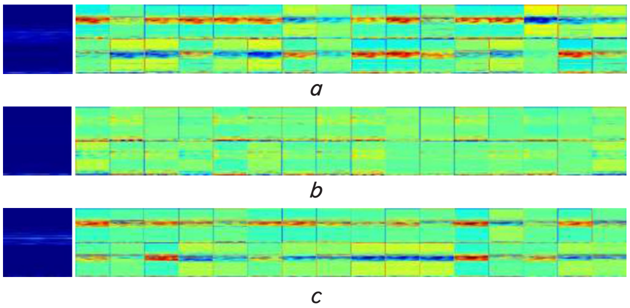


Fig. 13. Output of the first CNN layer: *a* – without defects; *b* – unbalance; *c* – mechanical weakening

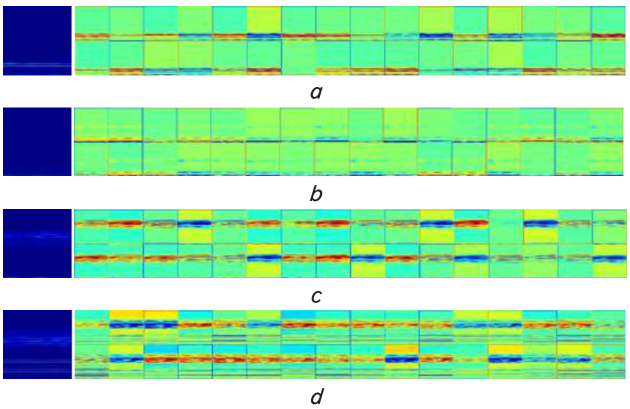


Fig. 14. Output of the first CNN layer: *a* – displacement; *b* – bent shaft; *c* – broken rod; *d* – bearing failure

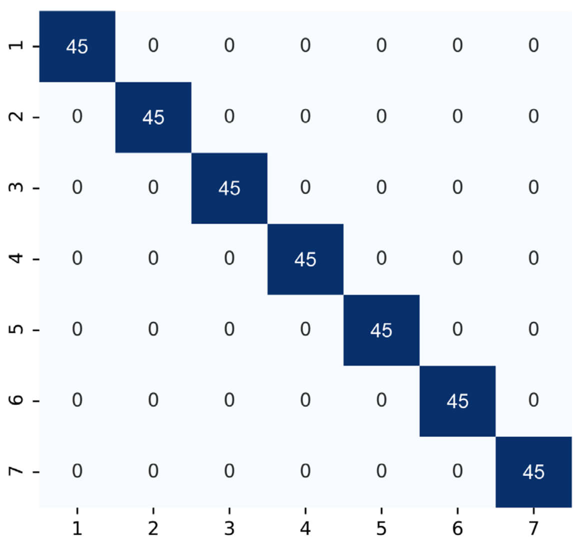


Fig. 15. Error matrix

It is necessary to pay attention to the numbers located on the main diagonal of the matrix (Fig. 15). The numbers outside it show the number of falsely classified examples.

6. Discussion of the results of electric motor diagnostics

Analyzing Fig. 1, it can be seen that the vibration signal in time is very similar for all operating modes; only the signal from the motor with a bearing failure has a very high amplitude compared to the other signals. However, it is not possible to be guided only by a high amplitude of vibration to identify a defect, and even more so to diagnose an existing defect. Therefore, in the presence of only the vibration signal in the time domain, it is impossible to obtain sufficient information for the detection and differentiation of defects.

Analysis of the vibration signal in the frequency domain makes it possible to identify signs for each of the defects. An unbalance defect (Fig. 2) is characterized only by an increase in rotation frequency, but when the defect increases, an increase in amplitude is observed. Mechanical weakening (Fig. 3), on the contrary, is manifested by a decrease in the amplitude of the main rotating components and their harmonics, as well as the appearance of new components in the spectrum. This indicates that low amplitudes are not always a sign of a healthy electric motor. A slight increase in amplitude for the second and third harmonics is characteristic of the shaft displacement defect (Fig. 4), which indicates that such a defect is not critical for the engine. In the engine with a bent shaft (Fig. 5), there is an increase in the rotational frequency with the dominance of the second harmonic, which indicates that the place of bending is closer to the clutch. For a motor with a broken rod (Fig. 6), components appear that are almost twice as far from the slip frequency of the motor. An engine with a bearing defect (Fig. 7) has a rotation frequency multiplied by the characteristic frequency of the defect.

After data preparation, namely, the application of the short-time Fourier transform, "time-frequency maps" (Fig. 8) were obtained, which can be used to work with CNN. To select the optimal CNN parameters, several training sessions with different parameters were conducted. In the first attempt, the batch size did not change, and the learning rate changed for each iteration. The number of epochs was also constant – 10. Based on the obtained results (Fig. 9), it becomes clear that if the learning speed is too high or too low, the accuracy of the model decreases, and the loss function increases. Therefore, the average values of the learning speed are optimal. In the subsequent training, the learning speed did not change, only the size of the packet changed. Analyzing Fig. 10, it can be determined that at smaller values of the packet size, the accuracy increases, and the loss function is minimized. Since very similar results were obtained for all combinations of parameters, it is necessary to rely on the analysis of the loss function, where there are significant differences between the configurations. With these parameters, 100 % accuracy is achieved in both training and testing. Analyzing the losses during training and testing for the selected parameters, low and similar values were obtained in both cases, indicating the stability of the network.

In the next step, the optimal number of epochs is selected. According to the results of training with different number of epochs (Fig. 11, 12), it is clear that after 130 epochs the network begins to lose accuracy due to retraining.

Analysis of the output data of the first layer of CNN (Fig. 13, 14) demonstrates how the network processes input signals. Bright areas on the graph indicate areas where a particular signal pattern was recognized. This testifies to the efficiency of the first-level filters, which ensure the extraction of the basic features of the input data.

The error matrix shown in Fig. 15 is used to evaluate the network performance. The number of rows and columns in it corresponds to the number of classes. The numbers at the intersection of rows and columns for classes of the same name (when the predicted class corresponds to the actual class) determine the number of correctly classified examples. According to this matrix, CNN achieves 100 % accuracy, that is, all the defects as well as the normal working condition can be identified and classified by the proposed CNN.

Unlike [9, 10], in which CNN is used only to detect bearing faults, the CNN proposed in this study allows diagnosing a wider range of faults by using data from motors with different types of defects.

Although CNN can perform its tasks effectively even with less data, compared to other networks, the availability of data for each defect is mandatory. That is, it should be possible to access the unit and be able to install sensors in the right places. In addition, the selection of optimal parameters is critical for achieving high model accuracy.

The development of this research may consist in the application of other machine learning methods, such as 1D Convolutional Neural Networks and Gaussian Mixture Model, for vibration signal processing.

7. Conclusions

1. The method of vibration analysis in the time domain performed the worst. Using this analysis, it is almost impossible to identify and classify most faults. This is due to the fact that the data for different faults are almost identical.

2. Analysis of the vibration signal in the frequency domain turned out to be more effective. The effectiveness of using FFT for fault detection has been demonstrated. All malfunctions were identified and could also be differentiated. In some cases, the signal amplitude of the electric motor with a defect increased by 2 times compared to the system without malfunctions. Also, this approach can be called universal because after determining the engine speed, this entire analysis can be applied to any engine. Although vibration analysis shows excellent results, it has some drawbacks. This technique requires a lot of professional skills and takes a lot of time. Also, there is a significant number of defects that can be confused with each other.

3. The convolutional neural network showed excellent results. When selecting the optimal parameters, the accuracy reaches 100 %. Such a neural network is one of the best solutions when the data has labels. Analyzing the obtained error matrix, it can be argued that this method allows for effective diagnosis of faults in electric motors. The main difficulty of this method is the correct selection of network parameters. This can be especially critical in more complex systems.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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Data availability

All data are available, either in numerical or graphical form, in the main text of the manuscript.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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