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METHOD OF NEURAL NETWORK DETECTION OF DEFECTS BASED ON THE ANALYSIS OF ROTATING MACHINES VIBRATIONS

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ABSTRACT

Context. The paper proposes a solution to the urgent problem of detecting equipment defects by analyzing the vibrations of rotating machines. The object of study is the process of detecting defects by analyzing the vibrations of rotating machines. The subject of study is artificial intelligence methods for detecting defects by analyzing the vibrations of rotating machines.

Objective. Improving the accuracy of detecting defects in the analysis of rotating machine vibrations by creating a method for neural network detection of defects in the analysis of rotating machine vibrations and a corresponding neural network model that can detect defects in the analysis of rotating machine vibrations without removal preliminary noise in order to preserve important features for more accurate classification.

Method. A method of neural network defect detection based on the analysis of vibrations of rotating machines is proposed, which is capable of predicting the presence or absence of a defect based on the input data of vibrations with the implementation of preliminary processing, namely the creation of a two-dimensional time-frequency image. The method differs from the existing ones in that the defect analysis is performed without removing noise by fine-tuning the model parameters.

Results. The proposed method of neural network detection of defects based on the analysis of rotating machines vibrations is implemented in the form of a web application and the effectiveness of the neural network model obtained by performing the steps of the method is studied.

Conclusions. The study results show that the model has achieved high accuracy and consistency between training and validation data, which is confirmed by high values of such indicators as Accuracy, Precision, Recall i F1-Score on the validation dataset, as well as minimal losses. The cross-validation confirmed the stable efficiency of the model, demonstrating high averaged metrics and insignificant deviations from the obtained metrics. Thus, the neural network model detects defects in rotating machines with high efficiency even without cleaning vibration signals from noise. Prospects for further research are to test the described method and the resulting neural network model on larger data sets.

KEYWORDS: defects, analysis, vibrations, rotating machines, neural network, ResNet50.

ABBREVIATIONS

CNN is a Convolutional Neural Network;
RNN is a Recurrent Neural Network;
SVM is a Support Vector Machine;
k-NN is a k-Nearest Neighbors;
AIoT is an Artificial Intelligence of Things;
1D-CNN is a One-Dimensional Convolutional Neural Network;
LMD is a Local Mean Decomposition;
EMD is an Empirical Mode Decomposition;
DT is a Decision Tree;
PNG is a Portable Network Graphics;
RNT is a ResNet Training.

NOMENCLATURE

X is a set of vibration signals;
x_1 is a first vibration signal;
x_2 is a second vibration signal;
x_n is a n-th vibration signal;
n is a number of vibration signals in the set;
x_i is a vibration signal;
R^T is a time series;
T is a time series length;
m_i is a class label;
$Model_\theta()$ is a neural network model;
θ is a set of parameters $Model_\theta()$;
$\hat{m}_i$ is a predicted class probability for the sample under study;
$\bar{x}$ is a vector of vibration signals;
x_{1t1} is a first vibration signal at a given time in vector of vibration signals;;
x_{2t2} is a second vibration signal at a given time in vector of vibration signals;
x_{nT} is a n-th vibration signal at a given time in vector of vibration signals;
$f(t_i)$ is a function that projects indices onto the signal amplitude;
t_i is a moment in time;
I is a pixel matrix;
H is an image height;
W is an image width;
$I`$ is an image of vibration signals;
k is a number of folds for cross-validation.

INTRODUCTION

Rotating machines, including electric motors, pumps, turbines, generators, and components of airplanes, heli-

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copters, and other mechanisms, are central to modern industry and transportation. They perform important functions such as energy conversion and transmission, as well as provide essential mobility and safety in aviation and automotive systems. The reliability of these machines is an important factor, as malfunctions can lead not only to financial losses but also to serious accidents. Regular monitoring of the condition of rotating machines through vibration analysis helps to detect early signs of defects, which in turn allows for timely maintenance and prevents disasters [1].

The vibration signals generated during the operation of these machines contain information about the condition of their components – bearings, shafts, gears, etc. Changes in the frequency, amplitude, and pattern of vibrations can signal defects such as cracks, wear, or imbalance.

Thanks to the introduction of new technologies, there is a continuous evolution in the areas of machine condition monitoring and performance evaluation. One of the main reasons for this progress is the significant reduction in the cost of sensors and data storage systems. Today, high-precision vibration, temperature, and other sensors have become available for a wide range of industries, allowing for continuous collection of important information about the condition of equipment [2].

On the other hand, the ever-increasing computing power of modern computers makes it possible to process and analyze huge amounts of data in real time, allowing for the application of sophisticated machine learning algorithms and neural networks to detect anomalies that may indicate potential malfunctions. Early detection of problems in rotating machines or other mechanisms allows timely elimination of them, which significantly reduces the risk of accidents and increases the overall efficiency of production [3].

The development of data-driven methods, as well as big data and computational intelligence technologies, is opening up new approaches to diagnosing rotating machinery faults. Modern approaches to data analysis use machine learning algorithms and artificial neural networks. These algorithms allow not only to detect faults but also to predict their occurrence, as well as to classify different types of defects based on the analysis of vibration data and other parameters. Thanks to these intelligent solutions, it is possible to proactively monitor the condition of rotating machines, which significantly increases their reliability and efficiency.

The object of study is the process of detecting defects by analyzing the vibrations of rotating machines.

The subject of study is artificial intelligence methods for detecting defects by analyzing the vibrations of rotating machines.

The purpose of the work is to improve the accuracy of defect detection by analyzing the vibrations of rotating machines.

1 PROBLEM STATEMENT

Rotating machines are key components in various industrial sectors. They are prone to wear and tear and defects that can cause unwanted vibrations, which in turn can lead to accidents and production stoppages. Therefore, timely detection of defects in them is of great importance to ensure equipment reliability, reduce maintenance costs, and increase overall efficiency. The development of a method for neural network detection of defects based on the analysis of vibration signals of rotating machines will allow detecting defects to avoid the emergency state of rotating machines.

Let $X = \{x_1, x_2, ..., x_n\}$ is a set of vibration signals, where each $x_i \in R^T$ is a time series of length T, representing data from the vibration sensor. Everyone x_i label corresponds to $m_i \in \{0,1\}$, where 0 indicates a good condition of the machine, and 1 indicates a faulty condition. It is necessary to determine the presence or absence of a defect for the input data from the vibration sensor. Thus, there is a need to develop a neural network method for detecting defects based on the analysis of vibrations of rotating machines and a neural network model is required $Model_\theta()$ with parameters θ at which each input value of the vibration signal x_i is processed and fed to the input of the neural network model to obtain the predicted probability of the class (“without defect” or “with defect”) $\hat{m}_i = Model_\theta(x_i)$. To study the effectiveness of the obtained neural network model, calculate the following metrics Accuracy, Precision, Recall, F1-score.

2 REVIEW OF THE LITERATURE

The urgency of the task of detecting defects in rotating machinery is due to the need to reduce the risk of failure, minimize downtime, and reduce maintenance costs. By detecting defects such as bearing wear, overheating, or mismatches in the lubrication systems, more serious failures can be prevented. The use of modern methods, including vibration sensors and infrared thermography, allows for effective diagnostics, and the integration of artificial intelligence and machine learning also increases the accuracy and speed of defect analysis [4].

Next, consider scientific research devoted specifically to the detection of defects in rotating machine parts using vibration methods.

In the article [5] The article considers the application of deep learning to diagnose malfunctions of rotating machines based on the analysis of vibration signals. In particular, considerable attention is paid to the use of CNN for feature extraction and classification of vibration data. CNN can detect defects, such as damage to bearings and gearboxes, using time-frequency signal analysis. In addition to CNN, the article discusses the use of auto-codes that are capable of self-learning and analyzing incoming vibration data. This approach makes it possible to detect defects even in difficult conditions, including in the presence of significant noise. In addition, the analysis of se-

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quences of signals that change over time can be performed using RNN, which makes it possible to track the development of defects in real time.

In the article [6] the authors solved the problem of detecting faults in rotating machines by analyzing vibration signals. They compared different classifiers, such as support vector machine SVM, naive Bayesian classifier, and k-NN nearest neighbors, to find the most effective approach for accurate diagnosis. According to the study, SVM proved to be the most effective classifier due to its high accuracy in detecting faults.

Authors [7] applied an AIoT approach to detect anomalies in rotating machines by monitoring vibrations. In their approach, vibration signals are collected using an MPU6050 accelerometer connected to a Raspberry Pi 4B device that acts as a peripheral computing device. For efficient implementation, this device uses SVM, which provides the ability to analyze data directly on the periphery.

Paper [8] describes the use of 1D-CNN to diagnose the condition of rotating machines. The authors propose to use 1D-CNN to automatically detect defects in gears based on vibration signals, which allows identifying various types of damage, such as wear or chipped teeth. The authors claim that this approach reduces the need for manual feature extraction, which is usually required for traditional machine learning algorithms. During the experiments, the authors compared 1D-CNN with other machine learning methods, including decision trees, random forests, and SVM, and demonstrated that 1D-CNN outperformed these algorithms, reaching 97.11% accuracy.

Article [9] discusses the diagnostics of rotating machines using adaptive processing of vibration signals. Experimental results show that the use of stochastic resonant wavelet decomposition and LMD morphological filtering reduces noise and increases fault identification accuracy by up to 95%. This approach demonstrates the effectiveness of adaptive processing of vibration signals to improve the accuracy of diagnostics of rotating machines.

In [10], the authors also investigate methods for detecting malfunctions of rotating machines. First, the vibration signals were pre-processed using EMD to extract the most important components while eliminating redundant information. After that, significant characteristics in the time and frequency domains were extracted from each channel of the processed signal, which were combined to create a clear representation of the features of each class. The characteristics were selected from a set including time, frequency, and statistical data based on long-term experiments. The combined feature vector was used to train and test the SVM classifier using 10-fold cross-validation. In addition, the basic SVM classifier was compared with the k-NN and DT methods. The proposed approach demonstrated the best results, reaching an accuracy of 99%.

Thus, the task of neural network defect detection based on the analysis of rotating machine vibrations is relevant, as timely diagnosis of equipment malfunctions is important for preventing accidents and optimizing maintenance costs. In modern research, neural networks are being actively studied, which have demonstrated high efficiency in classifying the state of machines based on vibration signals. Existing approaches for detecting defects in rotating machines are usually based on traditional signal processing methods with the removal of noise present in vibration signals. However, it is difficult to find the threshold for noise removal, which leads to the removal of important features that would indicate the presence of defects along with the noise. Thus, there is a need to develop a new method based on neural networks that can learn complex features in vibration data, even in the presence of noise, which allows for more accurate and reliable diagnostics.

3 MATERIALS AND METHODS

To solve this problem, propose a method of neural network detection of defects based on the analysis of rotating machines vibrations. The method scheme is shown in Figure 1.

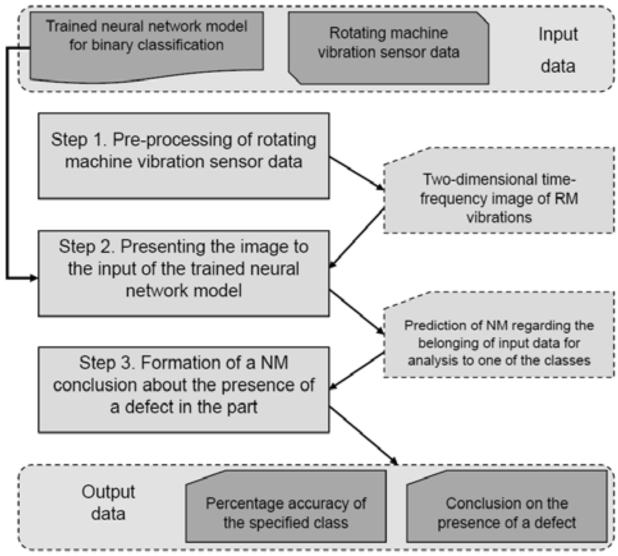

Figure 1 – Scheme of the method of neural network detection of defects based on the analysis of rotating machines vibrations

The input data of the method are $Model_\theta$ with θ for binary classification, as well as the set X and has the form shown in Figure 2.

The first step involves pre-processing the data from the vibration sensor, namely converting the vibration signal into a two-dimensional image. Data from the sensor is converted into an image by creating a graph of signal amplitudes over time. The set of vibration signals X is represented as a vector (1) with numerical values that will be used to plot the signal amplitudes over time, x_i represents the amplitude of the signal at a given time t_i.

$$\bar{x} = \left[x_{1t1}, x_{2t2}, \ldots, x_{nT} \right]. \quad (1)$$

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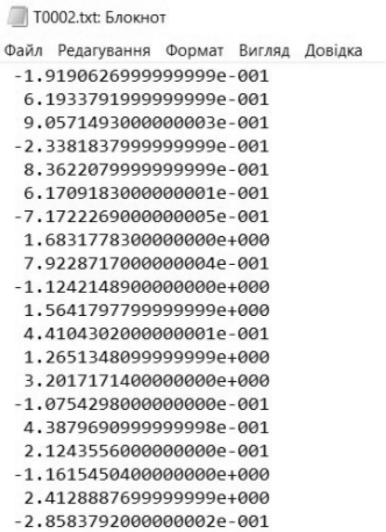
The *x-signal* is represented as a line graph, where the amplitude values are displayed along the *Y* and the time indices are displayed along the *X*. Thus, on the graph, each point (t_i, x_i) corresponds to the value of the signal at a given time t_i. This can be expressed as a function that projects the indices onto the signal amplitude: (2)

$$f(t_i) = x_i, i = 1, 2, ..., T \ . \tag{2}$$


T0002.txt: Блокнот
Файл Редагування Формат Вигляд Довідка

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 8.3622079999999999e-001
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-7.1722269000000005e-001
 1.6831778300000000e+000
 7.9228717000000004e-001
-1.1242148900000000e+000
 1.5641797799999999e+000
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 3.2017171400000000e+000
-1.0754298000000000e-001
 4.3879690999999998e-001
 2.1243556000000000e-001
-1.1615450400000000e+000
 2.4128887699999999e+000
-2.8583792000000002e-001
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Figure 2 – Example of sample vibration sensor input data

The graph is built by connecting the points $(t_i, f(t_i))$ lines, which visually represents the signal as a continuous curve. When a graph is created, it is saved as a PNG image. The image is saved as a raster representation, where each pixel contains information about the signal amplitude at the corresponding time. Let's denote the created image as a pixel matrix *I*, size $H \times W$. The image is then converted to an array of pixels and scaled to fit 224×224 pixels. When plotting, the dimensionality of the data is reduced, which is due to the peculiarities of working with images in most neural network architectures. The Matplotlib library automatically scales and arranges the data so that the plot fits into the dimensions of the generated image. At this point, the data is compressed to 50176 points. The image is formed as a two-dimensional tensor $I` \in R^{224 \times 224}$. The following image is then transmitted to the input $Model_\theta()$.

The second step is to feed the resulting image $I`$ to enter the previously trained $Model_\theta()$ for classification. $Model_\theta()$ with parameters $\theta$, receives at the entrance $I`$ and predicts the class $\hat{m}_i$, where $\hat{m}_i \in [0,1]$ is the probability of a signal belonging to one of the classes.

At step 3, based on the forecast, a conclusion is formed on the condition of rotating machine parts. If $\hat{m}_i \geq 0.4$, the conclusion indicates that the part has a defect, otherwise – without a defect. The value of 0.4 was chosen as a threshold that balances the sensitivity and specificity of the model, avoiding false negatives (when parts with defects are classified as defect-free) while minimizing false positives. This value was chosen empirically, taking into account the analysis of the model's performance on training and validation datasets, to ensure reliable diagnostics and timely detection of defects. This step also calculates the percentage accuracy of belonging to a particular class (3), which is the output of the described method of neural network defect detection based on the analysis of rotating machine vibrations:

$$\hat{m}_i \times 100\% \ . \tag{3}$$

To receive $Model_\theta()$, it is necessary to determine the type and architecture of the neural network and train it on the data set. The scheme for obtaining a typical neural network model used for the method of neural network defect detection, based on the analysis of rotating machine vibrations, is shown in Figure 3. This scheme illustrates the overall process of developing a neural network model that can detect defects in rotating machinery by analyzing the vibration data collected from the machines. Figure 3 provides a clear visual representation of the typical workflow involved in creating such a model.

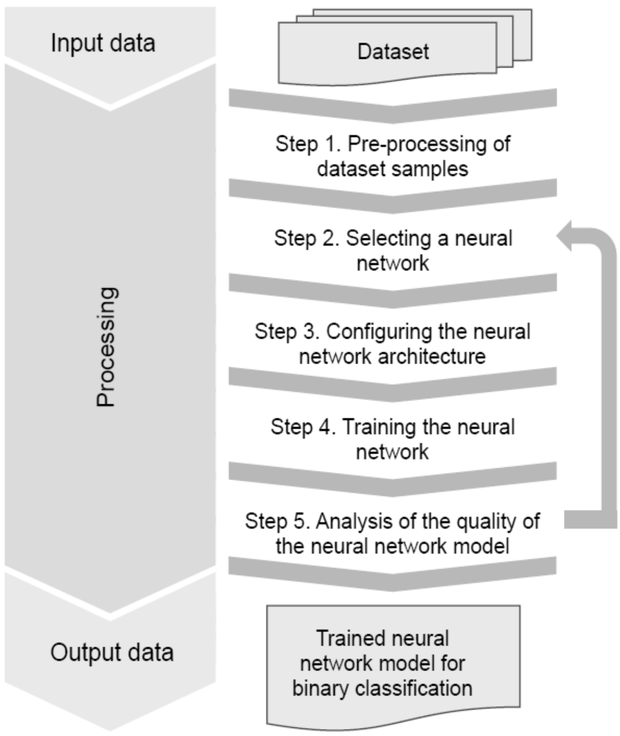

Figure 3 – Scheme of obtaining a typical neural network model for the method of neural network defect detection based on the analysis of vibrations of rotating machines

Input data to receive $Model_\theta()$ there is a dataset received for participation in the competition "All-Ukrainian competition of young scientists in the field of intelligent IT" (https://zp.edu.ua/vkiit/).

The first step is to preprocess the dataset. Since the dataset contains text files with numerical values of vibration that were taken from the sensors (Figure 1) and the

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key.txt file, which is the key to which class each file with signals from the vibration sensor belongs to, it is first necessary to represent the values of the vibration signals in the form I`. This is done in the same way as the transformation of the input data in step 1 of the neural network defect detection method described above for analyzing the vibrations of rotating machines. Figure 4 shows the image before and after preprocessing.

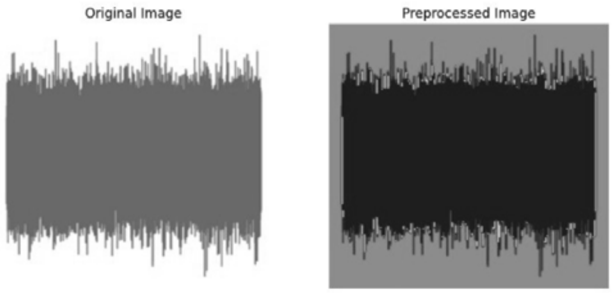

Figure 4 – Images before and after preprocessing

After converting data into images according to the key.txt file, the images are labeled with their “no defect” and “defect” classes. To train the neural network model, 80% of the data is selected from the dataset, and the remaining 20% is used to validate the model.

The second step is to select the architecture of the neural network model. In the task of classifying defects from vibration data converted to images, the choice of neural network architecture is important to achieve high accuracy. Among the various options, such as ResNet50, VGG, Inception, MobileNet, and DenseNet [11], The most reasonable solution is to use ResNet50. This architecture is characterized by its ability to maintain performance even with significant network depth, which is achieved by using resistive blocks. Residual blocks avoid the problem of gradient fading, which ensures stable training and efficient feature extraction, even when the data is complex or contains implicit patterns [12], as in the case of time signals of vibration data.

In addition, ResNet50 has a relatively moderate computational complexity compared to heavier models such as DenseNet, making it more practical for applications with limited computing resources [12]. Compared to models designed for lower computational cost, such as MobileNet, ResNet50 provides significantly higher accuracy, which is important for flaw detection where minimizing false positives is important, such as in rotating machinery. In general, thanks to the balance between accuracy and efficiency, as well as the ability to highlight complex features of the input data, ResNet50 is the optimal choice for the task of classifying defects from vibration signal analysis.

The second step is to configure the parameters of the chosen neural network architecture. First of all, the model architecture includes the number of layers and their configuration, which determines the depth and complexity of the network. Each layer contains a certain number of neurons involved in extracting features from the input data. It is also important to use convolutional layers, where the size of filters is customized. For example, the classic ResNet50 model also includes certain hyperparameters, such as the learning rate and the number of epochs. The learning rate determines how quickly the model adapts to new data during training, and the number of epochs indicates how many times the model will go through the entire training set [13]. It is also possible to define a loss function, in this case the loss function is a binary cross-entropy, which allows you to measure the quality of model predictions and adjust its weights during training.

The third step involves training the neural network. For training, 926 samples from the dataset are used. As a result of training, a neural network model is obtained, and then the model’s effectiveness is evaluated in step 4. To evaluate the model’s performance, various metrics are used, such as the confusion matrix, Accuracy, Precision, Recall, F1-score, and additionally, Accuracy and Loss graphs are built [14]. If the results are unsatisfactory, you should return to step 2. If the results of the metrics are satisfactory, a trained model is obtained for neural network defect detection based on the analysis of rotating machine vibrations.

Thus, these steps allow you to get $Model_{\theta}()$, for the above method of neural network defect detection based on the analysis of vibrations of rotating machines.

4 EXPERIMENTS

To test the described method of neural network detection of defects based on the analysis of rotating machines vibrations, a software application has been developed that is available for download and deployment via the link on GitHub (https://github.com/OlenaSobko/Sobko_Dydo/). To develop the software application and conduct experimental studies, we used hardware with the following parameters:

– Intel Core i5 processor;

– the amount of RAM is 8 GB;

Software:

– Python 3.11.6 interpreter;

– Library scikit-learn 1.3.2, imbalanced-learn 0.12.4, TensorFlow 2.14.0, Pillow (PIL) 10.1.0, NumPy 1.26.2, Flask 3.0.3;

– Windows 10 Home version 22H2 (kernel version 10.0.19045).

The software application was developed as a web application (Figure 5), and the interaction of its components is shown in Figure 6.

The diagram illustrates the layout of the components of a software application for detecting defects in rotating machines using vibration analysis. One of the input data is a data dataset containing vibration signals characterizing the state of the rotating machine. This data is processed and visualized using the Matplotlib library to create a graphical dataset that presents visual information about the vibrations. Next, a graphical dataset is passed to the component and the neural network model is trained. After that, a trained ResNet50 model is obtained, to which the

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user can provide either a graphical representation of vibrations from sensors or a numerical one in the form of a text file to detect defects in rotating machines. The web application is an "intermediary" between the user and the neural network model, which allows to upload input data from the user and provide a conclusion on the presence of defects in rotating machines.

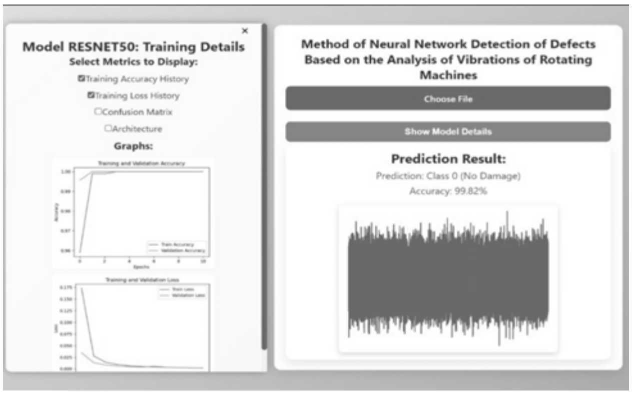

Figure 5 – A web application for testing the method of neural network defect detection based on the analysis of vibrations of rotating machines

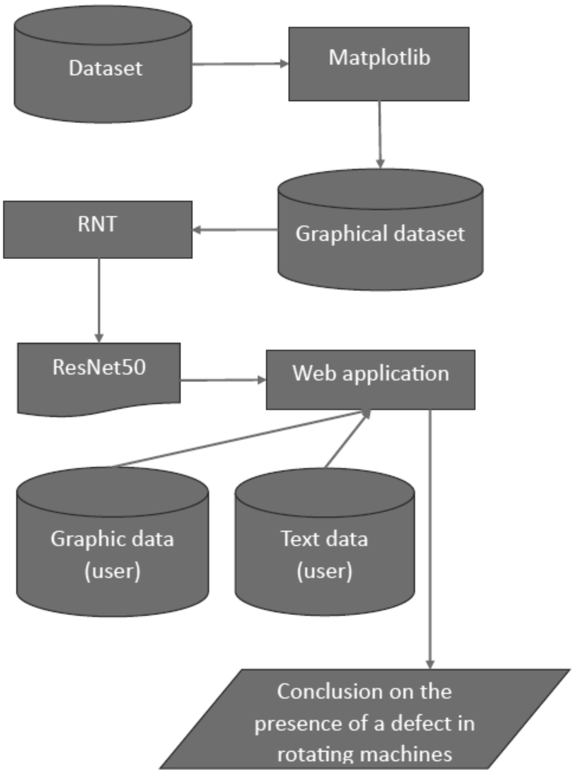

Figure 6 – Diagram of the components of the software application

To test the method of neural network detection of defects based on the analysis of rotating machines vibrations, a neural network model based on ResNet50 was obtained according to the steps of Figure 3, the architecture of which is shown in Figure 7.

The input is a 224×224 image with three channels corresponding to RGB color components. The first layer is the input layer, which accepts data in the format (None,224,224,3), where None indicates the size of the packet.

The next component is the ResNet50 kernel, which consists of pre-trained deep neural network layers. This part of the network converts input images into high-level features, and its output tensor has the dimension (None,7,7,2048), where 2048 is the number of extracted features. After that, a global feature averaging layer is applied (GlobalAveragePooling2D), which aggregates features from the entire field of view, reducing the dimensionality to (None,2048), which reduces the amount of data and avoids overtraining by keeping only the key generalized characteristics.

Next, two Dense layers are added to perform classification functions. The first dense layer with 256 neurons takes an input of 2048 features and performs a linear transformation with nonlinear activation, which helps to extract and classify relevant defect features. The last dense layer contains only one neuron with an activation function, which allows for the final binary classification that determines the presence or absence of a defect in the system.

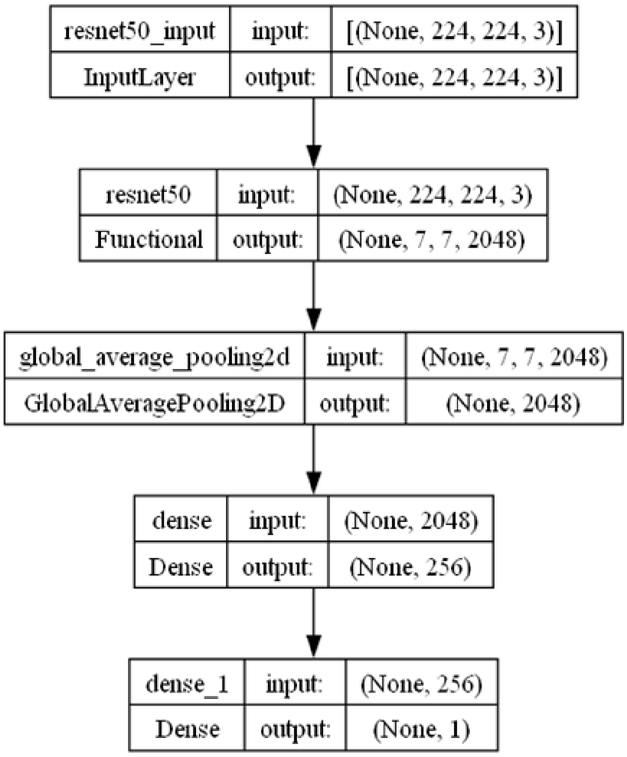

Figure 7 – Architecture of the resulting neural network model based on ResNet50

As for the dataset used for testing, in this case, randomly by means of scikit-learn (https://scikit-learn.org/stable/) 926 samples were selected for training, of which 689 were "without defect", and 237 were "with

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defect" and 232 for validation, of which 176 were "without defect" and 56 were "with defect".

To study the effectiveness of the proposed method, the following steps should be taken:

1. Build Accuracy and Loss graphs.
2. Build the entanglement matrix.
3. Calculate metrics Accuracy, Precision, Recall, F1-score.
4. Conduct a cross-validation test to assess the accuracy of the obtained neural network model.

The results of the study are presented below in Section 5.

5 RESULTS

The Accuracy and Loss graphs, presented in Figure 8 below, serve as fundamental tools for assessing the performance of a machine learning model throughout the training process. These graphs offer a detailed and dynamic representation of the model's progression as it learns from the training data over successive epochs. By tracking the changes in accuracy and loss values during training, they provide insights into the effectiveness of the model's learning process, the behavior of the optimization algorithm, and the ability of the model to generalize its learned patterns to unseen data.

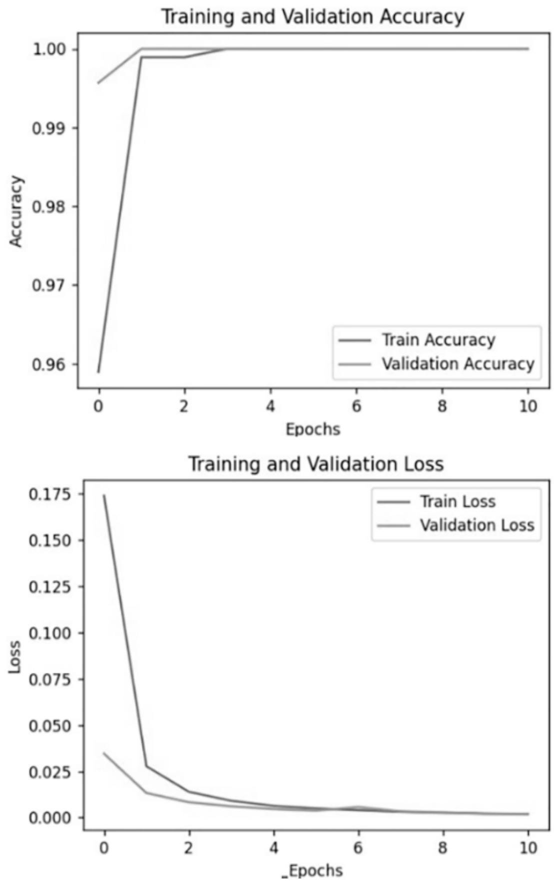

Figure 8 – Graphs of accuracy and losses of the neural network model based on ResNet50

Next, we constructed a confusion matrix for the validation data, which is shown on Figure 9.

As a result, the model received the following metric values: Accuracy 1.0, Precision 1.0, Recall 1.0, F1-Score 1.0.

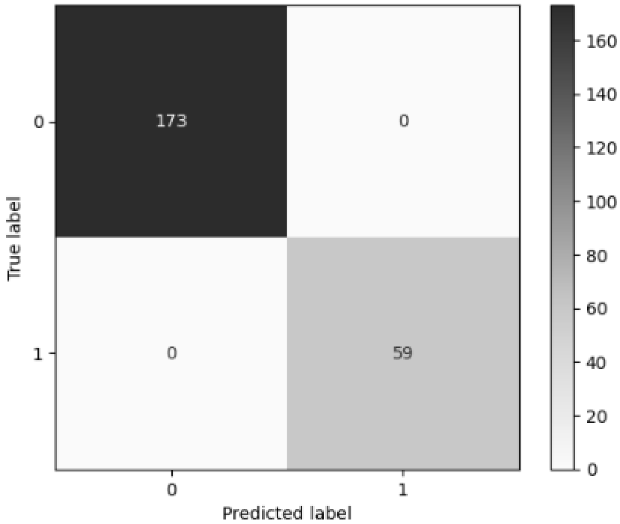

Figure 9 – Confusion matrix for validation data

The next step is cross-validation. Cross-validation is a method of assessing the accuracy of machine learning models by dividing data into several parts, or folds. In the classical case, for example, in k-fold cross-validation, the dataset is divided into k equal parts. The model is trained on k-1 parts of the data and then tested on the remaining part. This process is repeated k times, each time using a different fold for validation and the rest for training. After that, the results of each cycle are averaged to get an overall assessment of the model's performance [15]. The results of such cross-validation for the ResNet50 neural network model are shown in Table 1.

Table 1 – Metrics results for different folds

Fold	Accuracy	Precision	Recall	F1 Score
1	0.9855	0.9773	0.9806	0.9855
2	0.9982	0.9974	0.9913	0.9943
3	0.9986	0.9999	0.9913	0.9955
4	0.9838	0.9828	0.9896	0.9791
5	0.9887	0.9870	0.9851	0.9861
6	0.9904	0.9971	0.9988	0.9980
7	0.9841	0.9918	0.9894	0.9840
8	0.9986	0.9960	0.9985	0.9972
9	0.9886	0.9876	0.9844	0.9823
10	0.9945	0.9943	0.9981	0.9962

The average values of five fouls are Accuracy 0.9911, Precision 0.9911, Recall 0.9907, F1-Score 0.9898, and the deviations from the initially calculated metric values are obtained: Accuracy 0.0089, Precision 0.0089, Recall 0.0093, F1-Score 0.0102.

Compared to the works considered [8, 9, 10] in Section 2, the trained neural network model for the method of neural network detection of defects based on the analysis

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of rotating machines vibrations received a higher accuracy rate of 99.11% than in the cited works (Accuracy rates 97.11%, 95%, 99%).

Further, in Section 6, we discuss the results of evaluating the effectiveness of the obtained neural network model for testing the method of neural network defect detection based on the analysis of rotating machines' vibrations.

6 DISCUSSION

The accuracy and loss plots in Figure 8 show that the model's accuracy increases rapidly and reaches 1.0 already at the initial epochs. The accuracy on the training and validation sets is almost identical, which indicates that they are consistent. The losses decrease quite quickly, reaching very low values after a few epochs. The difference between the losses on the training and validation sets is insignificant, indicating that the model does not overlearn.

The resulting confusion matrix demonstrates that the model achieved perfect results on the validation data, as all model predictions are correct. The model classified 173 samples as class "0", i.e. without defects and 59 samples as a class "1", i.e. with defects, without making a single error. All model quality indicators, including Accuracy, Precision, Recall, and F1-Score, have a value of 1.0, which indicates no false positives and full coverage of both classes. This indicates the perfect ability of the model to distinguish between classes on the validation data, i.e., it not only correctly predicts class membership, but also does not allow false classifications, fully covering both classes.

To confirm the model's effectiveness, a cross-validation was conducted to ensure that the high performance was the result of a good generalization and not a coincidence. The results of the cross-validation demonstrate the model's consistently high performance across all key metrics in each of the five folds. Accuracy in all folds ranges from 0.9838 to 0.9887, indicating a high generalization ability of the model. Similarly, Precision, Recall, and F1 Score in each fold are close to 1.0, which confirms the absence of a significant number of false positives and false negatives.

The average metric values for the five folds are: Accuracy – 0.98614, Precision – 0.9853, Recall – 0.98582, and F1-Score – 0.9834, which once again confirms the overall reliability and efficiency of the model. A small deviation of the metrics from the initially selected values indicates the stability of the model, since these deviations are minimal and do not significantly affect its overall performance.

Thus, the neural network model obtained as a result of the experimental study is focused on detecting defects by analyzing the vibrations of rotating machines without preliminary noise removal. The ResNet50 base model is responsible for extracting high-level features, which allows the neural network to learn with a high level of detail. The use of a global feature averaging layer reduces the number of parameters, which reduces the risk of overfitting, allowing for better generalization of information. Due to the sequence of dense layers at the output, the network is able to convert the selected features into a binary decision (for example, the presence or absence of a defect), which is the result of the task. The above is confirmed by an experiment to study the effectiveness of the resulting model.

The study demonstrates that the proposed method of neural network defect detection based on the analysis of vibrations of rotating machines allowed us to create a neural network model as a result of the experiment, which achieved high accuracy and consistency between training and validation data, as evidenced by higher Accuracy, Precision, Recall, F1-Score indicators compared to [8, 9] and [10].

CONCLUSIONS

The paper solves an urgent problem of neural network defect detection based on the analysis of rotating machine vibrations.

The scientific novelty is to develop a method of neural network detection of defects by analyzing the vibrations of rotating machines based on the ResNet50 neural network model, which achieves high results of accuracy of defect detection by analyzing the vibrations of rotating machines. A distinctive feature of the method is that it does not require preliminary cleaning of vibration signals from noise, which is achieved by adjusting the parameters of the neural network architecture.

The practical significance the results obtained indicate that the method proposed in this work and the developed software can be used to detect defects by analyzing the vibrations of rotating machines, since it showed high performance on the proposed dataset.

Prospects for further research is to test the resulting neural network model on larger data sets.

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МЕТОД НЕЙРОМЕРЕЖЕВОЇ ВИЯВЛЕННЯ ДЕФЕКТІВ НА ОСНОВІ АНАЛІЗУ ВІБРАЦІЙ ОБЕРТОВИХ МАШИН

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АНОТАЦІЯ

Актуальність. У роботі пропонується вирішення актуальної проблеми виявлення дефектів обладнання за аналізом вібрацій обертових машин. Об'єктом дослідження є процес виявлення дефектів за аналізом вібрацій обертових машин. Предметом дослідження є методи штучного інтелекту для виявлення дефектів за аналізом вібрацій обертових машин.

Мета роботи. Підвищення точності виявлення дефектів за аналізом вібрацій обертових машин шляхом створення методу нейромережевого виявлення дефектів за аналізом вібрацій обертових машин та відповідної нейромережевої моделі, яка здатна виявляти дефекти за аналізом вібрацій обертових машин без попереднього видалення шумів з метою збереження важливих ознак для точнішої класифікації.

Метод. Запропоновано метод нейромережевої виявлення дефектів на основі аналізу вібрацій обертових машин, який здатен за вхідними даними вібрацій з виконанням попередньої обробки, а саме створення двовимірного часово-частотного зобра-ження, зробити прогноз щодо наявності чи відсутності дефекту. Метод відрізняється від існуючих тим, що аналіз на дефекти проводиться без видалення шумів за рахунок тонкого налаштування параметрів моделі.

Результати. Запропонований у роботі метод нейромережевої виявлення дефектів на основі аналізу вібрацій обертових машин реалізовано у вигляді вебзастосунку та проведено дослідження ефективності нейромережевої моделі, отриманої шляхом виконання кроків методу.

Висновки. Результати дослідження показують, що модель досягла високої точності та узгодженості між тренувальними та валідаційними даними, що підтверджується високими значеннями таких показників, як Accuracy = 1.0, Precision = 1.0, Recall = 1.0 і F1-Score = 1.0 на валідаційному наборі даних, а також мінімальними втратами. Проведена крос-валідація підтвердила стабільну ефективність моделі, продемонструвавши високі усереднені метрики та незначні відхилення від отриманих метрик. Таким чином, нейромережева модель виявляє дефекти обертових машин з високою ефективністю навіть без очищення вібраційних сигналів від шумів. Перспективи подальших досліджень полягають в апробації описаного метода та отриманої нейромережевої моделі на більших наборах даних.

КЛЮЧОВІ СЛОВА: дефекти, аналіз, вібрації, обертові машини, нейромережа, ResNet50.

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