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METHOD OF PREVENTING FAILURES OF ROTATING MACHINES BY VIBRATION ANALYSIS USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

Context. The problem of determining transitional conditions that precede the shift from an operating state to a non-operating state based on data obtained from the sensors of rotating machine elements is being solved. The object of the study is the process of detecting faults and states that indicate an approach to breakdown in rotating machine elements based on data obtained from sensors. The subject of the study is the application of *k*-means and the elbow method algorithms for clustering and convolutional neural networks for classifying sensor data and detecting near-failure states of machine elements.

Objective. The purpose of the work is to create a method for processing sensor data from rotating machines using convolutional neural networks to accurately detect conditions close to failure in rotating machine elements, which will increase the efficiency of maintenance and prevent equipment failures.

Method. The proposed method of preventing failures of rotating machines by vibration analysis using machine learning techniques using a combination of clustering and deep learning methods. At the first stage, the sensor data undergoes preprocessing, including normalization, dimensionality reduction, and noise removal, after which the *K*-means algorithm is applied. To determine the optimal number of clusters, the Elbow method is used, which provides an effective grouping of the states of rotating machine elements, identifying states close to the transition to fault. A CNN model has also been developed that classifies clusters, allowing for the accurate separation of nominal, fault, and transitional conditions. The combination of clustering methods with the CNN model improves the accuracy of detecting potential faults and enables timely response, which is critical for preventing accidents and ensuring the stability of equipment operation.

Results. A method of preventing failures of rotating machines by vibration analysis using machine learning techniques and a relevant software package have been developed. The implemented method allows us to identify not only normal and emergency states but also to distinguish a third class – transitional, close to breakdown. The quality of clustering for the three classes is confirmed by the value of the silhouette coefficient of 0.506, which indicates the proper separation of the clusters, and the Davis-Boldin index of 0.796, which demonstrates a high level of internal cluster coherence. Additionally, CNN was trained to achieve 99% accuracy for classifying this class, which makes the method highly efficient and distinguishes it from existing solutions.

Conclusions. A method of preventing failures of rotating machines by vibration analysis using machine learning techniques was developed, the allocation of the third class – transitional, indicating a state close to breakdown – was proposed, and its effectiveness was confirmed. The practical significance of the results lies in the creation of a neural network model for classifying the state of rotating elements and the development of a web application for interacting with these models.

KEYWORDS: rotation machines, element failure, transitional conditions, clustering, classification, CNN.

ABBREVIATIONS

AI is an artificial intelligence;
CAM is a computer aided manufacturing;
CNN is a convolution neural network;
DL is a deep learning;
LSTM is a long short-term memory;
ML is a machine learning;
NN is a neural network;
RGB is a red, green and blue color model;
RNN is a recurrent neural network;
SVC is a scalable video coding;
SVM is a support vector machine.

NOMENCLATURE

γ is an input sensory data converted into numerical representations;
x is a horizontal pixel coordinate in the resulting image;
y is a vertical pixel coordinate in the resulting image;
b_j is a bias for the neuron of the j-th dense layer;
f is an activation function;
g is a convolution kernel that moves through the data to extract features;
$P(i,j)$ is a value after the MaxPooling operation at position (i,j) in the original matrix;
w_{ij} is a weight between the neuron of the i-th layer and the j-th neuron of the dense layer;
$X(i+m, j+n)$ is a initial matrix of values that are passed to CNN for processing;
y_i is a output of the j-th neuron on the dense layer.

INTRODUCTION

Modern machine diagnostics systems use data from numerous sensors that measure key operating parameters in real time, such as vibration, temperature, pressure, and voltage. The problem lies not only in the sheer volume of data, but also in its complexity, which makes it difficult to apply classical analysis methods. Artificial intelligence

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solves these problems by detecting hidden patterns and anomalies in multidimensional data, which increases the accuracy of fault prediction [1].

The use of artificial intelligence tools in the diagnostics of machine elements allows timely detection and prevention of malfunctions and prediction of possible failures, which increases the reliability of maintenance, reduces repair costs and equipment downtime [2].

The development of tools for diagnosing the technical condition of machines should be aimed not only at detecting faulty or completely damaged components, but also at preventing possible failures. Ensuring early detection of critical changes in the condition of parts allows for timely action to prevent their failure during operation. This helps to reduce maintenance costs, increase machine efficiency and improve operational safety, which is critical in many areas where the stability of technical equipment is of key importance.

The object of study process of detecting malfunctions and states that indicate an approximation of a failure in the elements of rotating machines based on data obtained from sensors.

The subject of study application of clustering algorithms and convolutional neural networks to classify sensor data and detect near-failure states of machine elements.

The purpose of the work is the development of a method for processing data from rotating machine sensors using convolutional neural networks to accurately detect states close to failure in rotating machine elements, which will increase the efficiency of maintenance and prevent equipment failures.

1 PROBLEM STATEMENT

Let $X = \{x_1, x_2, ... x_n\}$ be a set of sensor data collected from rotating machine elements, where each $x_i \in \mathbb{R}^d$ represents a vector of d sensor records at a given time. The dataset X ϵ is unlabeled and consists of a set of text files x_n, where each file contains sensor data for a certain period of time and a key file $K = \{k_1, k_2, ... k_n\}$, where $k_i \in \{0,1\}$ is a binary label indicating whether the rotating element is in good condition $(k_i = 0)$ or faulty $(k_i = 1)$. The dataset X, containing sensor records is analyzed with the assumption that there is an intermediate class between fault and nominal, which means that the received sensor data on the element state does not belong to the nominal cluster and is approaching the fault condition.

The purpose of the study is to implement a method for identifying a transitional class of component condition based on indicators from sensors that read the condition of equipment. The study focuses on the possibility of identifying this class using clustering methods, such as the k-means method, and classification using convolutional neural networks.

This method allows identifying not only nominal and faulty parts, but also those that are on the verge of failure, which makes it possible to identify parts with an increased risk of failure in advance and organize timely maintenance.

2 REVIEW OF THE LITERATURE

Recent studies show that traditional diagnostic methods that involve manual analysis of sensor data are giving way to automated approaches that use machine learning and, in particular, deep neural networks [3], [4]. Convolutional neural networks have shown significant potential in processing complex, multidimensional data [5] from industrial sensors due to their ability to detect complex relationships between signals and identify anomalies that may indicate malfunctions.

In article [6], the authors review modern machine learning methods used to monitoring and predicting faults in glass industrial rotating machines. The focus is on the use of sensor data, which is important for accurate fault diagnosis. Both traditional methods, such as regression, decision trees, and SVMs, and more modern deep learning approaches, such as neural networks, CNNs, and RNNs, have been studied.

Deep neural networks have shown significant advantages in detecting complex patterns in sensor data, which has increased the accuracy of fault diagnosis to 93–97%. This is significantly higher than traditional methods, which have an accuracy of about 80–85%. RNNs [7] were particularly effective, demonstrating up to 90% accuracy when working with sequential data, such as vibrations and temperature measurements.

The study also showed that the use of NNs significantly reduced the processing time of large amounts of sensor data, which is especially important for systems with high performance requirements. In real-life examples, in particular when working with motors and rotary machines, the use of neural networks reduced the number of failures by 20–25% compared to traditional methods.

The authors of [8] also consider modern DL approaches for fault detection and prediction in industrial systems. The main focus is on how deep learning outperforms traditional diagnostic methods capable of working with large amounts of complex sensor data. Among the main methods discussed are CNNs used to process vibration signals and images, which facilitates early detection of faults.

The authors of [9] and [10] consider the use of machine learning methods to predict industrial equipment failures based on time series of sensor data. The researchers emphasize the importance of predicting the specific moment when equipment goes from a nominal to a faulty condition, which reduces the risk of unplanned machine downtime. The paper applies various machine learning models, such as RNN and LSTM, to capture and learn from temporal patterns that indicate the approach of a machine element failure. The results show that these models are able to effectively identify failure patterns in continuous time series, providing earlier and more accurate failure prediction.

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The authors of [11] also proposed a three-stage fault prediction method for rotating equipment. It uses a combination of CNN and LSTM to detect the degradation period and fault type, and (Bi)-LSTM and SVC to predict the trend and identify specific faults. The method has been successfully tested on the IMS dataset[12].

To solve such problems, authors often use the method of converting numerical data into graphs, as this allows to use CNNs to analyze them, making it possible to achieve comparable classification results to traditional machine learning algorithms such as XGBoost.

A study [13] was also conducted on the application of image-based methods for diagnosing machine faults using data from 6DOF IMU. Three methods are proposed: converting time data into a gray image, RGB image, and RGB image with X, Y, Z axes. All methods show high accuracy in classifying different operating states. The gray image provides faster training, while RGB methods offer additional analysis capabilities. The study also examines the interpretability of models using Grad-CAM [14].

Paper [15] compares methods of converting tabular data into images for use with convolutional neural networks, showing that even a basic CNN can achieve results similar to the XGBoost algorithm optimized by traditional methods.

Recent studies substantiate the effectiveness of artificial intelligence techniques, particularly neural networks, for monitoring and diagnosing the condition of rotating machinery. CNN and LSTM networks have demonstrated robust performance in detecting faults by analyzing sensor data, highlighting their potential for early fault identification. These architectures excel in extracting complex patterns and temporal dependencies within sensor readings, enabling them to recognize subtle indicators of equipment deterioration.

However, the critical issue of accurately pointing the transition from nominal operational to failure conditions remains underexplored. Current models predominantly focus on distinguishing between nominal and faulty conditions after critical issue become evident. Addressing this gap requires more advanced predictive modeling that can identify faults well before they become critical, thus providing a buffer for preventive measures.

Future research should therefore prioritize the development of sophisticated, multi-faceted models that incorporate predictive capabilities. By effectively forecasting potential failures before they manifest, such models could significantly reduce unplanned downtimes, cut maintenance costs, and enhance the operational safety and reliability of rotating machinery systems.

3 MATERIALS AND METHODS

To solve the problem of preventing failures of rotating machines by vibration analysis using machine learning techniques, it is necessary to implement an appropriate method (Fig. 1). The process begins with obtaining and downloading the input data, namely the "zeroShot" dataset [16], which includes 1158 files, each of which contains 93752 records with sensor readings. Then, the files contained in the dataset are converted into graph images and undergo a preprocessing stage, which includes resizing to 256x256 pixels, normalizing pixel values by dividing by 255, and eliminating noise using a median filter. The cluster features are also prepared for further analysis by converting the cluster labels to the one-hot encoding format [17] to ensure correct input into the model.

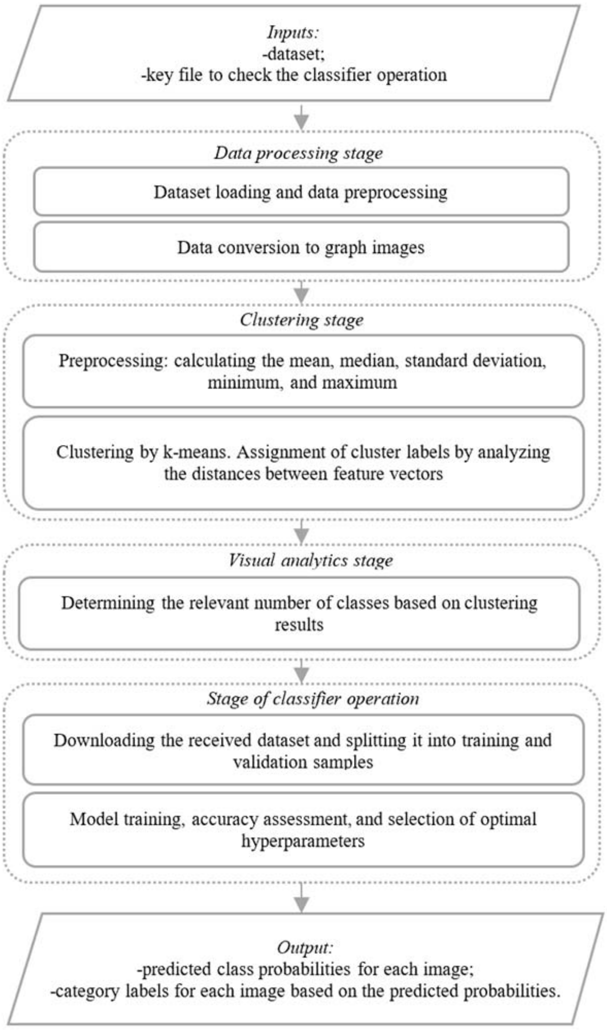

Figure 1 – A method of preventing failures of rotating machines by vibration analysis using machine learning techniques

For clustering, several important steps were taken to prepare the data and apply machine learning methods. First, basic statistical characteristics were calculated for each data file, including the mean, median, standard deviation, minimum and maximum values. These characteristics were used as features for further clustering. To ensure the uniformity of the scale of the features, the data was standardized using the StandardScaler method [18].

To determine the optimal number of clusters, it is necessary to apply the Elbow method, which helps to find the point where a further increase in the number of clusters

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does not significantly reduce the inertia, the sum of squared distances to the centroids.

To solve the clustering problem, the k-means [19] and Elbow Method [20] methods were used. The k-means algorithm is used to divide data into clusters, where each cluster is characterized by the average value of the coordinates of all points in the cluster. The basic principle of *k*-means is as follows [21]:

1) first, k cluster centers are randomly selected;

2) each data point is assigned to the closest cluster center;

3) after that, the cluster centers are recalculated based on the average value of all points belonging to each cluster;

4) the process is repeated until the centers stop changing, i.e., the algorithm converges.

The Elbow Method is used to determine the optimal number of clusters in the clustering process. The principle of this method is to analyze the inertia – the sum of distances between points and their respective centroids – for different values of the number of clusters. The inertia graph usually shows a breaking point or "elbow" after which further increase in the number of clusters does not lead to a significant decrease in inertia [22]. This point is interpreted as the optimal number of clusters, which ensures a balance between the compactness of the clusters and their number.

To evaluate the quality of clustering, metrics such as the average value of the silhouette score, inertia, Davies-Bouldin Index, adjusted rand Index, and normalized mutual information were calculated.

Fig. 2 shows the clustering process as part of a method to prevent failures of rotating machines based on vibration analysis by using machine learning techniques.

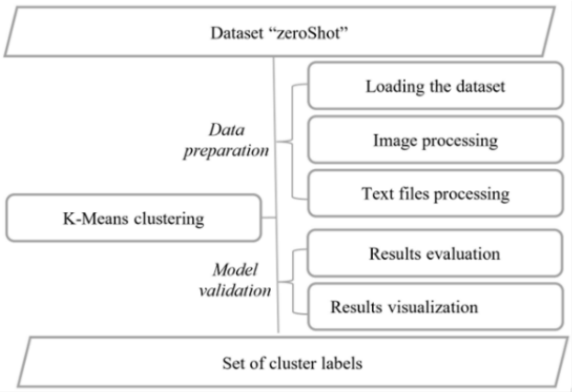

Figure 2 – The process of clustering, one of the stages of the method

The visualization of the clustering results was presented using two-dimensional scatter plot, silhouette plot, and parallel coordinates to reveal the internal structure of the clusters.

The obtained clustering results are stored for further use in the classification process. After that, the class labels preparation stage is performed, where the initial class labels are loaded from a file and converted to a one-hot encoding format for use in the classification model. Next, the obtained dataset is divided into training and test samples in the ratio of 80% to 20%. After the data is divided, the classifier is trained on the training set.

The final step is to predict classes for the test images. The obtained results are stored with the model for further use, which allows to reproduce the classification or clustering of new images.

To effectively classify the states of rotating machines based on vibration analysis, it is necessary to develop a neural network classifier. Fig. 3 shows a neural network architecture that receives an image as an input, represented as a multidimensional tensor, where each dimension corresponds to the width, height, and number of channels.

The neural network architecture for binary classification consists of three Convolutional Convolution2D layers and MaxPooling2D sub-sampling layers that help to extract local features, reduce dimensionality, and reduce computational costs. The Flatten layer transforms the data into a flat structure, after which two fully connected Dense layers provide the final classification with an output that determines the probability of belonging to one of the classes.

The neural network architecture for three-class classification is built in a similar way, but includes an additional input layer, InputLayer, which is combined with a multidimensional tensor by concatenation to take into account additional characteristics, allowing the model to recognize more classes. In the course of building the architecture and training the neural networks, we used the pillow and OpenCV libraries for basic image processing and computer vision, as well as TensorFlow with Keras for deep learning, which allows to build and train neural networks.

The first layer of the model is the Conv2D convolutional layer, which applies several filters to detect local features such as edges and textures. Convolution is a basic operation in CNNs that is used to extract features from input data, such as sensor values [23]. The convolution for two-dimensional data is represented by formula (1) [23]:

$$(\gamma \cdot g)(x, y) = \sum_i \sum_j f(i, j) \cdot g(\gamma - i, y - j). \tag{1}$$

The next layer of the neural network is MaxPooling2D, which reduces the spatial dimensions of the tensor by extracting the most important features, which improves efficiency and reduces the number of parameters to calculate. This operation selects the maximum value in each array and is calculated using the formula [23] (2):

$$P(i, j) = \max_{0 \le m < p, 0 \le n < p} (X(i + m, j + n)). \tag{2}$$

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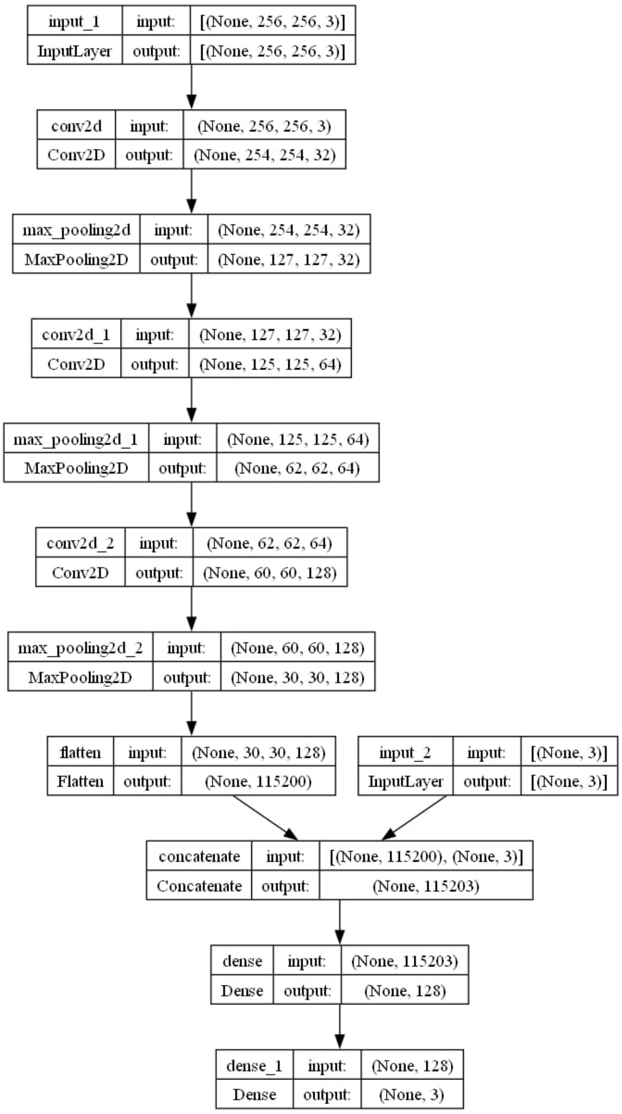

Figure 3 – Architecture of the developed convolutional neural network

After MaxPooling2D, a convolutional layer is implemented to enhance the feature analysis and help detect more complex structures. The pooling layer is again applied to reduce the size. The third convolutional layer continues to highlight complex image features, which prepares the data for the transition to the final layers. One more pooling layer completes this process and resizes the original tensor so that the data can be transferred to dense layers. The Flatten layer transforms the multidimensional tensor into a flat vector, which is necessary for further use in the fully connected Dense layers. A dense layer is a fully connected layer of a neural network, where each neuron from one layer is connected to all the neurons of the next layer. The first dense layer performs nonlinear transformations and combines the extracted features for better classification or prediction. The last dense layer completes the network, giving the final result, the probability of an image belonging to a certain class. The operation of this layer is based on matrix multiplication, which is performed according to formula (3) [24]:

$$y_i = f(\sum_{i=1}^{n} w_{ij} x_i + b_i). \tag{3}$$

The method of preventing failures of rotating machines based on vibration analysis by using machine learning techniques was proposed. The basis of the proposed method is a combination of classical machine learning methods, such as *K*-means and the elbow method for clustering, and a CNN neural network model for classifying the conditions of rotating machines.

4 EXPERIMENTS

According to the described method, a software package was implemented, including two machine learning models for clustering into two and three classes, two neural network models for classification into two and three classes, and a website for the practical use of the obtained models. The scheme of the system's program modules is shown in Fig. 4.

The dataset used for the study consists of sensor data collected from various mechanical rotating systems covering a wide range of operational parameters. These parameters, presented in text form, were converted into numerical values suitable for analysis.

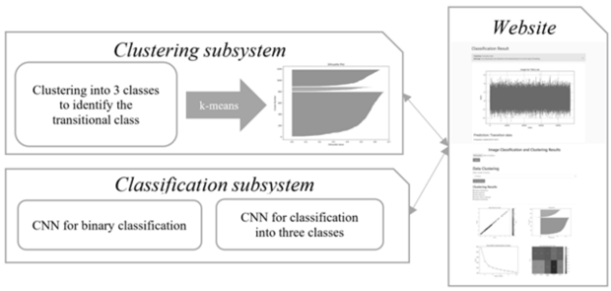

Figure 4 – Scheme of operation of the system program modules

The “zeroShot” dataset consists of 1158 files, each of which contains 93752 sensor records, as well as a file with labels for evaluating the model's performance

For clustering, no additional graphical interface was created: all processing and clustering results were displayed in the console, and the matplotlib and seaborn libraries were used for graphical representation of the data. The following libraries were used: numpy for working with multidimensional arrays, which optimizes the computations and matrix operations required to process large data sets; scikit-learn for access to machine learning algorithms, including clustering; matplotlib and seaborn for visualizing the results.

To perform the “Classifier operation” stage, the CNN neural network models were trained with the parameters shown in Table 1.

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Table 1 – A set of hyperparameters for classification

Hyperparameter name	2 classes classification		3 classes classification	
Model's version	**V1**	**V2**	**V3**	**V4**
Optimization hyperparameters				
optimizer	adam			
loss	binary_crossentropy		categorical_crossentropy	
Training hyperparameters				
metrics	accuracy			
batch_size	32		32	
epochs	6	3	10	5

The architecture of the neural network for binary classification includes three layers Conv2D and MaxPooling2D for feature extraction and dimensionality reduction, Flatten for conversion to a flat structure, and two layers Dense for classification. The architecture for three-class classification is similar, but an InputLayer with concatenation is added to take into account additional characteristics. Pillow and OpenCV were used for image processing, and TensorFlow with Keras was used to build and train neural networks.

A website based on the Flask framework [25] was also implemented to interact with AI models and display analysis results. An example of the website is shown in Fig. 5. The program codes implemented in the study were uploaded to the GitHub cloud platform to ensure accessibility and the possibility of their further analysis, verification, and reuse. [26].

The defined stages of the experiment and the methods used for data preparation and processing provide a comprehensive analysis and classification of the data. Further, the results of clustering and classification will be evaluated in terms of their accuracy, reliability, and ability to identify transient states.

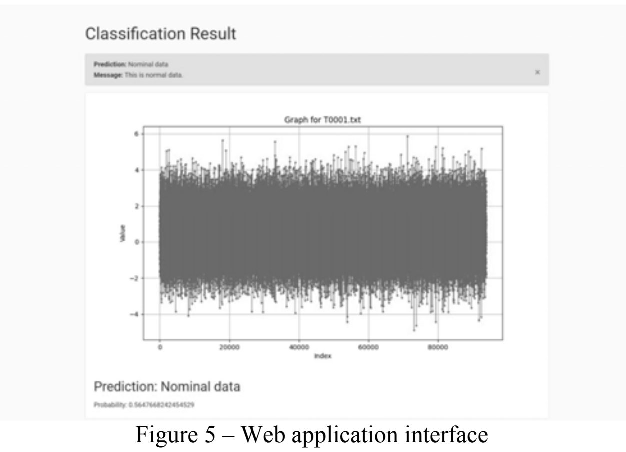

Figure 5 – Web application interface

These results will form the basis for building a prognostic model and identifying opportunities to improve the machine maintenance process, which has the potential to increase equipment stability and safety.

5 RESULTS

According to the outlined plan of the experiment, the following clustering results were obtained (Fig. 6), the distribution curve of the optimal number of Elbow method classes by the inertia parameter is presented, which decreases sharply when moving from 1 to 3 clusters, indicating that the optimal number of clusters is in the range of 2–3. This result shows that dividing the data into 3 clusters can be reasonable and will provide the best balance between clustering accuracy and model complexity.

The obtained indicators demonstrated the high accuracy of the model. For the nominal class, the model achieved precision of 0.9987, recall of 0.9885, and F1-score of 0.9936. The fault class showed precision of 0.9704, recall of 0.9966, and F1-score of 0.9833. For the transitional class, the precision is 0.9942, recall is 0.9896, and F1-score is 0.9958. The overall accuracy of the model was 0.9914. The macro- and weighted average F1-score are 0.9923 and 0.9914, respectively, which indicates high classification performance.

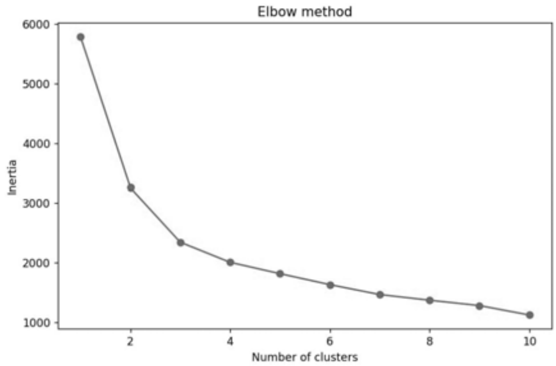

Figure 6 – Obtained clustering results

Also, according to the experimental conditions, a neural network multiclass classifier was created to distinguish three states of rotating machine elements: nominal, fault, and transitional. The confusion matrix shown in Fig. 7.

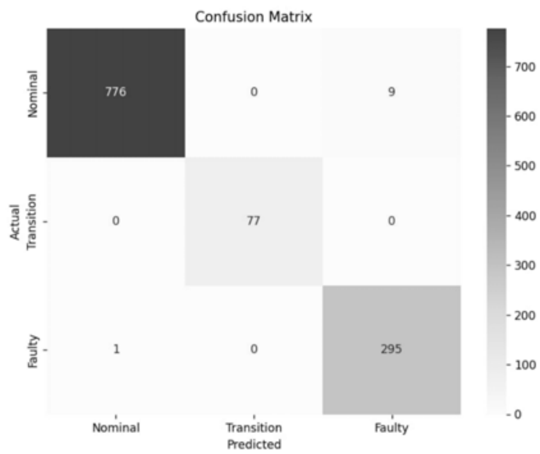

Figure 7 – Confusion matrix for multiclass model

Table 2 shows the results for binary and multiclass classification. The main focus is on the multiclass model v4, which demonstrates better classification results due to the improvement of its architecture.

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Table 2 – The results of classification by different models

	precision	recall	F1-score	support	required time, sec		precision	recall	F1-score	support	required time, sec
Binary classification (v1)						*Binary classification (v2)*					
Nominal data	0.9718	0.6511	0.7806	293	43	Nominal data	0.9763	0.9829	**0.9796**	293	91
Fault data	0.9032	0.9992	0.9485	865		Fault data	0.9942	0.9919	**0.9931**	865	
accuracy			0.9117	1158		accuracy			**0.9896**	1158	
macro avg	0.9375	0.8251	0.8646	1158		macro avg	0.9852	0.9874	**0.9863**	1158	
weighted avg	0.9197	0.9111	0.9048	1158		weighted avg	0.9897	0.9896	**0.9896**	1158	
Multi-class classification (v3)						*Multi-class classification (v4)*					
Nominal data	0.9718	0.6092	0.7493	785	102	Nominal data	0.9987	0.9885	**0.9936**	785	206
Fault data	0.1901	0.8192	0.3084	77		Fault data	0.9704	0.9966	**0.9833**	296	
Transi-tional class	0.9145	0.9972	0.9527	296		Transitional class	0. 9942	0.9896	**0.9958**	77	
accuracy			0.7217	1158		accuracy			**0.9914**	1158	
macro avg	0.6921	0.8085	0.6701	1158		macro avg	0.9897	0.9951	**0.9923**	1158	
weighted avg	0.9046	0.7228	0.7714	1158		weighted avg	0.9916	0.9914	**0.9914**	1158	

Based on the table, we can see significant improvements in the results between the v3 and v4 versions of the models for the multi-class classification task. In particular, for each of the three classes (“Nominal”, “Fault”, “Transitional”), the v4 version has higher precision, recall, and f1-score values compared to v3. This indicates the improved ability of the v4 model to correctly identify each class, especially for “Fault” and “Transitional” The overall precision score is also significantly higher in v4 (0.9914 vs. 0.7217 in v3), which demonstrates an overall improvement in model performance for all classes.

In the silhouette plots of Fig. 8a and Fig. 8b show the clustering quality assessment for two and three clusters.

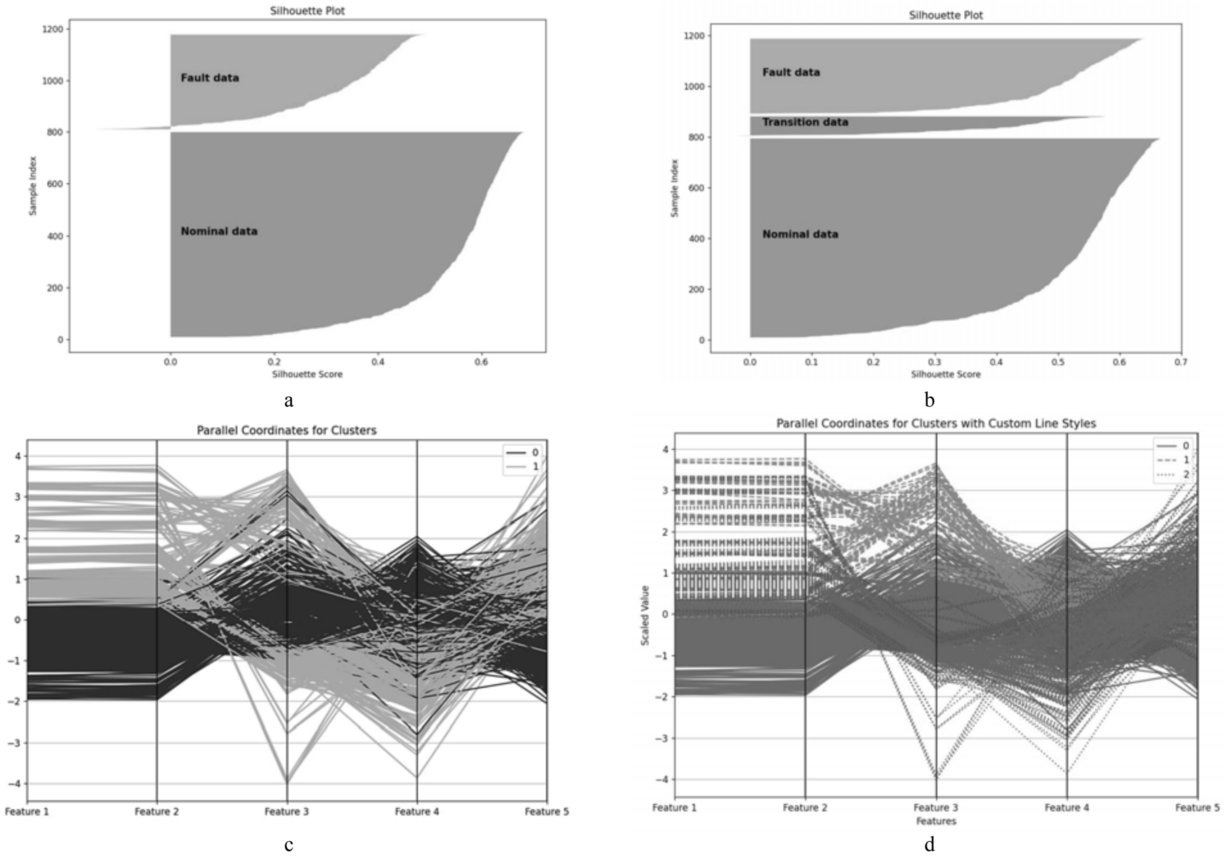

Figure 8 – Visualization of clustering results:
a – evaluation of the quality of clustering into two classes using the silhouette method; b – evaluation of the quality of clustering into three classes using the silhouette method; c – visualization of cluster division through parallel coordinates of features into two clusters; d – visualization of cluster division through parallel coordinates of features into three clusters

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For the two clusters (Fig. 8a), both clusters have positive silhouette coefficient values, indicating a clear separation between them, but the overall average silhouette score is limited, which may indicate a lack of detail in the internal structure of the data. For the three clusters (Fig. 8b), the silhouette score is also positive for each cluster, and the overall average silhouette score is higher, indicating a better distribution of the data. Fig. 9 shows a graphical representation of the clustering by two classes.

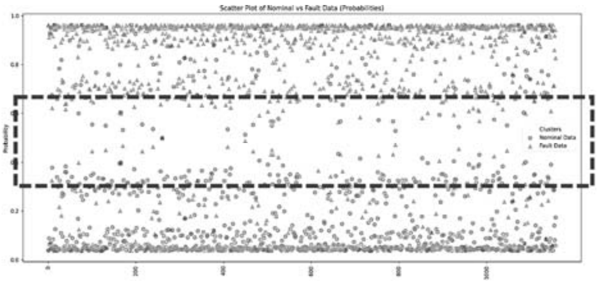

Figure 9 – Graphical representation of clustering by two classes

The above experiments were performed on the following hardware: Intel core i5-11400H processor, RAM: 16 GB. Software: Windows 11 Home, Python 3.9.0 programming language, JavaScript – ECMAScript 2023 (ES14), Visual Studio Code editor, TensorFlow/Keras, Scikit-learn, OpenCV, Matplotlib, Seaborn, Numpy, Pillow, Flask libraries were used.

6 DISCUSSION

According to the Elbow Method graph (Fig. 7), which shows the correlation between the number of clusters and the inertia value, the indicators decrease rapidly when moving from 1 to 3 clusters, after which the decrease becomes less noticeable. Such a sharp decline in the first steps usually indicates a zone of optimal distribution, where the addition of new clusters slightly improves the distribution but significantly increases the complexity of the model.

This result indicates that the optimal number of clusters may be in the range of 2–3, since further increasing the number of clusters does not significantly improve the inertia. The choice of 3 clusters is justified because this division provides an effective reduction of internal variance, which is important for more accurate modeling of the data structure, without excessive model complexity and excessive division of data into small groups.

According to Fig. 10, the third class is proposed to be the transitional class, which indicates a condition of a machine element that does not belong to either the nominal or fault classes. Based on the graphical analysis, it can be concluded that at a uniform distance from both main clusters, the model demonstrates a reduced ability to accurately determine the belonging to a particular cluster. This is due to the fact that the central points are equidistant from both clusters, combining the features of each of them. In this regard, it is advisable to expand the clustering model to three classes. Thus, in addition to the main classes (nominal and fault), a third transition class is added, which accumulates the common characteristics of both clusters, allowing the model to more accurately reflect the data structure.

Thus, the division into three clusters not only allows for a better representation of the data structure, but also provides a more reasonable representation of the internal features of the dataset. According to the visualizations of parallel coordinates for two- and three-class clustering, clustering into three classes is appropriate. Adding a third cluster (labeled #1 in the graph) in Fig. 9d reveals additional structural differences, especially on the features "Feature 3" and "Feature 4", which indicates the presence of unique features that were not visible in the two-class clustering. At the same time, there is an overlap of lines on certain features, which may indicate imperfect separation of the clusters. Nevertheless, the third cluster helps to segment the data more accurately, taking into account less pronounced differences.

Therefore, the division into 3 clusters supports a balanced decision between adequate clustering accuracy and overall model performance. This result indicates that the optimal number of clusters may be in the range of 2–3, since further increasing the number of clusters does not bring significant improvement in inertia. The choice of 3 clusters is justified because this division provides an effective reduction of internal variance, which is important for more accurate modeling of the data structure, without excessive model complexity and excessive breakdown of data into small groups. Thus, the division into 3 clusters maintains a balanced decision between appropriate clustering accuracy and overall model efficiency.

The clustering results show that the three-level classification is optimal, providing a clear separation and display of the data structure. Analysis using the elbow method and the silhouette coefficient confirmed the effectiveness of this method. In addition, a neural network model was created to recognize the third, transitional class, which increased the overall accuracy and flexibility of the model, providing better consideration of complex variations in the data when analyzing the condition of rotating machine elements.

CONCLUSIONS

The method of preventing failures of rotating machines based on vibration analysis by using machine learning techniques was implemented. The main feature of the proposed method is the ability not only to classify conditions as normal or faulty, but also to identify an intermediate condition characterized by an increased probability of element failure. The use of clustering has made it possible to achieve an accuracy of over 80% in identifying this third class, which makes it possible to predict probable failures at early stages.

In addition, the method is based on the use of a convolutional neural network that has been trained with an accuracy of 99% to classify states, including a new "transitional" class. This ensures high efficiency and reliability of the classification, which allows not only to increase the

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safety and reliability of equipment operation, but also to minimize the costs associated with emergency conditions and repairs.

The scientific novelty of obtained results is that the method of preventing failures of rotating machines based on vibration analysis by using machine learning techniques is firstly proposed. In the resulting dataset, it is proposed to distinguish a new, third class of transitional, which indicates a transient, close-to-failure state of a rotating element, and the effectiveness of introducing this class is proved.

The practical significance of the obtained results is the creation of application software, specifically neural network models for classifying the condition of rotating machine elements and the implementation of a corresponding web application for interacting with the obtained models.

Prospects for further research may be aimed at optimizing algorithms and neural network architecture to reduce training time, which will improve the efficiency of models with large amounts of data and different classes. Furthermore, it is also possible to develop methods for adaptive training of models based on new data, which will increase the efficiency of their application in real-world conditions.

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МЕТОД ПОПЕРЕДЖЕННЯ АВАРІЙНИХ СТАНІВ ОБЕРТОВИХ МАШИН ЗА АНАЛІЗОМ ВІБРАЦІЙ ЗАСОБАМИ МАШИННОГО НАВЧАННЯ

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АНОТАЦІЯ

Актуальність. Вирішується проблема визначення перехідних станів, що передують переходу з робочого стану у неробочий за отриманими даними з датчиків обертових елементів машин. Об'єктом дослідження є процес виявлення несправностей та станів, що свідчать про наближення до поломки у елементах обертових машин на основі даних, отриманих з сенсорів. Предметом дослідження є застосування алгоритмів *k*-means та методу Elbow для кластеризації та згорткових нейронних мереж для класифікації даних з сенсорів та виявлення близьких до поломки станів елементів машини.

Мета роботи. Метою роботи є створення методу обробки сенсорних даних обертових машин з використанням згорткових нейронних мереж для точного виявлення станів, близьких до відмови, в елементах обертових машин, що дозволить підвищити ефективність технічного обслуговування та запобігти відмовам обладнання.

Метод. Запропонований метод запобігання відмовам обертових машин базується на аналізі сигналів вібрації з використанням комбінації методів кластеризації та глибокого навчання. На першому етапі дані з датчиків проходять попередню обробку, що включає нормалізацію, зменшення розмірності та видалення шумів, після чого застосовується алгоритм *k*-середніх. Для визначення оптимальної кількості кластерів використовується метод Elbow, який забезпечує ефективне групування станів обертових елементів машини, виявляючи стани, близькі до переходу в несправність. Також була розроблена модель CNN, яка класифікує кластери, дозволяючи точно розділити номінальні, несправні та перехідні стани. Поєднання методів кластеризації з CNN-моделлю підвищує точність виявлення потенційних несправностей і дозволяє своєчасно реагувати на них, що є критично важливим для запобігання аваріям і забезпечення стабільності роботи обладнання.

Результати. Створено метод попередження аварійних станів обертових машин за аналізом вібрацій засобами машинного навчання та відповідний комплекс програмного забезпечення. Реалізований метод дозволяє ідентифікувати не лише нормальні й аварійні стани, але й виділяти третій клас – близький до поломки. Якість кластеризації для трьох класів підтверджується значенням коефіцієнта силуету 0,506, що свідчить про належну відокремленість кластерів, та індексом Девіса-Болдіна 0,796, що демонструє високий рівень внутрішньої когерентності кластерів. Додатково було натреновано CNN, яка досягає 99% точності для класифікації цього класу, що робить метод високоефективним і вирізняє його серед існуючих рішень.

Висновки. Було розроблено метод попередження аварійних станів обертових машин за аналізом вібрацій засобами машинного навчання, запропоновано виокремлення третього класу – перехідного, що вказує на стан, близький до поломки, і підтверджено його ефективність. Практичне значення результатів полягає у створенні нейромережевих моделей для класифікації стану обертових елементів та розробці вебзастосунку для взаємодії з цими моделями.

КЛЮЧОВІ СЛОВА: обертові елементи машини, відмова елемента, перехідні стани, кластеризація, класифікація, CNN.

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