UDC 004.8.

doi: 10.32620/reks.2026.1.07

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SIMPLIFIED CONVOLUTIONAL MODEL FOR DETECTING VIBRATION ANOMALIES IN HELICOPTERS OPERATION

The challenge in vibration analysis for helicopters is to automate anomaly detection to indicate possible equipment failure, especially in high-stakes scenarios where labelled failure data is rare and highly desirable for training modern models such as convolutional neural networks or autoencoders which require a lot of such data and are often used for this kind of analysis. ***The s****tudy focuses on vibration data generated by helicopters, focusing on anomalies in these vibrations that may indicate imminent equipment failure. These vibrations are often complex and change under different operating conditions, making them a valuable source of diagnostic information.* ***Objective and Approach.*** *This study presents a novel model for detecting abnormal vibrations in helicopter operations, minimising dependency on failure data. The model uses Fast Fourier Transform (FFT) and convolutional techniques to reduce high-dimensional vibration data into a three-dimensional vector, enabling effective anomaly detection through distribution metrics and Z-score-based thresholding.* ***Case Study.*** *The model was evaluated using a real-world dataset of helicopter vibration signals. The study successfully differentiated between normal and abnormal conditions without relying on explicit failure labels, validating its applicability in maintenance scenarios where early fault detection is critical.* ***Method.*** *Model was developed using Fast Fourier Transform (FFT) and convolutions to reduce vibration data to a low-dimensional vector representation that allows anomaly detection using distribution metrics. This method increases adaptability and reduces data requirements, making it suitable for expensive equipment with limited or no fault data. In addition, this model can be very flexible and extended to a model with additional training. It uses the Fast Fourier Transform as the first step to get the frequency components of a signal buried in vibrations. After FFT, we can represent the vibration data as a multidimensional vector. An example can consist of around 45000 dimensions after that vector simplifies to reduce the dimensions. The model uses convolutions to get only a 3-dimensional vector from the 45,000-dimensional vector. After convolutions, the data saves a clear correlation, and it is still possible to represent the vibration sample as a vector in 3-dimensional space and save its properties. Three dimensions were chosen for visualisation comfort, and it still works correctly. These vectors are located in space in two separate clusters for 0 and 1 corresponding labels, and they can be used for the next iteration of analysis. On the next iteration, the model gets a mean from x,y, and z and checks the distributions for class 0 and class 1. This step is possible because values after all convolutions for x,y, and z are close to each other. As distributions of these vectors are close to a bell shape, the model uses distribution metrics to predict fault by using a Z-score of the distribution of normal vectors. In this case, the model is close to the zero-shot learning concept because the model requires only data about expected behaviour.* ***Results****. The developed model showed high accuracy at a particular configuration when using different matrix convolutions and a different approach to setting the limit of anomalous values. At the final stage of the testing, the model reached an accuracy of 99.568%, which, under specific conditions, is not considered an overfitted model since the initial input parameters were clearly defined and limited by specific data. The model also demonstrated that when changing the input conditions, the model can be easily configured to new parameters.* ***Discussion.*** *The proposed model proved highly adaptable and accurate in detecting anomalies with minimal historical data. While it showed robustness across different configurations, future improvements could focus on refining sensitivity thresholds and integrating additional predictive techniques for enhanced performance.* ***Conclusions****. Tests validate the model's adaptability and scalability, recommending its use for fault detection in inexpensive, data-limited environments like helicopters.*

Keywords: *vibration analysis; helicopter; anomaly detection; convolutional model; fast fourier transform; zero-shot learning.*

1. Introduction

Helicopter vibration monitoring plays a critical role in ensuring flight safety and operational reliability. Excessive vibration often indicates mechanical problems, such as rotor imbalance, gearbox failure, or structural fatigue. Early detection of these anomalies is crucial, especially for safety-critical missions. Conventional methods typically rely on fixed thresholds or manual functions that are limited in their adaptability and often do not generalize to different flight conditions or aircraft types.

Machine learning models, particularly convolutional neural networks (CNNs) and autoencoders, have shown promise in capturing complex patterns in vibration signals. These models can learn directly from raw sensor data, enabling more flexible and accurate diagnostics. However, training most of these systems requires large, labeled datasets, which are rarely available in helicopter maintenance due to their high cost and the rarity of real-world malfunctions.

This study presents an efficient convolutional model for vibration anomaly detection that overcomes these limitations. The proposed approach does not rely on extensive labeled fault data and is designed to work with limited input data, making it suitable for real-world aviation scenarios. By applying the model to real-world helicopter vibration datasets, we demonstrate its potential as a scalable and practical tool for condition monitoring and early fault detection.

1.1. Motivation

Conventional methods for anomaly detection in vibration analysis often rely on fixed vibration thresholds, which lack the adaptability necessary to address the variety of conditions encountered by complex systems like helicopters. These methods may work well under specific, controlled conditions but often fail when applied to new equipment, operational environments, or unforeseen circumstances. The inability to dynamically adapt to changing conditions significantly limits the effectiveness of traditional techniques.

In contrast, advanced machine learning models, such as Convolutional Neural Networks (CNNs) and autoencoders, have shown considerable promise in detecting anomalies by learning from data. CNNs, for example, are widely used in image recognition tasks and have proven effective in recognising patterns and spatial hierarchies in data. In the context of vibration analysis, CNNs can learn complex features of vibration signals over time and frequency, providing a robust framework for anomaly detection. However, CNNs require large amounts of labelled training data to perform well, including standard and faulty vibrations. Acquiring such data, especially labelled fault data, is costly and logistically challenging, particularly in high-stakes industries where failures are rare and highly critical.

Similarly, autoencoders, a type of unsupervised neural network, are commonly employed for anomaly detection by learning to reconstruct input data. Autoencoders aim to learn a compressed representation of standard data so that when presented with new or abnormal data, the reconstruction error increases, signalling an anomaly. While autoencoders are effective in capturing hidden patterns in data, they, too, suffer from a reliance on substantial amounts of standard data for training. Moreover, like CNNs, autoencoders struggle in scenarios where labelled failure data is limited or unavailable.

The primary challenge with these advanced models is the need for substantial amounts of labelled data, particularly fault data, which is expensive, time-consuming, and challenging to collect in many operational environments. This is especially problematic in fields like helicopter maintenance, where failure data is scarce and valuable.

As a result, existing methods and models struggle to generalise to new equipment or operational conditions without requiring large amounts of fault data. Therefore, developing a model that can support zero-shot learning (ZST) and be flexible in new environments is necessary. The model should also be fast because it is required to work in different extra situations.

The study focuses on vibration data generated by helicopters, focusing on anomalies in these vibrations that may indicate imminent equipment failure. These vibrations are often complex and change under different operating conditions, making them a valuable source of diagnostic information.

The study focuses on models that detect abnormal vibrations in helicopter systems using minimal labelled data and zero-shot learning techniques. The research aims to use techniques such as Fast Fourier Transform (FFT) and convolutions to process and reduce the dimensionality of vibration data, allowing the model to identify anomalies without the need for extensive fault data.

1.2. State of the art

Li, Huang, Li, Liao, Chen, He, Yan, and Gryllias provide a comprehensive survey on deep transfer learning for fault diagnosis in industrial applications, discussing key theories, methodologies, and challenges in adapting models across different operating conditions [1]. Zhao and Chen explore extreme learning machines for transfer learning in aero-engine fault diagnosis, demonstrating their efficiency in adapting to new fault scenarios with minimal training data [2]. Huang, Chen, Chai, and Ma propose a unified framework for fault detection and diagnosis based on fractional-order chaos systems, highlighting their effectiveness in aerospace applications [3]. Han, Chen, Guo, Lu, Fei, Zhao, and Hu introduce a probability-based method for predicting the service life of turbine blades under combined cycle fatigue conditions, improving reliability assessments [4]. Li, Jiang, Liu, Wang, and Li develop a deep multiscale feature fusion network for predicting the remaining useful life of aero-engine components using multisensor data, enhancing predictive maintenance strategies [5]. Lu, Li, Han, Keshtegar, and Fei present a bi-iterative moving enhanced model for probability-based transient low-cycle fatigue (LCF) life prediction of turbine blisks, improving fatigue assessment accuracy [6].

Early detection of anomalies can prevent catastrophic failures. Given the unpredictability and complexity of faults, condition monitoring aims to detect deviations from normal behaviour, even when the fault modes are unpredictable, using various sensors and issuing safety warnings. This is usually modelled as semi-supervised or unsupervised anomaly detection in academic research.

The Decoupling Variational AutoEncoder (DVAE) offers an innovative approach to anomaly detection in helicopter transmission systems under variable flight conditions. DVAE employs domain adversarial regression to extract invariant features by decoupling flight regime information from original signals, eliminating the need for prior knowledge. Tests, including fault simulations and real-world scenarios, demonstrate that DVAE detects failures more effectively than traditional Health and Usage Monitoring Systems, providing timely alerts before system breakdowns. This method expands the applicability of anomaly detection in complex, dynamic environments [7].

Deep Transfer Learning (DTL) integrates the strengths of Deep Learning (DL) and Transfer Learning (TL), enhancing the reliability and robustness of fault diagnosis methods. While several reviews have focused on fault diagnosis algorithms, few have addressed practical industry applications. This article surveys the recent advancements in DTL-based Intelligent Fault Diagnosis (IFD), providing insights into how transfer learning is combined with deep models and offering practical guidelines for selecting appropriate algorithms. It also discusses the challenges and future directions, helping researchers and practitioners design practical solutions for fault diagnosis in complex systems [8].

Different methods based on Neural Networks for vibration analysis were defined and described in several articles, focusing on their use in predictive maintenance for various industries, including petroleum. These techniques are essential for detecting early faults in equipment, such as Electric Submersible Pumps (ESP), which can be challenging to monitor using conventional methods. Vibration data analysis was used in different cases to predict and identify faults, though challenges remain in achieving accurate predictions. The articles highlight the potential for vibration analysis to improve machine health, optimise performance, and reduce maintenance costs.

Chu, Nguyen, Yoo, and Wang review the state-of-the-art in vibration analysis techniques and their applications in various engineering fields, providing insights into emerging trends [9].

Avci, Abdeljaber, Kiranyaz, Hussein, Gabbouj, and Inman explore the evolution of vibration-based damage detection in civil structures, comparing traditional methods with modern machine learning and deep learning approaches [10].

Lv, Zhao, Zhao, Li, and Ng discuss the current state and applications of vibration signal-based early fault prognosis, detailing its role in predictive maintenance and anomaly detection [11].

Khan, Akhtar, Ahmad, Shah, and Khattak analyse the vibration behaviour of damaged and undamaged steel structures, offering insights into structural integrity assessment using vibration analysis [12].

Gholamy, Kreinovich, and Kosheleva explain the commonly used 70/30 or 80/20 ratio for training and testing datasets in machine learning, providing a pedagogical justification for these splits [13].

Willone Lim, Kelvin Sheng Chek Yong, Bee Theng Lau, and Colin Choon Lin Tan conducted a study that systematically reviews the literature on using GANs for network anomaly detection, focusing on representation training rather than data augmentation. Their research also evaluates the performance of GANs in this area by analysing their key characteristics. By providing valuable insights, their work helps researchers and practitioners understand the emerging field of network anomaly detection and the practical applications of GANs while addressing the challenges of building robust GAN-based detection systems [14].

Vladov, S.; Ścisło, Ł.; Szczepanik-Ścisło, N.; Sachenko, A.; Perzyński, T.; Vasylenko, V.; Vysotska, V. proposed a hybrid neural network architecture combining LSTM and GRU for anomaly detection in helicopter turboshaft engine sensors. The system demonstrated high detection accuracy (up to 99.327%) through temporal regularisation and adaptive discretisation techniques, significantly outperforming alternative models. Its ability to capture time-dependent features and minimise false omissions makes it highly effective for sequential sensor monitoring under real-world conditions [15].

Vladov, S.; Vysotska, V.; Sokurenko, V.; Muzychuk, O.; Nazarkevych, M.; Lytvyn, V. proposed an intelligent monitoring system for helicopter turboshaft engines, integrating SARIMAX-based preprocessing and an LSTM-based predictor to enhance anomaly detection under onboard conditions. The system achieved up to 97.9% prediction accuracy and effectively restored missing data with 98.73% precision. Its anomaly detector, based on the concept of dissonance, identified critical failures with minimal error rates and detection latency below 1.6 seconds, demonstrating high diagnostic reliability despite computational complexity [16].

Ballarin, P.; Sala, G.; Macchi, M.; Roda, I.; Baldi, A.; Airoldi, A. evaluated a strain-based Structural Health Monitoring System (SHMS) for detecting damage in a composite helicopter rotor blade root using Finite Element simulations. The approach integrated an Artificial Neural Network for both load recognition and anomaly detection, achieving high accuracy even under variable load conditions. This study demonstrated the effectiveness of SHMS for complex, real-world helicopter components, highlighting its potential for reliable damage localization and integrity assessment without destructive testing [17].

Sáenz-Hernández, C.; Cuadros, R.; Rodríguez, J.; Rativa, E.; Linares-Vásquez, M.; Donoso, Y.; Lozano, C. developed an automated digital test bench for diagnosing faults in the caution and warning panels of the UH-60 helicopter, applying NASA-inspired systems engineering practices. The system integrates real-time simulation and closed-loop diagnostics, significantly improving fault detection speed and accuracy while reducing maintenance costs. Its adaptability to other aeronautical components and novel application to UH-60 avionics represent a substantial advancement in automated aeronautical maintenance [18].

Roshchupkin, O.; Pavlenko, I. reviewed modern diagnostic techniques for rotor systems operating under complex and high-speed conditions, emphasizing real-time monitoring methods such as vibration analysis, thermography, acoustic emissions, and machine learning. These approaches enable early fault prediction and support preventive maintenance strategies, significantly improving the reliability and efficiency of rotor-based energy and mechanical systems. The paper offers a systematic evaluation of these methods, highlighting their practical implementation, limitations, and future innovation potential [19].

To summarise, the recent developments in vibration-based fault diagnosis reveal a shift towards AI-based models that do not require extensive fault data, favouring generalisable approaches. However, specific challenges remain in helicopter systems where data availability and environmental variability demand robust, fast, and low-data solutions. This justifies the development of the current model.

1.3. Objective and Approach

The goal of this study is to develop a fast, flexible, and data-efficient anomaly detection model capable of identifying abnormal helicopter vibrations without relying on fault-labelled data. The expected effect is a robust and scalable approach suitable for use in real-world maintenance environments where fault data is scarce or unavailable.

To achieve this goal, the study pursues the following specific objectives. It is necessary to design a vibration analysis pipeline based on Fast Fourier Transform (FFT) for extracting frequency-domain features, apply convolutional techniques for dimensionality reduction of high-dimensional vibration vectors, develop a Z-score-based thresholding method for anomaly detection using distribution metrics and validate the model using a real-world dataset of helicopter vibration signals.

Current approach combines Fast Fourier Transform (FFT) and convolutional techniques to transform high-dimensional vibration signals into a compact representation suitable for anomaly detection. The vibration data, consisting of approximately 45,000 dimensions, is processed using FFT to extract their frequency components. Subsequently, convolution operations reduce the dimensionality to a three-dimensional vector while preserving critical signal characteristics. This transformation facilitates the clustering of normal and abnormal data points, allowing the model to distinguish between expected and abnormal vibration patterns.

The model uses distribution metrics and a Z-score-based thresholding mechanism to achieve anomaly detection. By evaluating deviations from the standard vibration distribution, the model effectively identifies anomalies consistent with the principles of zero-based learning. This capability provides robustness and adaptability even when fault data is extremely limited or non-existent.

The following issues were addressed in the following sections of this study. The second section "Materials and methods of research" describes the methodology for analyzing helicopter vibration data using Fast Fourier Transform (FFT) and convolutional techniques. The third section, “Results,” presents the model testing results obtained from processing approximately 3 GB of helicopter vibration data. The fourth section "Case Study" demonstrates the model's practical application using real helicopter

vibration data. The fifth section "Discussion" evaluates the model's effectiveness and adaptability in detecting abnormal helicopter vibrations with minimal historical fault data. The sixth section "Conclusions" summarizes the model's viability for anomaly detection in helicopter vibration data and suggests directions for future research, including optimization of kernel sizes and training processes.

2. Materials and methods of research

The dataset used in this study consisted of vibration data files collected from helicopters, each accompanied by corresponding labels (0 or 1) representing two classes of vibrations. Label 0 indicates normal vibrations, while label 1 denotes anomaly vibrations indicative of equipment potentially nearing failure. Given the challenges of using large datasets for fault detection, especially with expensive machinery like helicopters, the goal was to develop a model that requires minimal fault data or does not require it at all. First, it is necessary to extract the frequency components from the vibration signals to see the difference between samples. Also, in this case, the input data for the next steps will be decreased by this step.

The Fast Fourier Transform (FFT) is an efficient algorithm for computing the Discrete Fourier Transform (DFT) and its inverse. Let $x_0, ..., x_{n-1}$ be complex numbers.

The DFT of a sequence x_n of length N is given by:

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i\frac{2\pi}{N}kn}, k = 0, 1, ..., N-1. \quad (1)$$

The FFT reduces the computational complexity of DFT $O(N^2)$ to $O(N \log N)$, making it highly efficient for large datasets. This allows for faster frequency analysis of signals, which is crucial for vibration data processing. Also, we need only the first half of the FFT part since it is symmetric. The original input data and data after FFT for one vibration sample with level 0 are shown in Fig. 1 and 2, respectively.

Fig. 1 and Fig. 2 show the original input data and data after FFT for one vibration sample with label 0, respectively.

After FFT, Figs. 3 and 4 show visual differences between the two classes with labels zero and 1.

In Fig. 4, which corresponds to the vibration sample with label one after FFT, the noises around peaks may be more visible than in Fig. 3, which corresponds to the vibration sample with label zero after FFT.

However, the most visible differences can be seen in the 3-dimensional spectrogram of the vibration sample with label 0, shown in Fig. 5, and the vibration sample with label 1, shown in Fig. 6.

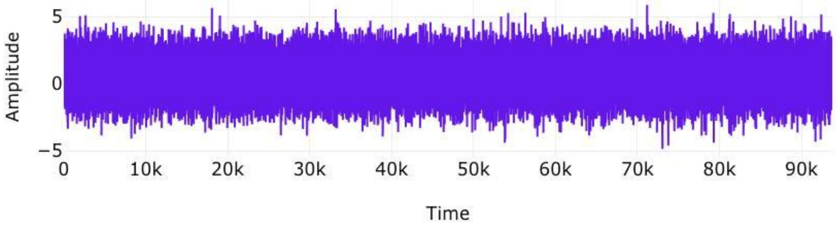

Fig. 1. Original input data for vibration sample with label 0

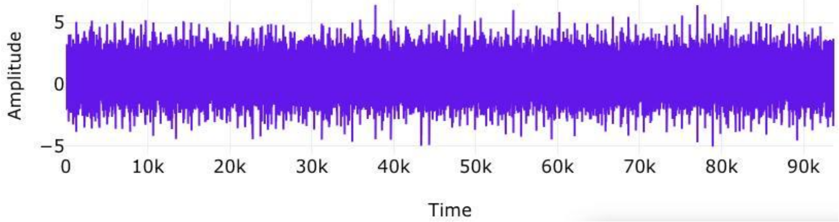

Fig. 2. Original input data for vibration sample with label 1

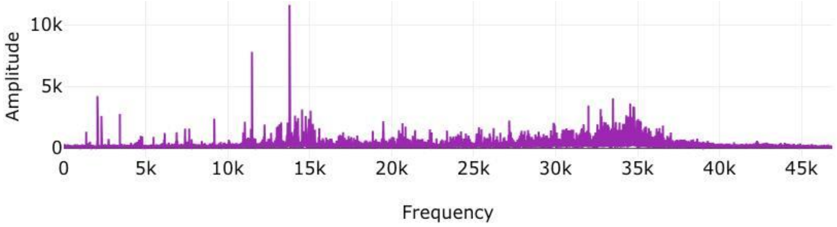

Fig. 3. Data after FFT for vibration sample with label 0

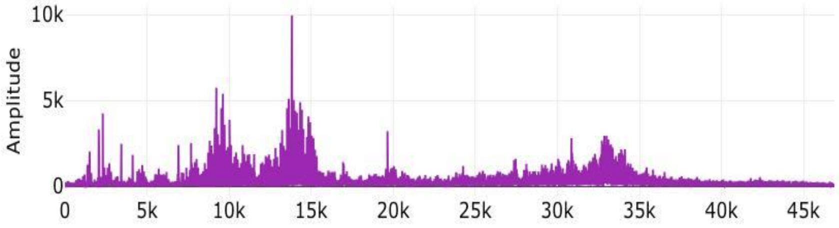

Fig. 4. Data after FFT for vibration sample with label 1

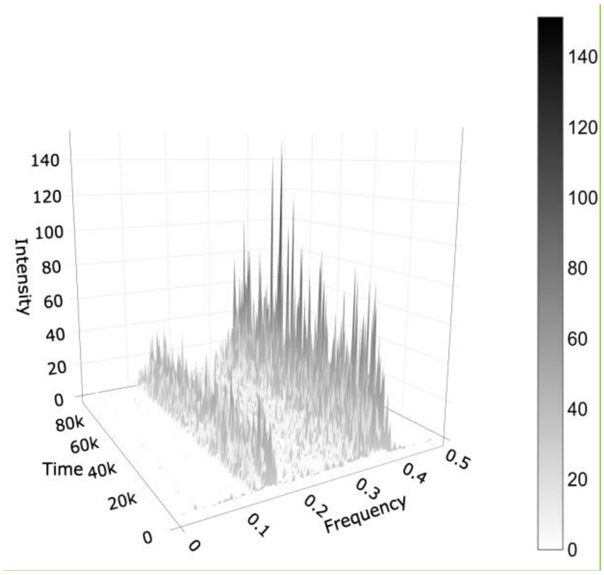

Fig. 5. 3-dimensional spectrogram
for vibration sample with label 0

Fig. 6 clearly shows the difference between vibration sample data with label zero and label 1. In the vibration sample with label 1, in the area of the highest peaks, there is a pronounced saturation of noises that broadens the peaks. That is precisely the difference that a model should handle and signalise about.

Many approaches that use CNN use a spectrogram as input to the model as an image. This input is a 3-dimensional matrix with time, frequency, and intensity as x, y, z coordinates.

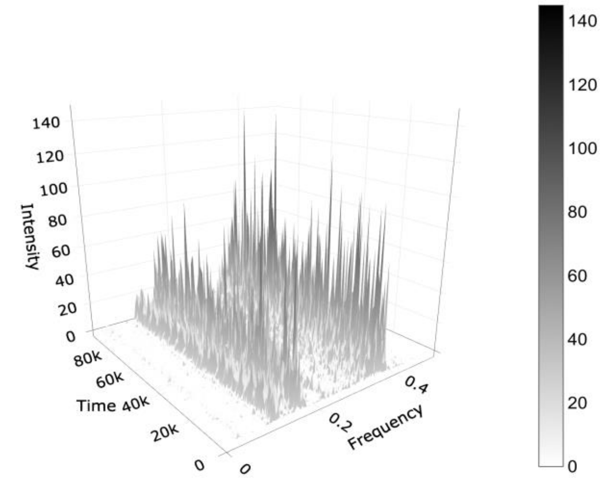

Fig. 6. 3-dimensional spectrogram
for vibration sample with label 1

In order to train an artificial intelligence model, data is needed, which will include enough data with label zero and label 1. Since label one now considering as samples of abnormal vibrations, it is possible to assume that such data is problematic to obtain since it is data when the system is malfunctioning and, most likely, if the system is in such a state that it is not possible to collect this data for a long time since a malfunctioning system can not only completely break down and this will be a significant loss of resources, but it can also harm life and health people.

Following the Zero-Shot Learning (ZSL) strategy is necessary in this case. ZSL is a machine learning technique that aims to classify objects the model has never encountered during training. This is achieved by leveraging prior knowledge, such as semantic attributes or word embeddings, to bridge the gap between seen and unseen categories, etc. In the current case, it is necessary to recognise different categories of vibrations even if they were not provided, like fault vibrations that cannot be provided for analysis. To realise this logic, it is necessary to somehow convert vibration data to a vector.

Using FFT, the model extracts the frequency components from the vibration signals and uses it as input for simple and pure convolution of two matrices. The convolution of two matrices A and B, often used in image processing, is given by:

$$C(i,j)=\sum_{m}\sum_{n}A(i+m,j+n)\cdot B(m,n)\,, \qquad (2)$$

Each element $C(i,j)$ in the output matrix C is computed by:

1. Placing the centre of the kernel B at position (i,j) A in.

2. Taking the element-wise product of overlapping entries.

3. Summing all the products to get a single value $C(i,j)$.

The convolution can be adjusted by padding around the edges A to control the output size. The summation represents the element-wise multiplication and sum of the overlapping elements.

It is possible to get any necessary vector as output from convolutions, and it has fewer dimensions than those used in the following analysis step. The final output dimensions from convolutions was chosen as 3 to provide valuable visualisations in the first stages of developing the model. The final vector for vibration data is shown in Fig. 7.

Now, it is necessary to build a training process for our model. The data split into 80% for training and 20% for testing. In this case, every vibration sample from 80% will be mutated to vectors, as shown in Fig. 8.

After that, was noticed that every vector, x, y, and z, are close to each other in value because of convolution calculation. In this case, it can be simplified from a 3-dimensional vector to a single value by using the mean from these three coordinates and calculating distributions for these vectors with different labels, as shown in Fig. 9.

Also, if the model needs to be tuned, it is possible to skip getting a single number from coordinates and calculate separate distributions for different coordinates. For additional tuning, it is possible to configure the convolution's output to different dimensions and transform data from FFT to different vectors.

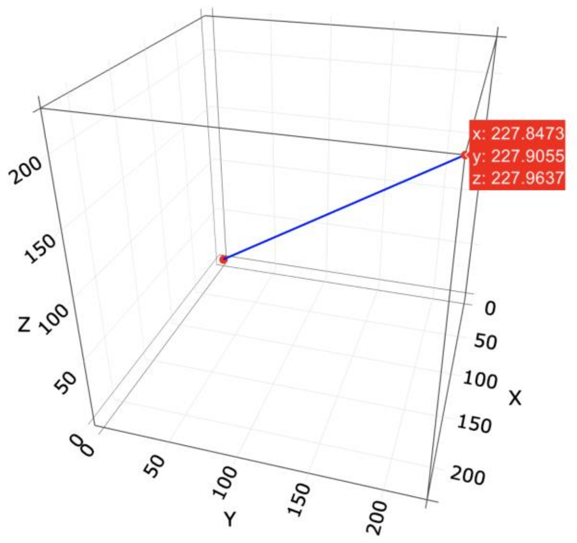

Fig. 7. Vector that corresponds to vibration data sample after FFT

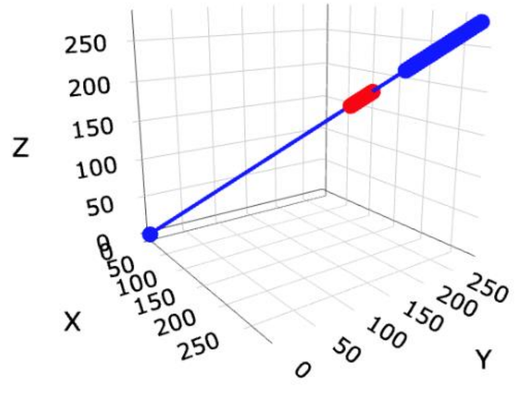

Fig. 8. Vectors that correspond to vibration data samples after FFT from 80% of the entire dataset that was provided for training

For the current solution, the 3-dimensional output after convolutions and the mean from x, y, and z is acceptable because it is enough to solve the current problem with a final model accuracy close to 90%.

After the model got distributions of vectors, it is possible to calculate the mean of a distribution with the formula:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i . \tag{3}$$

Standard deviation by formula:

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2} . \tag{4}$$

Moreover, calculate the Z-score by formula:

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2} . \tag{5}$$

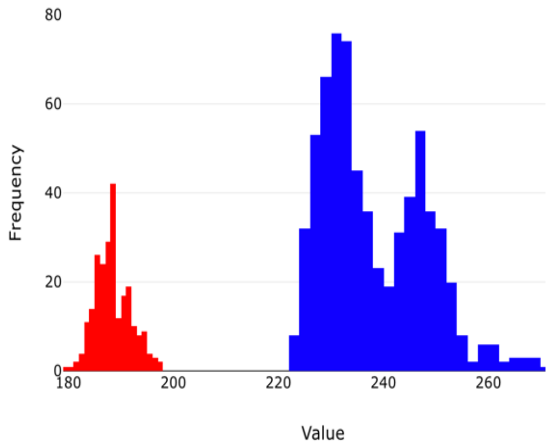

Fig. 9. Distributions of vectors corresponding to vibrations samples with labels 1 on left and 0 on right side

Based on the central limit theorem (CLT) that states that the distribution of a sample will approximate a normal distribution (i.e., a bell curve) as the sample size becomes more extensive, regardless of the population's actual distribution shape, that means that the model can use metrics of distribution like Z-Score to calculate a probability of the appearance of a given vibration sample in the distribution of the general samples. As a result, the model does not even need vibration samples with label one, which is an anomaly, fault, etc., because it is possible to calculate the probability of the appearance inside normal vector distribution, all values that are necessary to calculate the Z-score are saved in the training process and after for every prediction just will be reused. As a result, the model have such fast detection because it is based on simple math operations instead of an extensive and trained neural network or autoencoder.

A range was defined to include only values within two standard deviations from the mean, which is common in data analysis to focus on values likely to appear within approximately 95% of the data distribution (in a normal distribution). This range is defined as:

$$\mu - 2\sigma \le x \le \mu + 2\sigma . \tag{6}$$

Thus, the model only include values *x* that satisfy this condition:

- all values x where *x* there is no more than two standard deviations above the mean and

- all values x are x no more than two standard deviations below the mean.

Values outside this range are considered outliers for this analysis. They will be excluded and marked as anomalies or label 1 in the current problem.

Suppose not enough data is provided and the distributions are not normal. In that case, typically, this range can be changed even to 3 standard deviations, or the minimum and maximum for the distribution will be settled as limitations instead of the sigma range, depending on the type of distribution.

3. Results

Model testing involved processing files of vibration data with a total size of nearly 3 GB, labelled 0 (assumed as usual) and 1 (assumed as anomalous). The data split flow for the train and test, using 80% for training and 20% for testing based on standard practices described in various research [14]. The model was trained and the acceptable range was set for vibration samples inside the range of normal samples where values within two standard deviations from the mean are acceptable, as described earlier.

All other samples were marked as anomalies. On the first iteration of recursion convolving, was picked the kernel size as 95, and on the last layer, the value three was picked as the kernel because the output should be a vector with three coordinates.

To estimate a model, an accuracy was chosen, that can be written as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}. \quad (6)$$

The accuracy in this case was 76.2931%.

After that, the model was trained and the acceptable range was set for vibration samples inside the range of standard samples, and it was defined as:

$$\mu - 3\sigma \le x \le \mu + 3\sigma. \quad (8)$$

Thus, values only include x that satisfy this condition:

- all values x where x there is no more than three standard deviations above the mean and

- all values x are x no more than three standard deviations below the mean.

All other samples were marked as anomalies.

The accuracy in this case was 77.3241%.

Was noticed that in the current problem, all anomalies were located inside a separate distribution that was on the left side from the distribution of the standard samples, so an additional test of the model was performed when values x was included if the are satisfy this condition:

- all values x where x is no more than the minimum value of the left border of the distribution of the standard samples:

$$x < \varepsilon. \quad (9)$$

The accuracy in this case was 99.568%. An additional test of the model was performed when the ranges for both the left and right sides was applied; the accuracy was 99.568%. This is because the data clustered anomaly samples only from the left side, but it will work with another dataset where anomalies can be located on both sides.

As a result, the model was trained and tested on a 3 GB dataset for ~13 minutes in total with all operations. One operation for testing one vibration sample with a size of ~2.5 Mb took around ~600 milliseconds for all three tests. The top accuracy that we got was 99.568%.

The model effectively processed a large dataset of helicopter vibration signals, totalling approximately 3 GB. Through FFT and convolutional processing, we generated low-dimensional representations that distinguished between normal (label 0) and anomalous (label 1) vibrations with a high accuracy of 99.568%. The model identified clusters in the 3-dimensional vector space for each label, facilitating separation between normal and abnormal cases without requiring prior fault data. These vectors' spectrogram visualisations and distribution metrics confirmed the model's capacity to detect deviations indicative of potential equipment failures.

The model's reliance on frequency-domain analysis through FFT, followed by convolutional reduction, demonstrated a data-efficient approach to vibration anomaly detection. The model avoided high-dimensionality pitfalls by transforming vibration signals into three-dimensional vectors while preserving critical diagnostic information. Furthermore, this approach leverages zero-shot learning principles, where only standard data is required for training, minimising the need for labelled fault data. This flexibility could be advantageous in real-world applications where rare fault occurrences or equipment constraints limit data acquisition.

4. Case Study

A case study was conducted using helicopter vibration data provided in a dataset published by the authors in a repository [20]. The dataset included vibration signals recorded under various operating conditions, including standard and potentially faulty scenarios. The objective was to determine whether the proposed model could reliably distinguish between standard operating vibrations and vibrations indicative of equipment malfunction.

The model identified 458 out of 460 normal samples and 89 out of 90 anomalous samples correctly in the test set, resulting in an overall accuracy of 99.568%, precision of 0.987, and recall of 0.978. These results were obtained after comprehensive testing on a real-world helicopter vibration dataset totaling approximately 3 GB. The training and validation process followed an 80/20 split, and multiple strategies for anomaly boundary selection were evaluated: a default $\pm 2\sigma$ threshold (accuracy: 76.29%), a $\pm 3\sigma$ range (77.32%), and a minimal left-bound threshold (99.57%).

The last approach proved most effective due to the clustering of anomalies on one side of the distribution. The model architecture included recursive matrix convolutions with a kernel size of 95 in the first layer and a size of 3 in the final layer to produce 3D vectors. One full inference operation on a ~2.5 MB signal took ~600 ms, and the entire dataset was processed in ~13 minutes. These results confirm that the proposed FFT + convolution-based model is capable of detecting anomalies with high speed and accuracy, even when no prior fault-labelled data is available.

5. Discussion

The proposed model demonstrates effective detection of abnormal helicopter vibration patterns while maintaining a relatively simple architectural design compared to many modern deep learning approaches. Traditional convolutional neural network (CNN)-based fault diagnosis systems typically rely on deep multi-layer architectures with extensive parameterization, requiring large labeled datasets and significant computational resources. In contrast, the proposed method combines Fast Fourier Transform (FFT) preprocessing with a lightweight convolution-based dimensionality reduction mechanism, reducing the overall architectural complexity while preserving feature extraction capability.

Compared to deep autoencoder-based anomaly detection methods, which often involve multiple encoding and decoding stages and iterative reconstruction procedures, the presented workflow follows a more direct processing pipeline. The absence of deep hierarchical feature reconstruction reduces inference latency and simplifies model deployment in environments with limited computational capacity. This simplicity also contributes to improved transparency and interpretability of intermediate processing steps, as each stage of the workflow corresponds to a clearly defined transformation of the input signal.

Another advantage of the proposed approach is its reduced dependence on labeled fault data. Many transfer learning and supervised CNN-based diagnostic models require extensive datasets containing multiple fault classes, which may be difficult or costly to obtain in real-world industrial environments. The presented methodology supports detection of statistically anomalous vibration patterns without requiring pre-labeled fault categories, making it particularly suitable for early-stage anomaly detection or monitoring scenarios where labeled fault examples are scarce.

From an architectural perspective, the proposed model maintains a relatively low number of processing layers compared to typical deep CNN frameworks, thereby reducing both memory consumption and computational overhead. This characteristic enables faster inference times and facilitates integration into real-time monitoring systems. The observed processing time of approximately 600 ms per signal demonstrates the feasibility of applying the model in operational environments where timely detection is required.

Despite these advantages, several limitations of the proposed methodology should be acknowledged. First, the approach relies on statistical thresholding for anomaly boundary detection, which may require manual adjustment depending on the characteristics of the dataset. Second, while the model performs well on the evaluated dataset, its generalization capability across different helicopter platforms or sensor configurations has not yet been extensively validated. Third, the method focuses primarily on anomaly detection rather than precise fault classification, which may limit its applicability in scenarios requiring detailed fault identification.

Future research may address these limitations by evaluating the proposed workflow across multiple datasets, exploring adaptive threshold selection strategies, and investigating hybrid configurations that incorporate additional feature extraction mechanisms while preserving the overall architectural simplicity of the current design.

6. Conclusions

The proposed FFT and convolution-based model presents a viable solution for anomaly detection in helicopter vibration data, combining speed and data efficiency. Its adaptability suits high-stakes environments where fault data is scarce or unavailable.

However, some challenges remain. The choice of Z-score thresholds and the model's sensitivity to changes in operating conditions may require fine-tuning for different helicopter models or environmental factors. Future work may explore adaptive thresholding methods or the integration of additional machine learning models to improve the system's predictive capabilities further. Also, it could be expanded to other machinery or environments, potentially enhancing predictive maintenance practices across various industries reliant on vibration analysis.

The obtained results are scientifically novel because a new model was introduced for detecting different types of vibrations, including the logic of ZSL, when data about other classes of vibrations are not provided. Also, the problem of detecting anomaly vibrations in the provided dataset was solved with a maximum accuracy of 99.568%.

The practical significance of the obtained results is that the software was realised to use a new model and check additional necessary metadata for all processes of this data analysis. Also, the software is ready to analyse different datasets and make predictions. Predictions are made in less than seconds and can be used on actual equipment.

Prospects for further research include researching profoundly different sizes and types of kernels and their performance inside matrix convolution, optimising the training process with optimised parallel computing, training data on different datasets, and creating reports about their accuracy.

Contributions of authors: conceptualisation, methodology – **Yurii Hodlevskyi;** formulation of tasks, analysis **– Yurii Hodlevskyi, Tetiana Vakaliuk;** development of model, software, verification **– Yurii Hodlevskyi; Tetiana Vakaliuk;** analysis of results, visualisation **– Yurii Hodlevskyi;** writing – original draft preparation, writing – review and editing **– Tetiana Vakaliuk.**

Conflict of Interest

The authors declare that they have no conflict of interest related to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

This study was conducted without financial support.

Data Availability

The dataset used in this study was provided as part of the 2024 All-Ukrainian Competition-Hackathon of Scientific Works of Young Scientists in the Field of Intelligent Information Technologies. The event was organized by National University 'Zaporizhzhia Polytechnic'. The vibration dataset used in this study is publicly available in the Zenodo repository and can be accessed via link [20]. The dataset contains real operational vibration measurements obtained from a private aerospace maintenance organization. Certain technical details, including helicopter type, operational modes, and sensor configuration, are not provided.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence methods while creating the presented work.

Acknowledgements

The authors would like to express their gratitude to Eric Bechhoefer for providing the datasets utilized in this research. We also wish to acknowledge the National University 'Zaporizhzhia Polytechnic' for organizing the 2024 All-Ukrainian Competition-Hackathon of Scientific Works of Young Scientists in the Field of Intelligent Information Technologies (https://old.zp.edu.ua/vkiit), through which this data was made available.

All the authors have read and agreed to the published version of this manuscript.

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Received 17.03.2025, Received in revised form 10.11.2025
Accepted date 15.01.2026, Published date 22.01.2026

СПРОЩЕНА ЗГОРТКОВА МОДЕЛЬ ДЛЯ ВИЯВЛЕННЯ АНОМАЛІЙ В РОБОТІ ГЕЛІКОПТЕРІВ

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Проблема аналізу вібрацій у гелікоптерах полягає в автоматизації виявлення аномалій для індикації можливих відмов обладнання, особливо в критичних ситуаціях, де дані про відмови рідкісні, але дуже бажані для навчання сучасних моделей, таких як згорткові нейронні мережі або автоенкодери. Ці моделі вимагають великої кількості таких даних і часто використовуються для подібного аналізу. **Предмет дослідження**. Предметом дослідження є дані вібрацій, що генеруються гелікоптерами, з акцентом на аномалії у цих вібраціях, які можуть свідчити про наближення відмови обладнання. Ці вібрації є складними та змінюються за різних умов експлуатації, що робить їх цінним джерелом діагностичної інформації. **Мета та підхід -** це дослідження представляє нову модель для виявлення аномальних вібрацій під час експлуатації вертольотів, мінімізуючи залежність від даних про несправності. Використовуючи швидке перетворення Фур'є (ШПФ) і згорткові методи, модель зводить багатовимірні дані про вібрацію в тривимірний вектор, забезпечуючи ефективне виявлення аномалій за допомогою метрик розподілу та порогового значення на основі Z-показника. **Приклад.** Для оцінки моделі використовувався набір реальних даних вібраційних сигналів гелікоптера. Дослідження продемонструвало успішну класифікацію між нормальними та ненормальними умовами, не покладаючись на чіткі мітки несправностей, підтверджуючи його працездатність у сценаріях технічного обслуговування, де раннє виявлення несправностей є критичним. **Метод.** Було розроблено швидку модель, використовуючи швидке перетворення Фур'є (FFT) і згортки для зменшення вібраційних даних до векторного представлення низької розмірності, що дозволяє виявляти аномалії за допомогою статистичних метрик розподілу. Цей метод підвищує адаптивність та зменшує потребу у великих обсягах даних, що робить його придатним для діагностики дорогого обладнання, де дані про відмови обмежені або відсутні. Крім того, модель є дуже гнучкою та може бути розширена додатковим навчанням. Модель використовує швидке перетворення Фур'є як перший крок для отримання частотних компонентів сигналу, прихованого у вібраціях. Після швидкого перетворення Фур'є вібраційні дані представляються як багатовимірний вектор. У нашому випадку цей вектор може мати близько 45000 вимірів, які потім спрощуються для зменшення розмірності. Наша модель використовує згортки, щоб зменшити цей 45000-вимірний вектор до всього 3 вимірів. Після згорток дані зберігають чітку кореляцію, що дозволяє представляти зразок вібрацій у тривимірному просторі з його властивостями. Три виміри були обрані для зручної візуалізації, і модель продовжує працювати коректно. Ці вектори розташовуються у двох окремих кластерах для міток 0 і 1, що використовується для подальшого аналізу. На наступному етапі модель розраховує середнє значення для x, y і z і перевіряє розподіли для класів 0 і 1. Це можливо, оскільки значення після всіх згорток для x, y і z є близькими за значенням. Оскільки розподіли цих векторів наближені до нормального розподілу, модель використовує метрики розподілу для прогнозування відмов, застосовуючи Z-оцінку до розподілу векторів без аномалій. Таким чином, модель наближається до концепції нульового навчання, оскільки їй потрібні лише дані про поведінку без аномалій. **Результати.** Розроблена модель показала високу точність робити при певній її конфігурації коли використовувались різні матричні згортки та різний підхід для встановлення межі аномальних значень. На фінальному етапі експерименту модель досягла точності в 99.568%, що при конкретних умовах не вважається перенавченою моделлю так як початкові вхідні параметри були чітко визначені та обмежені певними даними. Також модель продемонструвала що при зміні вхідних умов модель може бути легко адаптована до нових параметрів. **Обговорення.** Запропонована модель виявилася високою адаптивністю та точною у виявленні аномалій з мінімальними історичними даними. Хоча він продемонстрував надійність у різних конфігураціях, майбутні вдосконалення можуть бути зосереджені на вдосконаленні порогів чутливості та інтеграції додаткових методів прогнозування для покращення продуктивності. **Висновки.** Експерименти перевірили адаптивність і масштабованість моделі, і рекомендують її використання для виявлення несправностей у середовищах з обмеженим обсягом даних, таких як вертольоти.

Ключові слова: аналіз вібрації; вертоліт; виявлення аномалій; згорткова модель; швидке перетворення Фур’є; навчання з нульовим ударом.

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