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COB-2023-2299 – CONVOLUTIONAL NEURAL NETWORKS FOR PATTERN-BASED FAULT DIAGNOSIS IN LOW-ROTATION EQUIPMENT.

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Abstract*. Continuous monitoring of critical industrial equipment is crucial to proactively prevent unexpected failures, minimizing downtime and production delays. Vibration analysis is a valuable diagnostic tool for effective predictive maintenance planning. Machine learning techniques have successfully monitored operational conditions and diagnosed failures in industrial components. However, identifying failures in equipment operating at low rotations is challenging due to low energy levels in vibration signals and interference from external noises. This study proposes an effective fault diagnosis system for equipment operating at low rotations using a Convolutional Neural Network (CNN). The methodology applies Wavelet Transform to obtain two-dimensional images from vibration signals and classifies the bearing's state. The neural network, comprising four convolutional layers, pooling layers, and a dense layer, extracts relevant features for fault detection. Training the network with signals from faulty and healthy bearings distinguishes patterns associated with different conditions. The proposed methodology achieves 96% accuracy. In summary, our study demonstrates the promising capabilities of the combined CNN and wavelet transform approach for vibration analysis in low-speed machinery. The methodology achieved high accuracy in identifying normal and faulty bearing conditions. This approach holds significant potential for enhancing maintenance strategies and preventing critical failures, making it a tool for various applications.*

Keywords: *Continuous monitoring, fault diagnosis, low rotations, vibration analysis, machine learning*.

1. INTRODUCTION

To minimize operational expenses, extend machine lifespan, and optimize operational uptime, the implementation of predictive maintenance is essential. Predictive maintenance enables the inspection of machine health and the timely detection of component failures. Among rotating machines, such as wind turbines, rolling-element bearings constitute a significant source of failures (LeCun, 2015). Vibration analysis is commonly employed for monitoring the condition of machine components, including rotors, shafts, couplings, gears, and bearings. Vibrations are inherent to systems with rolling elements in bearings, as the position of these elements continually changes in response to varying loads, exhibiting behavior closely tied to rotational speed. Moreover, vibrations can be caused by geometric irregularities and surface roughness. Notably, vibrations can occur not only during normal operational conditions but also due to specific faults, including outer-raceway faults, inner-raceway faults, rolling-element faults, cage faults, and misalignment (Lacey, 2008).

Detecting faults in low-speed bearings poses significant challenges due to the low energy levels of vibration signals (Lacey, 2008). The traditional approach of frequency spectrum analysis, which relies on calculating frequencies and monitoring their amplitudes for anomalies, is often inadequate in this context. This technique assumes no sliding motion, with rolling elements only rolling on the raceways, which is rarely the case. In practice, bearings experience a combination of rolling and sliding, leading to slight deviations of calculated frequencies from actual frequencies, typically in the range of 1% to 2% (Smith and Randall, 2015).

To overcome these challenges, convolutional neural networks (CNNs) offer a promising solution. By leveraging the power of deep learning, CNNs can learn intricate patterns and features directly from vibration signals. The application of CNNs enables the development of an automated fault detection system for low-speed bearings. This approach eliminates the need for manual feature engineering and allows for real-time detection, enhancing the interpretability and effectiveness of the analysis. CNNs have the potential to capture complex relationships within vibration data and provide accurate and reliable identification of faults in low-speed bearings, ultimately improving the maintenance and performance of industrial machinery (LeCun, 2015).

This study proposes the application of convolutional neural networks (CNNs) for detecting faults in low-speed bearings. Unlike traditional feature engineering approaches, the focus is on leveraging machine learning to directly learn discriminative representations from vibration data. The method aims to overcome limitations of conventional frequency spectrum analysis, which may be affected by sliding, interference, and challenges in detecting certain types of faults, such as lubrication-related issues. By employing CNNs, the system is trained using vibration data from both healthy and faulty bearings to identify distinctive patterns associated with different fault conditions. The performance of the method is evaluated on an experimental dataset comprising various classes of bearing faults. The results are compared with a classical approach based on manually engineered features. This research contributes to advancing fault detection in low-speed bearings by exploring the potential of CNNs as an effective tool for vibration analysis, enhancing diagnostic capabilities and monitoring in industrial settings.

2. THEORETICAL FOUNDATION

This chapter, the basic theoretical concepts of the work are presented. Firstly, the concept of machine learning will be discussed. Next, the concepts of the wavelet transform will be presented, for the development of prediction models of failures.

2.1 Feature Engineering

Vibration patterns provide valuable insights into the condition of a machine, making them suitable for detecting specific conditions. For instance, imbalance, resulting from a misalignment between the principal axis of inertia and the rotation axis, manifests as a high amplitude at the machine's rotation frequency in the frequency spectrum (Monte et al., 2014). Similarly, faults such as damaged raceways generate distinct peaks at specific fundamental frequencies (Graney and Rolling, 2012). Time-based statistical features like kurtosis, crest factor, and root-mean-square (RMS) have also been shown to be effective in identifying defective bearings and assessing lubrication conditions (Ohta et al., 2013).

While various features can be extracted from vibration data, the interpretation of these features still relies on human expertise to identify different machine conditions or anomalies. Therefore, the application of machine learning is crucial to automate this interpretation process.

2.2 Machine Learning

Machine learning for machine fault detection focuses on two major topics: anomaly detection and fault/condition classification. Anomaly detection involves identifying measurements that deviate from the normal patterns of the dataset (Purarjomandlangrudi, 2010). These anomalous measurements indicate a change in the machine's condition, such as the occurrence of a fault. Anomaly detection can be applied straightforwardly and typically uses features, as discussed in the previous subsection, with algorithms like one-class support vector machines (SVM), Gaussian distribution fitting, clustering combined with principal component analysis, hidden Markov models, and neural networks (Purarjomandlangrudi et al., 2014; Geramifard et al., 2010; Miao et al., 2010; Verma et al., 2013).

Condition/fault detection also employs features discussed earlier, which are processed by machine learning algorithms such as k-nearest neighbor classifiers, naive Bayes classifiers, decision trees, and multi-layer perceptron classifiers (Kateris et al.,2014; Ali et al., 2015; Kankar et al., 2011). With these classifiers, various types of faults, such as inner-raceway faults, outer-raceway faults, and rolling element faults, can be accurately detected.

In the context of low-speed rotations, the challenges of fault detection become more pronounced. Equipment operating at low rotations exhibits low energy levels in vibration signals, making it difficult to detect irregularities that may indicate potential faults. Additionally, external noises can further interfere with the reliability of the obtained vibration signals. These factors necessitate the development of specialized techniques, such as feature learning, to overcome the limitations of traditional fault detection methods in low-speed rotating systems.

2.3 Feature Learning

Feature learning involves methods that automatically learn optimal data representations or transformations for specific tasks, contrasting with feature engineering and feature selection. In feature engineering, input data (X) is subjected to feature extraction ($\emptyset$) to train a classification algorithm ($f_{\theta}(.)$) for generating predictions (Y), with θ representing the algorithm's parameters. In feature engineering combined with feature selection, a step for choosing a subset of features ($\psi \subseteq \phi$) is added. In feature learning, rather than manually crafting features, the input data undergoes a transformation using $t_{\theta 1}(.)$, with θ_1 representing the transformation's learnable parameters, creating a more suitable data representation for the classification task.

CNNs offer several advantages over other feature-learning techniques discussed previously. Firstly, similar to stacked autoencoders, CNNs autonomously learn multiple levels of data representations through their layered structure, allowing for the learning of complex features (Dieleman et al., 2015).

Secondly, CNNs are end-to-end learning systems, requiring optimization of only a single system. Finally, CNNs are adept at exploiting the spatial structure within the data. In the case of a frequency spectrum of a vibration signal, the spatial structure refers to the sequence of frequencies. For instance, the combination of sliding and rolling of a rolling element may distribute the expected energy of a fundamental frequency across frequencies close to it. Utilizing this information can enhance fault detection. To the best of our knowledge, only one recent article has employed convolutional neural networks for machine fault detection (Chen, 2015).

A CNN operates as follows: given an input that consists of multiple channels, such as an image or a combination of several vibration signals, a CNN layer performs a similar transformation as described in Equation (1), with the distinction that the adjustable parameters of the layer are organized as a set of filters (or a filter bank) and convolved over the input to generate the layer's output. The output of a CNN layer is a 2D tensor comprising a stack of matrices called feature maps, which can serve as input to a higher-level layer in the CNN model. This operation can be represented as follows:

$$X_k^{(m)} = \sigma\left(\sum_{c=1}^{c} W_k^{(c,m)} * X_{k-1}^{(c)} + B_k^{(m)}\right), \tag{1}$$

In Eq. (1), a layer of the network is represented by k, and the $*$ operator is used for the 2D convolution between the input X_{k-1}, channel c = 1, . . . c, and the filter $W_k^{(c,m)}$. This convolution produces the m-th output feature map $X_k^{(m)}$, where m ranges from 1 to M. The bias weights are contained in the matrix $B_k^{(m)}$. Finally, a nonlinear activation function σ is applied to the sum of convolutions to obtain the final output.

2.4 Tranform Wavelet

The wavelet transform is a mathematical technique that decomposes a signal into different components of frequency and spatial resolution, using wavelet functions. This allows you to analyze fine, smooth details in a signal, making it useful for vibration analysis applications. Letting T be the time, j the frequency, and s the scale, signal $x(\tau)$ is a time function and window $\mathrm{W}(\tau, f)$, which in general is a complex function and with a finite width of envelope, is assumed to be a function of time and frequency. The follow-ing equation defines a type of general form of the continuous wavelet transform (WT):

$$\mathrm{WT}(t, f, s) = \int_{-\infty}^{\infty} x(\tau)c(s)w(s(\tau - t), f)d\tau \qquad -\infty < t, \quad f < \infty \tag{2}$$

where t is the analysis time indicating the central location of the window, f the frequency in the ordinary sense related to a sinusoidal oscillation inside the window envelope, and S the time-scale parameter (s ≥ 0) That magnifies and shrinks the window function along the time axis thus providing a changing width for the window. $c(s)$ is a normalizing factor, a function of s. $\mathrm{W}(t, f, s)$ is then called a wavelet.

3. METHODOLOGY

In this experiment, a mechanical system was designed for conducting tests, located in the Vibration and Acoustics laboratory of the Department of Mechanical Engineering in Tucuruí, Pará, Brazil. The system consists of an electric motor connected to a shaft through a jaw coupling, establishing a direct connection without any reduction (1:1 ratio). After this connection, the shaft passes through a bearing housing equipped with a rigid ball bearing model 6202. This bearing serves as the mounting point for an accelerometer, which captures the vibration signals. The accompanying Figure 1 provides a detailed depiction of the system.

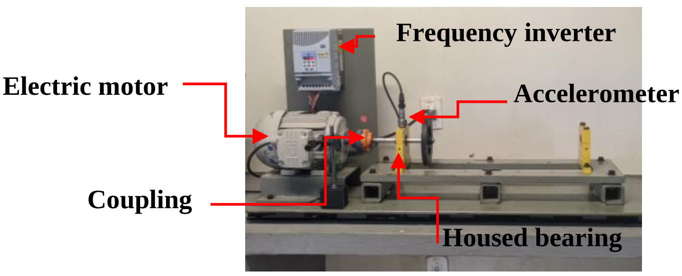

Figure 1. Mechanical system used for conducting the experiments.

3.1 Instrumentation and Experimental Materials

- **Frequency analyzer**

To capture and analyze vibration signals, a vibration collector and analyzer were required, as depicted in Figure 2.

Figure 2. NK820 Vibration Collector and Analyzer

- **Bearings**

Fig. 3 illustrates the bearing under investigation, which is identified as the SKF 6202 deep groove ball bearing. These bearings belong to the category of single row deep groove ball bearings, known for their exceptional versatility and characteristics such as low friction and optimized performance concerning noise and vibration levels. Notably, they are designed with the capability to withstand high rotational speeds.

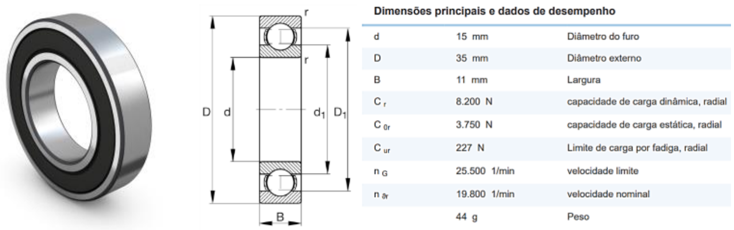

Figure 3. Model 6202 bearing and its characteristics

For the experiments, were used two bearings model 6202. One of the bearings was purposefully caused a fault condition, with several defects intentionally introduced on the outer race and inner race. The other bearing was used as a reference and remained in its initial condition, considered a healthy bearing.

3.2 Data acquisition

Tab. 1 presents the parameters defined for data acquisition, where "D" denotes a dataset, and there are 4 (four) datasets obtained based on the shaft speed, all acquired at 60 rpm. The datasets differ primarily in terms of the frequency range and sampling rate. Although the proposed method is specifically designed for the evaluation of low-speed rotations, these four datasets acquired at 60 rpm offer valuable insights for assessing its performance.

Table 1: Parameters adjusted for vibration signal acquisition

Parameters	D1	D2	D3	D4
Frequency Range (Hz)	0.1 – 500	0.1 - 1000	0.1 – 2000	0.1 - 5000
Sampling Rate (KHz)	1.25	2.5	5.0	12.5
Number of Points	2048	4096	8192	16384
Time Step (ms)	0.80	0.40	0.20	0.08
Time Period (s)	1.6376	1.6380	1.6382	1.3106

At the conclusion of the experiment, a total of 1000 observations were collected for each dataset (D1, D2, D3, and D4). Out of these observations, 500 samples were taken from a good bearing (representing the normal condition), while the remaining 500 samples were taken from a bearing with a simulated weak fault in the outer race.

The scalograms shown in the figure show the time-frequency representation of the first measured vibration signal for each condition. The scalograms were obtained by performing continuous wavelet transform on the signal using the analytic Morse wavelet with a symmetry parameter 3, a time-bandwidth product of 60, and 10 Hz per octave. The minimum and maximum amplitude scales were determined based on the energy distribution of the wavelet in the frequency and time domains.

3.3 Fault detection algorithm.

Firstly, the wavelet transform of the vibration response signal is determined throughout the bearing degradation process. Second, two-dimensional images of the transformation graph are generated. These images will feed the neural network for training. As an example, shown in Figure 4.

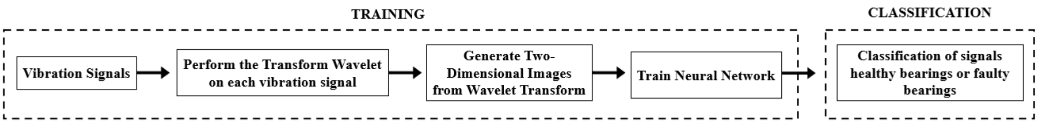

Figure 4. Procedure of the proposed method.

3.4 Structure of neural network

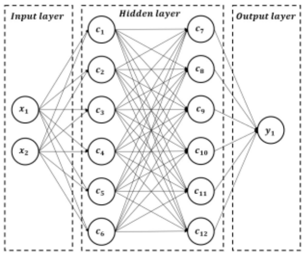

Figure 5. Structure of neural network

It consists of three layers: an input layer with 2 neurons, two hidden layers with 6 neurons and an output layer with one neuron. Input values are transferred from the input layer for the hidden layer. Base works on hidden layer will respond to inputs and generate outputs in the neurons of the output layer.

4. RESULTS

The figures show the results for different frequency ranges, 1-500 Hz, 1-1000 Hz, 1-2000 Hz, and 1-5000 Hz.

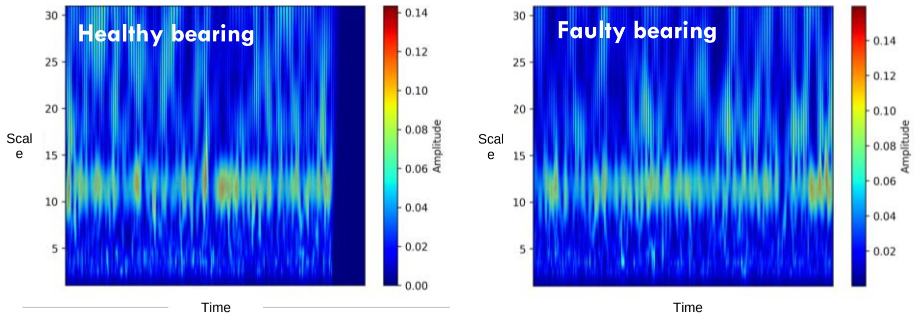

Figure 6a. Healthy bearing signal in a frequency range 1-500 Hz. Figure 6b. Faulty bearing signal in a frequency range 1-500 Hz.

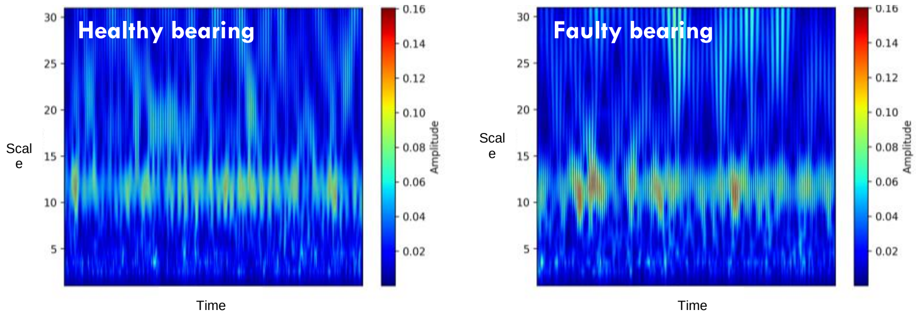

Figure 7a. Healthy bearing signal in a frequency range 1-1000 Hz. Figure 7b. Faulty bearing signal in a frequency range 1-1000 Hz.

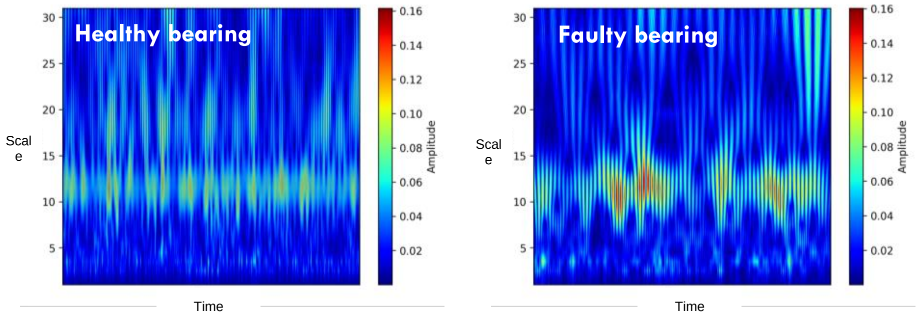

Figure 8a. Healthy bearing signal in a frequency range 1-2000 Hz. Figure 8b. Faulty bearing signal in a frequency range 1-2000 Hz.

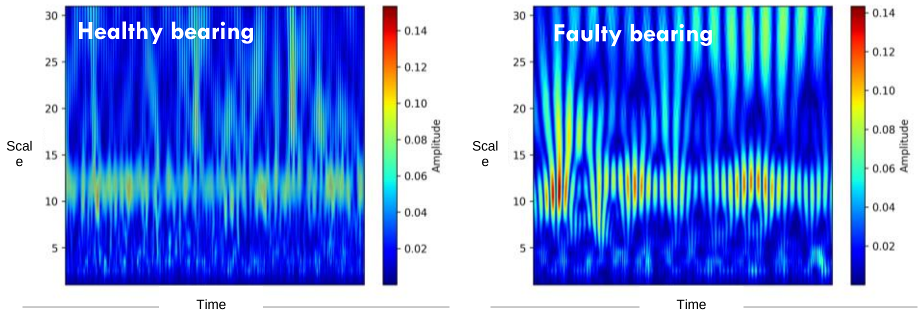

Figure 9a. Healthy bearing signal in a frequency range 1-5000 Hz. Figure 9b. Faulty bearing signal in a frequency range 1-5000 Hz.

This technique is represented in a two-dimensional plane, with the Y-axis representing scale and the X-axis representing time. The Y-axis in Wavelet Transform represents scale and varies from high to low frequencies. Smaller Y values analyze high-frequency details, while larger values focus on low-frequency features. The X signifies time, with left values indicating earlier time points and right values indicating later ones. This dual-axis representation enables the analysis of a signal's features across different time and frequency scales.

The results achieved by the proposed method are presented below.

I. Frequency range of 1-500 Hz:

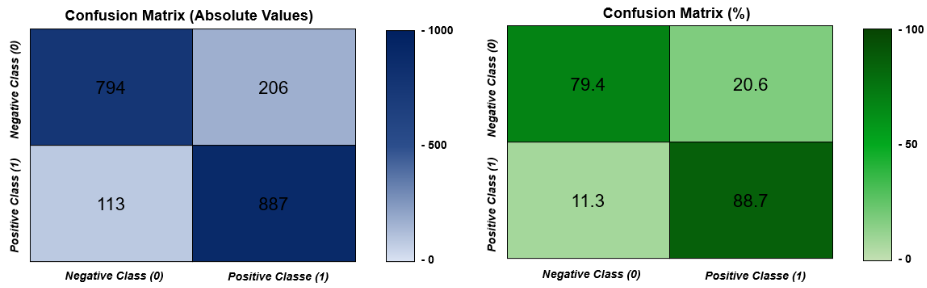

Figure 10a. Confusion Matrix (Absolute Values). Figure 10b. Confusion Matrix (Percentage)

- In this range, the system achieved an accuracy of 84% in classifying the bearing conditions.
- The model performed well in classifying between healthy and faulty bearing conditions.
- The training process was able to perceive important frequency patterns within this range, contributing to satisfactory predictions.

II. Frequency range of 1-1000 Hz:

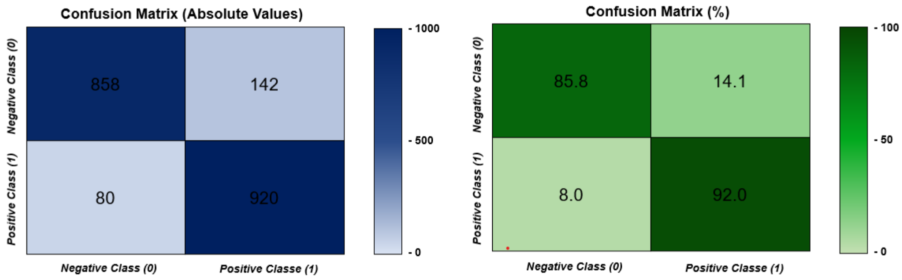

Figure 11a. Confusion Matrix (Absolute Values). Figure 11b. Confusion Matrix (Percentage)

- The expanded frequency range improved 89% accuracy in classifying the bearing conditions system.
- The model demonstrated a higher sensitivity to fault patterns at higher frequencies.
- The additional frequency information provided a more detailed analysis of the bearing condition, enhancing the predictive capabilities of the model.

III. Frequency range of 1-2000 Hz:

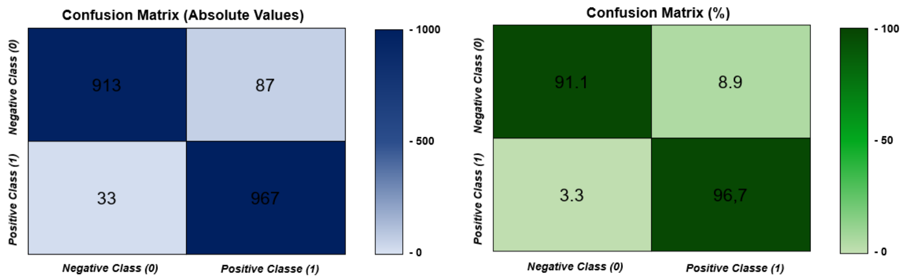

Figure 12a. Confusion Matrix (Absolute Values). Figure 12b. Confusion Matrix (Percentage)

- As the frequency range increased, the accuracy increased to 94%
- The model exhibited improved performance in detecting subtle fault signatures at higher frequencies.
- In a greater frequency range, there was a better characterization and differentiation of different types of faults, allowing better diagnoses.

IV. Frequency range of 1-5000 Hz:

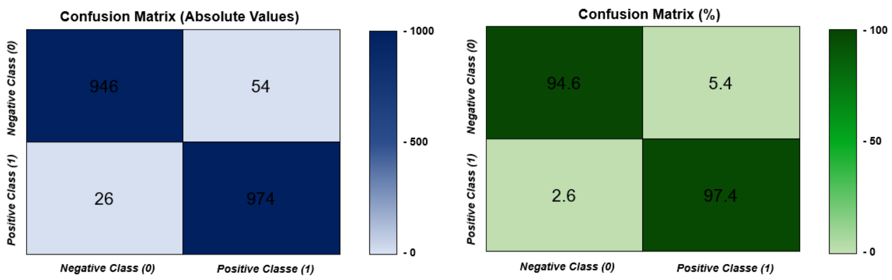

Figure 13a. Confusion Matrix (Absolute Values). Figure 13b. Confusion Matrix (Percentage)

- The largest frequency range resulted in the highest accuracy in classifying bearing failures, at 96%.
- The model demonstrated exceptional sensitivity to even the smallest fault pattern across the entire frequency.
- The comprehensive frequency range allowed for an optimal assessment of bearing health. This makes it very suitable for condition monitoring and fault detection.

Overall, the results indicate that the wider signal acquisition frequency range significantly improves the accuracy and sensitivity of the identifying bearing faults system.

5. CONCLUSION

In conclusion, the convolutional neural network (CNN) used with wavelet transform has demonstrated satisfactory results in low-speed rotating machinery vibrations analysis. Leveraging the deep learning capabilities of CNN and the wavelet transform time-frequency representation, it was possible to effectively detect and classify fauty and healty bearing conditions.

The results obtained from the experiments indicate that the proposed approach achieved high accuracy in diagnosing a bearing contidion. The combination of CNN's ability to automatically learn discriminative features and the wavelet transform time-frequency representation contributed to the success of our methodology.

Furthermore, the use of the GBR 6202z bearings allowed to experiment simulate a realistic fault in the outer race, which closely resembles real-world industrial scenarios. The obtained scalograms clearly demonstrated the differences in vibration patterns between healty and faulty bearings, further validating of the approach effectiveness.

These findings highlight the potential of CNN and wavelet transform for vibration analysis in low-speed rotating machinery. The ability to accurately identify and classify faulty conditions can significantly enhance maintenance strategies, enabling timely intervention and prevention of critical failures. Future research can explore the application of this methodology to a broader range of rotating machinery and further optimize the CNN architecture and wavelet parameters for improved performance.

In this study, is demonstrated the promising capabilities of the combined CNN and wavelet transform approach for vibration analysis, showcasing its potential for condition monitoring and fault detection in industrial equipment.

6. ACKNOWLEDMENTS

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8. RESPONSIBILITY NOTICE