e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:05/Issue:10/October-2023 Impact Factor- 7.868 www.irjmets.com

VIBRATION SIGNALS ANALYSIS BY EXPLAINABLE ARTIFICIAL INTELLIGENCE (XAI) APPROACH: APPLICATION ON BEARING FAULTS DIAGNOSIS

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ABSTRACT

In this research, we present a transparent approach to using Convolutional Neural Networks (CNNs) for classifying vibration signals. The process starts by converting vibration data into image-like representations through the Short-Time Fourier Transform (STFT). We employ a CNN as the classification model, and to better understand how the model works, we use Gradient Class Activation (Grad-CAM) to visualize where the model focuses its attention during analysis. Vibration analysis has long been a valuable tool for diagnosing such faults, and the integration of Explainable Artificial Intelligence (XAI) techniques promises to enhance the accuracy, interpretability, and practicality of this critical task. This research paper proposes a novel approach that combines advanced machine learning models with XAI methods to analyze vibration signals for bearing fault diagnosis. By doing so we aim to not only improve the diagnostic accuracy but also provide insights into the reasoning behind the model's decisions.

Keywords: Vibration Analysis, Explainable Artificial Intelligence (XAI), Neural Networks, Fault Detection, Bearing Health.

I. INTRODUCTION

In this research, the focus is on using vibration signals to diagnose faults in rolling element bearings (REBs). Traditional methods for signal analysis, such as Fast Fourier Transform (FFT), empirical mode decomposition, and statistical analysis, have been employed. However, with the rise of machine learning models, including Convolutional Neural Networks (CNNs), are used for prediction and classification of these features, particularly those obtained from frequency domain analysis. CNNs, which automatically extract features, are gaining popularity in this field [6].

The reliability and efficiency of industrial machinery depend on the condition of various components, with bearings being one of the most critical elements. As we all know, the key to achieve bearing fault diagnosis is to extract useful information which is related to fault characteristics from the analyzed signals [4]. Faults in bearings, if undetected downtime, extensive maintenance strategies leverage vibration signals, which are sensitive to the early stages of bearing degradation.

While machine learning models have demonstrated remarkable success in automating the fault detection process, their "black-box" nature often hinders practical adoption [6]

The introduction of XAI methods aims to bridge this gap by providing transparent and interpretable insights into model decision -making, thereby enhancing the trust and usability of such models.

II. METHODOLOGY

In this section, specific fault classes in the context of bearing condition monitoring and vibration analysis can be defined as follows:

1. Normal condition:

In the normal condition class, the bearing is in good working order, with no detectable faults or abnormalities. Vibration signals from bearings in this class represent the baseline behavior, serving as a reference for comparison with faulty bearings.

2. Inner Race Fault:

An inner race fault occurs when there is damage or degradation in the inner ring of the bearing. This type of fault typically results in distinctive vibration patterns, often characterized by localized impacts, harmonics, or changes in the frequency domain. The vibration signature for inner race faults is unique and can be detected through appropriate analysis techniques.

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3. Outer Race Fault:

An outer race fault is characterized by damage or deterioration in the outer ring of the bearing. Similar to inner race faults, outer race faults produce specific vibration patterns. These patterns are often related to the rotational frequency and harmonics associated with the outer ring's imperfections. Detecting these patterns is crucial for bearing fault diagnosis.

4. Rolling Element Fault:

Rolling element faults pertain to issues with the rolling elements, such as balls or rollers, within the bearing. These faults can manifest as surface pitting, wear, or spalling of the rolling elements. Vibration signals associated with rolling element faults often exhibit impacts, cyclic patterns, and non-stationary behavior, which are different from the behavior of healthy bearings.

III. MODELING AND ANALYSIS

Initially, we examined the frequency distribution of bearings with various conditions in the CRWU bearing dataset. Upon visual inspection of these spectra, we noticed distinctions within the range of 1000 to 4000 Hz among the different bearing conditions. These differences provided an initial basis for classifying and distinguishing between the various bearing conditions.

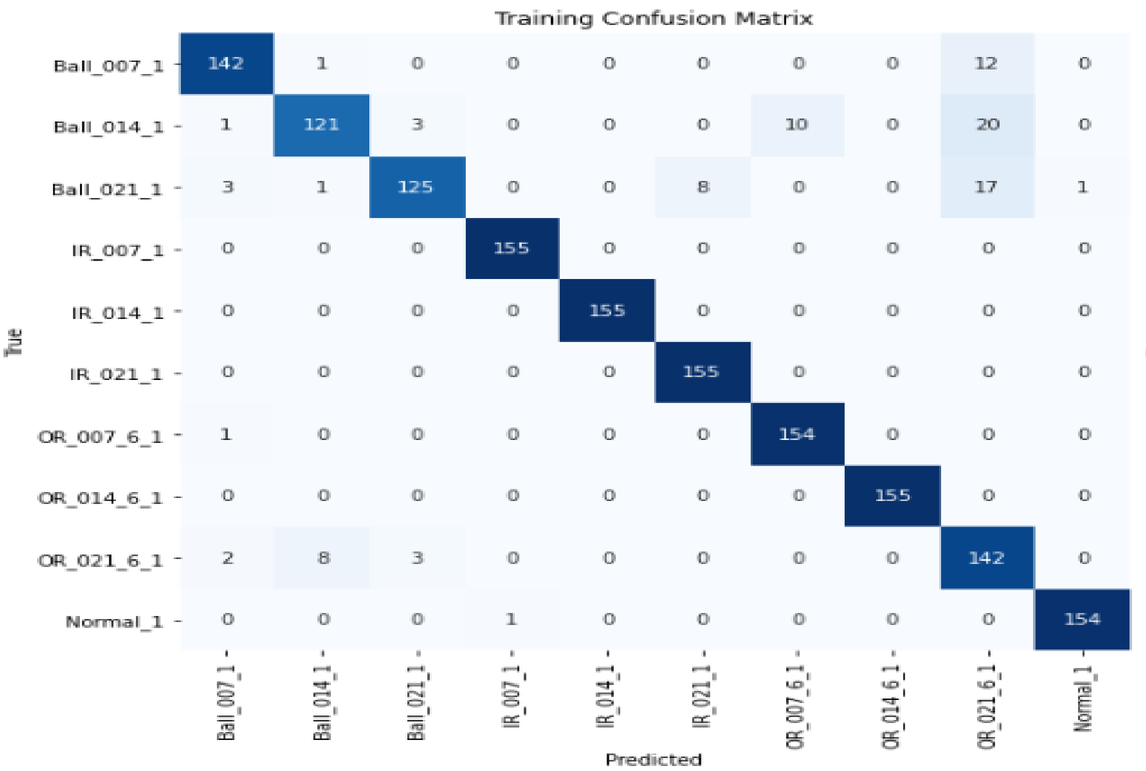

Figure 1: Training Confusion matrix

We computed and presented the confusion matrix for classifying bearing faults using features of high-frequency bands shows in FIGURE 1.

IV. RESULTS AND DISCUSSION

The study investigated the attention maps for different bearing conditions: normal, inner ring fault, outer ring fault, and ball fault, all operating at 1797 rpm. The attention maps revealed insights, for normal bearings, the model focused on low-frequency bands as there were no structural resonances. However, for bearings with inner ring faults, the attention shifted to high-frequency bands due to structural resonance, this pattern persisted across various rotation speeds. The conclusion is that high-Frequency features are more suitable for machine learning classification than traditional characteristics. Further verification of this explanation is discussed in the next section.

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Table 1: Accuracy table

	max	min	mean	sd	rms	skewness	kurtosis	crest	form	fault
0	0.35986	-0.41890	0.017840	0.122746	0.124006	-0.118571	-0.042219	2.901946	6.950855	Ball_007_1
1	0.46772	-0.36111	0.022255	0.132488	0.134312	0.174699	-0.081548	3.482334	6.035202	Ball_007_1
2	0.46855	-0.43809	0.020470	0.149651	0.151008	0.040339	-0.274069	3.102819	7.376926	Ball_007_1
3	0.58475	-0.54303	0.020960	0.157067	0.158422	-0.023266	0.134692	3.691097	7.558387	Ball_007_1
4	0.44685	-0.57891	0.022167	0.138189	0.139922	-0.081534	0.402783	3.193561	6.312085	Ball_007_1
...	...	...	...	...	...	...	...	...	...	...
2295	0.21425	-0.19839	0.010769	0.064100	0.064983	-0.212497	-0.119312	3.297037	6.034174	Normal_1
2296	0.21967	-0.20882	0.013136	0.068654	0.069883	-0.061308	-0.295122	3.143410	5.319958	Normal_1
2297	0.20799	-0.21613	0.012571	0.067128	0.068279	-0.154754	-0.071405	3.046161	5.431299	Normal_1
2298	0.21425	-0.22405	0.012608	0.066813	0.067977	-0.326966	0.023662	3.151821	5.391672	Normal_1
2299	0.19610	-0.24721	0.012209	0.063243	0.064396	-0.351762	0.226294	3.045244	5.274392	Normal_1

2300 rows × 10 columns

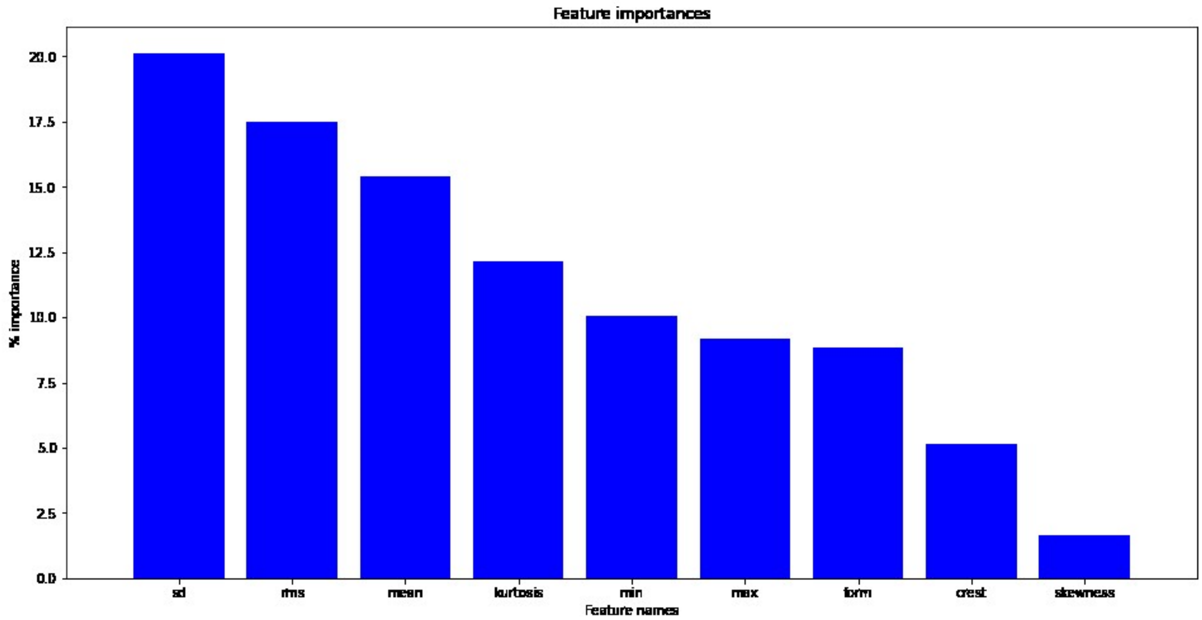

Figure 2: Feature importance

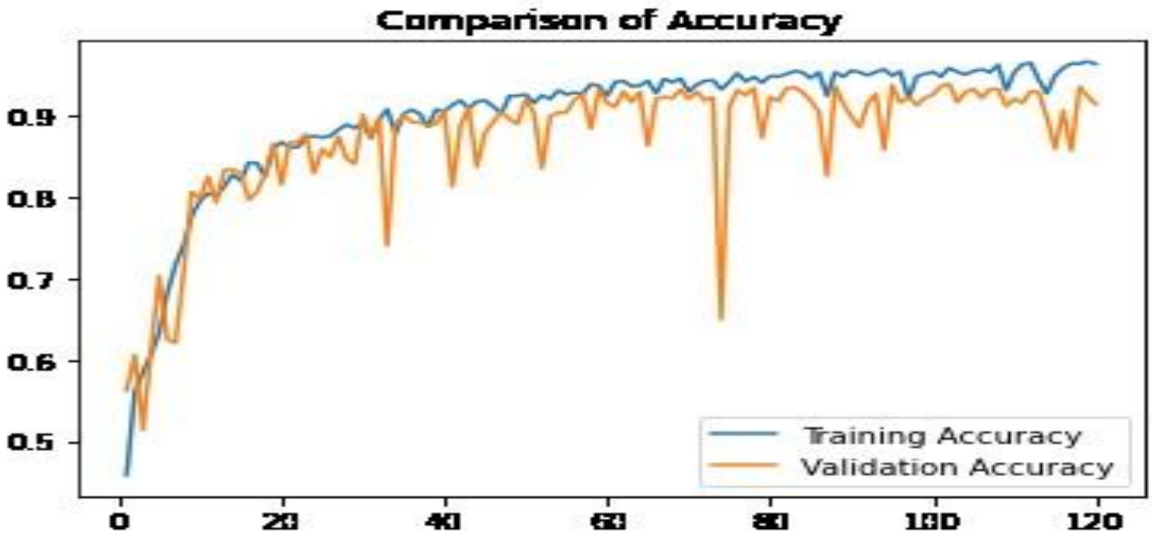

Figure 3: Accuracy Comparison Graph

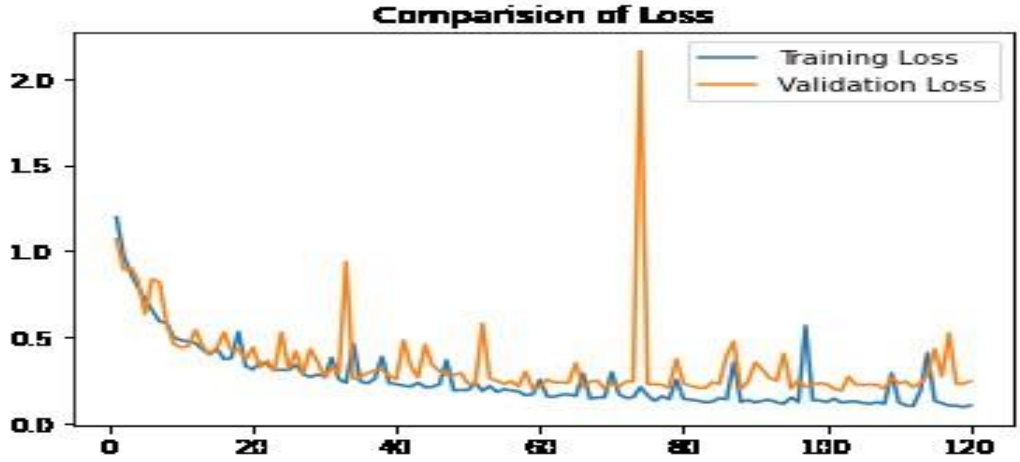

Figure 4: Loss Comparison Graph

Based on the verification results shows in TABLE 1, FIGURE 2, FIGURE 3 and FIGURE 4 it is confirmed that our initial assumption, deduced from attention maps, holds true. The model's effective classification of CRWU bearings relies on features in the high-frequency band, rather than the conventional use of characteristic frequencies seen in most research. This explanation gains further credibility through validation with simple neural network models, adaptive network-based fuzzy inference systems (ANFIS). In summary, the research supports the idea that high-frequency features are the key to successful classification by our model.

V. CONCLUSION

In this research paper, we explore the application of Convolutional Neural Networks (CNNs) with an Explainable Artificial Intelligence (XAI) to classify bearing faults through vibration analysis. We first implement a CNN model to classify these faults using time-frequency representations. Our results confirm the effectiveness of CNNs for vibration analysis, showcasing their high performance. We then delve into the explanatory aspect of the CNN model, shedding light on how it arrives at its classification decisions.

Grad-CAM is applied to visualize where the model focuses its attention during vibration analysis. It is observed that the model places more emphasis on high-frequency bands generated by structural resonance. The explanation is further validated through neural networks (NN), adaptive network-based fuzzy inference systems (ANFIS), and decision trees. This process confirms that features in high-frequency bands are more suitable for machine learning-based classification compared to conventional signal analysis characteristics.

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