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RESEARCH ARTICLE

Bearing Fault Diagnosis With Envelope Analysis and Machine Learning Approaches Using CWRU Dataset

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ABSTRACT Predictive maintenance in machines aims to anticipate failures. In rotating machines, the component that suffers the most wear and tear is the bearings. Currently, based on the Industry 4.0 paradigm, advances have been made in obtaining data, specifically, vibration signals that can be used to predict deterioration using various techniques. In this study, we have applied vibration analysis to obtain features that can be used in an optimal Machine Learning model using a public dataset from CWRU, widely used in research, which contains data on bearing failures. The main objective of this research is to detect bearing failures using a minimum set of observations and selecting the minimum number of features. To achieve this, frequency domain vibration analysis, combined with envelope analysis, is utilized as an effective method for detecting bearing failures. The results were further improved by incorporating an optimal bandwidth determined using the kurtogram. When the results of the envelope analysis are applied to various machine learning models, using the calculated amplitudes as predictors, the Kernel Naive Bayes model achieved an accuracy of 94.4%. Meanwhile, the Decision Tree (Fine Tree) and KNN (Fine KNN) models demonstrate exceptional accuracy, achieving a perfect accuracy rate of 100%.

INDEX TERMS Bearing fault, deep learning, industry 4.0, machine learning, predictive maintenance.

I. INTRODUCTION

Prognostics and Health Management (PHM) [1] in Industry 4.0 enables predictive maintenance, condition monitoring, data-driven decision making [2], integration with digital twins, and optimization of Overall Equipment Effectiveness (OEE). By leveraging advanced technologies and data analytics, PHM empowers organizations to achieve higher levels of asset reliability, efficiency, and productivity in the context of the fourth industrial revolution.

PHM is an important step towards improving asset management and maintenance practices, it is indeed incomplete without the capabilities of remaining useful life (RUL) prediction and fault diagnosis [3].

RUL prediction techniques enable us to estimate the remaining operational lifespan of a component or system. By analyzing historical data, sensor readings, and other relevant information, RUL prediction models can forecast when a particular component or system is likely to fail or require maintenance. Fault diagnosis involves the identification and localization of faults or anomalies within a system. By analyzing sensor data, performance metrics, and other available information, fault diagnosis techniques can detect, classify, and diagnose faults, helping maintenance personnel understand the root causes of failures. Accurate fault diagnosis enables timely and appropriate actions to be taken, such as

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repairs, part replacements, or adjustments, improving system reliability, safety, and performance.

To enhance RUL prediction, researchers have investigated an approach called the Dual-Thread Gated Recurrent Unit (DTGRU) [4].

One of the promises of the Industry 4.0 paradigm is the reduction of unplanned downtime and unexpected breakdowns [5]. This is when the importance of predictive maintenance (PdM), also referred to as e-maintenance, emerges [6]. PHM enables predictive maintenance strategies by leveraging advanced analytics, machine learning, and real-time data monitoring. Predictive maintenance is based on the problem that machines often go through a measurable degradation process before they fail, which will allow us to predict when preventive maintenance should be carried out. Advances in the connectivity of industrial networks and the obtaining of data from processes and systems will allow us to meet the challenge of predictive maintenance [7]. In industry, rotating machines are of great importance. Therefore, the diagnosis of faults in these types of machines is a critical point for the maintenance of an industrial system. Most rotating machines have bearings among their mechanical elements. Bearings consist of balls or other rolling elements that rotate on raceways within rings. Faults in bearings occur due to the deterioration of the outer track, the inner track, the ball, or the cage [8]. The analysis of vibrations and specifically the frequency spectrum is the most widely used methodology for detecting defects in bearings. This technique has a well-defined model, which depends on the speed of the motor, the geometry of the bearings, and the location of the defect in the bearing [9] and has been widely researched in recent decades.

Bearings in general consist of several elements: outer ring, rolling elements (balls, needles, rollers, etc.), cage and inner ring [8]. Wear in each of these parts will produce characteristic defect frequencies in the frequency spectra, which will allow us to identify the failure. That is, when a bearing component is damaged, the characteristic frequency of the failure appears in the frequency spectrum along with harmonics.

The associated frequencies are:

- BPFO (Ball Pass Frequency Outer) is the characteristic frequency for a defect in the outer track.
- BPFI (Ball Pass Frequency inner) is the characteristic frequency for a defect in the inner track.
- BSF (Ball Spin Frequency) is the characteristic frequency for defects in balls or rollers.
- FTF (Fundamental Train Frequency) is the characteristic frequency for a defect in the cage.

"Defective bearings produce vibrations equal to the rotation speed of each of the bearing frequencies. They are strongly related to the rotation of the balls, the cage, and the passage of the balls through the inner and outer tracks." [10].

This model describes certain types of errors based on frequencies, but typically failures occur at the same time as noises or other vibrations from other elements that make diagnosis difficult. Due to this variability it is very difficult to directly recognize failure patterns through simple observation.

The defect signals obtained directly from rotating machines are in the time domain and contain complex information from other machine elements. To solve this, the amplitude of the signal in the frequency domain is analyzed, and the resulting graph is called a spectrum. The most common way to perform this transformation is to use the Fast Fourier Transform (FFT) or also the Wavelet Packet Transform (WPT) [11] and Short-time Fourier Transform (STFT) [12]. With these tools, a signal in the time domain with a lot of information is transformed into a series of signals in the frequency domain, focusing on the values of amplitude and frequency.

The characteristics obtained by applying these transformations create a dataset of a large dimension that contains irrelevant information and makes Machine Learning (ML) methods ineffective. Therefore, a good selection of features is necessary to improve the effectiveness of algorithms both computationally and in terms of model accuracy.

Machine Learning (ML) is the creation of systems or models that "learn" automatically. Automatic, because they are problems that are to complicated to be solved manually and also have a large dimensionality or are large volumes of data. The goal of ML is to create models (programs) capable of generalizing behaviors from the information provided in the form of examples.

Among the problems that ML solves is classification, i.e. predicting the category of a new observation or, in other words, predicting whether an element belongs or does not belong to a predefined category.

The goal of this research is to classify bearings that are in good condition versus those that are faulty and also to determine whether the fault is located in a specific area. This will be achieved by using classification algorithms from machine learning (ML).

Among the most widely used supervised classical algorithms in the literature on bearing fault diagnosis [13] are K-Nearest Neighbors, Support Vector Machines (SVM), Decision Trees, and Naive Bayes [14]. In the studies [15], [16], the researchers achieved a perfect accuracy rate of 100% by performing a more efficient classification than with the SVM model. Another approach that takes advantage of the particularity of artificial neural networks (ANN) [17] is Deep Learning (DL) [18] algorithms, which have the ability to automatically extract features; among the most widely mentioned in articles are Convolutional Neural Network (CNN) [19], [20], [21], [22], [23], Auto-Encoders [24], [25], Deep Belief Network (DBN) [23], and Recurrent Neural Network (RNN) processes [26].

In Kaya et al. [27], the authors suggested continuous wavelet transform CWT and convolutional neural networks to predict the bearing fault size diagnosis based on deep transfer learning algorithms (DTL) and time-frequency images.

Transfer learning (TL), originally derived from the field of computer vision, in particular, developed for image classification tasks, has proven to be applicable and effective in various domains, including the fault diagnosis of rotating machines. By leveraging pre-training models and adapting them to the specific fault diagnosis task, transfer learning can improve diagnostic accuracy, even with limited labelled data, and capture important fault-related features from raw sensor data or vibration signals.

DL-based diagnosis methods have emerged as a prominent area of research. These have gained significant attention due to their ability to mitigate the influence of human experience, distinguishing them from traditional machine learning diagnosis methods [28].

Traditional deep transfer learning models facilitate the extraction of domain-invariant representations and the alignment of different domains, ultimately improving the performance and generalizability of the model across diverse domains using a convolutional auto encoder [29].

Joint Distribution Adaptation (JDA) improves the performance of machine learning models on the target domain by reducing the discrepancy between source and target distributions. By aligning the joint distributions, JDA facilitates effective knowledge transfer and adaptation, enabling models to generalize well in real-world scenarios where labelled data may be scarce or unavailable in the target domain. A fault bearing diagnosis method was introduced in [30], which combines Joint Distribution Adaptation (JDA) with Deep Belief Network (DBN) techniques.

This research aims to reduce the number of features and samples and to improve the accuracy and processing of classical ML algorithms for classifying bearing failures.

The rest of the article consists of the following sections: Section II briefly describes the set of fault data to be used in the research. Section III presents the method of extracting features and the vibration analysis technique to be developed. Section IV details the selection of the features to be used in Section V, which describes the experiment carried out. Section VI presents the conclusions and future work.

II. DATA SET REVIEW

Data is the basic unit for all machine learning (ML) or deep learning (DL) architectures. The literature shows that many authors have opted to use existing public data sets to test the validity and effectiveness of the techniques and algorithms developed. The most widely used data set is the CRWU dataset [31] which is taken as a standard to validate many ML and DL algorithms.

This data set was generated by the Case Western Reserve University (CRWU) Bearing Data Center. Experiments were conducted in which data was collected on the accelerations produced by an electric motor in different situations, varying the type of failure, its severity, or the rotational speed of the shaft.

The experimental set for collecting data consists of a 2.03 HP electric induction motor at one end, a torque transducer in the middle, and a dynamometer at the other end that simulates the load. In addition, it includes control electronics [31].

The sensors, specifically accelerometers, were placed on the bearings at the end of the motor shaft and on the fan within the motor housing and collected 12,000 and 48,000 samples per second of the defects. For the fault-free samples, 48,000 per second were obtained. Speed and power were obtained through the torque transducer and recorded manually. The samples were recorded in MATLAB format files.

Defects were added to SKF bearings using electric discharges that caused failures in the inner crown, balls, and outer track with different diameters from 0.007 inches to 0.04 inches. In addition, these tests were performed by varying the rotational speed and load.

The data set consists of 161 records divided into four groups named: 48k normal-baseline (fault-free data), 48k drive-end fault, 12k drive-end fault, and 12k fan-end fault. They contain information based on the resulting loads and speeds of the motor.

As for the file names, the first letter represents the position of the defect, the next three numbers are the diameter of the failure, and the last number indicates the load. For example, the file IR007_0 has the data of the inner crown failure, with a 0.007-inch diameter of failure for a motor load of 0 HP. In the same way, the file OR007@6_0 contains the data of the outer crown failures with a diameter of 0.007 inches in the centered load zone (at position 6 on the clock) and the motor load operating at 0 HP.

It should be noted that each data file in the CWRU data set consists of data of different lengths and is not a multiple of 2, in addition, it is a large, varied, and complex set.

In addition to CWRU, other data sets have been used in the literature for detecting defects in bearings such as MFPT (Machinery Failure Prevention Technology) [32] or the Paderborn bearing dataset from Paderborn University [33]. Among the data sets used to predict the useful life of bearings are FEMTO_ST [34], IMS (Intelligent Maintenance System) from the University of Cincinnati [35], and Xi'an Jiaotong University (XJTU-SY) [36] in all of which the test method to generate the defect has been to accelerate the device's life. Currently, the most widely used data set is CWRU. The defects in this data set are caused, by evident characteristics and relatively easy diagnosis, so it can be used as a basic data set for model validation.

III. FEATURE EXTRACTION

Features are essential in ML, in this study they are extracted from the vibration signals of the bearings when there is a defect in the inner track, outer track, ball, or normal state.

Initially, it is difficult to extract features from the original signal that can distinguish the different defect states from the normal state of the bearing. To solve this problem, vibration analysis techniques are applied.

A. VIBRATION ANALYSIS

There are multiple techniques for analyzing the vibrations produced by electric motors [37]. They can be grouped into the time domain, frequency domain, and time-frequency domain analysis techniques.

1) TIME DOMAIN ANALYSIS

In this type of analysis, the shape of the vibration signal is analyzed with respect to time. To analyze the obtained signal, indicators such as the mean, peak-to-peak amplitude, root-mean-square (RMS), crest factor, or kurtosis are used. These indicators will be used as features for ML. It should be noted that this signal is the one obtained directly from the accelerometers.

2) FREQUENCY DOMAIN ANALYSIS

This technique consists of transforming the signal into a series of discrete frequency components so that the characteristic frequency components of the failure can be easily analyzed. The transformed signal is called the signal spectrum.

To perform this transformation, the Fast Fourier Transform (FFT) [38] is typically used because it requires less computational time. Other transformations include the Power Spectrum or Envelope Analysis.

FFT is an algorithm that efficiently calculates the discrete Fourier transform (DFT) [39] by transforming the discrete signal obtained from sensors in the time domain to the frequency domain. The result is the spectrum of the signal.

The DFT of the signal $x_{\mathbf{n}}$ is defined as:

$$X_{\mathbf{k}} = \sum_{n=0}^{N-1} x_{\mathbf{n}} e^{(-2\pi i/N)\mathbf{kn}} \tag{1}$$

where $x_{\mathbf{n}}$ is the discrete signal obtained in the time domain, k is an integer ranging from 0 to $N-1$ and $x_{\mathbf{k}}$ is a set of complex numbers that will be the resulting spectrum. The number of samples N must be a power of two.

When there is a localized defect in a bearing, the surface of the bearing elements interacts with the defect, producing an impact that repeats with each rotation of the shaft. These impacts excite high-frequency resonances. However, the diagnostic information revealing the type of defect is in the repetition frequency, not the resonance frequency [40].

In addition, due to the load variations caused by the passage of the defect through the load zone, an amplitude modulation of the repetition frequency in the signal is produced [41]. Therefore, it is necessary to perform demodulation that allows the defect signal to be extracted in order to analyze it in the frequency domain. The demodulation is what is called the envelope spectrum.

Envelope Analysis allows this demodulation to be carried out, even if random fluctuations occur, and extract the masked signal in the carrier signal that also contains noise and signals from other components.

To carry out an optimal extraction, the signal must be analyzed in the appropriate band, where the signal-to-noise ratio (SNR) is higher. To this end, techniques such as Ordender Tracking (OR), Adaptive Noise Cancellation (ANC), self-adaptive Noise Cancellation (SANC), or Discrete/Random Separation (DRS) have been developed, which aim to eliminate the background noise that hinders diagnosis. Another alternative is the use of the Kurtogram to extract the optimal frequency band, especially when there is no prior knowledge of the behavior of the monitored machine [42].

This technique is based on Spectral Kurtosis (SK) [43]. SK has high values in those bands where the signal caused by the defect is dominant and values close to zero when the band is dominated by stationary components [38]. In other words, it has a high sensitivity to detect in which frequency band the impulsivity of the signal generated by defects is greater.

The Kurtogram consists of performing the spectral kurtosis of all frequencies and bandwidths to extract in which band the Kurtosis is greater, which is directly proportional to the amount of signal impulse and related to the possible defects that this article seeks.

It should be noted that computationally speaking, this process is very costly, there is a less costly version, The Fast Kurtogram [44]. However, a lower computational cost may mean a lower signal-to-noise ratio, which can be a problem when analyzing the signal.

Using the previously described techniques, it is possible to detect anomalies in the different parts of a bearing according to the characteristic frequencies present in the spectrum. However, the difficulty in detecting failures in bearings is different depending on the element of the bearing where it occurs. When there is a defect in the inner track or the outer track, the possibility of the Envelope Analysis detecting a harmonic at the characteristic fault frequencies is much greater than if the failure is present in the bearing balls.

From the set of vibration data of an electric motor for normal operation and for operation with failures in the inner track, outer track and the balls, the envelope spectrum is obtained, and the PCA technique is applied to reduce dimensionality [45].

3) TIME-FREQUENCY DOMAIN ANALYSIS

In these types of techniques, a simultaneous approach of the time domain and the frequency domain is provided. The algorithms available for performing these types of transformations are the Short-time Fourier Transform (STFT) [12], the Wagner-Ville distribution (WVD) and the Wavelet Analysis (WA) [11].

4) VIBRATION ANALYSIS ON CWRU

Next, the vibration analysis methods will be applied to the CWRU data set. A comparison has been made with the signals of the bearings in good condition with the defective ones; the data obtained are those of the motor rotating at a speed of 1797 rpm and without load 0 hp, the data without defects (Normal_0), with a sampling rate of 12000 samples per second, a diameter of 0.007 inches has been chosen as

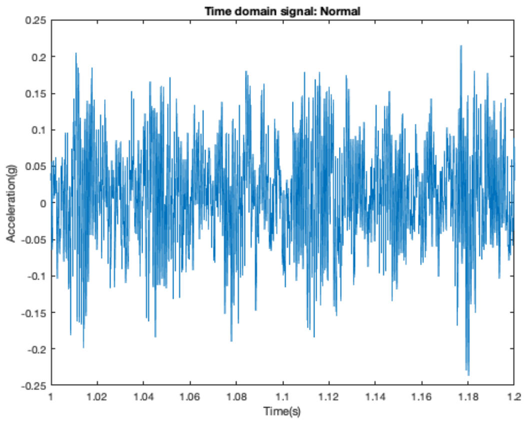

FIGURE 1. The signal in the time domain without defects.

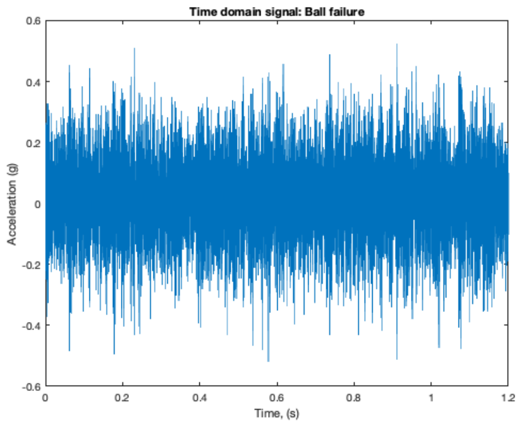

FIGURE 2. The signal in the time domain with a defect in the ball.

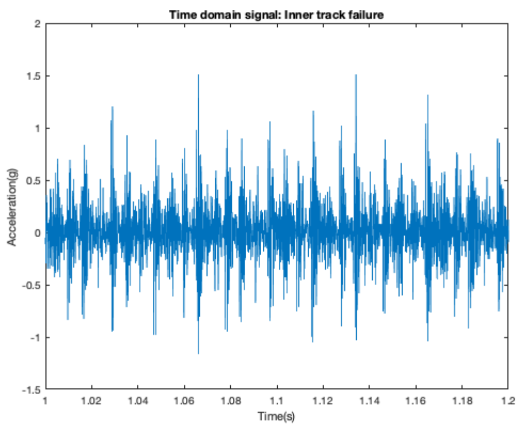

FIGURE 3. The signal in the time domain with a defect in the inner track.

the failure diameter in the inner track (IR007_0), the outer track in the centered position (OR007@6_0) and on the ball (B007_0).

The signals obtained in the time domain for the different situations, that is, as captured by the accelerometer, are shown in Fig. 1, 2, 3 and 4.

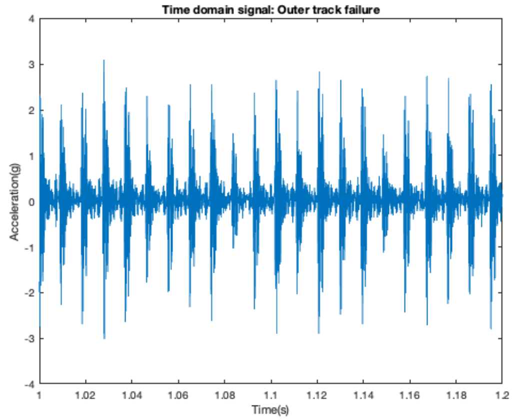

FIGURE 4. The signal in the time domain with a defect in the outer track.

As can be observed by comparing the signals of defects in the inner track Fig. 3 and outer track Fig. 4, it is difficult to distinguish the failure with the signals (in the time domain). However, if it is compared with the signal without defects, it is clear that the amplitude of the failure is greater than in the healthy bearing. In the case of a failure in the ball Fig. 2, it can be highlighted that the impulsiveness of the signal is lower than in the other failures and is similar to the signal without defects Fig. 1, which makes it difficult to discover the anomaly.

IV. FEATURE SELECTION

The goal of feature selection is to remove redundant and irrelevant features as much as possible and to retain relevant features. This selection is an important part of ML because it reduces the dimensionality of the feature vector and transforms the data into information that is usable by ML algorithms in a more efficient manner.

One way to improve anomaly detection is to apply analysis in the frequency domain, specifically Envelope Analysis. This method detects resonant vibrations caused by defects in bearings. The frequency at which these pulses repeat is what allows us to diagnose which component of the bearing has caused the defect.

Envelope Analysis demodulates the signal and extracts the envelope signal, which will contain harmonics at the fault frequencies (BPFI, BPFO, BSF, and FTF). This process is performed using the Hilbert transform [46].

In Fig. 5, the fault signal on the inner track corresponds to BPFI harmonics, which means there is a defect on the inner track of the bearing. Next, in Fig. 6, the signal with the fault on the outer track is shown, where the same scenario as previously discussed for the inner track can be verified.

Next, in Fig. 7, the signal from the bearing in good condition is shown, where there are no high amplitudes in any of the characteristic failure harmonics BPFI, BPFO, or BSF, and the peak amplitudes are lower in comparison to the failures on the inner track.

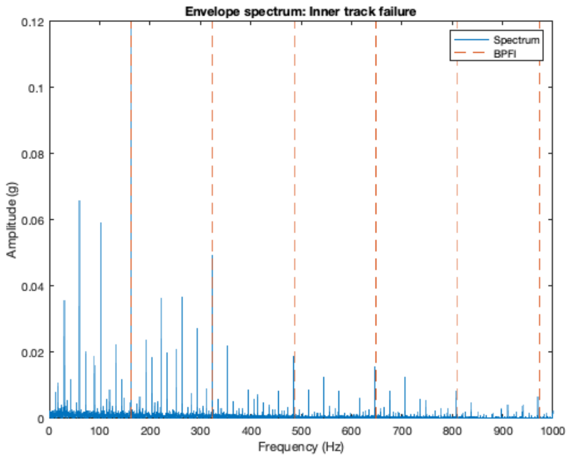

FIGURE 5. Spectrum of the inner track envelope signal and BPFI harmonics.

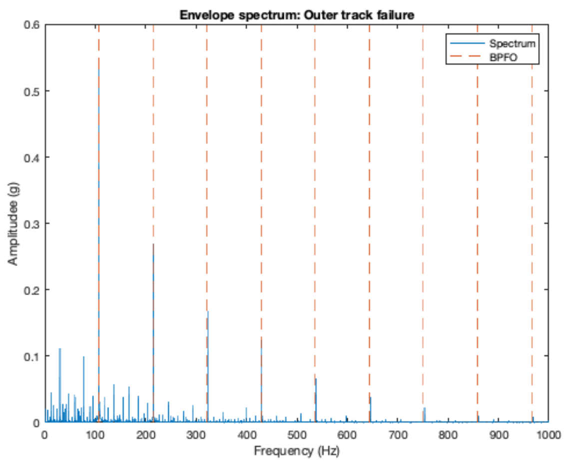

FIGURE 6. Spectrum of the outer track envelope signal and BPFO harmonics.

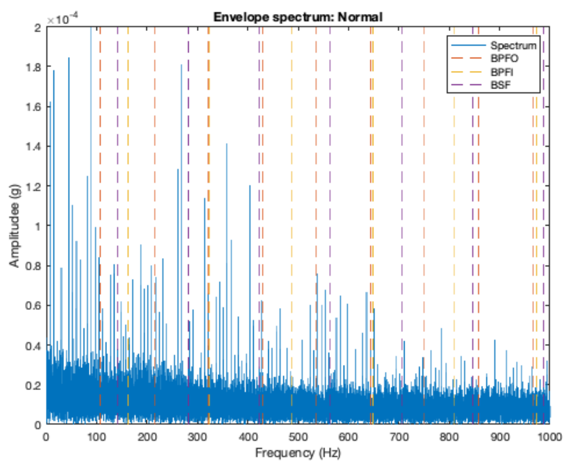

FIGURE 7. Spectrum of the good condition envelope signal and BPFI, BPFO, and BSF harmonics of the inner track.

Finally, in Fig. 8, the signal from the ball bearing failure is visualized, where the characteristic frequency harmonics (BSF) do not coincide with the highest peaks. Therefore, envelope analysis cannot detect this type of failure.

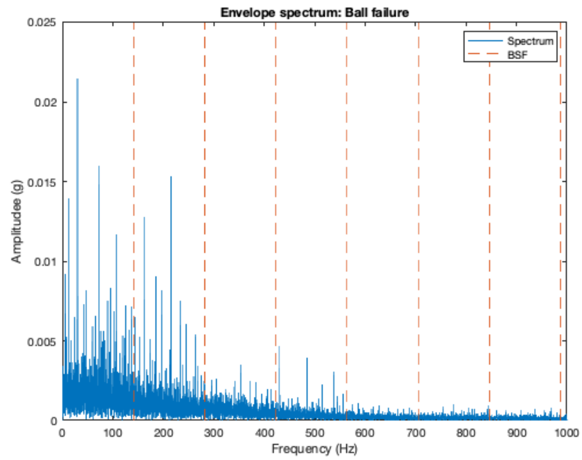

FIGURE 8. Spectrum of the ball envelope signal and BSF harmonics.

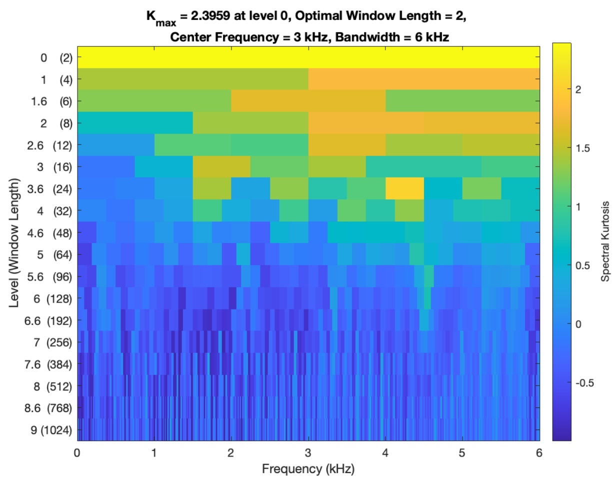

FIGURE 9. Kurtogram of the signal with a defect on the inner track.

One way to improve envelope analysis is to apply a band-pass filter to the original signal to extract the band with the most diagnostic information. To extract this band, the Fast Kurtogram technique has been used [44].

Thanks to the Fast Kurtogram, the frequency band in which the signal/noise ratio is highest can be obtained and therefore contains the most diagnostic information. The more precision we can achieve in detecting the frequency band that the Envelope Analysis is going to demodulate, the easier it will be to detect the bearing defect.

In summary, applying this technique extracts a portion of the signal containing diagnostic information (analytical signal). To increase the signal/noise ratio and make the detection of fault frequencies more effective, a band-pass filter is applied where the defect causes greater impulsivity. This band is detected using the Fast Kurtogram. Finally, the spectrum of the analytical signal is obtained to see if there are harmonics at the fault frequencies of the bearings.

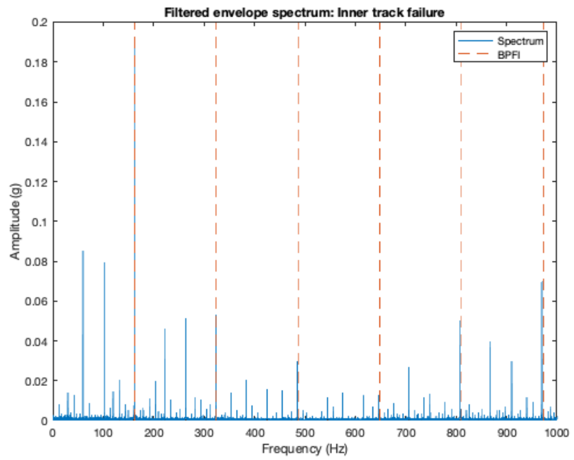

FIGURE 10. Spectrum of the filtered inner track envelope signal and BPFI harmonics.

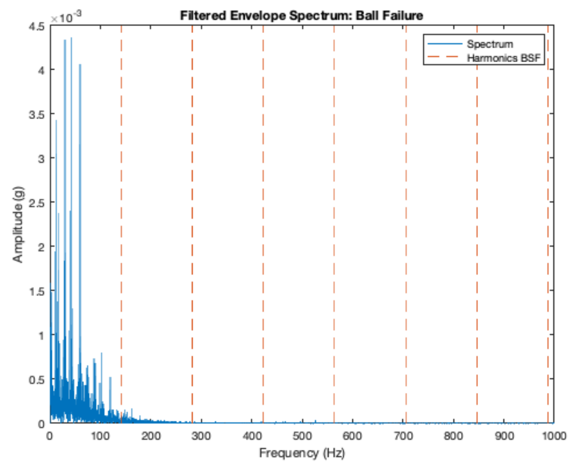

FIGURE 11. Spectrum of the filtered ball envelope signal and BSF harmonics.

Before obtaining the spectrum of the envelope signal, it is necessary to calculate a band where the diagnostic signal has more presence, this is obtained through the Fast Kurtogram, the filter removes all frequencies that are not within the band 3 kHz ± 6 kHz as shown in Fig. 9.

The amplitude of the harmonic that coincides with the characteristic frequency BPFI has increased from approximately 0.14 to 0.18, as shown in Fig. 10. Therefore, using the bandwidth indicated in the Kurtogram has improved impulsivity.

In the case of the ball defect, the kurtogram has been carried out with the maximum window width allowed by MATLAB, which is 2048 and corresponds to level 10.

However, even if the bandwidth suggested by the kurtogram is used to filter, it has not been effective as the harmonics still do not coincide with the characteristic frequency BSF as shown in Fig. 11, which implies the inability to detect the failure with this method.

Based on the analysis of vibrations in the frequency domain developed it is observed that the difference in the amplitude

TABLE 1. Models accuracy.

Model	Accuracy
Kernel Naive Bayes	94.4%
Fine Tree	100%
Coarse Gaussian SVM	77.78%
Fine KNN	100%
Coarse KNN	44.4%

TABLE 2. Comparison of the computation time.

Model	Train(s)	Predict (s)	Total (s)
Kernel Naive Bayes	34.20	0.24	34.44
Fine Tree	21.04	0.14	21.18
Coarse Gaussian SVM	36.23	0.26	36.49
Fine KNN	12.14	0.12	12.26
Coarse KNN	22.01	0.24	22.25

shown by the BPFI signal spectrum is more significant than that of the BPFO signal spectrum for a bearing with a defect on the outer track. In the case of a defect-free bearing, there is no appreciable difference, and the amplitudes are reduced.

Therefore, as a first approximation, the amplitude is selected as a candidate and thus obtains the necessary features to include in the various ML algorithms; for this purpose, the CWRU data set is processed and the amplitudes of the envelope signal spectrum in BPFI and BPFO are calculated for each of the data sets available in CWRU.

V. EXPERIMENT

The experiment mainly consisted of applying vibration analysis in the frequency domain, specifically Envelope Analysis, Hilbert Transform, and Fast Kurtogram. Based on the results obtained, the amplitudes for the characteristic frequencies of defects (BPFI, BPFO) on the inner and outer track are calculated. These amplitudes will be the features to be applied in the ML algorithms.

The resulting data will have three features: AmplitudeBPFO, AmplitudeBPFI and DataSet.

AmplitudeBPFO and AmplitudeBPFI will be the predictors, and DataSet indicates which CWRU data set the information was obtained from to perform the amplitude calculations. The defect will be the classification target, each observation can be labelled with one of three classes: Normal (defect-free bearing), Outer Track (defect on the outer track), or Inner Track (defect on the inner track).

Once the data set has been processed to classify the defects of the bearings on the inner and outer track, the number of observations is reduced to 81, of which 63 have been used for training and 37 for validation. Cross-validation with 5 partitions has been used to avoid overfitting. The performance evaluation of the model, that is, the classification, is performed through confusion matrices [47]. The tool used in the experiment was MATLAB R2021B Update 3 (9.11.0.1873467) and the ML and DL Classification Learner app. Next, the results obtained with the different models and the achieved precisions are shown in Table 1.

TABLE 3. Comparison of the accuracy and performance with previous studies.

Reference	Model/Algorithm	Dataset	Accuracy	Performance
[48]	RestNet50	Case Western Reserve University (CWRU) bearing	99.97%	*
[22]	CNN	Case Western Reserve University (CWRU) bearing	99.74%	**
[16]	1D_LBP+GRA	Created by the author	100%	****
[49]	GoolLeNet	Case Western Reserve University (CWRU) bearing	97.60%	*
To this article	Fine KNN	Case Western Reserve University (CWRU) bearing	100%	****

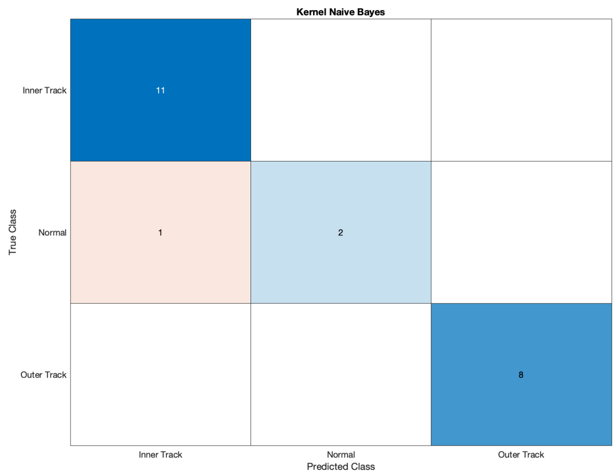

FIGURE 12. Confusion matrix of kernel naive bayes.

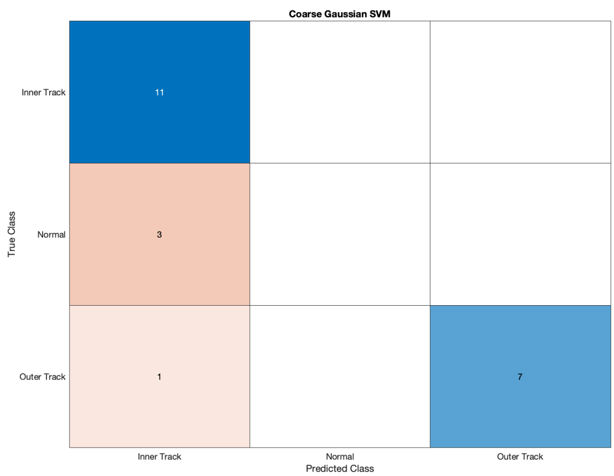

FIGURE 13. Confusion matrix of coarse gaussian SVM.

Table 2 displays the computational times for training and prediction across different models. The observation reveals that Fine KNN exhibits the best performance when utilizing the amplitude of the envelope as the predictor. This choice is particularly significant as it aligns with the characteristic frequency of the fault.

In addition, Fig. 12, 13 and 14 show the different confusion matrices of the models that have not achieved 100% precision.

A. MOTIVATION

This work aims to detect faults in bearings by selecting the minimum number of features with a minimal set of observations. It starts with the hypothesis of using simple models and architectures of Artificial Intelligence, so classic machine learning algorithms that align with this initial idea are chosen. The goal is to minimize computation time and maximize fault classification accuracy.

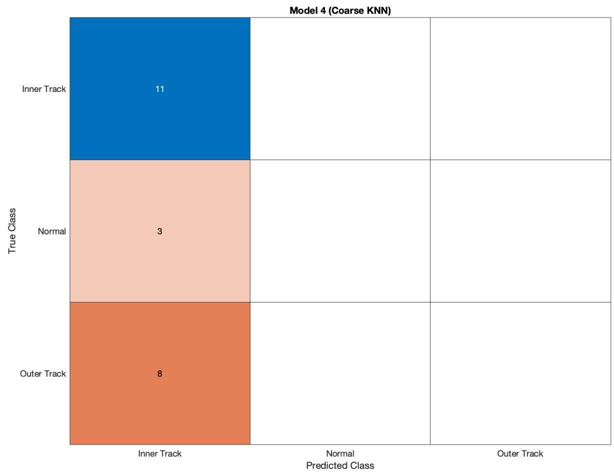

FIGURE 14. Confusion matrix of coarse KNN.

B. COMPARISON OF AI ALGORITHM PERFORMANCE AND ACCURACY

Table 3 presents a systematic comparison of the classification accuracy and performance of various ML algorithms using the Case Western Reserve University (CWRU) bearing dataset. It is evident that the DL-based models exhibit slightly lower performance, despite having comparable accuracy. It should be noted that DL-based models have the need for large volumes of data [13].

VI. CONCLUSION

Based on the initial hypothesis of minimizing the number of observations and characteristics and utilizing vibration analysis with classical ML methods featuring a simple architecture, the following conclusions have been reached.

On the one hand, vibration analysis in the frequency domain, specifically using envelope analysis, has proven to be an optimal technique for detecting bearing faults. Furthermore, incorporating the optimal bandwidth obtained from the curtogram enhances the accuracy of the results. However, it is important to note that ball defects pose an exception as they cannot be effectively characterized using this method.

On the other hand, when the outcomes of envelope analysis are applied to different ML models with calculated amplitudes as predictors, the Decision Tree (Fine Tree) and KNN (Fine KNN) models achieve a remarkable accuracy of 100% with high performance.

Future work will involve applying these models to a dataset obtained through an Internet of Things (IoT) prototype and simulating failures on good bearing data for real-time prediction. Additionally, efforts will be directed towards exploring more efficient methods for detecting ball defects.

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