Machine Learning-based Predictive Maintenance for Fault Detection in Rotating Machinery: A Case Study

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ABSTRACT

In the realm of industrial production, condition monitoring plays a pivotal role in ensuring the reliability and longevity of rotating machinery. Since most of the production facilities rely heavily on vibration analysis, it has become the cornerstone of condition monitoring practices. However, manual analysis of vibration signals is a time-consuming and expertise-intensive task, often requiring specialized domain knowledge. The current research addresses the aforementioned challenges by proposing a novel semi-automated diagnostics system. The approach leverages historical vibration data in the form of Fast Fourier Transform (FFT) spectrums. The system extracts energy features from the frequency domain by dividing the frequency range into a predefined number of bins and summing the energy values within each bin. Subsequently, each datapoint is labeled based on the corresponding machine condition, enabling the system to learn diagnostic patterns by employing machine learning models. This approach facilitates efficient and accurate diagnostics with minimal manual intervention. The resulting dataset effectively represents and provides an interpretable result. Support Vector Machines (SVM), and ensemble algorithms are utilized to diagnose the faults instantaneously and with minimal error rates. The proposed system is capable of providing early warnings and thus prevents further deterioration and unplanned downtimes. Experimental validation using real-world data demonstrates the system's efficacy, achieving an accuracy of over 90%.

Keywords-condition monitoring; predictive maintenance; FFT; SVM; ensemble

I. INTRODUCTION

Industry 4.0 is characterized by the integration of advanced technologies, such as artificial intelligence, Machine Learning (ML), and Internet of Things (IoT) into industrial processes and maintenance. Maintenance technologies have evolved considerably to address the challenge of machine reliability. This integration allows for the collection and analysis of large amounts of data from machines, which can be used to optimize maintenance activities and improve the reliability and availability of machinery. Besides that, vibration signals and their analysis have become an integral part of every industrial plant worldwide, and ML techniques, either classical [1-3] or deep learning [4-6] models have been employed extensively for fault detection using these signals. The vibration signals from rotating equipment can be gathered easily during operation, reflecting their operating conditions in real-time, thus, current trends in machinery fault diagnostics mainly rely on vibration signal analysis [7].

Most of the vibration signals are of non-linear nature. This characteristic of the machinery vibration signals is mainly due to the changing states of loading, interaction between parts, and loading variations. For this purpose, many works in the field of condition monitoring, justify the wide use of entropy as a measure for signal complexity and feature engineering. Therefore, the use of different entropy methods (i.e approximate, multiscale, and sample entropies) has been widely associated with vibration signal analysis and machinery fault diagnostics [8], even though many works in this field do not require the use of entropy for feature engineering. For instance, authors in [9] developed an automatic feature learning neural network eliminating the need for a conventional feature development step. This network achieved high accuracy.

Authors in [10] proposed a novel deep learning algorithm utilizing the power of Recurrent Neural Networks (RNNs) combining Bidirectional Long-Short-Term Memory (BiLSTM) and Support Vector Machines (SVMs). Additionally, authors in [11] utilized BiLSTM models with autoencoders. The proposed hybrid model for wind turbine gearbox fault detection and diagnosis exhibited higher accuracy than conventional models. SVM, as a versatile supervised learning algorithm excels in both classification and regression tasks [12-13] and is well-suited for classification problems involving small datasets [14]. In addition to linear classification, nonlinear classifications are also possible, by fine tuning the hyper parameters, and the kernel type [15-16]. Authors in [17] introduced a vibration signal dataset acquired from a laboratory testing rig. Three ML algorithms, namely k-Nearest Neighbors (kNN), SVM, and Gaussian Naive Bayes (GNB) achieved an overall accuracy of 99.75% on fivefold cross-validation using SVM. Authors in [18] developed an innovative fault diagnosis system for rolling bearings defects, powered by SVMs and Bayesian optimization. Discrete Fourier Transform (DFT) was used for feature extraction in both time and frequency domains. The work demonstrated a significant improvement from 85% to 100% accuracy compared with the base SVM model.

Further research explored other approaches to fault diagnosis using ML. Authors in [19] proposed a high-accurate early fault diagnosis method based on the Reinforcement Learning (RL) optimized SVM model. Authors in [20] developed a test rig to collect vibration signals under different bearing conditions, utilizing a Quadratic SVM model, achieving high accuracy in fault diagnosis. Authors in [21] utilized a combination of Principal Component Analysis (PCA) and SVM for fault diagnosis. The method demonstrated high accuracy in fault diagnosis under varying operating speeds. Authors in [22] proposed a fault identification method that combines variational mode decomposition, average refined composite multiscale dispersion entropy, and an SVM model optimized by Multi-strategy Enhanced Swarm Optimization achieving high classification accuracy. Authors in [23] described the development of a ML pipeline using SVMs for diagnosing bearing faults. The SVM classifier achieved an overall accuracy of 91%-99% and F1-score of 0.81-0.99. Other researchers utilized Wavelet Packet Transform (WPT), Empirical Mode Decomposition (EMD), and Variational Mode Decomposition (VMD) hybrid methods [24-26]. They were proven to be effective for fault diagnosis, achieving superior classification accuracies.

Continuing the above directions, ensemble learning has emerged as a prominent tool for classification problems, offering a robust and effective approach to enhancing predictive performance, and is poised to play an increasingly vital role in addressing real-world prediction tasks [27-29]. Authors in [30] presented an innovative diagnosis model using Complementary Ensemble Empirical Mode Decomposition (CEEMD) with SVM kernel to evaluate the health condition of bearings. This method has a high prediction accuracy and is easy to implement. Authors in [31] utilized the Multi-Scale Sample Entropy-based Energy Moment (M-SSampEn-EM) method and proposed an innovative approximate distance-based metric to optimize the feature extraction parameters. Authors in [32] adopted an EMD method to extract features from denoised signals and classify them using multiple classifiers. The best results were achieved with a hybrid of time and spectral features using SVM with a Gaussian kernel.

To develop an interpretable dataset, for fault detection in rotating machinery, the first step is to extract the energy from each frequency band, through FFT transformation of the raw time waveform signal. The FFT has emerged as a widely used and indispensable tool in signal processing. By employing this transformation, signals can be effectively transformed to the frequency domain. Several algorithms have been developed to efficiently calculate the FFT, paving the way for the implementation of high-performance FFT processors. The Fourier transform essentially converts a signal's representation from the time domain to the frequency domain [33-35]:

$$X(f) = F\{X(t)\} = \int_{-\infty}^{\infty} X(t)e^{-j2\pi ft}dt \quad (1)$$

where $X(t)$ is the time domain signal, $X(f)$ is the FFT, and ft is the frequency to be analyzed.

To measure the size or strength of a signal, signal energy as a concept in signal processing is used. If $(|x(t)|)$ is a continuous-time signal, its energy is given by (2) and if it is a discrete-time signal, it is given by (3) [36-37]:

$$E(x) = \int_{-\infty}^{\infty} |x(t)|^2 dt \quad (2)$$

$$E_x^{time} = \sum_{n=-\infty}^{\infty} |x[n]|^2 \quad (3)$$

Signal energy can also be computed in the frequency domain, using the Fourier transform of the signal. The total energy of the signal is equal to the integral of the spectral energy density over all frequencies. This is a consequence of Parseval's theorem [37], which states that:

$$\int_{-\infty}^{\infty} |x(t)|^2 \, dt = \frac{1}{2\pi} \int_{-\infty}^{\infty} |X(f)|^2 df \quad (4)$$

where $(|X(f)|)$ is the Fourier transform of $(|x(t)|)$.

In order to calculate the cumulative energy of each individual bin, (5) [26] is used where $X(f)$ is the frequency domain signal, M denotes the number of frequency bins, each with width Δf, and the frequency range for the i^{th} bin is $[f_i \, , f_i + \Delta f]$:

$$\{E_1, E_2, \ldots, E_M\} \quad (5)$$

To this end, the primary objective of this research work is to critically assess the practicality of incorporating ML methodologies as a diagnostic instrument within industrial environments. Also, its innovative aspect is underscored by the application of traditional ML algorithms to pre-existing historical data taken from a real-world industrial context as a case study, involving machinery that operates under severe conditions, exposed to both gradual and abrupt degradation of components. The process involves converting raw vibration waveform signal with FFT, then extracting the energies from the different frequency bands, creating a dataset that is fed into an ensemble model with SVC as the base estimator. The resulting model can classify various faults with high efficacy across various performance metrics including accuracy, precision, and F1-score.

II. METHODOLOGY

A. The Proposed Model

The proposed model for predictive maintenance comprises three key components: machine identification, data acquisition, and automated diagnosis. The system outputs one of the four predicted conditions: normal operation, unbalance, bearing defect, or a combined case of unbalance and bearing defect. This system is scalable to a wide range of similar machinery due to its reliance on dividing the FFT spectrum into frequency bins and measuring the cumulative energy in each bin. This approach offers interpretable results that are readily applicable in real-world scenarios. Figure 1 presents an overview of the proposed automated diagnosis system. The system consists of three primary components:

1. Rotating machinery: The selected rotating machinery in this study is an Induction Draft (ID) fan.
2. Vibration signal acquisition device and analysis system: This component collects the time-domain vibration signal from the rotating machinery and converts it into its FFT representation.
3. Automated diagnostic part: This component receives the FFT spectrum and extracts energy features by summing the energy values within pre-defined bins across the frequency domain. Each data point is labeled according to the corresponding machine condition.

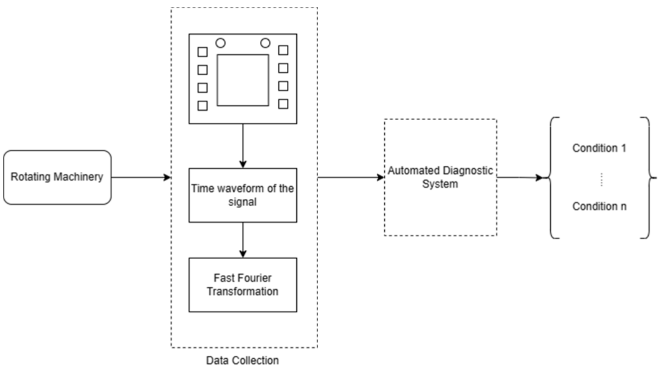

Fig. 1. Overview of the automated diagnosis system.

Subsequently, the extracted features are fed into an ML model with parameters optimized through cross-validation process. The model's output provides a textual classification, identifying one of the four predefined conditions. Figure 2 illustrates the internal workings of the automated diagnostic component. It depicts the flow of data through the component, from the input of the FFT spectrum to the final textual classification of the machine condition.

The combined use of vibration signal analysis and ML offers a promising approach for automated diagnostics of rotating machinery. This system provides potential advantages, such as improved accuracy, reduced reliance on human expertise, and increased efficiency in condition monitoring and fault detection.

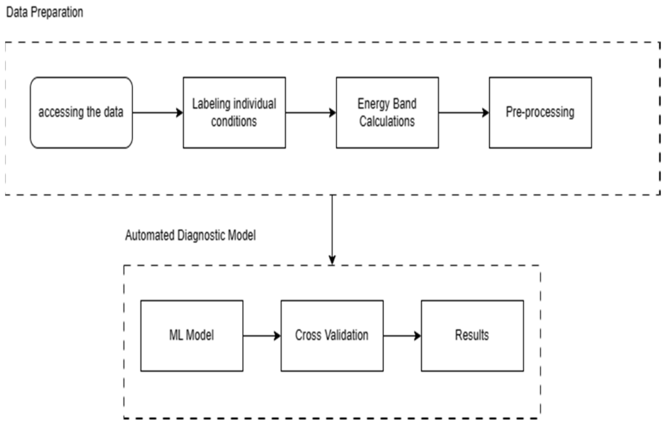

Fig. 2. Flow chart of the automated diagnostic system.

Rolling Contact Fatigue (RCF) [38-39] is a detrimental wear process that occurs in rolling bearings, characterized by the gradual deterioration of the bearing surface due to repeated rolling contact stresses. This progressive wear process can be broadly divided into five distinct stages, each marked by unique surface topology changes and accompanied by specific physical measurements. Elevated stresses in rolling contact arising from increased operating loads, faults like imbalance, misalignment, bent shaft, looseness, or distributed defects such as high surface roughness and waviness, contaminations, and inclusions, may induce topological alterations. The progression of RCF can be significantly accelerated by the presence of the above-mentioned faults within the rotating machinery. These faults introduce additional dynamic forces and stress concentrations, exacerbating the wear process and potentially shortening the bearing's lifespan as shown in Figure 3.

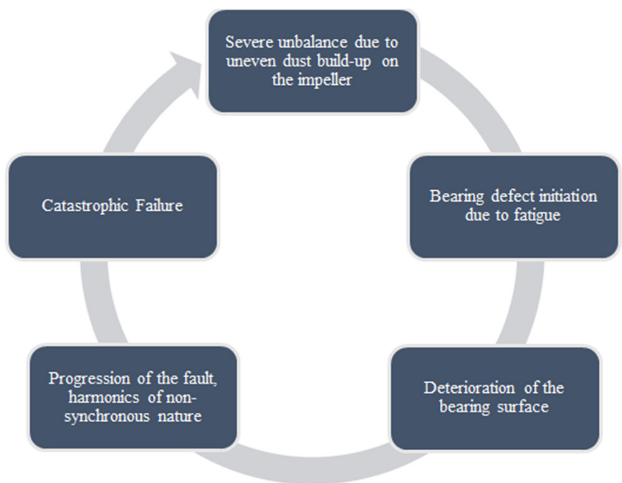

Fig. 3. Cycle of bearing failure pattern of the induction draft fan.

Rolling element bearings exhibit distinct vibrational signatures that serve as indicators of the degradation stage. These signatures arise from the interaction of rolling elements with fatigue-induced defects on bearing surfaces, generating periodic impulses known as "fundamental defect frequencies".

These frequencies are influenced by the bearing's geometrical configuration and the rotational speed of the shaft resulting in frequencies that lie within the high-frequency range of the vibration spectrum. These defect frequencies were categorized to: Ball Pass (BP) frequencies, Ball Pass Outer Race Frequency (BPFO), Ball Pass Inner Race Frequency (BPFI), Ball Spin Frequency (BSF), and Fundamental Train Frequency (FTF) as in (6-9), which are defined by:

$$\mathrm{BPFO} = \frac{n f_r}{2}\left\{1 - \frac{d}{D}\cos\phi\right\} \tag{6}$$

$$\mathrm{BPFI} = \frac{n f_r}{2}\left\{1 + \frac{d}{D}\cos\phi\right\} \tag{7}$$

$$\mathrm{FTF} = \frac{f_r}{2}\left\{1 - \frac{d}{D}\cos\phi\right\} \tag{8}$$

$$\mathrm{BSF} = \frac{D}{2d}\left\{1 - \left(\frac{d}{D}\cos\phi\right)^2\right\} \tag{9}$$

B. Real World Dataset

Vibration signal data are acquired with an Emerson CSI 2140 data collector equipped with a 100 mV/g accelerometer. The data are collected from an ID centrifugal fan in the pyro-processing area of the local cement manufacturing facility at XYZ Company. The fan is driven by a 1600 kW medium voltage drive connected by a coupling to a shaft hanging an impeller centrally between two bearings. The rotating parts of the equipment are subjected to high-magnitude forces due to structural loads, multi-axis dynamic loads acting during operation, and rotational inertia. Rotating element bearings, including two spherical roller bearings of types SKF 22244, and SKF C2244, are mounted on the fan's shaft. The weight of the whole shaft along with the impeller exceeds 10,000 kg, exerting very high loads on these bearings, rendering them as the most critical components of the fan.

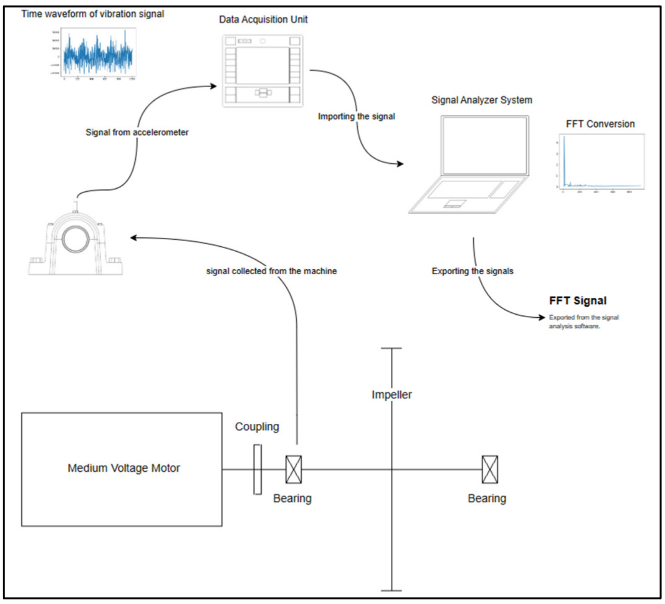

Fig. 4. The data acquisition process.

The signal is collected from three directions (horizontal, vertical, and axial) by placing a uniaxial accelerometer attached to a data collection unit. The vibration signal is collected in the form of a time waveform, and then exported to the signal analyzer software. The signals are analyzed either by using the raw time waveform signals or by converting them digitally and displaying the signal in FFT form. This study exclusively employed the frequency-domain representation, extracting peak amplitudes and their corresponding frequencies as well as orders from the FFT spectra provided by the software. Figure 4 visually depicts the complete workflow of signal acquisition and subsequent data extraction.

III. RESULTS AND DISCUSSION

This section outlines the implementation process of the proposed model for early fault prediction, encompassing data labeling, dataset summarization, condition representation analysis, ML model evaluation, and accuracy assessment.

A. Labeling

Data labeling is a crucial step in the development of ML models, as it involves annotating raw data with meaningful labels that enable the model to learn patterns and make predictions. The historical dataset from 2016 to 2023 falls mainly into four major conditions, as shown in Figure 5.

B. Unbalanced Rotor

Unbalanced rotor is a prevalent type of machinery fault observed in rotating systems. The fault arises from an uneven distribution of mass within a rotating component about its axis of rotation. The resulting unbalanced force acts radially and increases with the square of the shaft's rotational speed [40]. The unbalanced force introduces additional fatigue stress on the bearings, potentially leading to premature failure of both bearings and rotating shafts as shown in Figure 6.

C. Results of Bearing Faults

In the case of the existence of bearing faults, the forcing frequencies show up as a multiple of the rotating speed in the frequency domain as per Table I (SKF- bearing properties).

TABLE I. FREQUENCIES FOR THE ID FAN BEARINGS (HZ)

Designation	Rotational frequency				Over- rolling frequency		
	Inner race	Outer race	Rolling element set and cage	Rolling element about its axis	Inner race	Rolling element set and cage	Outer race
C2244	1	0	0.418	2.978	9.308	6.692	5.955
22244 CC/W33	0	0	0.431	3.484	10.817	8.183	6.968

Figure 7 displays an example of an outer race defect harmonics in the spectrum. The number of harmonics along with their corresponding amplitudes are indicative of the severity of the fault. The Figure indicates the existence of a defect on the outer race of the bearing. Since this work focuses on supervised ML, it is imperative to label every data point as per its corresponding condition by individually analyzing every data point acquired from the industrial facility, and combining them with the historical database on Computerized Maintenance Management Systems (CMMS). The aim of this procedure is to correlate the dates of repairs, and emergency repairs to the condition of the machine, to further verify the correctness of the labels used.

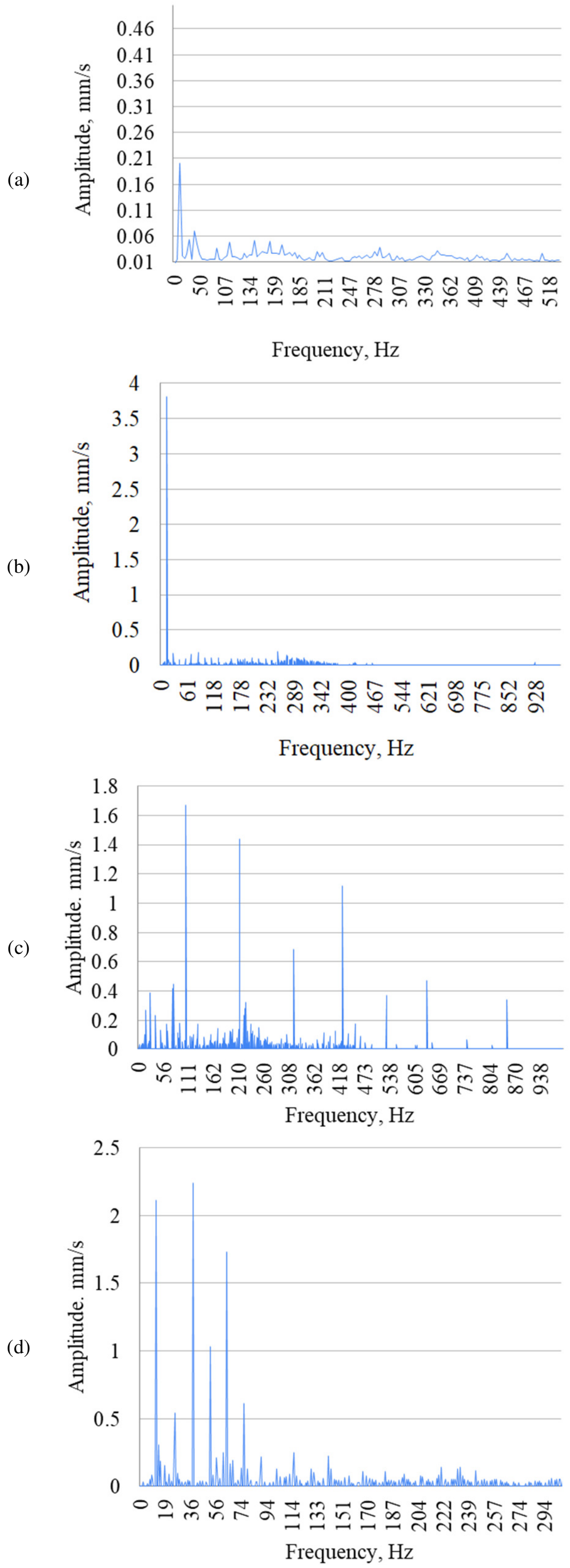

Fig. 5. Different machinery conditions. (a) Normal, (b) unbalanced, (c) bearing defect, (d) combined effect of unbalanced and bearing defect.

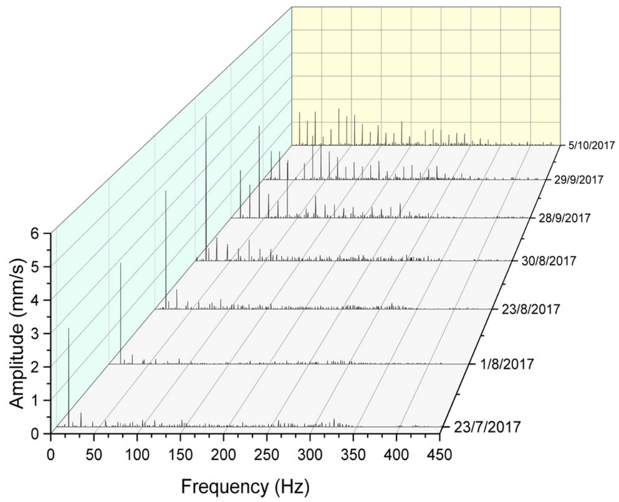

Fig. 6. Illustration of the bearing defect progression due to severe unbalance.

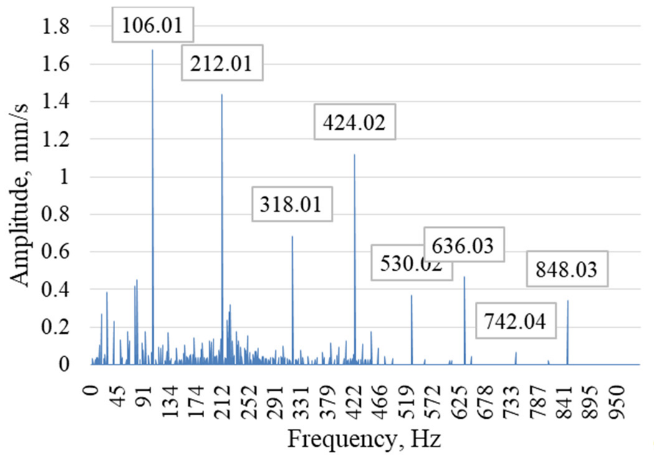

Fig. 7. FFT spectrum with 8x non-synchronous harmonics of BPFO of C2244 bearing.

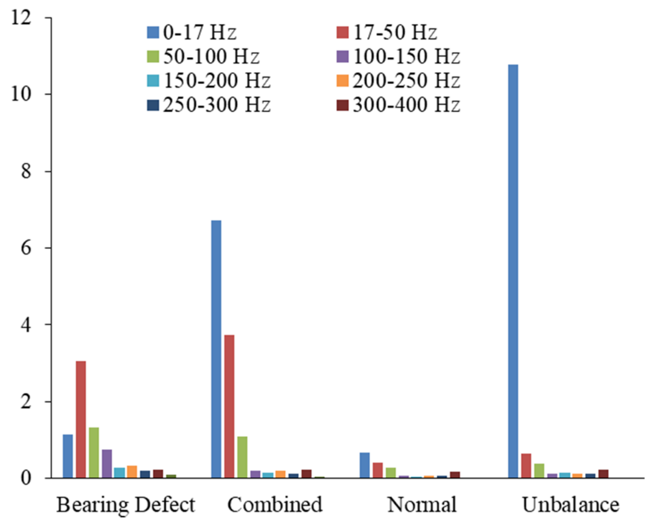

Fig. 8. Energy bands corresponding with the condition of the machinery.

The final dataset represents these cases by their energy bands. The division and width of each energy band are intrinsic to the type of fault it corresponds to. For example in pure unbalance case the band from 0-17 Hz shows the highest of the rest of the energy bands, thus indicating the unbalance case. Figure 8 summarizes energy bands of each case.

The resulting dataset labels are portrayed in Figure 9. Evidently, the dataset was unbalanced, it caused unpredictability to the model, and relies mainly on the randomness of the label distribution, to offset the effect of this unbalance. The dataset was resampled to 40 counts of each case (except the combined case), hence, overcoming the reliance on the randomness of the train/test sample distribution.

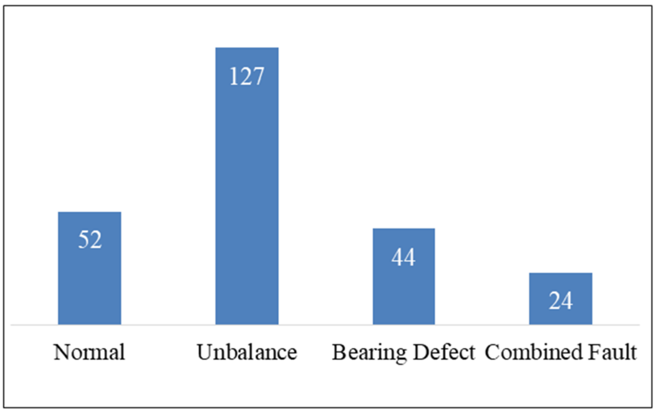

Fig. 9. The distribution of the labels in the dataset.

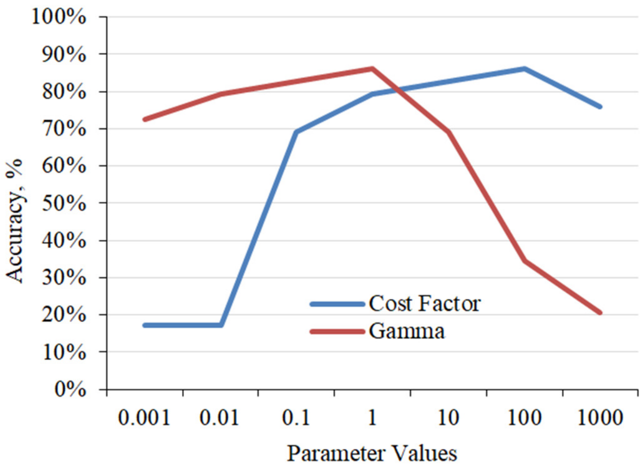

Fig. 10. SVC parameter values.

TABLE II. PERFORMANCE METRICS VALUES

Metric	SVC	Adaboost classifier	Bagging classifier	Multi-Layer Perception (MLP) classifier
Accuracy	86.21%	86.21%	89.66%	93.10%
Precision	89.22%	93.53%	92.67%	94.40%
F1 Score	86.90%	88.78%	90.43%	93.24%

Utilization of ensemble models has a very significant impact on improving the performance metrics of an SVM model significantly across all metrics. As illustrated in Table II, the base model is SVC's accuracy after cross-validation of the parameters, which only reached 86.2% with parameter values C=100, Gamma=0.1, Kernel= Radial Base Function being chosen as optimal (Figure 10). The hyper-parameters for the models are shown in Table III. The SVC parameters, which are used as base estimator for the different ensemble models employed, were fixed across different ensemble algorithms. Figure 11 illustrates the results of experimenting with different numbers of estimators and their corresponding effect on the performance metrics. The findings show no significant difference when the number of estimators increased from 500 to 1000, justifying the choice of 500 estimators.

TABLE III. OPTIMIZED HYPER-PARAMETERS OF THE VARIOUS CLASSIFICATION MODELS

Model	Hyper parameters
SVC	(gamma=1, C=100, random_state = 42, kernel='rbf', probability=True)
Bagging	(base_estimator=svm, n_estimators=500, random_state=314)
Adaboost	(base_estimator=svm, n_estimators=500, learning_rate=0.0002, algorithm='SAMME.R')
MLP	(hidden_layer_sizes = (5000,), max_iter=3500, final_estimator =svm)

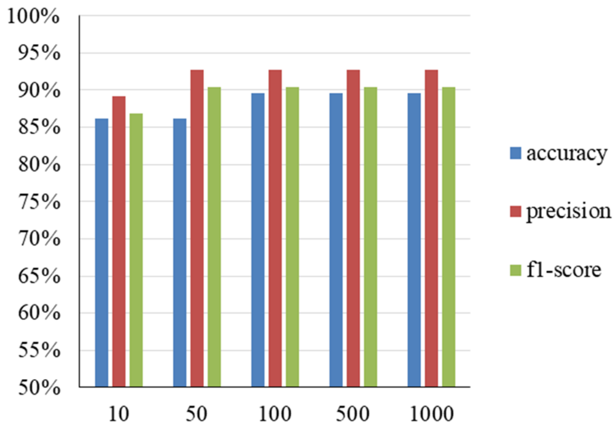

Fig. 11. Changes in performance metrics under varying number of estimators for Bagging ensemble classifier.

The same experiment was carried out on the MLP classifier. In that case, instead of the number of estimators, the experiment was conducted on varying the number of neurons in the ANN layer, and then examined the performance metrics for improvements. The results did not improve when the number of neurons increased from 500 to 5000 as depicted in Figure 12, and the number of iterations required for convergence decreased from 3500 for 10 and 50 neurons to 1500 iterations for 100 neurons and above, decreasing the computation time for the model to train.

The MLP classifier, an ensemble of SVC and ANN with two hidden layers of 500 neurons reached an accuracy of 93.1% and was most capable of recognizing the different conditions with ease and high precision, as shown in Figure 13. The numbers 0, 1, 2, and 3 denote the conditions normal, unbalanced, bearing defect, and combined, respectively.

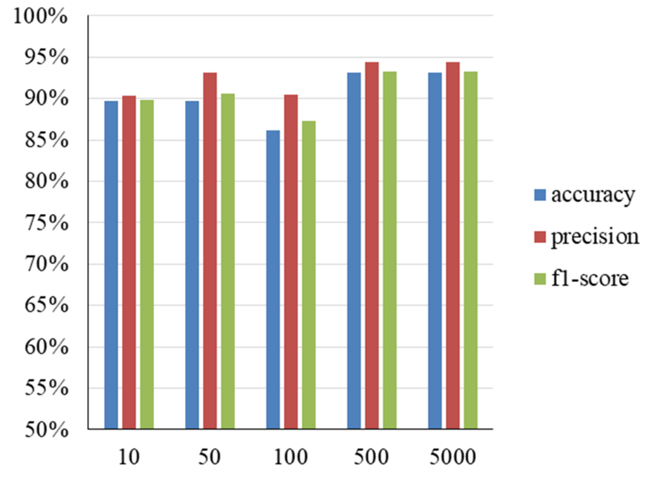

Fig. 12. Effect of the number of neurons on the performance metrics for MLP classifier.

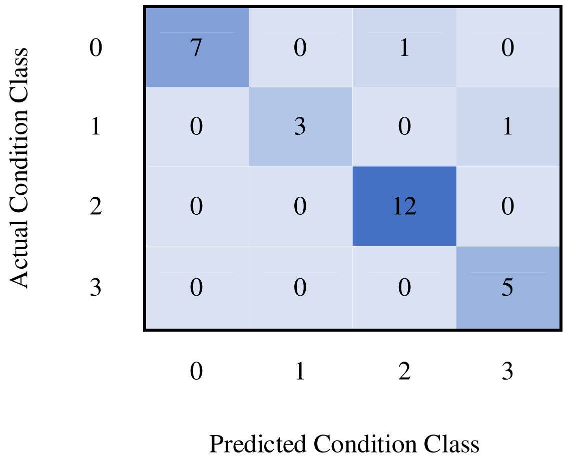

Fig. 13. Confusion matrix of stacking algorithm (SVC, ANN).

The first misclassified condition is a combined condition, whereas the model predicted an unbalance case, after examining the FFT spectrum, shown in Figure 14. However, instead of having multiple bearing defects harmonics, the existing harmonics were more sporadic and spaced out leading to misclassification.

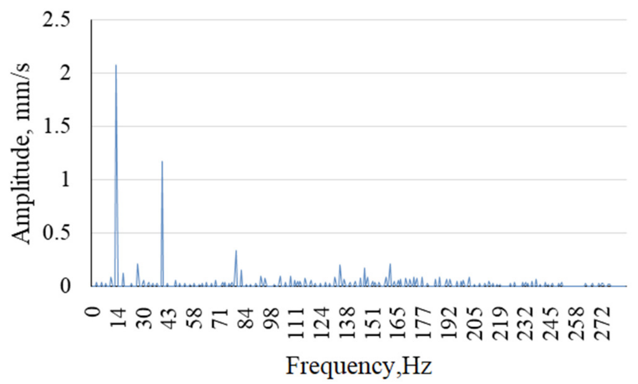

Fig. 14. FFT spectrum of the misclassified condition.

The second misclassified condition is an unbalance condition at 1x peak of 0.7 mm/s amplitude, coupled with high noise floor as displayed in Figure 15.

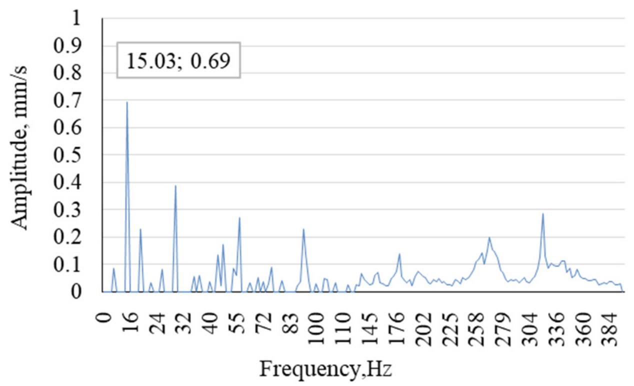

Fig. 15. Existence of 1x peak and high noise floor.

The above experiments can be seen as a feasibility study for integrating ML into an already functional system to improve quality and reduce the time taken for fault diagnosis. Thus, it is a stride towards automating fault detection and streamlining the usage of ML into local production facilities, by experimenting with the already existing data. Table IV portrays a comparison between the current work and other research works in this field.

TABLE IV. COMPARISON BETWEEN CURRENT AND RECENT WORKS

Ref.	Method	Accuracy
[17]	SVM (using test rig.)	99.97%
[22]	VMD-ARCMDELCPGWO-SVM (using test rig)	97.14%
[20]	SVM (using test rig)	97%
Current	SVM (using real-world data)	93.24%

The use of test rig data is widely employed in the field, (Table IV), and numerous datasets have been developed for this purpose, having a specified max frequency and sampling rates, as well as yielding less noisier data. The real-world dataset, however, faces several obstacles, including the non-public nature of the vibration signal data collection system, an insufficient quantity of data points, and non-standard data collection protocols (non-uniform maximum frequency limit and sampling rates). Despite those drawbacks, the findings are promising, indicating that the proposed methodology is a practicable and effective solution for automated machinery fault detection in industrial environments. Additionally, the model can effortlessly integrate with current systems without incurring additional financial costs. Besides, the findings demonstrate that the proposed model, employing a stacking ensemble of MLP classifier and SVC coupled with ANN, achieved an accuracy of 93% in identifying machinery faults, surpassing the baseline SVC model, which achieved an accuracy of 86%. It is evident that the findings are significant and showcase the potential of ML to automate machinery fault detection in cement plants.

The novelty of this work lies in its interpretability, and ease of use. As shown in the dataset, the energies from each band can be associated with a specific case and can be used as a platform for further modifications to fit certain configurations of machinery as well as the fault types, based on the intervals of the frequency bands. This has the potential to revolutionize the way that cement plants (as an example) maintain their equipment, leading to broader adoption of ML techniques leveraging historical data to help improve production efficiency, reduce costs, and extend the equipment lifespan of the machinery.

IV. CONCLUSION

The current work assessed the feasibility of incorporating/integrating an automated fault diagnostic system upon the already existing manual condition monitoring layer, without additional costs. Once the failure pattern of the machine is understood, it is relatively easy to recognize when the fault is initiated and act ahead for a planned shutdown and replacement. In most cases, the bearings did not reach their normal end of life but were rather affected by the severely unbalanced rotor, exerting extreme loads on the bearings, leading to the initiation and development of cracks and spalling on the races of the bearing that eventually end with catastrophic failures.

The usage of machine learning algorithms was justified, as it can be scaled to encompass all similar equipment and be employed simultaneously across different devices at once, with minimal input from the domain expert. The dataset used contained varying conditions, however, there was a focus on the ones that contributed most to the failure of the equipment and excluded rare events. The most repeated conditions were normal, unbalanced, bearing defect, and a combination of the faulty states of unbalance and bearing defect. The performance across different traditional machine learning models shows a promising result, especially when a combination of more than one method was used, showing significant improvement from using standard SVC to a more accurate ensemble method yielding a change in accuracy from 86% to 93%.

As a future direction, the proposed model can be developed in several ways, including expanding the number of data points to improve the model's accuracy and robustness and developing an online real-time system.

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