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Development Of Ml Model For Rotating Machinery

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Abstract :
This paper explores using machine learning to spot faults in bearings of rotating machinery. By studying data gathered from LabVIEW, the aim is to find the most effective ML techniques to find whether a bearing is faulty and what kind of fault it has. This research can help to improve maintenance and reliability in industries relying on rotating machinery. This project focuses on using advanced machine learning and Fast Fourier Transform (FFT) analysis to detect faults in bearings before the machine failure. By analyzing vibration data, transformed it into frequency components, allows to identify potential faults. The training of machine learning models is to distinguish between healthy and faulty conditions. The goal is to enhance predictive maintenance, reduce downtime, and improve safety across various industries. The project not only advances bearing fault detection but also sets a new standard for using machine learning in predictive maintenance.

Keywords: *Fast Fourier Transform, LABVIEW, data acquisition, feature extraction, Linear regression, decision tree*

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I. Introduction

In this research paper, the focus is on addressing a critical challenge in industrial machinery: the timely detection of bearing faults to prevent costly downtime and ensure operational efficiency. Bearings, essential components in rotating machinery, are prone to wear and deterioration over time, leading to potential failures if not detected early. Traditionally, manual inspections or periodic maintenance routines have been employed to identify bearing faults. However, these methods are labor-intensive, time-consuming, and often fail to detect subtle early warning signs. To overcome these limitations, advanced technologies can be used, specifically machine learning and signal processing techniques, to automate the fault detection process. In this study, vibration signals are leveraged, which provide valuable insights into the health and condition of bearings. By analyzing these signals using sophisticated algorithms, the aim is to develop a robust and accurate model capable of distinguishing between healthy and faulty bearings. This model holds the promise of revolutionizing maintenance practices by enabling proactive, data- driven decision-making. Through this research, the goal is to demonstrate the effectiveness of the proposed approach in improving equipment reliability, reducing maintenance costs, and enhancing overall operational efficiency in industrial settings. By combining domain expertise with cutting-edge technology, the aspiration is to contribute to the advancement of predictive maintenance strategies and drive innovation in the field of condition monitoring. Randall, R. B. and Antoni, J's [1] paper focuses on advanced signal processing techniques for bearing fault diagnosis and their research highlights the importance of signal processing in condition monitoring and predictive maintenance of machinery. McFadden and Smith's [2] paper explores the use of acoustic emission (AE)techniques for bearing fault detection. Rao and Wang's [3] paper investigates machine learning approaches for bearing fault classification. They explore various algorithms such as decision trees, support vector machines, and neural networks for classifying healthy and faulty bearings based on vibration data. The research demonstrates the potential of machine learning in automated fault diagnosis systems for industrial applications. Antoniou and Wang's [4] paper focuses on time-frequency analysis techniques for bearing fault diagnosis. The research highlights the importance of advanced signal processing in fault diagnosis and condition monitoring. Chandra and Prasad's [5] paper explores wavelet-based feature extraction techniques for bearing fault detection. Sharma and Gupta's [6] paper explores predictive maintenance strategies for bearing health monitoring. They discuss the importance of proactive maintenance approaches in reducing downtime and optimizing equipment performance. The research highlights the role of bearing health monitoring systems in 4predicting impending failures and scheduling maintenance activities. Gupta and Sharma's [7] paper explores feature selection techniques for bearing fault diagnosis. They investigate methods for identifying the most relevant features from vibration data to improve the accuracy and efficiency of fault detection algorithms. The research demonstrates the importance of feature selection in enhancing the performance of bearing health monitoring systems.

The paper is organized as: In section 2, Experimental setup and components are explained. Section 3 discusses fault created by using Electrical discharge machining technique. Section 4 represents utilization of Fast Fourier Transform for signal processing. In section 5 signal acquisition is performed and dataset is obtained by extracting the features using supervised machine learning method. The last section concludes the paper.

II. Experimental Setup

The set up consists of motor, VFD, rotating shaft, bearing housing in a controlled laboratory environment. As shown in Fig 1 VFD is connected to motor and shaft is mounted on motor. At the other end of the shaft Housing of a bearing is mounted.

Fig 1: Experimental Setup

Components: Accelerometer sensor is used to capture the signals and which is connected to DAQ. DAQ converts analog signals to digital and the other end of DAQ is connected to LABVIEW Software in the PC which can able to generate the acceleration vs time graphs.

Fig 2 represents DAQ assistant and accelerometer.

Fig 2: DAQ Assistant and accelerometer

LABVIEW Software: LabVIEW (Laboratory Virtual Instrument Engineering Workbench) is a graphical programming platform. It is widely used for data acquisition, instrument control, and industrial automation. LabVIEW provides a visual programming language called G (Graphical Programming Language), where development of applications by connecting different function blocks, or "virtual instruments," on a graphical interface is done. Fig 3 below shows virtual interface of LABVIEW software, by constructing the block diagram two graphs are generated of amplitude vs. frequency and amplitude vs. time.

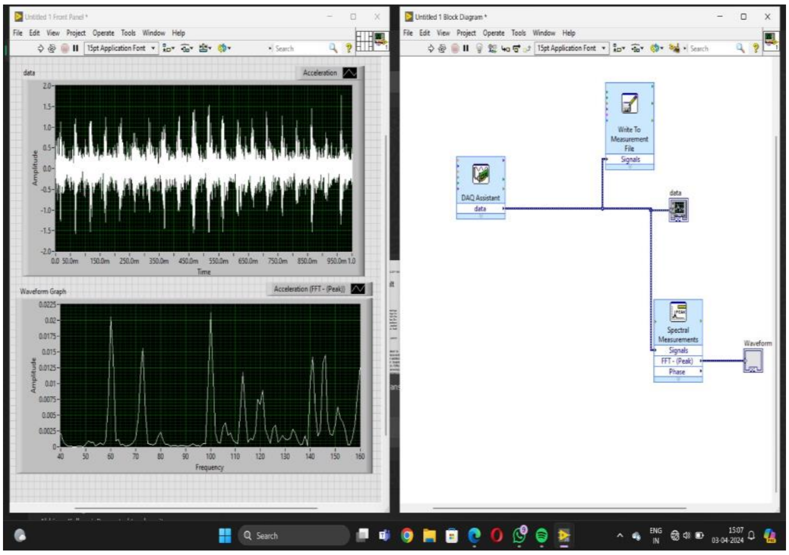

Fig 3: Interface of LABVIEW Software

III. Fault Creation

To simulate bearing faults, Electrical discharge machining technique is employed for creating the faults on bearings. Different types of faults like inner race, outer race with various diameters like 2mm,2.5mm were created as shown in Fig 4.

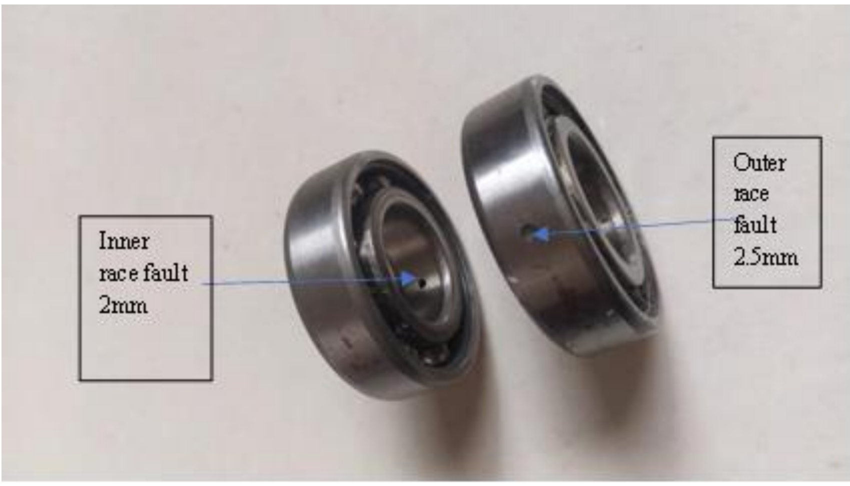

Fig 4: Faulty Bearings

IV. Fast Fourier Transform (FFT) For Signal Processing And Analysis In Bearing Fault Detection

The Fast Fourier Transform (FFT) is a powerful mathematical algorithm used to convert signals from the time domain to the frequency domain as shown in Fig 5. By decomposing a signal into its constituent frequencies, the FFT provides valuable insights into the underlying patterns and characteristics of the signal. In the context of bearing fault detection, the FFT allows to identify specific frequency components associated with fault-induced vibrations. In this study, the FFT method is applied to analyze vibration signals collected from bearings under various operating conditions. By performing FFT analysis on the raw vibration data, identification of frequency components corresponding to different fault types, such as outer race faults, inner race faults, and rolling element defects are done. The FFT results serve as the basis for feature extraction, where key frequency-domain features are derived to characterize the condition of the bearings.

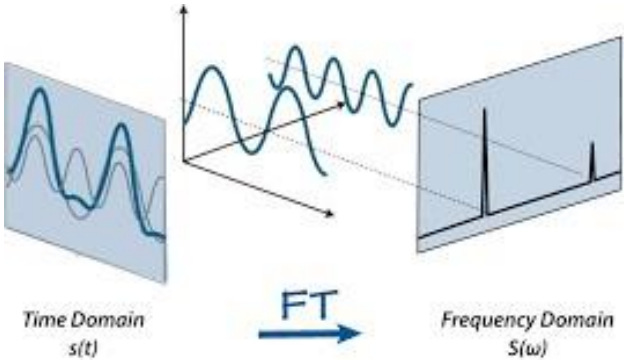

Fig 5: Vibrational Analysis of Signal using FFT

V. Signal Acquisition And Dataset Creation

Vibration signals are captured based on the outer race frequency factor, calculated as 0.06 times the shaft's rotational speed. Peaks in the amplitude vs. frequency graphs at these points are recorded and saved in Excel format. This process generates a dataset comprising acceleration data for healthy and faulty bearings. For example, the rotating speed of shaft is 1200RPM so Peak Factor will be 1200*0.06=72, here the peak is achieved at 72 and on its multiple as shown in graphs in Fig 6.

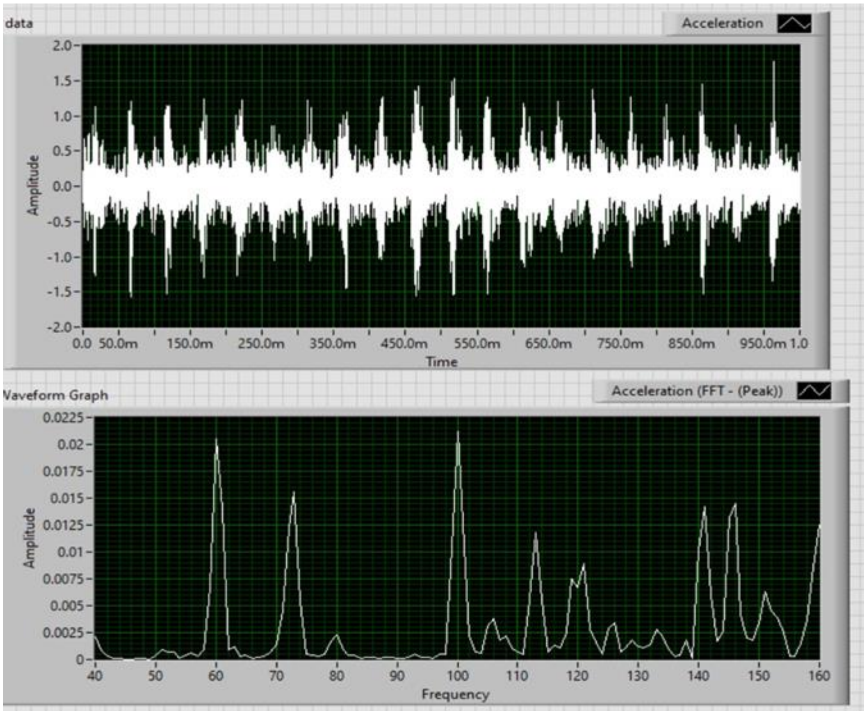

Fig 6: Time domain waveform and spectrum of defect free bearing vibration signal at 1200 rpm

Feature Extraction: Mathematical features are extracted from the vibration signals to characterize the health condition of bearings as shown in Fig 7. Key features such as mean, mode, median, standard deviation, skewness etc. are computed from the dataset to capture relevant information about the vibration patterns.

Actual Procedure : Requried signals are aquaired by using accelerometer sensor. Those signals are saved in excel in the form of accleration, by using data analysis tab in excel extracted all mathematical terms which are explained below.

Mean: The mean, often referred to as the average, is the sum of all values in a dataset divided by the total number of values. It provides a measure of central tendency and represents the typical value in a dataset.

1. Standard Error: The standard error measures the variability or uncertainty of the sample mean estimate. It quantifies how much the sample mean is likely to vary from the true population mean and is calculated as the standard deviation of the sample divided by the square root of the sample size.
2. Median: The median is the middle value in a sorted list of numbers. It divides the dataset into two equal halves,

with half of the values falling below and half above the median. The median is less sensitive to outliers than the mean and provides a robust measure of central tendency.

Sr. No	Mean	Standard_Error	Median	Mode	Standard_Deviation	Sample_Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	Condition
1	-0.00073	0.001686358	-0.00062	-0.03642	0.269817218	0.072801331	2.165362	0.100478	2.844474	-1.36207	1.482401	-18.6725	Healthy
2	-0.00123	0.001640256	-0.00056	-0.04538	0.262441002	0.068875279	3.349666	0.237567	3.100418	-1.3992	1.701214	-31.5096	Healthy
3	-0.00078	0.001578287	0.000732	-0.08467	0.252525855	0.063769308	2.57816	0.071195	3.002287	-1.34569	1.656592	-20.0217	Healthy
4	-0.00111	0.001512998	-0.00033	0.151267	0.242079637	0.058602551	3.856178	0.353462	3.052368	-1.3572	1.695169	-28.2976	Healthy
5	-0.00162	0.00159785	0.00061	0.049044	0.255655941	0.06535996	3.851383	0.236326	3.102553	-1.46491	1.63764	-41.4502	Healthy
6	-0.0008	0.001643116	-1.84E-05	0.128356	0.262898573	0.06911566	3.980674	0.330306	3.222271	-1.41745	1.804822	-20.6006	Healthy
7	-0.00109	0.001683062	0.001415	0.020862	0.269289941	0.072517072	3.773702	0.261724	3.090798	-1.36554	1.72526	-27.9949	Healthy
8	-0.0011	0.001650573	-0.00037	0.070424	0.264091721	0.069744437	4.015519	0.311767	3.308439	-1.39657	1.911865	-28.266	Healthy
9	-0.00053	0.00159881	0.004749	0.02182	0.2558096	0.065438552	3.844808	0.215897	3.100418	-1.40279	1.697627	-13.5803	Healthy
10	-0.00114	0.001650064	0.002815	0.003038	0.264010316	0.069701447	2.888116	0.163803	3.208735	-1.47192	1.736813	-29.07	Healthy
11	-0.00039	0.001640363	0.001369	-0.01593	0.262458103	0.068884256	2.811452	0.177874	3.178845	-1.44301	1.735837	-9.86574	Healthy
12	-0.00091	0.001649413	0.001616	0.082545	0.263906007	0.06964638	2.675541	0.163595	2.950766	-1.35465	1.596117	-23.2367	Healthy
13	-0.00073	0.00159479	0.000116	-0.066	0.255166351	0.065109867	3.354451	0.180804	3.064379	-1.3347	1.729676	-18.674	Healthy
14	-0.00126	0.001583707	0.000961	0.05615	0.253393175	0.064208101	2.890586	0.193927	2.978094	-1.36291	1.61518	-32.2487	Healthy
15	-0.00072	0.001529408	-0.00337	-0.0222	0.244705326	0.059880696	3.027528	0.237115	3.231024	-1.59187	1.639159	-18.5053	Healthy
16	-0.00096	0.001522379	0.000412	0.063501	0.24358067	0.059331543	2.689012	0.232665	2.964479	-1.25756	1.706917	-24.695	Healthy
17	-0.00068	0.001450013	-0.00089	-0.00754	0.232002087	0.053824968	2.231071	0.215405	2.783608	-1.20006	1.583545	-17.3175	Healthy
18	-0.0011	0.001454523	0.000357	0.063269	0.232723657	0.0541603	2.656425	0.226507	2.758757	-1.20596	1.552795	-28.057	Healthy
19	-0.00068	0.001450013	-0.00089	-0.00754	0.232002087	0.053824968	2.231071	0.215405	2.783608	-1.20006	1.583545	-17.3175	Healthy
20	-0.00088	0.001495571	-0.00072	0.152274	0.239291366	0.057260358	3.088987	0.254185	2.803586	-1.32491	1.47868	-22.5372	Healthy
21	-0.00034	0.001463544	0.002791	0.076036	0.234167009	0.054834188	2.336632	0.145679	2.695695	-1.13213	1.563562	-8.67184	Healthy
22	-0.00069	0.001518962	0.0005	0.062031	0.243033865	0.05906546	2.319885	0.246848	2.853112	-1.32833	1.524778	-17.604	Healthy
23	-0.00041	0.001524036	0.002693	-0.06486	0.243845723	0.059460737	1.782863	0.156235	2.902577	-1.32234	1.580239	-10.4666	Healthy
24	-0.0007	0.001445735	0.002016	0.196145	0.231317638	0.05350785	2.579618	0.18129	2.916759	-1.41376	1.503001	-17.9935	Healthy
25	-0.0011	0.001516916	0.002324	0.076872	0.242706565	0.058906476	2.457622	0.137581	2.736126	-1.31933	1.416796	-28.2529	Healthy
26	-0.00105	0.00148767	0.002986	0.094519	0.23802719	0.056656943	1.708891	0.039627	2.61775	-1.22512	1.392634	-26.8109	Healthy
27	-0.00086	0.001551085	0.001921	-0.00979	0.24817358	0.061590126	1.519727	0.084682	2.724652	-1.29815	1.426501	-22.085	Healthy
28	-0.00035	0.001402467	-0.00205	0.002287	0.224394711	0.050352986	2.050477	0.197599	2.552882	-1.12497	1.427916	-8.88073	Healthy
29	-0.00135	0.001475767	-0.00055	-0.1076	0.236122681	0.055753921	2.167034	0.186225	2.90703	-1.36767	1.539363	-34.6228	Healthy

FINAL DATASET OF BEARINGS

Fig 7: Dataset of Extracted Features

3. Mode: The mode is the value that appears most frequently in a dataset. Unlike the mean and median, which represent central tendencies, the mode identifies the most common value or values in the dataset.
4. Standard Deviation: The standard deviation measures the dispersion or spread of values in a dataset. It quantifies the average distance between each data point and the mean, providing a measure of variability. A higher standard deviation indicates greater variability, while a lower standard deviation suggests more consistency.
5. Sample Variance: The sample variance is the average of the squared differences between each data point and the mean. It provides a measure of the dispersion of values around the mean and is calculated by dividing the sum of squared deviations by the sample size minus one.
6. Kurtosis: Kurtosis measures the sharpness or flatness of the probability distribution of a dataset relative to the normal distribution. Positive kurtosis indicates a more peaked distribution (leptokurtic), while negative kurtosis indicates a flatter distribution (platykurtic).
7. Skewness: Skewness measures the asymmetry of the probability distribution of a dataset. Positive skewness indicates a longer tail on the right side of the distribution (right-skewed or positively skewed), while negative skewness indicates a longer tail on the left side (left-skewed or negatively skewed).
8. Range: The range is the difference between the maximum and minimum values in a dataset. It provides a simple measure of the spread or variability of values in the dataset.
9. Minimum: The minimum is the smallest value in a dataset, representing the lowest observed value.
10. Maximum: The maximum is the largest value in a dataset, representing the highest observed value.
11. Sum: The sum is the total of all values in a dataset, obtained by adding together all individual values.

V.II Linear Regression: Linear regression is a supervised machine learning algorithm used for predictive modeling of continuous target variables. It models the relationship between one or more independent variables (features) and a dependent variable (target) by fitting a linear equation to the observed data points. Fig 8 represents visual representation of simple linear regression which segregates labelled and unlabeled data.

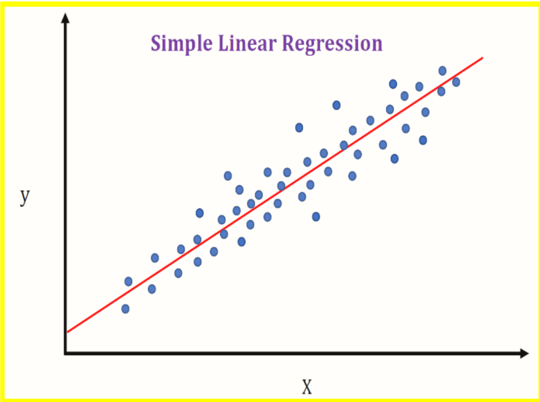

Fig 8: Linear Regression

V.III Decision Tree Algorithm: Decision trees employed as a machine learning algorithm to predict the condition of bearings based on vibration signals and mathematical features. Decision trees were chosen for their simplicity, interpretability, and ability to handle both numerical and categorical data., decision trees are able to effectively classify bearings as healthy or faulty, providing valuable insights into the condition monitoring of rotating machinery. The use of decision trees in our project highlights the versatility and practicality of this algorithm in predictive maintenance applications. Decision trees are a type of supervised learning algorithm used for both classification and regression tasks. Fig 9 represents they are tree-like structures where each internal node represents a decision based on the value of a feature, and each leaf node represents the outcome or class label.

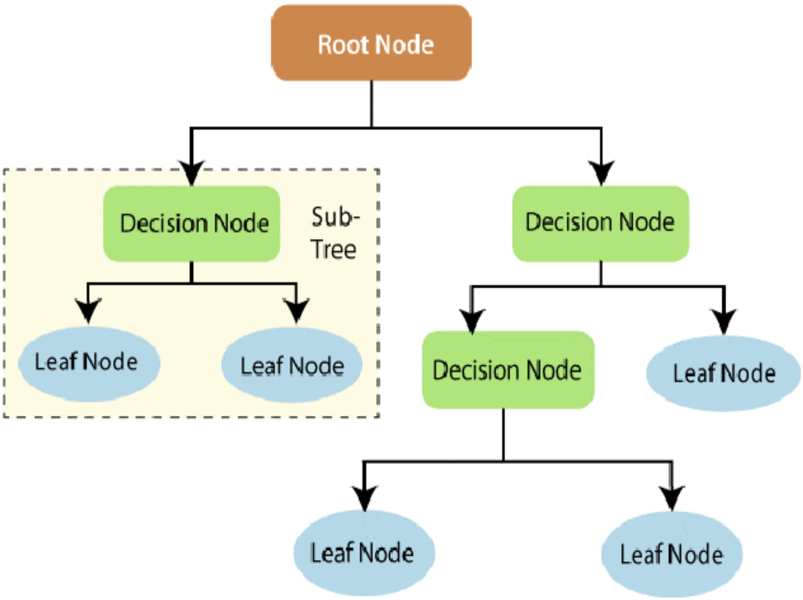

Fig 9: Decision Tree

VI RESULTS AND DISCUSSION

Preliminary results demonstrate the effectiveness of the decision tree algorithm in accurately classifying healthy and faulty bearings. The model achieves high accuracy and provides valuable insights into the condition monitoring of rotating machinery. The implications of the findings for predictive maintenance strategies and industrial applications are discussed. The performance of linear regression and decision tree algorithms for identifying faulty bearings was assessed. Real-world case studies demonstrated the practical application of these methods in industrial settings, highlighting their usefulness in monitoring machine conditions and predicting maintenance needs. Overall, linear regression and decision tree algorithms proved to be suitable for bearing fault detection tasks, providing valuable insights for machinery health monitoring. Following image (Fig 10) shows the output by applying decision tree algorithm of the manual input for prediction.

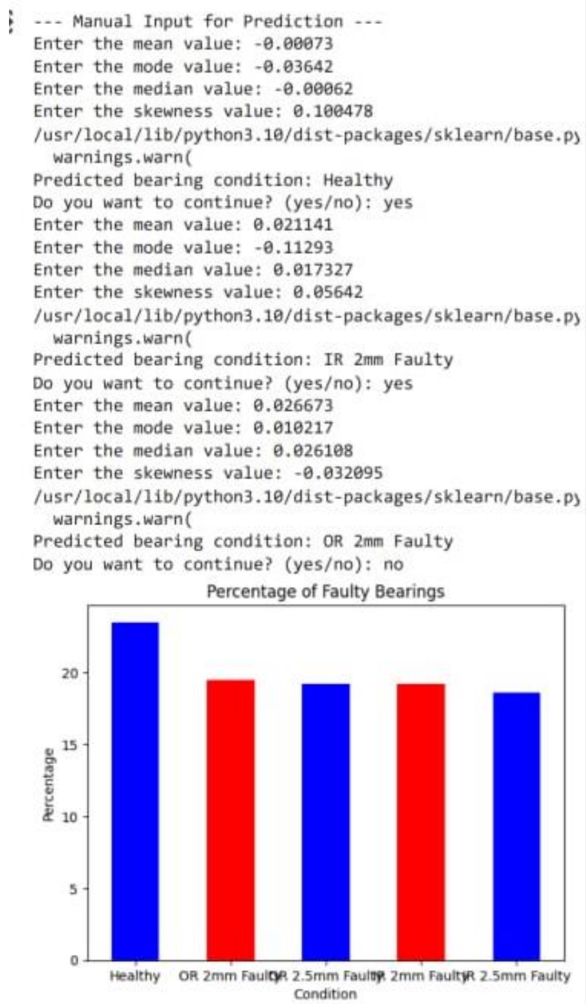

Fig 10: Output by applying decision tree algorithm

Conclusion: In conclusion, this research highlights the potential of machine learning techniques in automating bearing fault detection. By leveraging vibration signals and mathematical features, the proposed approach offers a data-driven solution for early fault detection and predictive maintenance. Future research directions include the integration of additional sensor data and the exploration of advanced machine learning algorithms for enhanced fault diagnosis.

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