BEARING FAULT DIAGNOSIS USING MACHINE LEARNING & DEEP LEARNING TECHNIQUES

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Abstract.

Machine Fault diagnosis plays a vital role in ensuring the reliability and efficiency of industrial systems. Among various components, roller element bearing are prone to failures due to critical function in supporting rotating machinery. This paper proposes a machine fault diagnosis approach specifically tailored for roller element bearings. The methodology combines vibration analysis, signal processing techniques and machine learning algorithms to accurately classify bearing faults. Firstly vibration signals are acquired from the machine using accelerometers, and relevant features are extracted using time domain frequency domain and statistical methods. Subsequently Autoencoders are also used to extract more features with the aid of existing features. Finally few state of the art Machine Learning algorithms such as support vector machines, random forests etc. are trained to classify the fault types. Experimental results on a simulated dataset and real world scenarios illustrates effectiveness and accuracy of proposed approach in diagnosing rolling bearing faults. This developed methodology offers a practical solution for conditional monitoring and predictive maintenance, enabling timely detection and mitigation of bearing faults, thereby enhancing system reliability, minimizing downtime and reducing maintenance costs

Keywords: Machine Fault Diagnosis, Autoencoder,Machine Learning, Deep learning.

1 Introduction

The process of analyzing the reason behind failure of machine(mechanical) components is known as Machine Fault Diagnosis. Due to intricate and harsh circumstances like heavy loads, high temperatures, and high speeds, the intricate elements of mechanical equipment would inevitably give rise to diverse faults of varying magnitudes.

Machine fault diagnosis is a critical aspect of modern industrial systems, aiming to ensure the reliable operation and longevity of machinery. With the increasing complexity and integration of machines, the detection and identification of faults have become essential to prevent costly breakdowns, minimize downtime, and optimize maintenance activities. Machine faults can arise from various sources, including mechanical wear, electrical malfunctions, lubrication issues, and environmental factors. These faults can manifest in different forms such as abnormal vibrations, temperature variations, irregular noises, or performance degradation. Therefore, an effective fault diagnosis methodology must be able to analyze and interpret multiple types of signals to accurately identify the root causes of the faults.

Traditional approaches to fault diagnosis often rely on manual inspections and periodic maintenance schedules, which can be time-consuming, labor-intensive, and may not capture incipient faults. However, advancements in sensor technology, data acquisition systems, and computational techniques have paved the way for more efficient and automated fault diagnosis methods. One prominent technique used in machine fault diagnosis is vibration analysis. Vibration signals which usually carry valuable details about the condition and behavior of the machine components. By analyzing the frequency, amplitude, and other characteristics of these signals, it is possible to detect the presence of faults and determine their severity. Other techniques, such as acoustic analysis, thermal imaging, oil analysis, and electrical measurements, can also provide valuable insights into machine health.

In recent years, the field of machine fault diagnosis has witnessed significant advancements with the integration of machine learning and artificial intelligence algorithms. These approaches leverage the power of data-driven models to automatically learn patterns and correlations from large volumes of sensor data. By training these models on historical data containing known fault patterns, they can be used to classify and diagnose faults in real-time. The benefits of effective machine fault diagnosis are far-reaching. It enables proactive maintenance strategies, such as condition-based maintenance and predictive maintenance, which optimize maintenance schedules, reduce costs, and minimize unplanned downtime. Moreover, by detecting faults at an early stage, potential safety hazards can be mitigated, and the overall reliability and productivity of the machinery can be improved.

In this paper, we present a comprehensive overview of machine fault diagnosis techniques, and machine learning algorithms. We will explore their applications, strengths, and limitations in different industrial scenarios. By understanding and leveraging these techniques, engineers and maintenance professionals can implement efficient and accurate fault diagnosis strategies, leading to improved system performance, reduced maintenance costs, and enhanced operational safety.

2 Related Work

This section reviews the traditional techniques employed for machine fault diagnosis using the IMS dataset. It explores signal processing methods, such as time-domain analysis, frequency-domain analysis, and statistical features extraction. Additionally, classical machine learning algorithms, including decision trees, support vector machines, and k-nearest neighbors, are discussed in the context of IMS dataset analysis. With the advancements in machine learning and data-driven techniques, this section examines the application of advanced algorithms for machine fault diagnosis using the IMS dataset. It delves into the utilization of artificial neural networks, deep learning models, and ensemble methods for accurate fault detection and classification. Moreover, it discusses feature extraction and selection techniques specifically tailored for the IMS dataset.

Adapted weighted Signal Preprocessing technique for Machine Health Monitoring, which uses Signal Processing methods as pre-processing techniques for conditional health monitoring with an accuracy of 98%[2]. A fault diagnosis technique for induction motor bearing has been developed, utilizing cepstrum-based fault pre-processing and ensemble learning algorithms, achieving an impressive accuracy rate of 99.58%[3].

Second Step in the Fault Diagnosis is Feature Extraction, there are many Feature extraction techniques including statistical, time domain, frequency domain, wavelet features and pattern recognition models. There have been limited research studies on the topic of bearing fault diagnosis. One such study explores the application of deep learning extraction techniques combined with handcrafted feature extraction in the time and frequency domains. This approach achieves a commendable accuracy rate of 95.8%. an another study which implements Singular value decomposition technique as a feature extractor which achieved an accuracy of 98.33%.

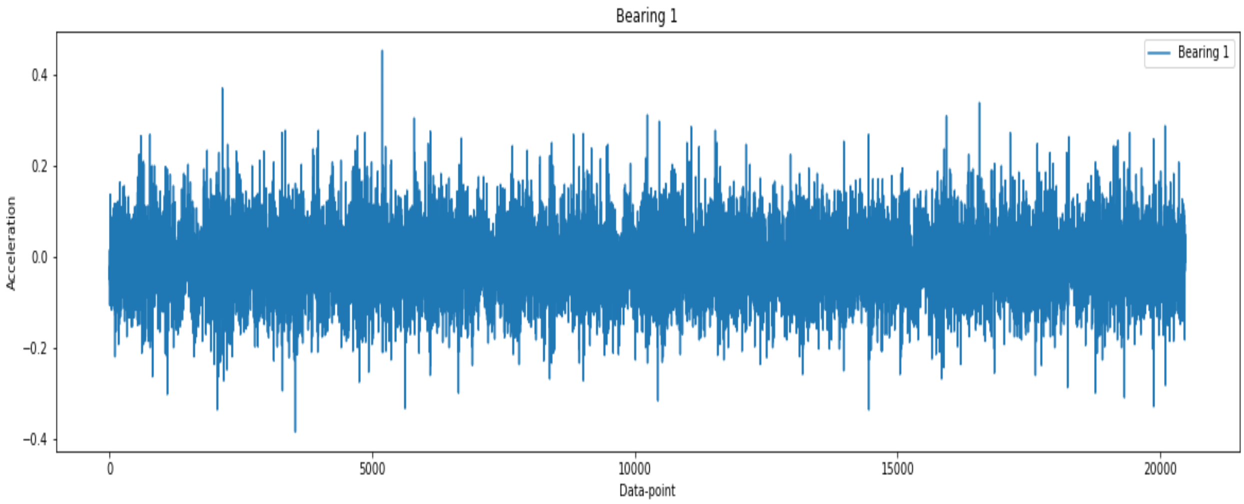
Final Step in the Fault Diagnosis is Fault Classification, once input pre-processing and feature extraction is done, Faulty and Healthy data is segregated and then Machine learning Algorithms were used Classification. This can be posed as a Multi-class classification problem, with the four classes being Healthy (which means under Normal working condition without any flaws), Faults in outer race region of Bearing, Faults in Inner race region &Faults in rolling elements. A study used combined approach using SVM & CNN for fault classification which achieved an accuracy of 98.9%. and another study which uses Ensemble models like random forests & XGBoost for classification with an accuracy of 99.3%.

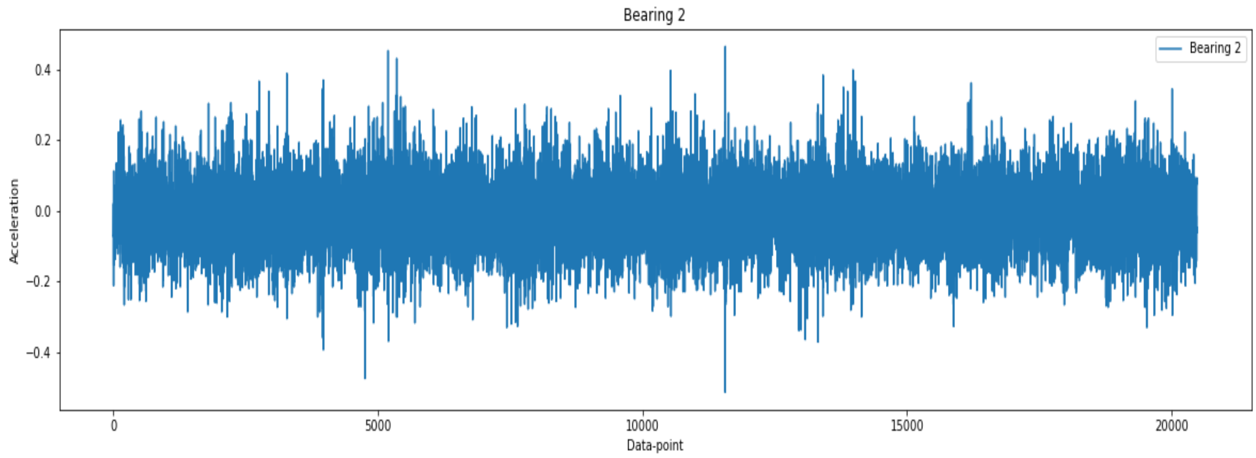
3 Proposed Work

3.1 Feature Extraction

Each File in three datasets contains one second signal snapshots recorded. We are converting this huge data in a single file into a data with features with that time stamp.

So each time stamp represents one second signal snapshots, useful features are extracted from those data for fault diagnosis. Time domain and statistical features like Peak Value, Minimum Value, Mean Value, Root Mean Square value, Standard Deviation, kurtosis, Skewness, crest factor and form factor. These useful information is extracted and represented as a single row in the pandas data frame. In such manner we have represented data as a single row for all available files provided in the dataset with the extracted features.





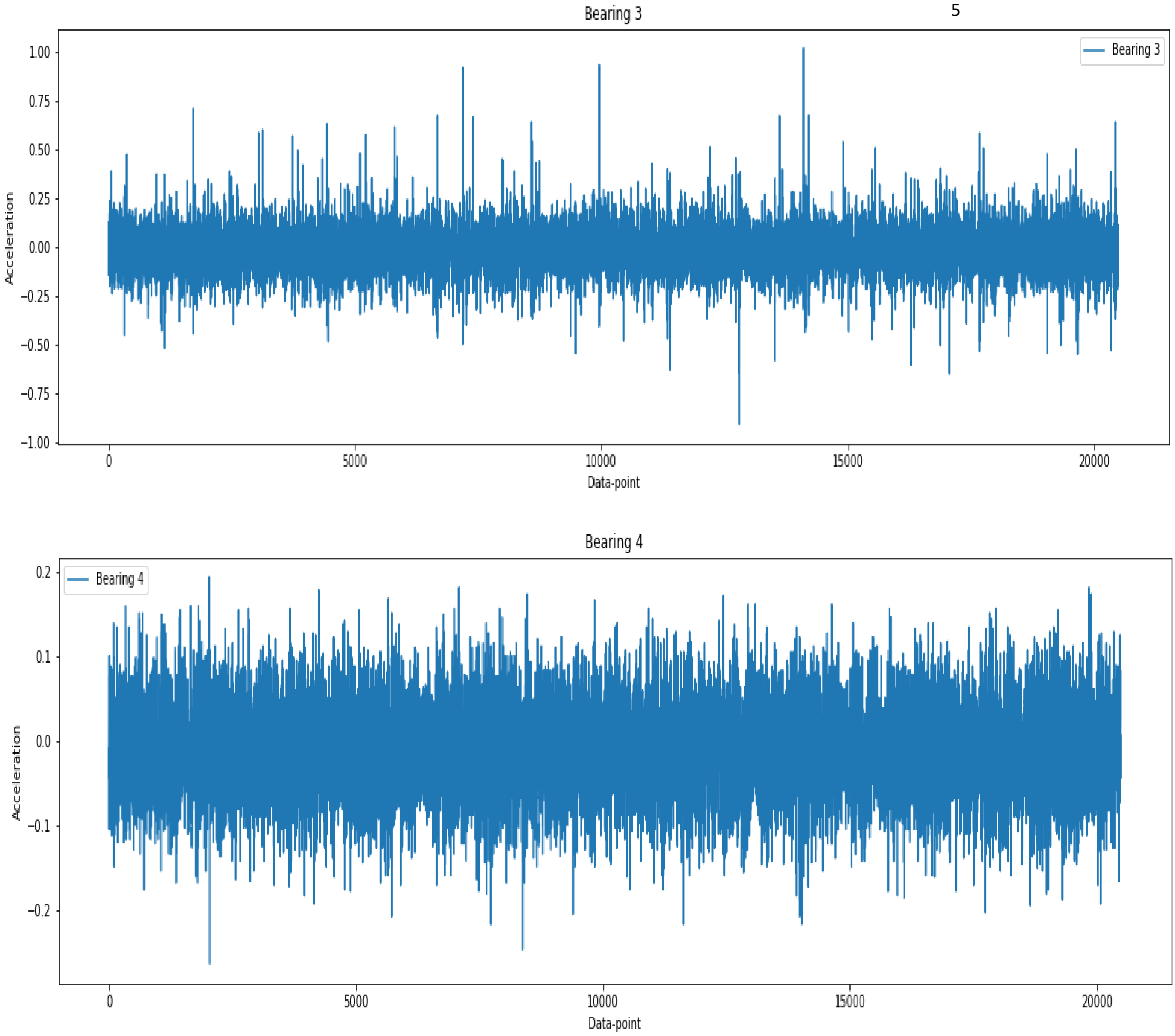


Fig. 1. Time Domain Plot for all Four Bearings for one second snapshot for test setup

Features Extracted from the Signal Snapshots are Peak Value, Minimum Value, Mean Value, Root Mean Square Value, Standard Deviation, Kurtosis, Skewness, Crest Factor and Form Factor. The Importance of these Features are listed in the below table:

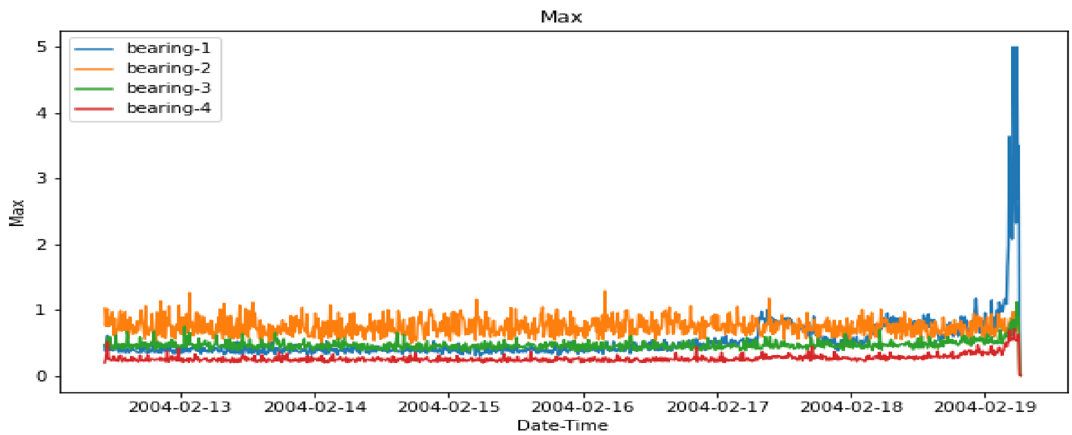
Feature	Mathematical Formula	Description
Maximum Value	$\max(x) = \max\{x1, x2, x3, \dots, xn\}$	The maximum value in a time series is obtained by compressing each sampling observation.
Minimum Value	$\min(x) = \min\{x1, x2, x3, \dots, xn\}$	The minimum value in a time series is determined by compressing each sampling observation.
Mean Value	$mean(x) = ((x1 + x2 + x3 + \dots + xn))/n$	The average value in a time series is calculated by compressing each sampling observation and taking the simple average.
Root Mean Square Value (RMS)	$RMS(x) = \sqrt{}(((x1^2 + x2^2 + x3^2 + \dots + xn^2))/n)$	The measure quantifies the dispersion of predicted values around the regression line. In this context, 'n' corresponds to the sample size, indicating the number of timestamps acquired after pre-processing.
Standard Deviation	$\sigma = sqrt((1/N) * \Sigma(x - \mu)^2)$	Obtained by taking the square root of the variance, it signifies the distribution of a reduced time-series sample in relation to its mean.
Kurtosis	$Kurt(X) = (1/n) * \Sigma((x - \mu)^4) / \sigma^4$	It quantifies the deviation of the tail of a distribution from the normal distribution and is defined as the fourth moment of the distribution.
Skewness	$Skew(X) = (1/n) * \Sigma((x - \mu)^3) / \sigma^3$	It quantifies the divergence of a distribution from the normal distribution, either towards the left or right. This measure is defined as the third-order moment of the distribution.
Crest Factor	$Crest\ Factor = Peak\ Value / RMS\ Value$	Crest factor is a measure used in signal processing to quantify the peak-to-average ratio of a waveform. It provides information about the amplitude variations or "peaks" in a signal relative to its average value.

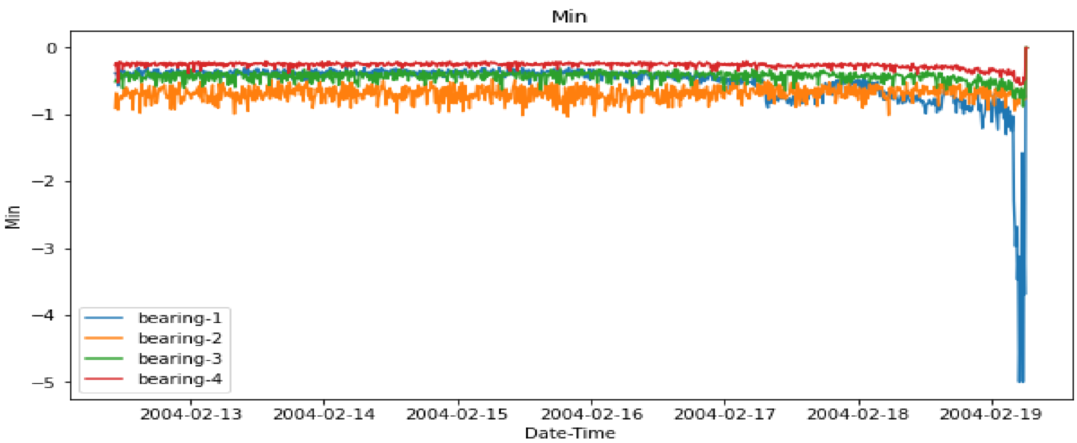
Form Factor	$Form\ Factor$ $=\ RMS\ Value$ $/\ Average\ Absolute\ Value$	It quantifies the ratio between the RMS (root mean square) value and the average absolute value of a signal, providing information about the symmetry and smoothness of the waveform.
Clearance Factor	$Clearance\ Factor$ $=\ Maximum\ Value$ $/Squared\ Mean\ of\ Squared\ root\ o$	The peak value is determined by dividing the squared mean value of the square roots of the absolute amplitudes by the peak value itself. This characteristic is maximized in the case of healthy bearings and gradually diminishes for faulty bearings.

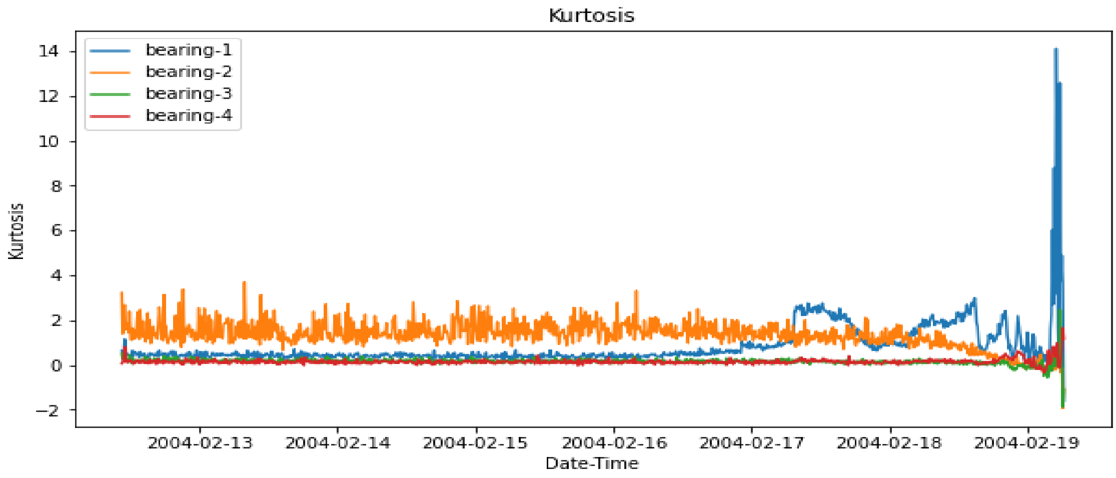
Once the feature extraction is done, we are supposed to detect fault degradation which is possible with the help of features extracted and all possible plots are investigated for each test setup to know where the fault occurs and types of fault.

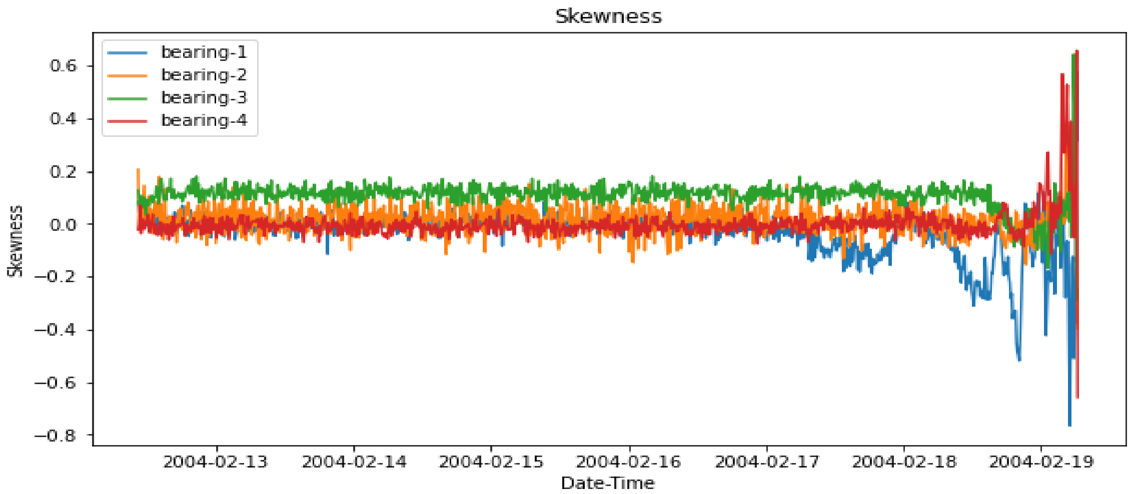
Here are few images which illustrates the Behaviour of bearings with respect to features we extracted: (for 2nd test setup)

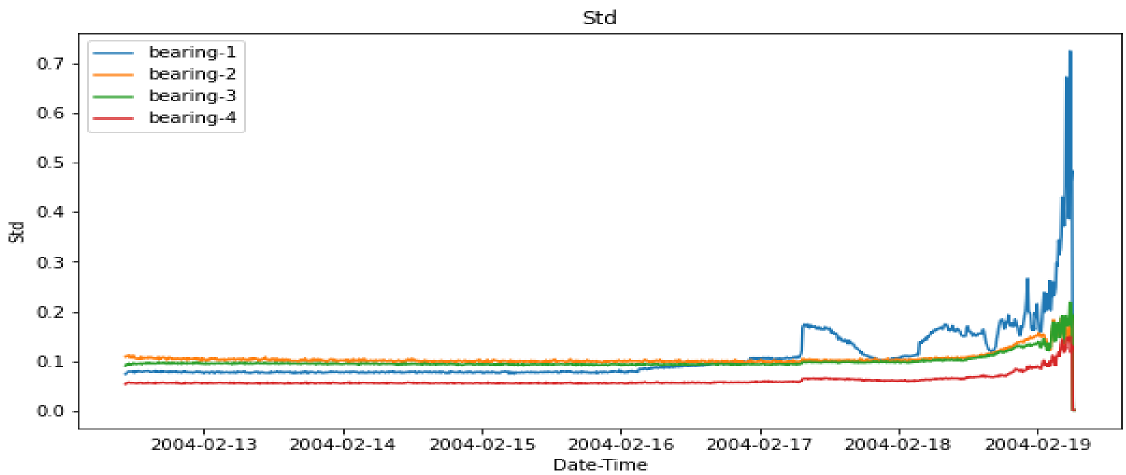
Fig. 2. Behaviour of Bearings with respect to Extracted Features for 2nd Test Setup

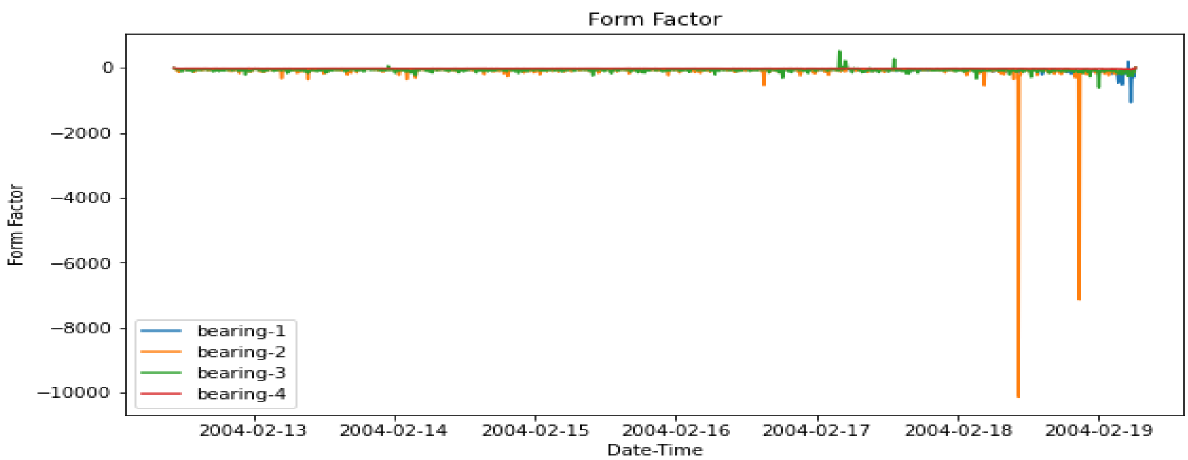





Kurtosis
bearing-1
bearing-2
bearing-3
bearing-4
Kurtosis
14
12
10
8
6
4
2
0
−2
2004-02-13
2004-02-14
2004-02-15
2004-02-16
2004-02-17
2004-02-18
2004-02-19
Date-Time


Skewness
bearing-1
bearing-2
bearing-3
bearing-4
Skewness
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.8
2004-02-13
2004-02-14
2004-02-15
2004-02-16
2004-02-17
2004-02-18
2004-02-19
Date-Time


Std
bearing-1
bearing-2
bearing-3
bearing-4
Std
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
2004-02-13
2004-02-14
2004-02-15
2004-02-16
2004-02-17
2004-02-18
2004-02-19
Date-Time


Form Factor
Form Factor
0
−2000
−4000
−6000
−8000
−10000
bearing-1
bearing-2
bearing-3
bearing-4
2004-02-13
2004-02-14
2004-02-15
2004-02-16
2004-02-17
2004-02-18
2004-02-19
Date-Time

3.2 Methodology

Fault degradation is detected manually with the help of above plots, as we inspect those plots it is very obvious that bearing 1 in the second test setup is behaving abnormally toward the end of the plot, from which we can infer that bearing 1 is undergoing fault detection from timestamps towards the end. So in this second test setup we can create data for healthy data and data with fault in outer race. Similarly for all three tests this process is done and data is segregated into healthy and non-healthy, where non-healthy data refers to data in which faults in outer region of bearing race, inner race & faults in rolling elements in the bearing.

Thus the data is Labelled manually with the help of timestamps available, now we have labelled data which is posed as a supervised Learning problem. With four different target labels, four class classification problem. Data is Split into 70% Training & 30% for testing. Now we implemented Machine learning algorithms to solve this like To tackle this problem, several algorithms such as K-Nearest Neighbors, Support Vector Machines, Random Forest, Decision Trees, CatBoost, LightGBM, and other techniques have been employed. In the process of Training neither Overfitting nor Underfitting is observed.

Besides this we have incorporated the same methodology by adding new other features which were obtained from Autoencoder architecture. Earlier we have only 10 features now with the aid of autoencoder 256 new features were extracted and concatenated with the 10 time domain features we had and once again it is posed as a Four class classification problem. And the same machine learning algorithms were address this problem and hyperparameter tuning is also done to achieve better results.

3.3 Deep Learning Based Feature Extraction

The code Implementation for extracting Deep Learning based Features makes use of Deep Learning Model using Sequential API from Keras, which allows Linear stack of layers.

The first layer added to the model is dense layer with 64 neurons, which makes use of “relu” activation function to introduce non linearity, which is followed by a dropout layer which aids in regularization, in this case 50% is dropped out. The next layer is another dense layer with 128 neurons and “relu” activation function, another dropout layer is added after second dense layer. The model continues with two more dense layers of 256 and 512 units The model is compiled with the aid of Adam

Optimizer and loss function as “Categorical Cross Entropy” which suits for multi class classification problem. The model will also compute the accuracy metric.

4 Experimental Results And Analysis

4.1 Dataset Collection and Description

In this particular research study, the NASA Bearing Dataset, also referred to as the IMS (Intelligent Machines Dataset), was utilized. The dataset comprised of a shaft with four bearings, subject to a consistent rotational speed of 2000 RPM generated by an AC motor linked to the shaft via rubs. A spring mechanism was employed to apply a radial load of 6000 pounds to the shaft and bearing. It is noteworthy that all failures transpired after surpassing the bearing's designated lifetime of over 100 million revolutions.

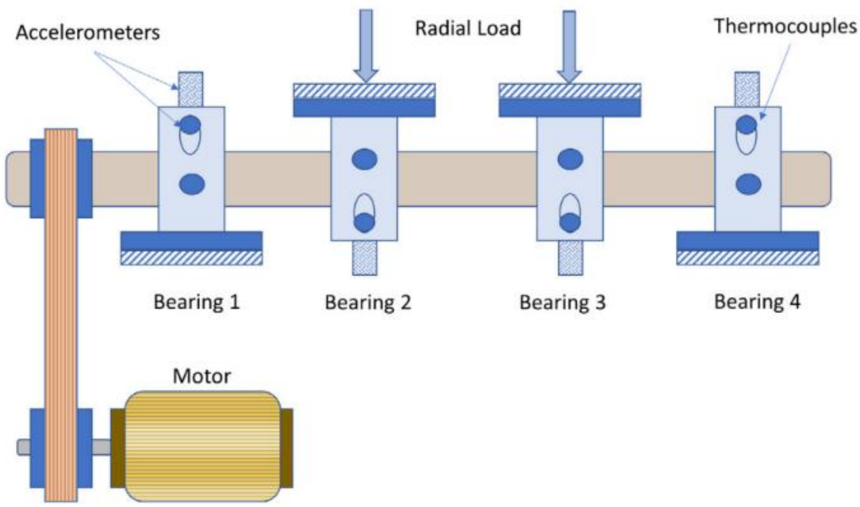


Fig. 3. The IMS dataset experiments were conducted using a bearing test rig, and careful consideration was given to the placement of sensors.

The dataset is structured as follows: it is provided in a zip format with a size of approximately 1.6 GB. Within the dataset, there are three individual datasets, each describing a test-to-failure experiment. Each dataset comprises multiple files, where each file represents a one-second snapshot of vibrational signals recorded at different time intervals.

The sampling rate for the signals was set at 20 KHz. For further details regarding the dataset description and other relevant information, please refer to the table presented below.

Description	Dataset 1	Dataset 2	Dataset 3
No: of Files	2156	984	4448
No: of Channels	8	4	4
File recording Interval (in Minutes)	Every 10 min Interval	Every 10 min Interval	Every 10 min Interval
Failure Description (Occurred during End to End Failure Test)	• Inner race Defect in Bearing 3 • Roller element defect in bearing 4	• Outer race Failure occurred in Bearing 1	• Outer race Failure occurred in Bearing 2

4.2 Result And Discussion

The proposed method is simulated in Python, running on a 64-bit Windows 11 platform with Intel Core i7-11800H @ 2.30GHz 2.30 GHz and 32 GB RAM.

Fig. 4. Results with Statistical Features

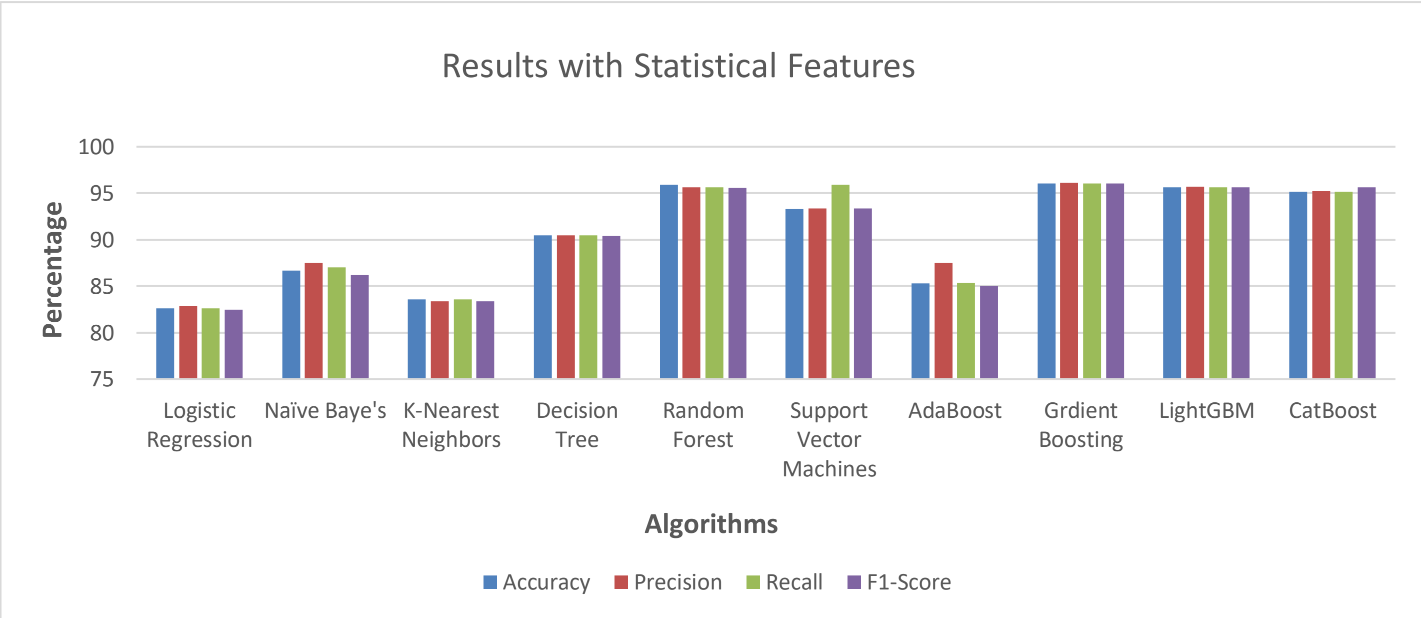
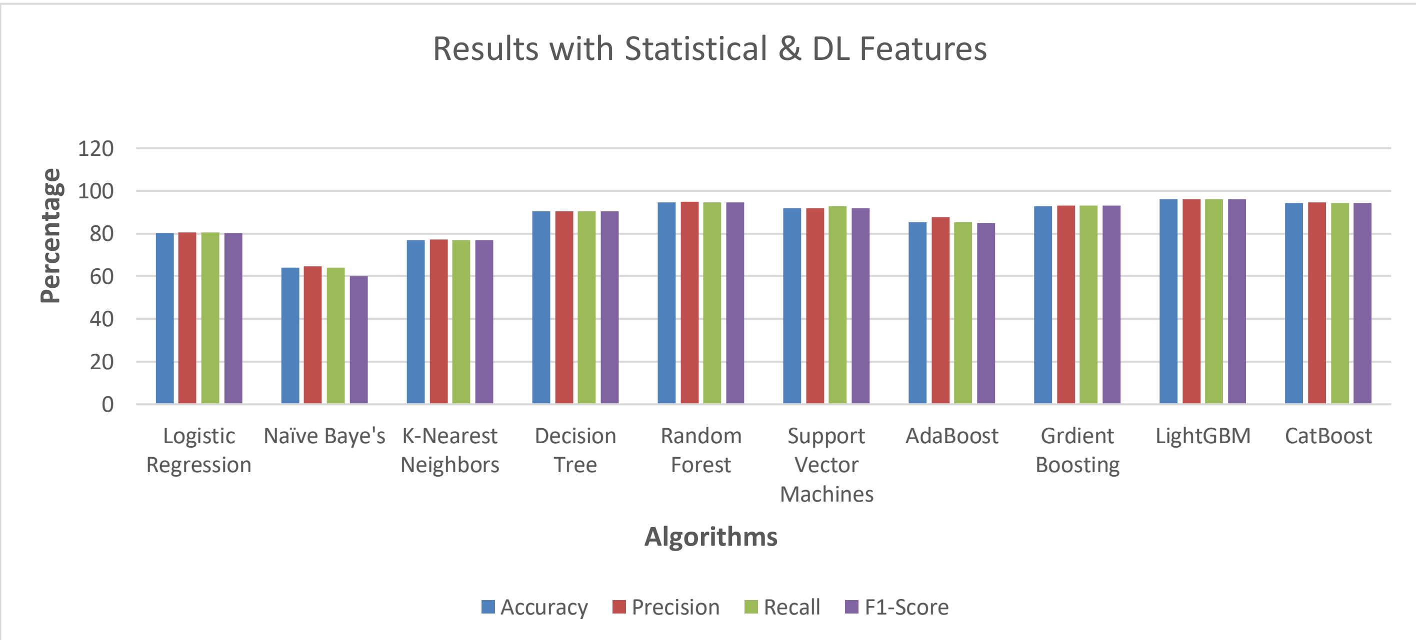


Fig. 5. Results with Statistical and Deep Learning Features



5 Conclusion

In this work performance analysis of our work is compared with only statistical Features and the other being Statistical and Deep Learning based Features. When implementation is done only with statistical features Highest accuracy of 96.05% is achieved with Gradient Boosting Algorithm, whereas when the implementation is done with both Statistical & Deep Learning based Features an Highest accuracy of 96.05% is achieved with LightGBM Algorithm. All the results obtained are Maximum Possible results as all Agorithms are fine tuned for better results with the help of HyperParameter Tuning.

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