11-2023

Bearings Fault Classification Using Machine Learning and Dashboard for Bearing Signals Vibration

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by

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A Thesis Submitted in Partial Fulfilment of the Requirements for the Degree of Master of Science in Professional Studies:

Data Analytics

Department of Graduate Programs & Research

Rochester Institute of Technology (RIT Dubai)

Nov.2023

RIT Dubai

Master of Science in Professional Studies:

Data Analytics

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Acknowledgments

I would like to express my thanks to Dr. Ehsan, my mentor, for his guidance and support through the research process. His mentorship has been a source of inspiration, providing me with the necessary tools to navigate the complexities of academic research.

I extend my appreciation to my colleagues for their collaborative spirit and input that made our studies much deeper. The times we explored ideas together really made a big difference in how I learned and gained the knowledge.

Finally, I want to thank my family for their constant encouragement and understanding. Their continuous support gave me strength and motivated me to pass the challenges.

Abstract

Bearings are crucial components for the mechanical system that allows relative motion between two parts. Bearings primarily used to reduce the friction on the component. However, Bearings can fail for several reasons such corrosions, fatigue and electrical damage ..etc .This research aims to develop an accurate prediction model and visualization dashboard to avoid the costly downtimes, high repair cost and enhance the maintenance experience for workers and engineers. The data used in this research is CASE WESTERN RESRVE UNIVERSITY (CWRU) bearing data set. The data set contains signals vibration readings of bearings that can used for bearings fault detection. The method used for building the model is Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology which is commonly used in machine learning, The algorithms used are SVM and RF. However, RF showed higher accuracy for fault classification. Then random forest for feature reduction used for knowing the main attributes, the algorithm showed that attributes sd, rms, mean, kurtosis and max are the top five attributes but that caused a minimal reduction in accuracy. The model using RF with all attributes achieved 95.7% while after the feature reduction achieved 95.6%. the second part form this research is to study the relationship between signals vibration with fault size and location. Moreover, fault located in the outer ring demonstrated higher values while the bearings working normally had the lowest signal vibration values.

Key words: Machine learning, SVM, RF, bearings, fault classification, CRISP-DM, signals vibration.

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Chapter 1- Introduction

Bearings are an essential part of rotating machinery and mechanical systems. Bearings ensure that machines are working smoothly while being used for heavy work. However, the performance of the bearings significantly impacts equipment or machine performance. In the case of bearing failure, this can result in machine damage [1]. Therefore, there is a need to use machine learning for fault prediction of bearings to ensure that faults are detected on time to achieve reliability, safety, and efficiency in several sectors, such as manufacturing, energy, and transportation.

The topic of bearings fault classification was chosen to spotlight its significance in the field of mechanical engineering. The manufacturing processes are complex, which will result in higher maintenance costs [2]. Moreover, there is a need to reduce machine downtime resulting from maintenance intervals and to minimize the unexpected failure of bearings. An accurate predictive model can lead to cost savings, increased efficiency, and improved safety of the mechanical system from hazards.

Analysing the historical data to understand the performance and the patterns of the bearings system is a useful way to do the fault detection of bearings and this exceeds the traditional ways of fault detection [3].

This research paper presents using two methods of classification, which are support vector machine (SVM) and random forest (RF), on the vibration signals of bearings to see which model can achieve higher prediction for bearing faults. Then, use feature reduction and see how the accuracy is affected, and a dashboard for signal vibrations was built. The dataset used in this research is CASE WESTERN RESERVE UNIVERSITY (CWRU) bearing dataset. The dataset is from an open source, which is Kaggle.

1.2 Background

1.2.1 Bearings Fault Background

Bearings are small parts but have huge impacts on machines. Ensuring bearings are working normally without any faults is crucial to ensure continuous work with no breakdowns, the need for high-cost repairs, unnecessary maintenance, and no safety risks. One of the mandatory things is to have a technical background to be able to classify the results [4]. This section will show the structure of the bearings and possible faults that can occur in bearings.

Bearings are assembled from four parts: rolling elements (balls), cage, and the inner and outer rings. The rolling elements are placed in between the outer and inner rings. Moreover, the cage is used to keep the rolling balls in a loop as shown in Fig (1). The faults of the bearings can occur in all four parts, but most of the faults appear in the outer and inner rings. This is because these two parts are exposed to high stress and fatigue caused by the balls [5]. However, faults in the balls and cages have a lower percentage of occurrence but can be found due to some reasons such as wear, corrosion, and material defects [6]. Bearing faults can present in three forms: single point defects, multiple point defects, and distributed faults. However, the single point defect is when the fault occurs on the bearing surface at a single point, and the other parts are working in normal condition. Cracks, pits, and spalls are examples of single point defects. However, most recent research focuses on this type of fault. The second type is multiple point defects when the bearing surface has more than a single point defect, like more than one crack. Finally, distributed faults occur when the fault covers a large area of the bearing surface; corrosion and wear are examples [7]. These faults arise from several factors such as contamination, inadequate lubrication, and misaligned coupling. These faults lead to a rough bearing surface, which will cause high friction [8].

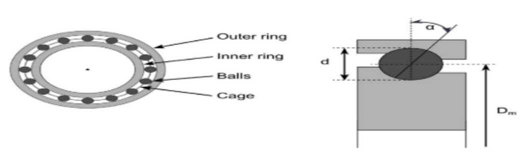

Fig (1). Bearings Components

1.2.2 Bearings Data Background

In this research, the data that will be used is from Kaggle, it is an open source for data. The data were provided by Case Western Bearing Data Centre. Moreover, the data were collected after a test for a motor used to measure the performance of an electric motor. The test includes a motor with 2 HP power, Torque transducer, Dynamometer, and control electronics. In addition, the telemetry measurements are from three accelerometers installed on the Drive end (DE), Fan end (FE), and base (BA).

The data measurements are the outcome of these conditions: 1 HP load was applied to the motor, the shaft rotating speed was 1772 rpm, and the accelerometers have a sampling frequency of 48 KHz. Furthermore, the defects found in the bearings were single point defects in three parts of the bearings, which are the balls, inner, and outer rings. However, the diameters of the defects are 0.007 inches, 0.014 inches, and 0.021 inches. The data contains 9 attributes and 2300 observations.

1.3 Problem Statement

Bearings are small parts but have huge impacts on machines. Ensuring bearings are working normally without any faults is crucial to ensure continuous work with no breakdowns, the need for high-cost repairs, unnecessary maintenance, and no safety risks.

Having faults, for example, like cracks or scratches in bearings, can affect bearing performance, and the earlier detection of faults is better to avoid a bigger breakdown. However, detecting faults in bearings is a challenging task that requires the usage of advanced tools like AI. To avoid unscheduled maintenance that can result in stressing the team or causing delays in delivery time. Using the traditional ways like scheduled maintenance can results on unnecessary maintenance.

The main problem is to overcome sudden faults and have a model for the detection and classification of bearings. This research aims to enhance the maintenance experience, save repair costs, and ensure safety by addressing bearing faults.

1.4 Research Aim and Objectives

This research main goal is to have a high accurate prediction model using two Machine learning algorithms. Also, to have a visualization dashboard to understand signals vibrations on bearings faults. This research aims to:

1- Investigate the challenges and the gaps on bearings faults: this study conducts a literature review for previous works on the domain of bearing fault maintenance prediction, to understand the limitations and the gaps.
2- This thesis to build an accurate machine learning model that detect bearing's fault location and sizes: SVM and Random Forest algorithms will be used to do the prediction, then compare the accuracy of the prediction using confusion metrics such as accuracy, precision, recall, and F1 score. Then apply Random Forest feature importance for feature reduction and compare the accuracy.
3- Build a visualization dashboard illustrates main insights from the signals vibration and how the values can affect the fault size and location.

1.5 Research Questions

The research goal is to find answers for these questions:

- RF or SVM can achieve higher accuracy for bearings fault prediction?
- Does applying Feature reduction algorithms always can improve the accuracy of prediction?
- What are the main attributes for making the prediction and how they affect the fault location and sizes?

1.6 Limitations of the study

The limitations are related to the data. There is not much available data about bearing faults, and CWRU data was used in previous research as it is the available choice. Bearings are wide and there are many types of bearings. The data provides the readings of one type of bearing, which are ball bearings, which means the machine learning algorithms will work only for this type of bearings. However, the data sample size is small and only addresses single point defects.

1.7 Structure of the Thesis

The thesis is structured as shown below:

Chapter 2: includes a comparative review of 30 previous research papers in the domain of bearing fault classification. This chapter underlines the theories and progress in the domain, including the methods used for prediction, challenges, and gaps.

Chapter 3: presents the methodology used for the research. Moreover, it covers a summary of the process flow from preparing, splitting, and scaling the data, moving to the algorithms that will be used and compared.

Chapter 4: illustrates in detail the findings and the data analysis process, from the exploratory data analysis, the method used for preparing the data, and the method used for building the prediction model. It also illustrates the visualization dashboard.

Chapter 5: discusses the results and answers the research questions according to the findings of the research.

Chapter 6: summarizes the research process and results, showing the limitations of the research with suggestions for future research works.

Chapter 2- Literature Review

In the last years predictive maintenance became an essential aspect of ensuring reliability and safety of industrial equipment, and bearings are one of these equipment's. The use of Machine learning methods has gained popularity as a powerful tool to predict bearings failure.

Several studies have investigated the use of vibration signals to predict failure of bearings. V. Vakharia [9] used Artificial Neural Network (ANN) and Random Forest (RF) to detect failure from measured vibration signals. However, they used chi-square and relief -F methods to reduce features size. The results show that the minimum number of features using chi-square and RF algorithm achieved a higher accuracy with 93.54%. S. Patil [10] applied five algorithms on bearings data set in WEKA and K-star algorithm achieved the highest accuracy on both training and testing datasets. However, K-star achieved 100% accuracy in the training data set and 86.95% on testing data set. Achieving 100% accuracy on training data set and less in the testing data set means there is an overfitting, and the algorithm is well trained on training data set and may not work well on unseen data. However, 86.95% still acceptable but comparing to other researcher they achieved higher accuracy. M. Unal [11] used acoustic analysis, which uses the sound wave with classification to diagnosis the bearing fault. First, they used Hilbert transform (HT) and power spectral density (PSD) to have attributes from sound signal. Then applied three algorithms which are decision tree, support vector machines (SVMs) and boosting. Boosting showed the highest accuracy, in addition in the comparing classifiers process Receiver Operating characteristic (ROC) curve used. L. Saidi [12] their approach for bearing fault diagnosis is using higher order spectra analysis and support vector machine (SVM). Bi-spectrum vibration patterns are reduced using principal component analysis (PCA). What's more, to evaluate the method used is demonstrated through sensitivity and robustness evaluation metrics and ROC curve. The SVM model including selected features had the higher accuracy for both training and testing data compared to the SVM model with all features. However, the accuracy achieved in testing is 96.98 which is high and shows how this method is effective.

X. Zhang [13], in this research they built a new method to detect failure in bearings using premutation entropy (PE). The model calculates the PE of vibration signals to detect failure and the PE breaks down the signal into functions to show the characteristics of the signal. In addition, to have a classification for faults Support vector machines (SVM) optimized by inter-cluster distance used. The accuracy rate was 97.91% which is a high-rate accuracy that shows the effectiveness of the model. Furthermore, S. Kang [14] research aimed to investigate the extraction of multiple domain features from vibration signals, and four algorithms were tested for feature reduction. Out of all the algorithms, locally linear embedding was found to be most effective in improving classification precision. Furthermore, a new multiple state assessment model was suggested, which yielded positive results in detecting various fault locations. However, to further improve the method and its accuracy, they suggest that future research should test the proposed approach using real vibration data from a rolling bearing.

N. Sharma [15], in this research they delivered a comparative study of ML algorithms for fault diagnosis for several machine types. However, one of the cases they used a bearing dataset and applied five algorithms to diagnosis the fault on bearings and Random Forest (RF) achieved the highest accuracy. In addition, RF achieved the highest accuracy across all data sets not only for bearings. Furthermore, to measure the performance Area Under the Curve of the Receiver Operating Characteristic (AUC_ROC) were used and the results show RF achieved 99.8%. S. Schwendemann [16], in this survey they gathered approaches of bearings faults to give an overview about the status. However, this survey provides research used classification of bearings using Neural network (ANNs), convolutional neural network (CNNs), SVM and hidden Markov model (HMMs). However, most of these techniques achieved a high percentage for fault classification. On the other hand, the survey provided papers tried to do a prediction for the remaining useful life (RUL) for bearings but achieved very low accuracy. The reason behind the low accuracy as the researchers mentioned that this is because the available data. The available approaches are not suitable for real application because they do not take on consideration the noise from other machine components, also, the algorithms are not suitable for all types of bearings.

A. Soualhi [17], proposed a method that gathers Hilbert–Huang Transform (HHT), Support Vector Machine (SVM), and Regression (SVR) for mentoring ball bearings. HHT analyses the vibration signals and extracts the health of bearings to monitor the process of degradation over time. SVM is used for fault detection. Moreover, remaining useful life is estimated using SVR's series prediction. However, to be able to use the proposed approach, historical data on bearing degradation are needed to train the SVM and SVR. This limits the approach usability in situations where obtaining historical data is challenging. G. K. Durbhaka [18], The research paper focused on the prediction of bearing faults by using signal processing for feature extraction and various machine learning models, which included the Collaborative Recommendation Approach. The paper aimed to demonstrate the effectiveness of this methodology in diagnosing bearing faults by analysing them with multiple machine learning models. Furthermore, the paper demonstrated how CRA was utilized in recommending faults with a high accuracy of 93%

X. Ye[19], The paper introduces a new technique for hyperparameter optimization in fault diagnosis, which can adjust the hyperparameters of feature extraction and machine learning algorithms automatically. The approach involves dimension reduction based on utility and identifies the sensitive intervals of hyperparameters through partial dependencies. Furthermore, the proposed method achieves a high accuracy rate of 96.80%. However, a limitation of the approach is that it only considers partial dependencies in 2 dimensions. A. Malhi[20] used (PCA) for feature selection and test its effectiveness on a bearing using supervised and unsupervised defect classification approaches. The proposed method showed a higher accuracy with lower number of features which shows the usefulness of the method.

G. Xu *et al* [21] in This article shows the application of deep model-based domain adaptation for fault diagnosis for the big data of industrial area. They used several data sets and one of them is CWRU data set was used for diagnostic. Moreover, they spotlighted the importance of fault diagnosis to detect faults by using feature extraction and classification to classify several types of faults. However, they also focused on fault prognostics, which means doing a prediction for faults before it happens and estimating the remaining useful life (RUL) of bearings. The prognostics process mainly involves three steps: health indicator construction (HI), health stage division (HS) and prediction of the RUL. This article gives a brief overview of past research worked in predictive maintenance, and several methods were used like ANN, SVM, and deep learning models such, convolution neural network and deep belief networks. Furthermore, they suggested for future works to work in the development of the accuracy of hybrid methods which includes data driven and model-based approach and enhance the efficiency of the diagnostics and prognostics methods.

S. Zhang [22] In this paper he focused on the usage of both ML and DL methods in the case of bearing fault diagnostic. Moreover, the paper shows popular data sets such CWRU data set used for bearings fault detection, and examines ML methods such: ANN, PCA and SVM. Also, in this paper they investigate and examine the current research in the field of DL. However, in ML they showed the traditional methods for fault detection and provide a main publication applied ML. On the other hand there is an increase of using DL for fault diagnosis out of 80 papers from 180 used DL approach. This paper conducted a comparative study to see how successful is using classification for several algorithms using CWRU data set. The results show many DL algorithms achieved excellent results and the accuracy was over 95%. In addition, they mentioned the challenges of using ML and DL in real world applications, and some changes are the data distribution discrepancies, splitting the data sets randomly into training and testing and the accuracy saturation.

V. Sugumaran [23] In this paper he illustrated several tools for features and classification for roller bearings. However, in this paper the data were used is a vibration signals reading for bearings. The researchers explored a new method for feature reduction using a decision tree algorithm. The algorithm of the decision tree chooses the more useful attributes for classification based on the occurrence of the attributes in the decision tree. In addition, in this paper they performed two methods for the classification, which are SVM and Proximal Support Vector Machine (PSVM). As a result, they found that PSVM performs better than SVM. PSVM in some cases requires less iterations and less training time so it has faster learning capability. The limitation of this method is that it needs a large number of data points in the data. P. K. Kanka [24] in this paper authors focus on the diagnosis of bearings fault using SVM and statical method for feature selection using artificial immunization algorithm and do a comparison between SVM with and without using feature selection. This paper spotlights the main gap between (ANNs) and SVM, ANNs uses the empirical risk minimization (ERM) to reduce the error of the training data. On the other hand, SVM uses the structural risk minimization (SRM) to reduce the upper bound on expected risk. The data used is vibration data and the paper focuses on fault classification. The defects were in ball corrosion, bearings have rough inner ring, combined defects, healthy bearings, and outer ring cracks. The result in this paper shows that ANN and SVM both achieved accurate prediction. A. Esteban [25] published a systematic review which starts with formulation of the research questions. Moreover, these questions include several aspects of the predictive maintenance with using data mining methods, such the base tasks in PdM, machine learning methods, most known scenarios for using PdM, types of data used, and the challenges in using PdM. However, the strategy that the researchers used is to gather the recent works that used DM approach for the PdM task. The literature review had mentioned some papers about the PdM about bearings. The study consists of 132 papers published from 2015 to 2021. The mentioned articles provide information about tasks, frameworks, the language used in programming and libraries of software used for PdM. In addition, they mention the challenges in PdM from a DM perspective like to propose the taxonomy for the latest update of task in PdM, and taking the data from physical environment, processing and building the proper model. Also, the available data from open sources are limited and may not be good enough for giving accurate prediction. However, knowing the challenges can help in improving accuracy.

C.-Y. Lee [26] In this paper he and researchers showed some methods and techniques, such rolling parts in a sliding window, time domain analysis, frequency domain analysis and several statistical and ML methods like SVM for prognostics health management (PHM) of bearings. The method used is to be able to handle large scale raw date, be able to choose the main features and do a prediction for the RUL of the bearings. Moreover, researchers conducted an empirical study to validate the method.

The data in this study were collected from sensors and accelerometers and are signals vibration. However, as a suggestion from the study the researchers suggest using SVM for having accurate prediction. Furthermore, in this paper they also conducted a comprehensive review for related works in the field of PHM and PdM. The review includes ML and statistical methods, large scale signal data sets, segmentation methods and using time series data mining techniques for dimension reduction. S. Prabhakar [27] In this study the S. Prabhakar and researchers aim to diagnosis the two cases of fault; single and multiple ball bearing race with wavelet transform. However, they believe that the traditional methods such Fast Fourier Transform (FFT) may not give promising results, because it is masking the noise that defect frequencies. Moreover, there are some signal processing techniques can enhance from the results such; averaging, adaptive noise cancelling, and high frequency resonance were developed. This method gives time scale information of the signal which will make them ready for analysing transient. However, discrete wavelet transform (DWT) is obtained from the discretization of continuous wavelet transform (CWT), splits a signal into low frequency approximations and high frequency details. In this study they scratched the inner and outer races of ball bearings and while testing if there is a fault it shows impulses and when the fault is in the two races two sets of impulse were shown. This method is useful for condition monitoring.

S. Nezamivand [28] The researchers in this article developed an intelligent method which is empirical mode decomposition (EMD) and wavelet packet decomposition (WPD). These methods are for signal processing and features reduction. Moreover, the goal of this method to take the main features and determine the parameters which are optimal using FDAF score and binary partical swarm optimization (BPSO) algorithm, this BPSO algorithm used to have the main features for SVM classifier. However, the researchers did a comparison of his method compared with other methods used for bearing faults detecting and showed that their method outperforms the other methods especially for early defects. P. Bangalore [29] In this paper the researchers discussed the use of the ANN approach for early fault diagnosis of bearings on gearbox. The data used in this paper is data collected from supervisory control and data acquisition system (SCADA) which is sensor collected data for a wind turbine. However, SCADA system records the temperature of the bearings, and by training the model by ANN it can estimate the temperature and compare it with the real temperature of bearings. Moreover, the results showed that this method was able to detect the damage of bearings one week before. I think this is really helpful and allows for optimal decisions in the maintenance field. Y. Fan [30] in the paper aims to improve the accuracy of bearings fault diagnosis. However, to achieve the goal they proposed a method of using SVM and optimized by self-regulating particle swarm optimization (SRPSO). The data used in this paper is CWRU data set. The proposed method gathers the multikernal least square support vector machine (MK-LSSVM) with SRPSO algorithm, the MK-LSSVM used for the prediction while the SRPSO used for optimizing the parameters. In addition, the researchers compared their method with other methods of SVM and showed that their method had achieved the highest accuracy among all other method, the accuracy reached 99.72%. This accuracy is also the highest accuracy I found in all research papers. The limitation in this research as researchers mention is about the data because it has only single fault signals.

Lei Guo [31] In this paper applied envelope spectrum analysis and SVM for fault diagnosis for bearings. Moreover, they proposed a system that utilizes the envelope spectrum that got from muti classification SVM model. However, that analysis of the envelope spectrum was used to get the characteristics frequencies of the vibration signals, and SVM was used for fault classification. The researchers proved that the combination of this method is very useful and gives promising results for bearing fault diagnosis and classification. The signals vibrations have impulses that carry useful information, the envelope spectrum analyses these impulses and gets the main features for fault diagnosis then the SVM applied for recognizing patterns and classification. However, they mentioned that the accuracy of the model of testing data was 100%. S. G. Kumbhar [32] In this paper he and researchers filled a gap as they believe, the previous research highlighted the vibration characteristics of surface faults in bearing by dimensional analysis (DA). While this paper focuses on both the influence of surface faults and the temperature of the bearings. However, they aimed to develop a DA model that investigates the impact of the volume of the fault on bearing characteristics. Moreover, they created a surface fault in the outer ring inner ring and balls of bearing then they tested the model and found that it works well for defecting faults based on factors such speed, temperature, and imbalance. However, they mentioned the limitation of this model that the model is not able to distinguish between the faults type. V. R. Patil [33] In this paper aims to study the correlation between several variables and their effect on vibration response using response surface method (RSM) and DA analysis. They conducted multiple trials to get vibration amplitudes and the faults frequencies. Moreover, they did a comparison between the experiment analysis and the DA model analysis. The results were in a line and have demonstrated string consequences, meaning; experiment values closely match the predicted values. However, the analysis of variance was performed to get insights from the results and know the significant features, they found that internal radial, clearance, speed, and unbalanced mass all are important parameters impact the vibration amplitude. Al-Najjar [34] In this research paper they discussed the condition monitoring for bearings in paper mills. They mentioned how crucial detecting failure of bearings in paper mills is and how can the early detection affect positively in decision making. However, the researcher studied three conditions of bearings: working normally, initiation and growth of the defect, and failure. Moreover, the researcher built a model based on signal vibration using time to failure (TTT) plots. Also, they introduced a model with conditional residual time (CRT) to predict the remaining useful life for the bearings. in addition, they used the non-gaussian and non-linear filtering methods to have more accurate prediction.

C. Mo, H [35] In this research paper they introduced the challenges that he can find while diagnosing bearing fault. However, the challenges according to the paper are data volume, weak signals, and noise inference. To tackle these challenges for example the noise, the researcher developed an enhanced method that gathers complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) and wavelet thresholding to make decrease the noise and enhance data quality. Moreover, the mutual dimensionless metrics were used for features extraction. The approach was validated using several experiments on bearings with different statues. However, the SVM model was used for doing the prediction and a multi population genetic algorithm (MPGA) to improve the SVM model, and the results show how the accuracy increased from 89.87% to 95.3%. Then to validate the model with different datasets he applied the algorithm to CWRU dataset, and the accuracy was 97.1% which is shows how the model is effective. H. Yuan [36]in this paper used a new method which is invariant sparse feature and optimized SVM. The algorithm that was used for feature extraction is shift invariant K singular value decomposition (K-SVD). Next, the optimized SVM applied using three methods; grid search, genetic algorithm (GA), and particle swarm optimization (PSO), and these used to optimize the SVM model for accurate fault classification. Moreover, this paper validates the effectiveness of this model, the KSVD worked well for distinguishing several bearings states. However, the optimized SVM with PSO achieved the highest accuracy among the three methods which is 96.3%, but it took the longest running time about 112.44s. However, Grid search achieved 96% with running time around 57.3s which is around half PSO waiting time with accuracy different equals 0.3, which is in my opinion it is small different with double time waiting. T. Han [37] in this paper deployed an intelligent method for fault diagnosis and classification. The method is built with dictionary learning and sparser representation-based classification (SRC). Moreover, the researchers mention that normal methods are limited as they just do a feature selection and classification. So, the method they proposed uses dictionary learning to have a self-adaptive extraction for the attributes and SRC to diagnosis the faults. However, the results validate the method with 97.50% accuracy for using DL-SRC. However, the proposed method has some limitations such, spares coding complexity, limited signals dimensions and limited noise estimation.

L. Meng, [38] In this research paper they discussed using SVM for fault classification for bearings. The advantage of SVM is that the model can work with small sample size, patterns with nonlinear behavior and high dimensional data. The SVM model is used for two class and multi class classification. Moreover, to extract eigenvectors from the signals, they used Wavelet packet denoising and decomposition methods. The sample used has 40 bearings working normally and 40 with faults in the outer ring. However, to evaluate the model kernel functions were used. As a result of the research SVM gives high classification accuracy and it outperforms Radial Basis Function (RBF) neural network in speed of training and rate of recognition. The limitation in this research is having small fault samples.

Previous research achieved a high accuracy in diagnosis of the faults of bearings using several methods and algorithms. However, what will be different in my research is that I will add a visualization dashboard presenting graphical representation of data for the signal's vibration and how the signal vibration can impact fault size and location.

2.2 Learnings from literature review

- Random forest shows higher performance than other algorithms not only for bearings failure.
- Most of the research achieved a high accuracy on predicting bearings failure, but the opposite for the RUL because of the available data quality.
- When the researchers applied features reduction methods the accuracy improved.
- Most of the research in the literature achieved high prediction accuracy but no one studied the relation between signal vibrations with fault size and location.

Chapter 3- Research Methodology

The research aims to understand the challenges in the field of bearings fault and identify the keys for enhancing the maintenance experience for workers, engineers, and customers. Also, to have an accurate prediction model for bearings fault classification followed with a visualization dashboard for understanding the signals vibration. However, from the literature review we founded that available data for bearings are limited and cannot be used for predicting the remaining life of bearings. however, the methods vary and did achieve very good results for bearings fault prediction, but no one did a visualization dashboard for the signal vibration.

This research will employ CRISP-DM (Cross Industry Standard Process for Data Mining) methodology, as shown in fig (2). This methodology is used widely in data mining projects to ensure having high and accurate model. CRISP-DM gives a plan for planning and implementing the data mining project. Moreover, this methodology will be used to have valuable outcomes.

Fig (2). CRISP-DM Methodology

This research will adapt a quantitative method that measure and compare the performance between two classifications algorithms, analyzing the impact of feature reduction on model accuracy, and knowing the main attributes that impact the fault location and size.

The data will split into 75% training dataset to train the algorithms and 25% testing dataset to validate the used models as shown in fig (3). However, for the data preprocessing the data will be scaled to improve the performance of the machine learning and to make sure that all variables equally contributed. Moreover, to understand how the attributes are correlated with each other a correlation matrix will be used to identify the correlations. Then the SVM model will be applied and will calculate the accuracy of the model and will have the confusion matrix to evaluate how the model did the prediction. The true positive, false positive and the false negative for each label will be calculated followed by F1 score and recall for each label, as this is a multiclassification problem. Moreover, the same procedure will be used for the random forest model. Then will compare with the prediction accuracy to have the accurate model for bearings faults classification. In addiction random forest feature importance will be applied for feature reduction and to see if that will improve the accuracy or not. However, using the attributes for the feature reduction will build a dashboard that shows how each attribute affects the location and the size of the fault for better understanding, this process is shown in summary in fig (4).

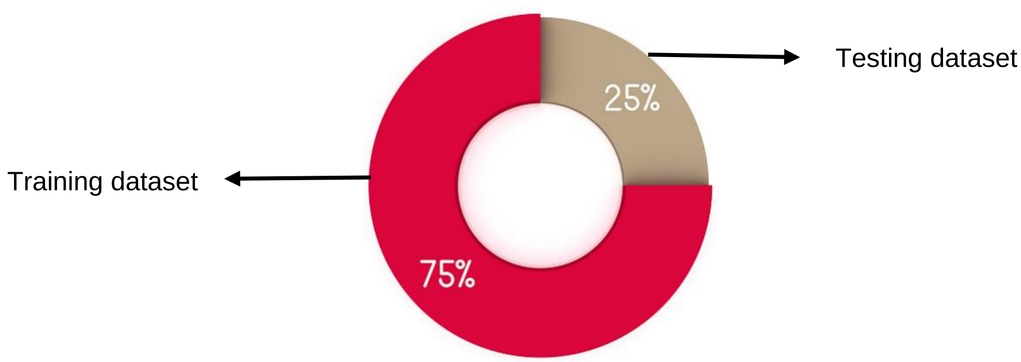

Fig (3). Data Splitting Percentage

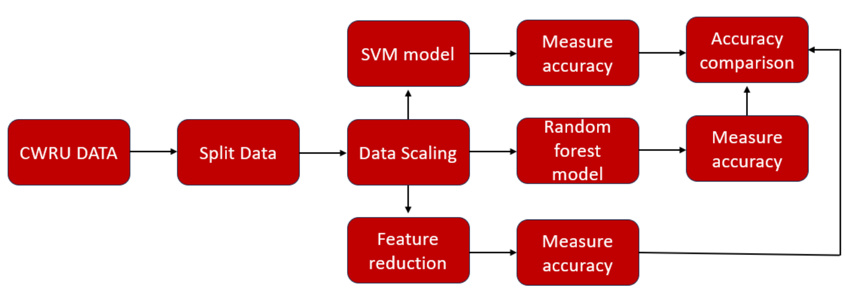

Fig (4). Process Flow Cha

Chapter 4- Findings and Data Analysis

4.1Dataset

In this research the data used is from Kaggle which is an open source for data. The data were provided by Case Western Bearing Data Centre. Moreover, the data collected after a test for a motor to measure the performance of an electric motor. The data has 9 attributes and 2300 observations. However, the data is complete and does not contain missing values.

4.2 Data dictionary

Name	Type	Class	Description
max	Numeric	Measure	The highest signal value in given period
min	Numeric	Measure	The lowest signal value in given period
mean	Numeric	Measure	The average signal value in given period
sd	Numeric	Measure	Standard deviation: A measure of the spread signal values around the mean
rms	Numeric	Measure	Root mean square: A measure of signals overall energy
Skewness	Numeric	Measure	A measure of signals' distribution
kurtosis	Numeric	Measure	A measure of peakedness of the signal distribution
crest	Numeric	Measure	A measure of signals' peakiness
from	Numeric	Measure	A measure of signals' shape
fault	Categorical	Character	Contains information about the location and the size of the fault

Table (1). data dictionary

4.3 Data description and distribution

To understand the data properly here is in fig (5) a summary of the attributes showing the range of each attribute.

```
      max                 min                  mean
 Min.    :0.1573    Min.    :-6.2926    Min.    :0.003246
 1st Qu.:0.4564    1st Qu.:-2.1750    1st Qu.:0.011236
 Median :0.7945    Median :-0.7337    Median :0.013730
 Mean   :1.5751    Mean   :-1.5510    Mean   :0.015711
 3rd Qu.:2.2784    3rd Qu.:-0.4270    3rd Qu.:0.018638
 Max.   :6.8259    Max.   :-0.1602    Max.   :0.038386
       sd                  rms               skewness
 Min.   :0.05914    Min.   :0.06107    Min.   :-1.089928
 1st Qu.:0.13551    1st Qu.:0.13637    1st Qu.:-0.103426
 Median :0.18855    Median :0.19066    Median :-0.002465
 Mean   :0.34160    Mean   :0.34229    Mean   :-0.042251
 3rd Qu.:0.55559    3rd Qu.:0.55567    3rd Qu.: 0.061093
 Max.   :1.25658    Max.   :1.25631    Max.   : 1.059513
    kurtosis              crest                form
 Min.   :-0.80380    Min.   :2.429     Min.   :  3.484
 1st Qu.:-0.01516    1st Qu.:3.260     1st Qu.:  7.413
 Median : 0.81697    Median :3.922     Median : 13.123
 Mean   : 2.66444    Mean   :4.173     Mean   : 26.545
 3rd Qu.: 3.90229    3rd Qu.:4.816     3rd Qu.: 39.912
 Max.   :30.38533    Max.   :8.822     Max.   :313.743
    fault
 Length:2300
 Class :character
 Mode  :character
```

Fig (5). R output for data summary

4.4 Number of NA's

Using R, we can check the number of NA's in the data and fig (6) shows the result of 0 NA's which means all the values are there.

```
#have a look at the first six and the last six observations and NAs'
```{R}
  head(fault_data)
  tail(fault_data)

  fault_data[sample(nrow(fault_data))[1:10],]

  which(is.na(fault_data))
```

data.frame 6 x 10   data.frame 6 x 10   data.frame 10 x 10   R Console

integer(0)
```

Fig (6). R output number of NAs

4.5 Data Correlation

one of the mandatory things in understanding the data is to see the correlation between the attributes and how they correlated to each other specially with attribute fault. As the attribute fault has a categorical reading a conversion from categorical to numerical reading was done to have the correlation matrix in fig (7).

The attribute max shows a very strong negative correlation with attribute min and a strong positive correlation with attributes sd, rms, and form. However, the attribute form has a strong positive correlation with max, sd and rms while has a strong negative correlation with min. the most important attribute fault has positive correlation with min, sd, rms, form and kurtosis and a negative correlation with attribute min. from the correlation matrix we can see that attributes like mean, crest and skewness are less correlated with the fault.

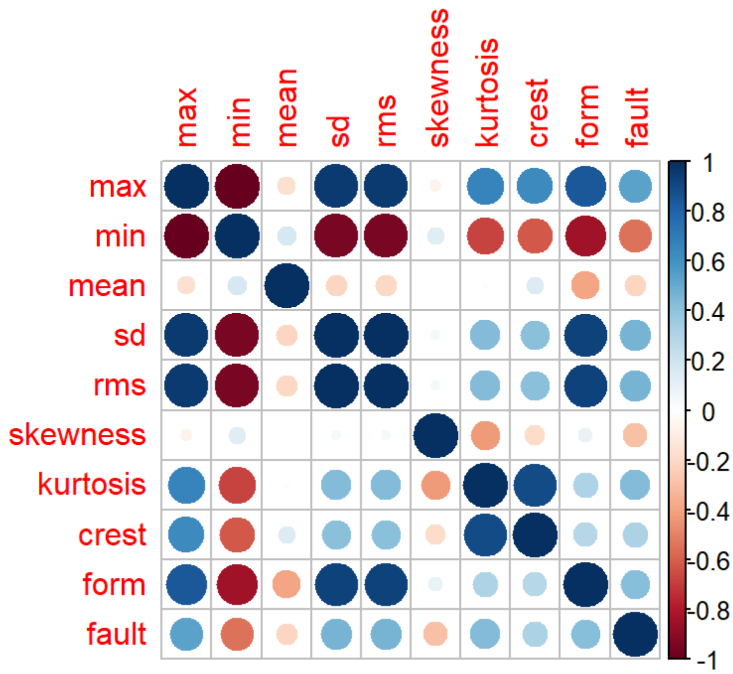

Fig (7). Correlation matrix of data attributes

4.6 Data Splitting

To have training and testing datasets the date was split into two datasets one to train the model and the second to test the model performance the next code used for splitting the data into 75% training dataset and 25% testing dataset.

```
#Split into training and testing
```{r}

fault_data$fault = as.factor(fault_data$fault)

set.seed(1234)
split <- createDataPartition(fault_data$fault, p = 0.75, list = FALSE)
training_da <- fault_data[split, ]
testing_da <- fault_data[-split, ]

table(testing_da$fault)
```
```

4.7 Data Scaling

As a crucial step before applying the ML algorithms, data scaling is mandatory to improve the stability of the data and enhance the performance by making all the attributes in the same range the following code used for the scaling.

```
#Scaling
```{R}
# Select numeric columns
numeric_columns <- sapply(training_da, is.numeric)
numeric_training_da <- training_da[, numeric_columns]
numeric_testing_da <- testing_da[, numeric_columns]

# Scale the numeric columns
scaled_training_da <- scale(numeric_training_da)
scaled_testing_da <- scale(numeric_testing_da)

# Replace the scaled numeric columns in the original data
training_da[, numeric_columns] <- scaled_training_da
testing_da[, numeric_columns] <- scaled_testing_da
```
```

4.8 SVM Model

The first algorithm applied for the training dataset is the SVM algorithm and achieved around 94% accuracy of bearings failure classification. The following code was used for the algorithm:

```r
#SVM model
```{r}
svc_model <- svm(fault ~ ., data = training_da)
svc_model
predictions <- predict(svc_model, testing_da)

# Calculating the accuracy of the model
actuals <- testing_da$fault
accuracy <- sum(predictions == actuals) / length(actuals)
cat("Accuracy:", accuracy)
#confusion matrix
confusion_mat <- confusionMatrix(predictions, actuals)
cat("Confusion Matrix:\n")
print(confusion_mat$table)
```

```
Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  radial
       cost:  1

Number of Support Vectors:  708

Accuracy: 0.9403509
```

Used the ggplot to have the confusion matrix of the SVM model.

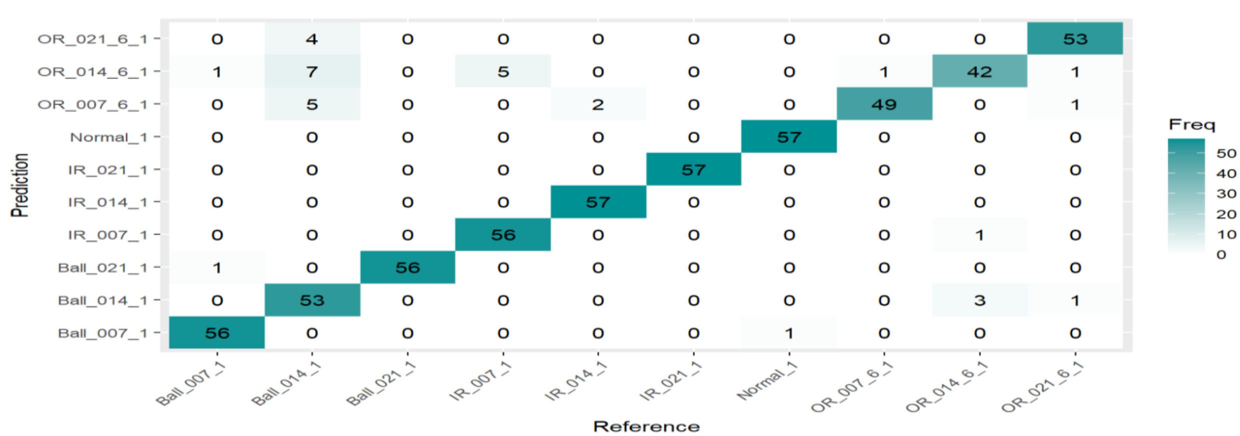

Fig (8). Confusion matrix of SVM model
```

Calculated the Precision score, ReCall score and F1 score for each label.

Fault classification	Precision score	Re-call score	F1 score
Ball_007	0.9824	0.9655	0.9739
Ball_014	0.9298	0.7681	0.8412
Ball_021	0.9824	1	0.9911
IR_007	0.9824	0.9180	0.9491
IR_014	1	0.9661	0.9827
IR_021	1	1	1
Normal	1	0.9827	0.9913
OR_007	0.8596	0.9800	0.9158
OR_014	0.7368	0.9130	0.8155
OR_021	0.9298	0.9464	0.9380

Table (2). Accuracy measures of each label of SVM model

4.9 RF Model

The second algorithm applied is random forest and achieved around 95.7% accuracy for bearings fault classification the following code used for the model.

```
#Random forest model
```{r}

# Fit the Random Forest model
rf_model <- randomForest(fault ~ ., data = training_da)

# Make predictions
predictions.RF <- predict(rf_model, testing_da)

# Calculate accuracy
actuals.RF <- testing_da$fault
accuracy.RF <- sum(predictions.RF == actuals.RF) / length(actuals.RF)
cat("Accuracy:", accuracy.RF, "\n")

```

Accuracy: 0.9578947
```

Confusion matrix for random forest model

Fig (9). Confusion matrix of RF model

Calculated the Precision score, ReCall score and F1 score for each label

Fault classification	Precision score	Re-call score	F1 score
Ball_007	0.9649	0.9649	0.9649
Ball_014	0.8947	0.8360	0.8644
Ball_021	1	0.9827	0.9913
IR_007	1	1	1
IR_014	1	0.9661	0.9827
IR_021	1	1	1
Normal	1	0.9827	0.9913
OR_007	0.8771	0.9615	0.9174
OR_014	0.9122	0.9122	0.9122
OR_021	0.9122	0.9629	0.9369

Table (3) Accuracy measures of each label of RF model

In order to check if the model is overfitted or not I applied k-fold cross validation with k=10, and the results show that with different mtry numbers the model is working well and there is no overfitting.

```
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 1558, 1556, 1557, 1557, 1556, 1557, ...
Resampling results across tuning parameters:

  mtry  Accuracy   Kappa
  2     0.9612672  0.9569586
  5     0.9601077  0.9556704
  9     0.9618351  0.9575896
```

4.10 Random Forest feature importance for feature reduction

To see which attributes are more relevant and the most affects the failure on bearings. The algorithm gives a score for each attribute according to its importance. The attributes rms, sd, mean, kurtosis and max are the top five and the following shows the result.

	Feature <chr>	Importance <dbl>
max	max	138.19870
min	min	130.92216
mean	mean	245.29229
sd	sd	297.49834
rms	rms	313.76890
skewness	skewness	30.22517
kurtosis	kurtosis	189.37410
crest	crest	83.18021
form	form	127.63369

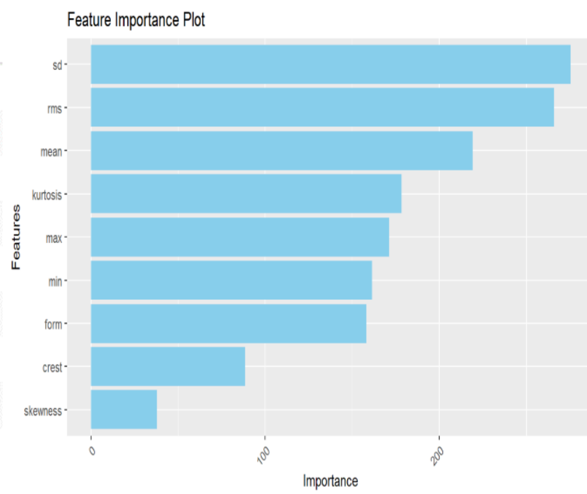

Fig (10). R result for feature reduction

4.11 Model Accuracy After Feature Reduction

After having the most relative features for bearing fault prediction, the top 4 attributes were selected and applied the random forest algorithm for the selected attributes the model achieved 95.4%. Moreover, then the number of attributes increased using 5 attributes the model achieved 95.6%

```
Accuracy (Selected Features): 0.954386
```
4 Attributes

```
Accuracy (Selected Features): 0.9561404
```
5 Attributes

4.12 Dashboard

A dashboard for the top 5 attributes Rms, mean, sd, Max and kurtosis was built to understand how the signal vibration affects the fault location and sizes.

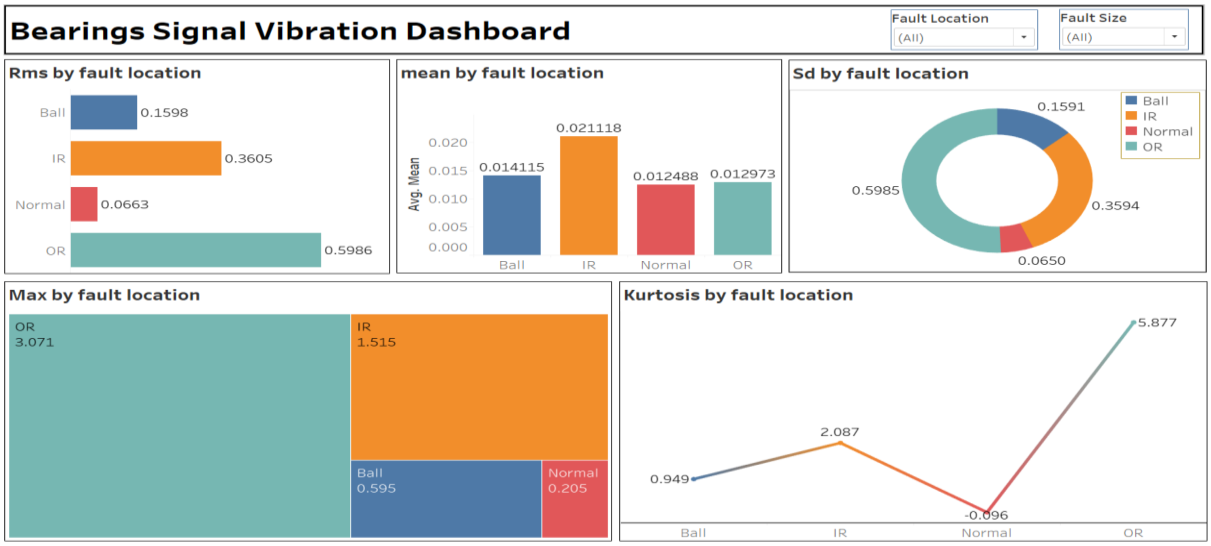

Fig (11). Signal vibration dashboard for top 5 attributes

The following dashboards are the signals vibrations according to different sizes of faults and locations.

Signal vibration of the main valuable attribute with 0.007-inch size of fault in 3 locations of the bearings, inner, outer rings, and balls

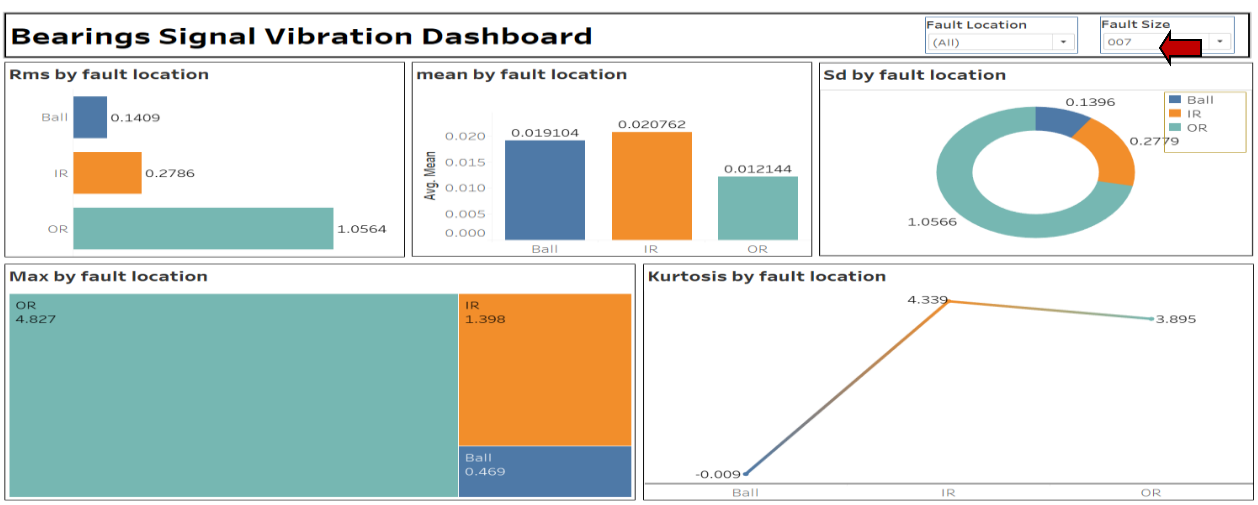

Fig (12). Signal vibration dashboard for top 5 attributes-fault size 0.007-inch

Signal vibration of the main valuable attribute with 0.014-inch size of fault in 3 locations of the bearings, inner, outer rings, and balls

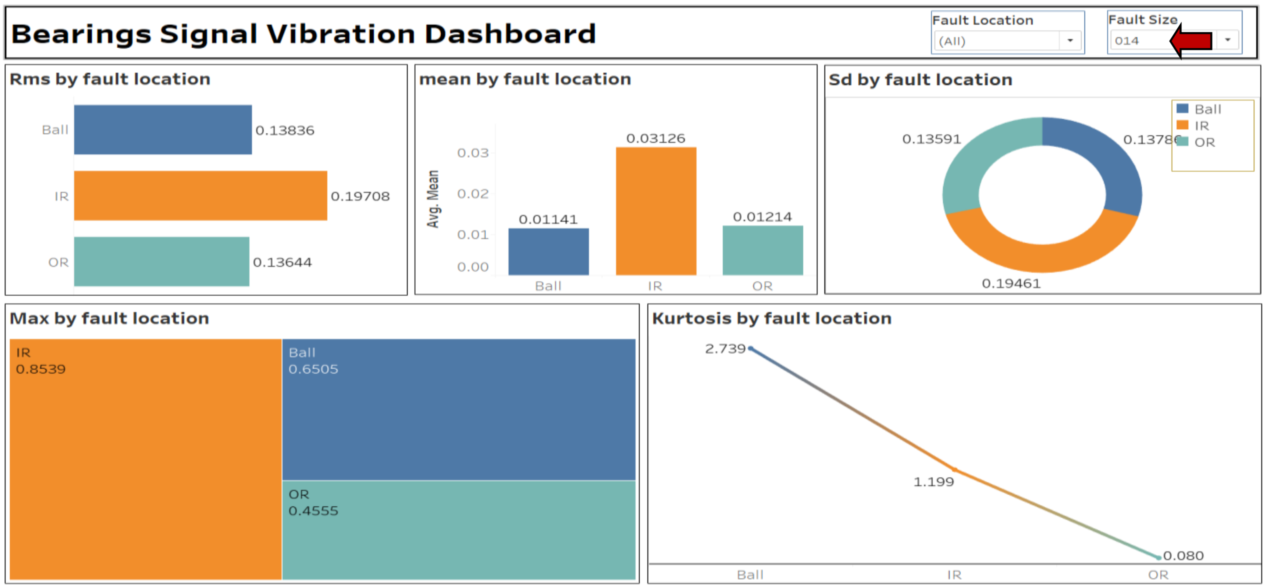

Fig (13). Signal vibration dashboard for top 5 attributes-fault size 0.014-inch

Signal vibration of the main valuable attribute with 0.021-inch size of fault in 3 locations of the bearings, inner, outer rings, and balls

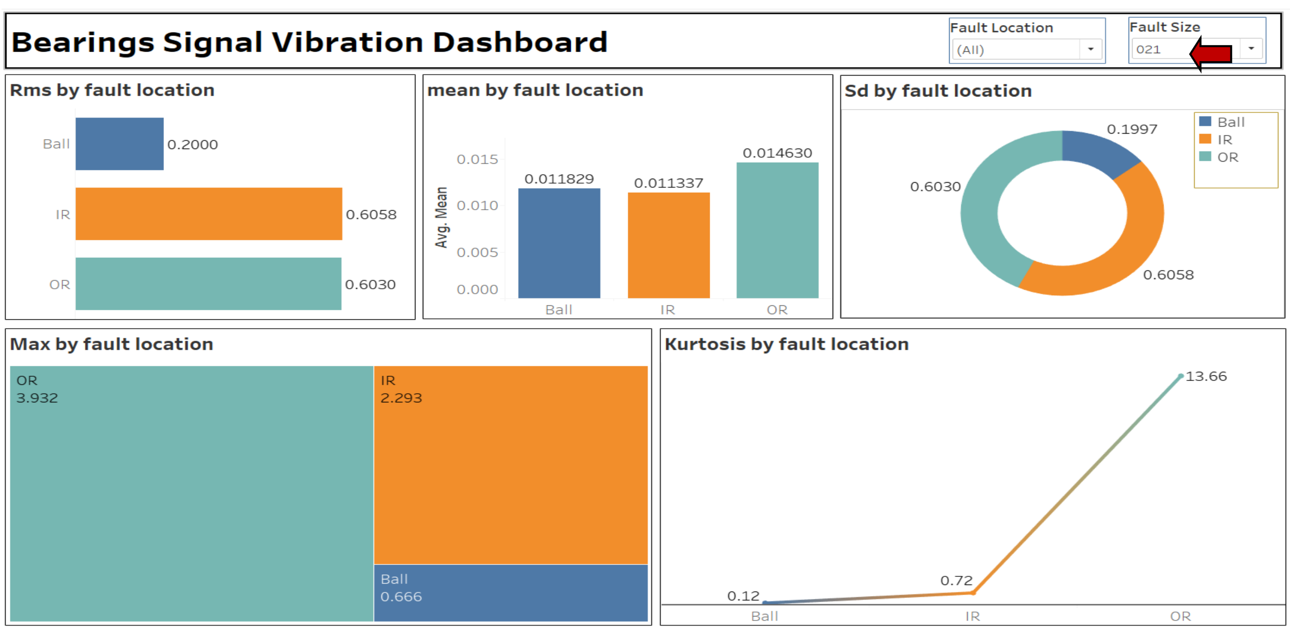

Fig (14). Signal vibration dashboard for top 5 attributes-fault size 0.021-inch

Chapter 5- Discussion

This research aims to find answers for the main business questions. The first question was which algorithm can achieve a higher prediction accuracy for bearings fault classification. However, after applying the two algorithms SVM model achieved 94% while RF achieved 95.7%. RF achieved a higher prediction accuracy.

The second question concerns if the reduction of features can always improve the accuracy of the model. Moreover, the result of using random forest feature importance achieved 95.4% accuracy using 4 attributes and 95.6% using 5 attributes, while the model with all attributes achieved 95.7% accuracy. The difference between the two model is around 0.3 and 0.1. However, having less attributes is better, but the accuracy was decreased instead of improving the accuracy. However, the previous research in the literature review when the feature reduction was applied the accuracy was improved and this can be a result of the choice of the algorithm used of feature reduction or the type of data used.

The third question is about the main features that can affect the fault sizes and locations. We have three sizes for each location, 0.007-inch, 0.014-inch, and 0.021-inch for inner ring, outer ring, and balls. The result of random forest feature importance showed that rms, Sd, mean, kurtosis and max are the main five attributes that can do the prediction. Moreover, the dashboard illustrates the top 5 attributes to have a clear image of the effect of this signal vibration on bearings fault. The following summarizes the outcomes from the dashboard in fig (11). as the higher values of the most attributes caused faults in the outer ring, then the inner ring, and the lowest was for bearings working normally. When the study involved the relationship according to both fault size and location the higher values for most attributes were in the outer ring while the size varies. However, the location of the fault found in the outer ring but the size 0.007 inch and another in the outer ring and the size 0.014 inch. This study included only 5 attributes from signals vibration and including more can give more conclusions.

Rms by fault location: The higher Rms attribute values are found on faults in the outer ring, and the average of the Rms values found on faults in the outer ring is 0.5986. The Rms values found on faults in the inner ring have an average of 0.3605. Moreover, the average Rms value for faults found in the balls is 0.1598. Bearings that work normally had an average RMS value of 0.0663.

Mean by fault location: The higher mean attribute values are found on faults in the inner ring, and the average of the mean values found on faults in the inner ring is 0.02118. The mean values found on faults in the balls have an average of 0.014115. Moreover, the average mean value for faults found in the outer ring is 0.012973. Bearings that work normally had an average mean value of 0.012488.

Sd by fault location: The higher Sd attribute values are found on faults in the outer ring, and the average of the Sd values found on faults in the outer ring is 0.5985. The Sd values found on faults in the inner ring have an average of 0.3594. Moreover, the average Sd value for faults found in the balls is 0.1591. Bearings that work normally had an average Sd value of 0.0650.

Max by fault location: The higher max attribute values are found on faults in the outer ring, and the average of the values of max found on faults in the outer ring is 3.071. The max values found on faults in the inner ring have an average of 1.515. Moreover, the average max value for faults found in the balls is 0.595. Bearings that work normally had an average max value of 0.205.

Kurtosis by fault location: The higher kurtosis attribute values are found on faults in the outer ring, and the average of the values of kurtosis found on faults in the outer ring is 5.877. The kurtosis values found on faults in the inner ring have an average of 2.087. Moreover, the average kurtosis value for faults found in the balls is 0.949. Bearings that work normally had an average kurtosis value of -0.0965.

The following table shows the results of signals vibration according to different sizes.

	rms	sd	mean	kurtosis	max
0.007-inch	Highest rms average 1.0564 results on faults in the outer ring, while the lowest average 0.1409 results on faults in the balls	Highest sd average 1.0566 results on faults in the outer ring, while the lowest average 0.1396 results on faults in the balls	Highest mean average 0.020762 results on faults in the inner ring, while the lowest average 0.012144 results on faults in the outer ring	Highest kurtosis average 4.339 results on faults in the inner ring, while the lowest average -0.009 results on faults in the balls	Highest max average 4.827 results on faults in the outer ring, while the lowest average 0.469 results on faults in the balls
0.014-inch	Highest rms average 0.19708 results on faults in the inner ring, while the lowest average 0.13836 results on faults in the balls	Highest sd average 0.19461 results on faults in the inner ring, while the lowest average 0.1378 results on faults in the balls	Highest mean average 0.03126 results on faults in the inner ring, while the lowest average 0.01141 results on faults in the balls	Highest kurtosis average 2.739 results on faults in the balls, while the lowest average 0.080 results on faults in the outer ring	Highest max average 0.8539 results on faults in the inner ring, while the lowest average 0.4555 results on faults in the outer ring
0.021-inch	Highest rms average 0.6058 results on faults in the inner ring, while the lowest average 0.02000 results on faults in the balls	Highest sd average 0.6058 results on faults in the inner ring, while the lowest average 0.1997 results on faults in the balls	Highest mean average 0.014630 results on faults in the outer ring, while the lowest average 0.011337 results on faults in the inner ring	Highest kurtosis average 13.66 results on faults in the outer ring, while the lowest average 0.12 results on faults in the balls	Highest max average 3.932 results on faults in the outer ring, while the lowest average 0.6666 results on faults in the balls

Table (4). Dashboard summary of signal vibration with fault size

Chapter 6- Conclusions

6.1 Conclusion

This research aimed to address the challenge of bearings fault classification using the techniques from machine learning. SVM and RF algorithms were used for building the prediction model then compared the accuracy of each model using all the attributes. Moreover, the feature reduction using random forest feature reduction used and see how this affects the prediction accuracy. The following conclusions highlight the main outcomes from this research:

- RF outperformed SVM model in term of model accuracy showing that RF is better in term of decision making for bearings fault classification.
- Feature reduction using random forest feature reduction caused a minimal reduction of accuracy. Showing that we can use less attributes and simpler models without making the accuracy much worse.
- The relationship between the fault size, fault location and signal vibration successfully demonstrated in a visualization dashboard revealing several patterns and characteristics.

6.2 Recommendations

According to the research findings and limitations this are some proposed recommendations:

- Further explorations of feature reductions methods to achieve a more optimized model without compromising the accuracy.
- Following the new data analysis and data visualization techniques to ensure improving the performance.

6.3 Future work

According to the limitations and considering work improvements there are some suggestions for future works:

- Using the streaming data of bearings faults for earlier detection and minimize the downtime.
- In depth analysis for the relationship of signal vibration with fault size and locations and underline the mechanical behavior of bearings.

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