FAULT DETECTION OF ROLLING ELEMENT BEARING USING MACHINE LEARNING

Presentation

Amol Mathur

ME: 801984003

Department of Mechanical Engineering

Thapar Institute of Engineering & Technology, Patiala

Supervisors:

Dr. Jaskaran Singh
(Assistant Professor)

Dr. Prashant Singh Rana
(Associate Professor)

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Introduction

- **Machine wear have a problem:**
  - Lead time of production
  - Decline in the quality of product
- **Condition monitoring:**
  - Mostly used in process based industries.
  - Where machine is continuously running.
  - Example fertilizer industry, oil and gas industry, and pharmaceutical industries, chemical industry etc.
  - Condition monitoring is focused on real time conditions, while predictive maintenance has focused on the early detection of defects in advance.
  - Predictive maintenance is the application of data-driven i.e it is dependent upon the previous history of the machine component.

Effect of wear on machinery

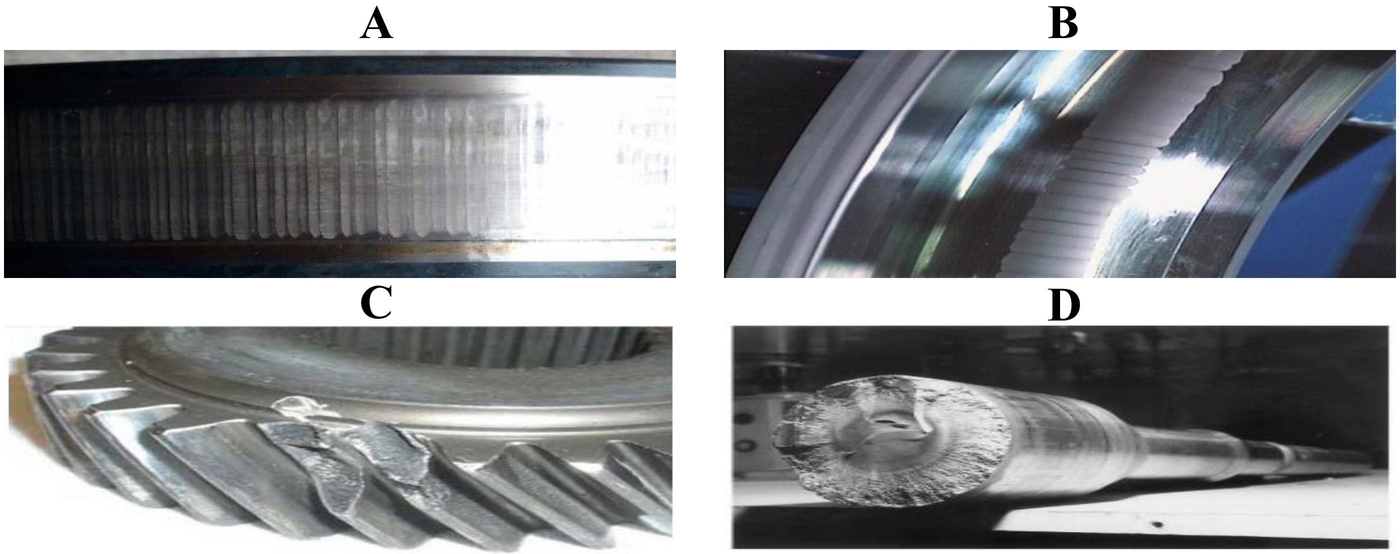
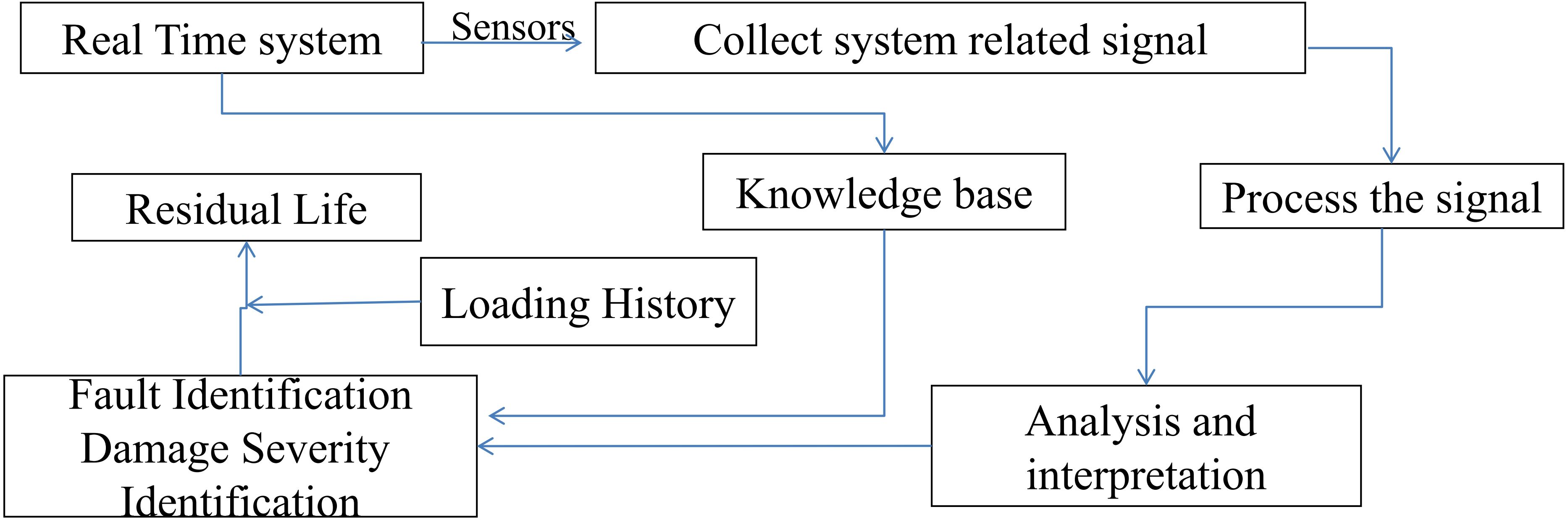


Fig 1: (**A**) Damaged Bearing outer race; (**B**) Damaged bearing inner race
(C) Damaged gear; **(D)** Damaged shaft [1-3]

Condition Monitoring - Flow



Different types of Condition Monitoring

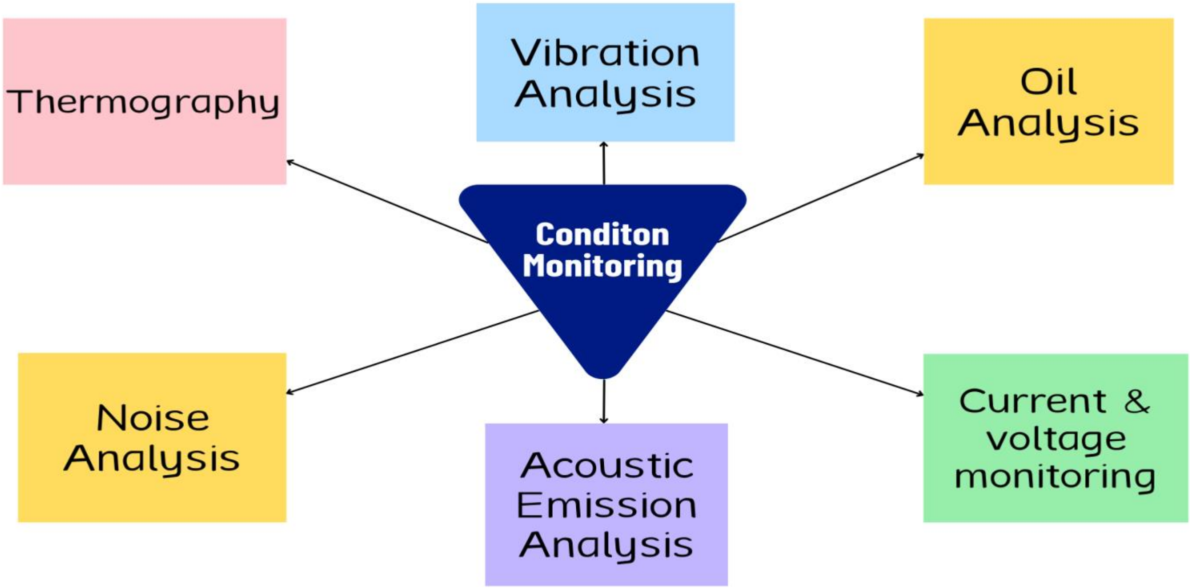


Fig 2: Representation of types Condition Monitoring

Different types of maintenance

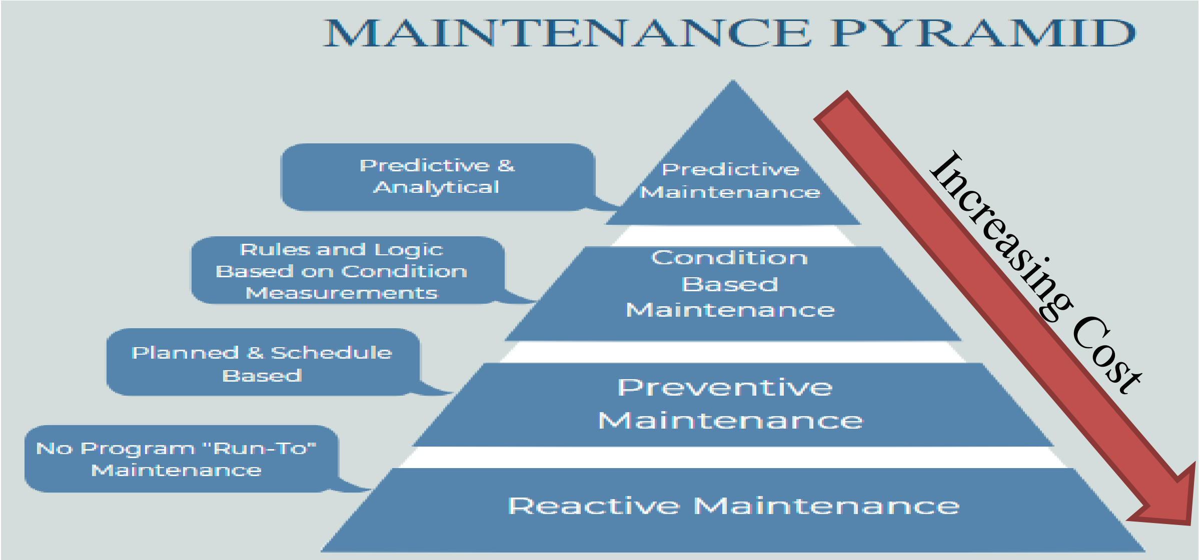
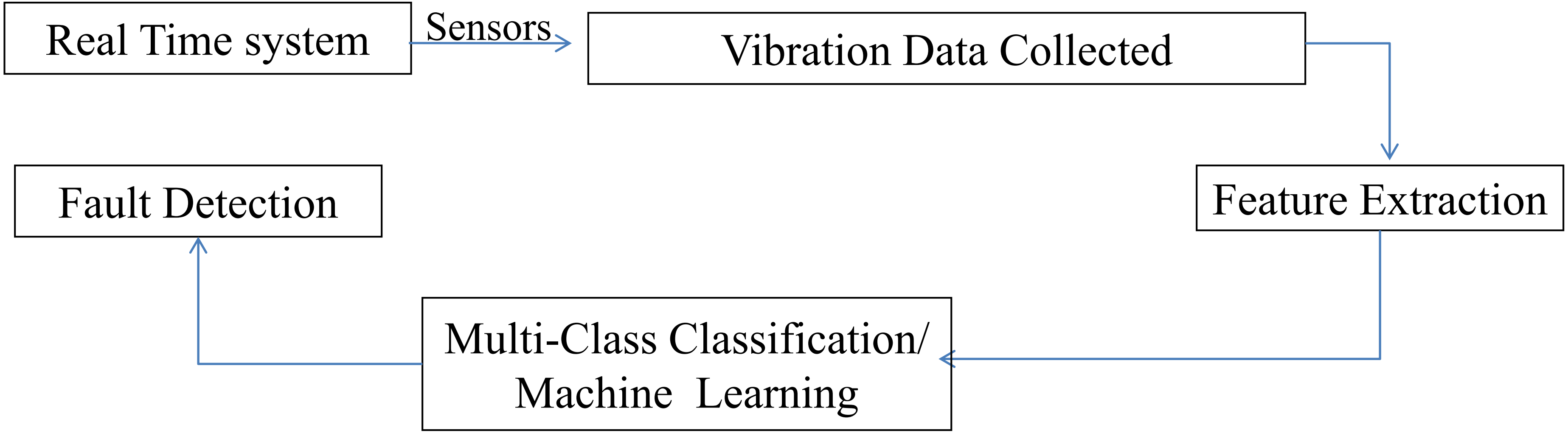


Fig 3: Types of Maintenance

Brief Overview of our work



Literature Review

Author's	Observations
Eren et al (2019) [4]	➢1D Convolutional Neural Network (CNN) classifier is used ➢ To make it more independent with respect to F.F.T or D.W.T transformations
Barbieri et al (2019) [5]	➢Auto Regressive modeling used for selecting features ➢machine learning based on the logistic regression algorithm
Xenakisa et al (2019) [6]	➢ IoT and Cloud based decentralised framework for real time machine condition monitoring (MCM) and fault prediction ➢Fog nodes perform feature extraction and health condition classification ➢For solving it in a distributed manner by applying asynchronous altering direction method of multipliers (ADMM) algorithm was used
Laith et al (2020) [7]	➢Features were chosen by using a genetic algorithm, emphasis given for using the raw data ➢Artifical Neural Network with optimized structure using genetic algorithm has been used.

Literature Review

Author's	Observations
Singh et al (2020) [8]	➢Provides a comprehensive overview of recent efforts and developments in applying machine learning (ML) approaches to rolling element bearing diagnostics and prognostics ➢The advantages and disadvantages of the described ML algorithms have been thoroughly examined and analyzed.
Neupane et al (2020) [9]	➢Deep learning methods to detect and diagnose machinery faults
Moshrefzadeh et al (2021) [10]	➢This study can distinguish between different machine health states regardless of load or speed ➢SVM and subspace k-nearest neighbours are the two data classification methods used
Mehta et al (2021) [11]	➢Infrared thermography is used, 2D-DWT has been applied for the decomposition of the thermal image ➢PCA used for extracting features ➢SVM, LDA, K-NN were used, SVM outperforms all

Research Gap

- Difficult to implement in the real world situations.
- Computationally expensive transformations were used.
- Limitations to classifying when ever the number of fault types increased.

Objective of research

- To have a real time indication of fault detection.
- To be able to work without undergoing any predetermined transformations or signal processing transformations.
- To reduce computational expense during detection and diagnosis.

Experimental Setup

- Data set from C.W.R.U bearing data center.
- Data taken from drive end bearing.
- H.P = 0 hp to 3 hp
- Rpm = 1797 to 1720
- Secondary Data Set

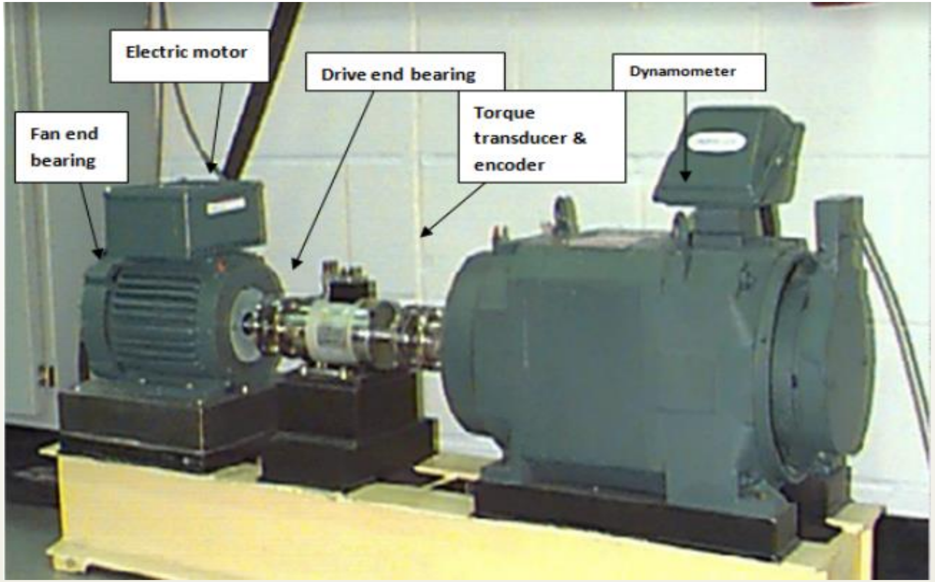


Fig:4 Illustration of the Experimental Setup[12]

Research Methodology

- **WORK FLOW**

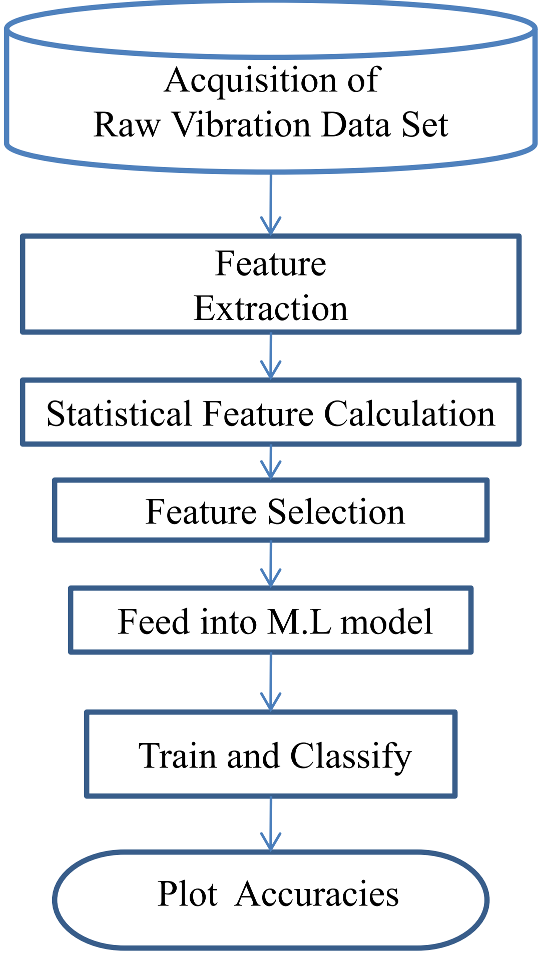
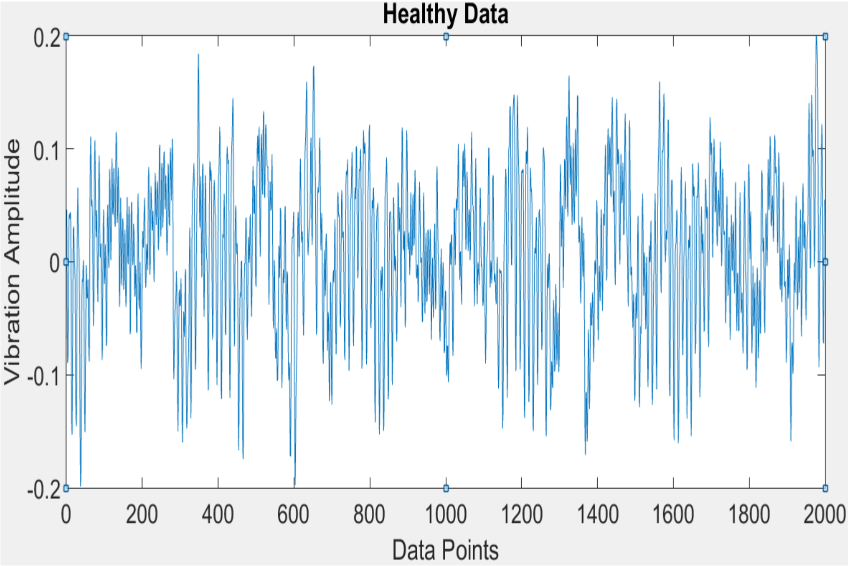


Illustration of Data Set



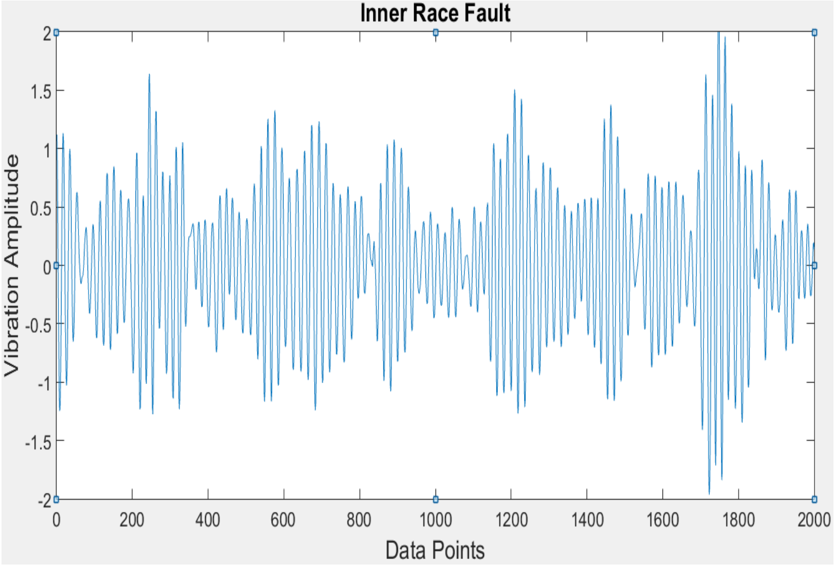


Fig 5: Illustration of Healthy Bearing and Inner Race

Illustration of Data Set

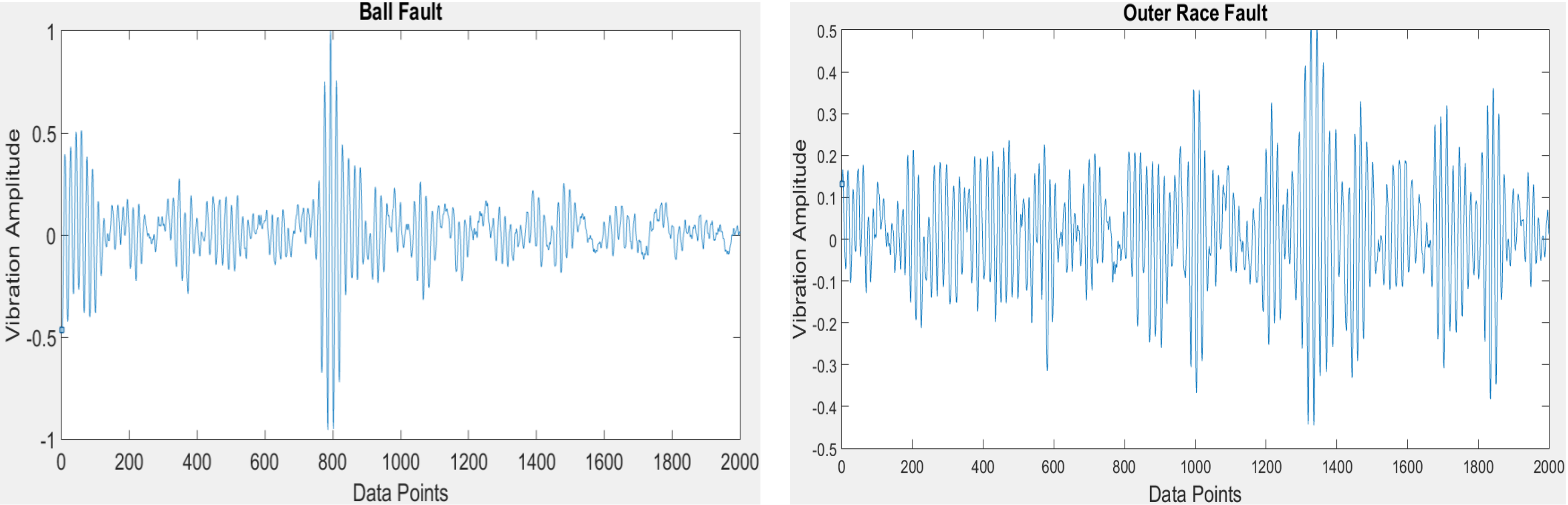


Fig 6: Illustration of Ball Fault and Outer Race Fault

Extracted Feature Importance

- **Maximum:** The place where a function reaches its highest point or vortex on a graph is called as maximum value of the function.
- **Minimum:** The smallest mathematical value in the data set is called as minimum value in a data set.
- **Note:** The minimum and maximum value can also be called as outlines. Outliners is a value that is much larger or smaller than the other values in a data set or values lies outside the data set.
- **Mean:** It is found by adding all numbers in the data set and then dividing by the number of values in the set.
- **Standard Deviation (s.d):** It is a statistic which measures the dispersion of a data set with respect to its mean and is calculated as a square root of the variance.
- **R.M.S:** It is the square root of the mean square (the arithmetic mean of the squares of a set of numbers)..

Extracted Feature Importance

- **Skewness:** It means a distortion or symmetry that deviates from the symmetrical bell curve or normal distribution in a data set. If curve is tilted to the left or right side it is called skewed.
- **Kurtosis:** It is a measure of whether the data are heavy tailed or light tailed with respect to normal distribution. Kurtosis greater than 3 then data set has heavier tail than normal distribution, if less than 3 then data set has lighter tail than normal distribution. It is the forth statistical moment and indicates major peaks in the samples, which are related to an increased vibration level.
- **Crest Factor:** The crest factor focuses on impulsive vibration source, such as bearing damage. It is basically the ratio of the peak (max) level to R.M.S

Data Visualizations

Healthy v/s Ball Fault

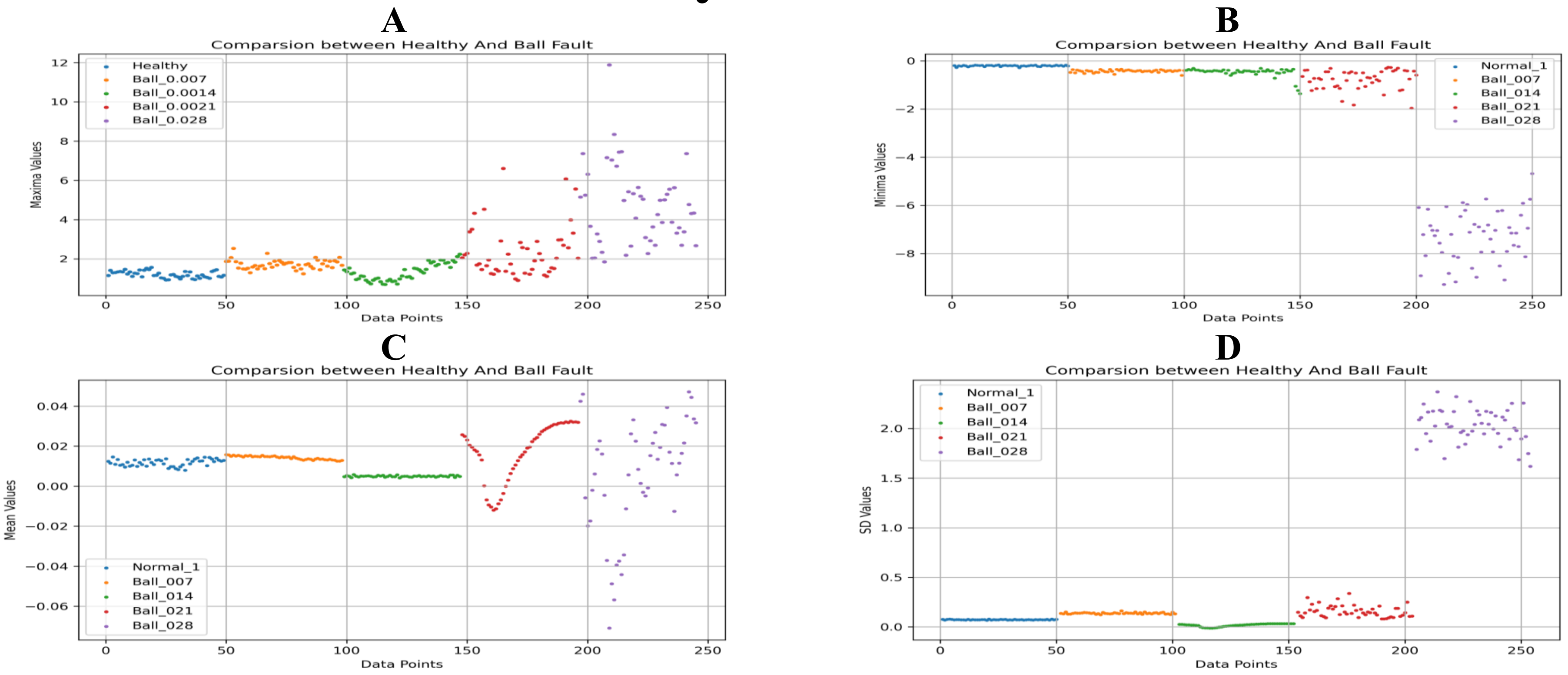
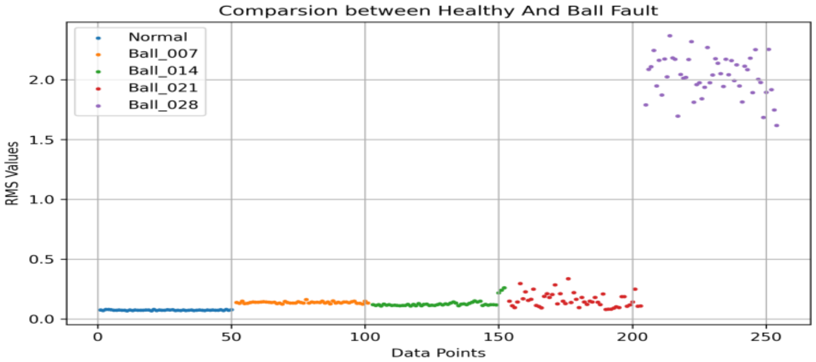


Fig 7: (A) Maxima values; (B) Minima values; (C) Mean values; (D) SD values

Healthy v/s Ball Fault

E



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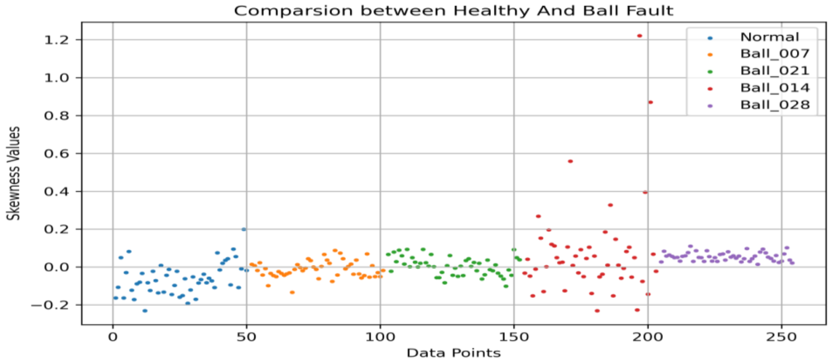

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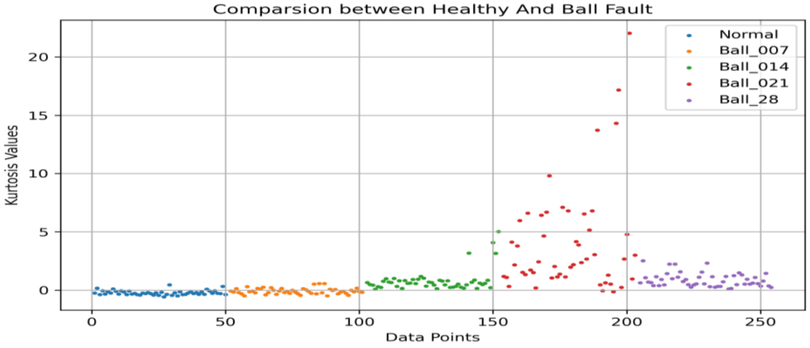

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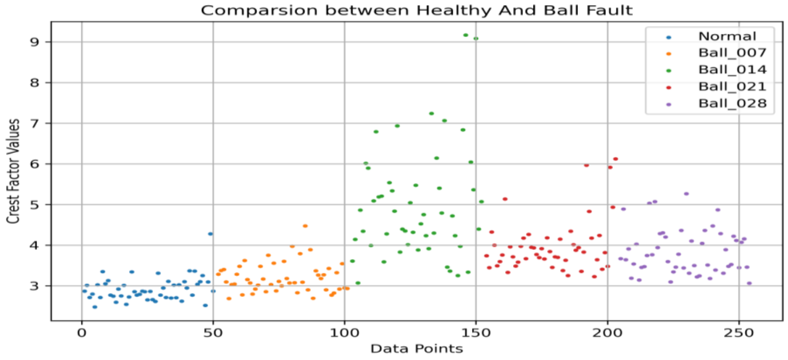
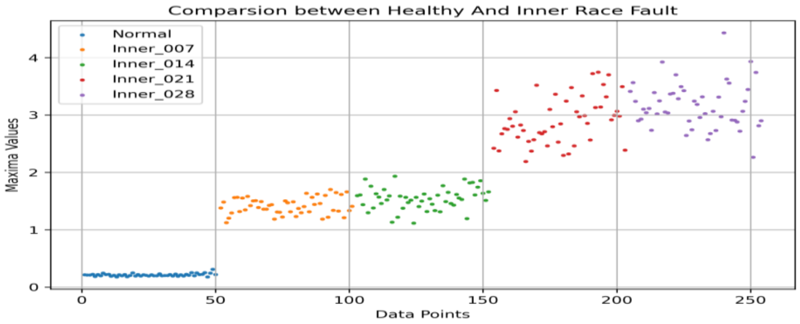


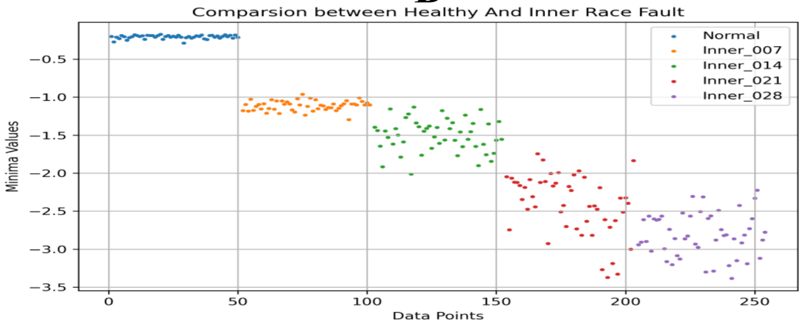
Fig 7: (E) RMS values; (F) Skewness values; (G) Kurtosis values; (H) Crest Factor values

Healthy v/s Inner Race Fault

A



B



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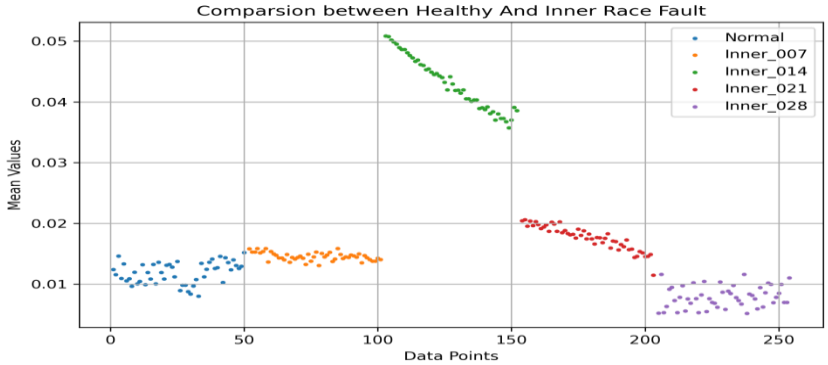


D

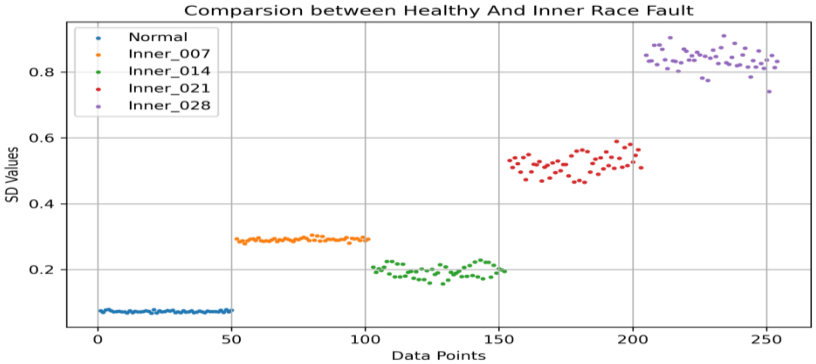


Fig 8: (A) Maxima values; (B) Minima values; (C) Mean values; (D) SD values

Healthy v/s Inner Race Fault

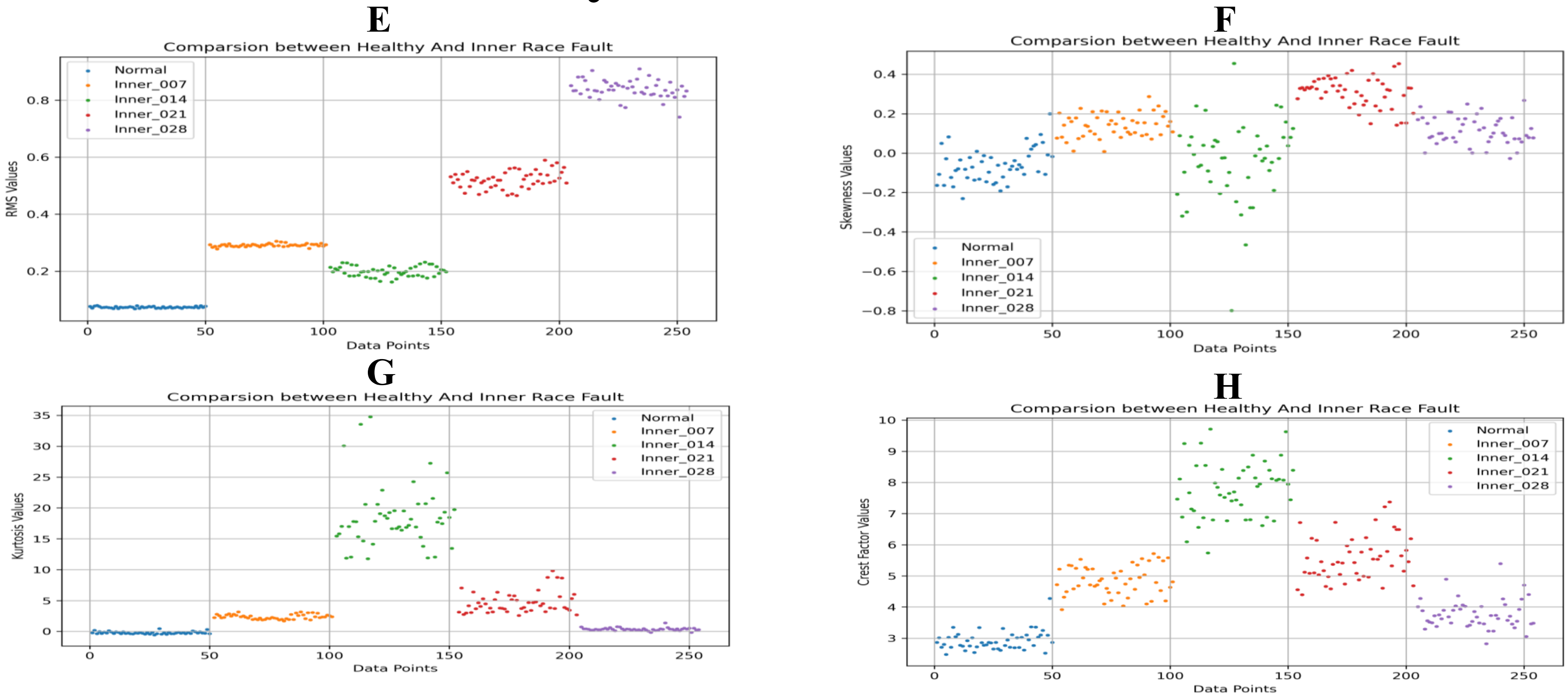


Fig 8: (E) RMS values; (F) Skewness values; (G) Kurtosis values; (H) Crest Factor values

Healthy v/s Outer Race Fault

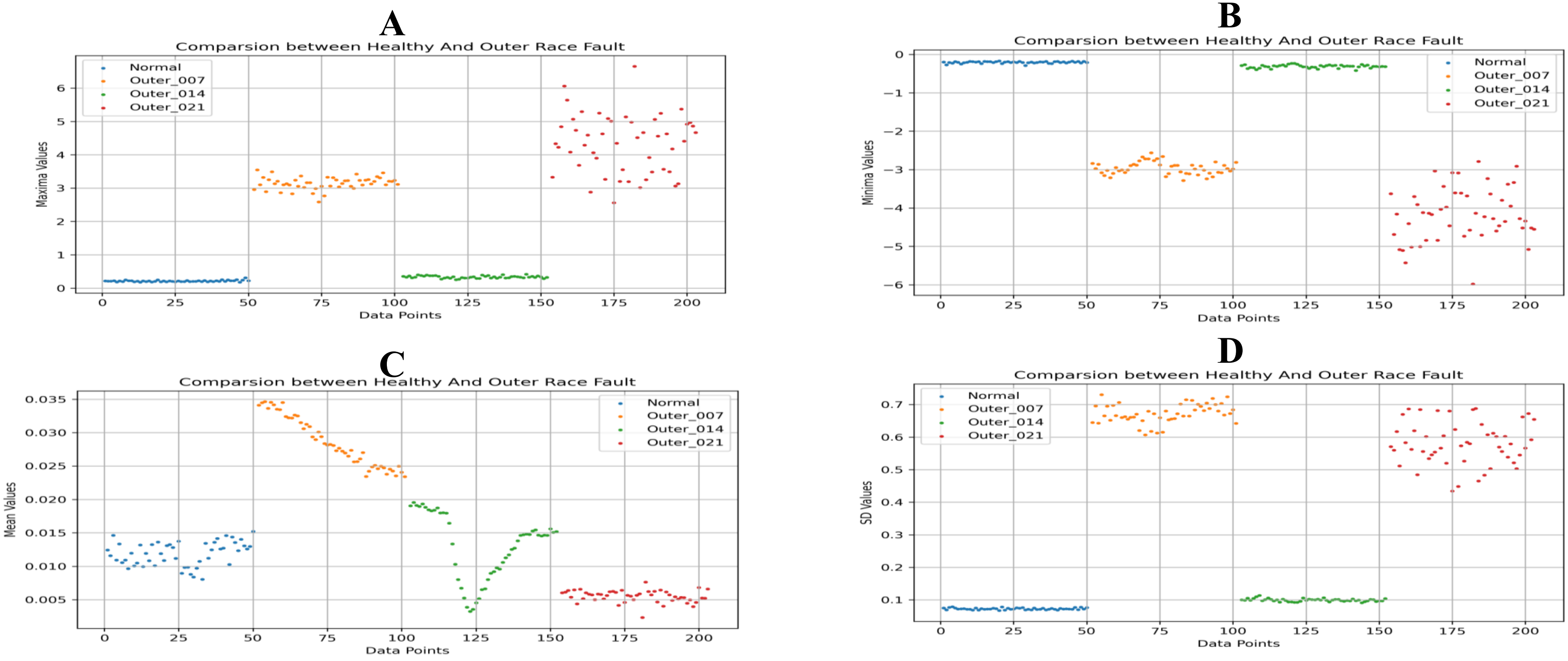


Fig 9: (A) Maxima values; (B) Minima values; (C) Mean values; (D) SD values

Healthy v/s Outer Race Fault

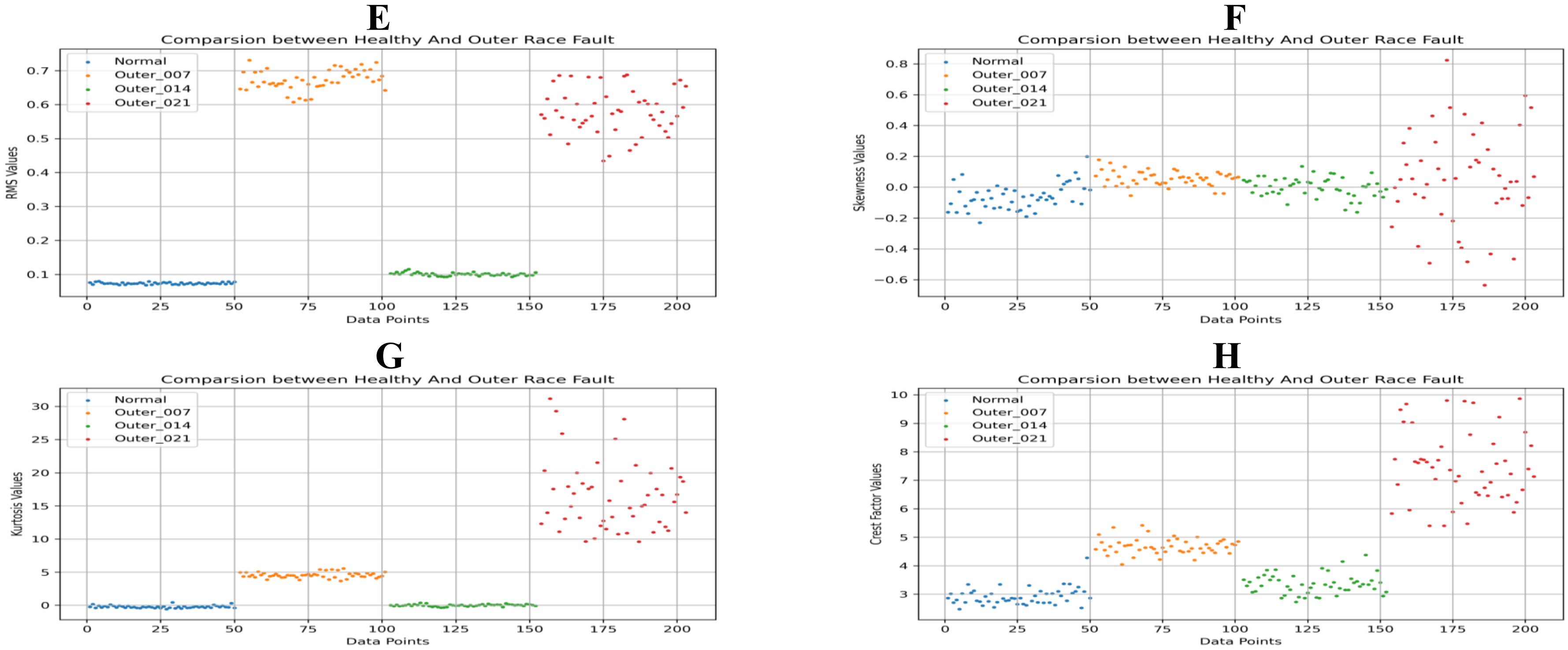


Fig 9: (E) RMS values; (F) Skewness values; (G) Kurtosis values; (H) Crest Factor values

Sample Dataset

max	min	mean	sd	rms	skewness	kurtosis	crest	form	fault
0.35986	-0.4189	0.01784	0.122746	0.124006	-0.11857118	-0.042219	2.901946	6.950855	**Ball_007_1**
0.46772	-0.36111	0.022255	0.132488	0.134312	0.174698897	-0.081548	3.482334	6.035202	**Ball_007_1**
0.35903	-0.32523	0.011007	0.10132	0.101891	-0.12557618	0.6391284	3.523651	9.257353	**Ball_014_1**
0.54532	-0.48545	0.01018	0.120743	0.121142	0.126083478	2.553367	4.501499	11.90015	**Ball_014_1**
0.72577	-0.73036	0.009639	0.202982	0.203161	0.047942123	0.1842567	3.572382	21.07694	**Ball_021_1**
0.50151	-0.47105	0.008832	0.153959	0.154174	-0.00079198	-0.23693	3.252875	17.45655	**Ball_021_1**
1.3458	-1.2283	0.022641	0.300779	0.301557	0.146702053	3.64727	4.462839	13.31935	**IR_007_1**
1.569	-1.4338	0.021687	0.265542	0.266361	-0.10401904	5.0606219	5.890501	12.28231	**IR_007_1**
0.75936	-0.74997	0.03125	0.201683	0.204041	-0.0317438	0.5473288	3.721611	6.529254	**IR_014_1**
0.91186	-0.60352	0.0306	0.17517	0.177781	0.059971278	1.49562	5.129128	5.809906	**IR_014_1**
1.6088	-2.0634	0.003246	0.528455	0.528336	-0.04758171	0.2216871	3.045031	162.789	**IR_021_1**
2.4619	-2.2568	0.010738	0.628748	0.628686	0.113583289	0.8544196	3.915947	58.54961	**IR_021_1**
4.2547	-4.1884	0.009404	1.029835	1.029627	0.081579377	3.3790519	4.132273	109.4864	**OR_007_6_1**
4.8594	-5.0869	0.010526	1.042177	1.041976	0.074873001	4.4782646	4.663639	98.99042	**OR_007_6_1**
0.49317	-0.47105	0.011703	0.144158	0.144597	-0.0291305	0.1495524	3.41064	12.35534	**OR_014_6_1**
0.51904	-0.43371	0.011712	0.130228	0.130722	0.023732985	0.4060898	3.970566	11.16152	**OR_014_6_1**
5.7584	-5.2509	0.01457	0.787581	0.787524	0.279032853	16.896728	7.312035	54.05178	**OR_021_6_1**
2.0458	-2.0358	0.014712	0.30929	0.309565	-0.1441385	10.124046	6.608634	21.04195	**OR_021_6_1**
0.19026	-0.17983	0.00935	0.065445	0.066094	-0.13616855	-0.369161	2.878627	7.069191	**Normal_1**
0.20194	-0.19067	0.010006	0.063999	0.064761	-0.17415557	-0.18361	3.118245	6.472259	**Normal_1**

Case Study 1: Effect of Load

	Fault Type	Fault Size (inches)	RPM/Load(HP)								
			1797/0			1772/1			1730/3		
			Data Set ID	Number of Classes	Samples considered	Data Set ID	Number of Classes	Samples considered	Data Set ID	Number of Classes	Samples considered
Case Study 1	Inner Race Fault	0.007	Data Set 2	5	40	Data Set 5	5	40	Data Set 9	5	40
		0.014			40			40			40
		0.021			40			40			40
		0.028			40			40			40
		Normal			40			40			40
	Ball Fault	0.007	Data Set 1	5	40	Data Set 4	5	40	Data Set 8	5	40
		0.014			40			40			40
		0.021			40			40			40
		0.028			40			40			40
		Normal			40			40			40
	Outer Race Fault	0.007	Data Set 3	4	40	Data Set 6	4	40	Data Set 10	4	40
		0.014			40			40			40
		0.021			40			40			40
		Normal			40			40			40

CASE STUDY 2

- **Effect of different sample size under different frequencies**

	Sampleing Frequencies	Fault Size (inches)	RPM/Load(HP)								
			1797/1								
			Data Set ID	Number of Classes	Samples considered	Data Set ID	Number of Classes	Samples considered	Data Set ID	Number of Classes	Samples considered
Case Study 2	12 kHz	I.R_0.007	Data Set 12	12	20	Data Set 14	12	30	Data Set 16	12	40
		I.R_0.014			20			30			40
		I.R_0.021			20			30			40
		I.R_0.028			20			30			40
		Ball_0.007			20			30			40
		Ball_0.014			20			30			40
		Ball_0.021			20			30			40
		Ball_0.028			20			30			40
		O.R_0.007_6			20			30			40
		O.R_0.014_6			20			30			40
		O.R_0.021_6			20			30			40
		Normal			20			30			40
	48 kHz	I.R_0.007	Data Set 7	10	20	Data Set 11	10	30	Data Set 13	10	40
		I.R_0.014			20			30			40
		I.R_0.021			20			30			40
		Ball_0.007			20			30			40
		Ball_0.014			20			30			40
		Ball_0.021			20			30			40
		O.R_0.007_6			20			30			40
		O.R_0.014_6			20			30			40
		O.R_0.021_6			20			30			40
		Normal			20			30			40
		I.R_0.007	Data Set 15	10	50				Data Set 17	10	60
		I.R_0.014			50						60
		I.R_0.021			50						60
		Ball_0.007			50						60
		Ball_0.014			50						60
		Ball_0.021			50						60
		O.R_0.007_6			50						60
		O.R_0.014_6			50						60
		O.R_0.021_6			50						60
		Normal			50						60

Results and discussion for Case Study 1

Comparative Table Data Set 5

In the Table below Naïve Bayes is the most accurate predicting model; with an accuracy of 91.98%

Model	Accuracy	AUC	Recall	Prec.	F1	Kappa
Naive Bayes	0.9198	0.9085	0.9102	0.9072	0.9133	0.9145
Decision Tree Classifier	0.9042	0.8611	0.9182	0.9189	0.9007	0.9109
Random Forest Classifier	0.872	0.8573	0.879	0.9001	0.9087	0.9051
Quadratic Discriminant Analysis	0.8562	0.8457	0.8591	0.8983	0.8991	0.8728
Extra Trees Classifier	0.8329	0.8398	0.8561	0.8756	0.8976	0.8452
Light Gradient Boosting Machine	0.7996	0.8298	0.8494	0.8496	0.8796	0.8394
Logistic Regression	0.7692	0.8186	0.7987	0.8292	0.8592	0.8289
K Neighbors Classifier	0.7288	0.7896	0.7881	0.7988	0.8288	0.7693
Gradient Boosting Classifier	0.6988	0.759	0.7381	0.7588	0.7988	0.7383
Linear Discriminant Analysis	0.6872	0.7499	0.7256	0.7273	0.7472	0.7296
SVM - Linear Kernel	0.6756	0.6984	0.7049	0.6956	0.7256	0.6937
Ridge Classifier	0.6594	0.6723	0.6702	0.6725	0.6906	0.6666
Ada Boost Classifier	0.6344	0.6404	0.6503	0.6543	0.6775	0.6371

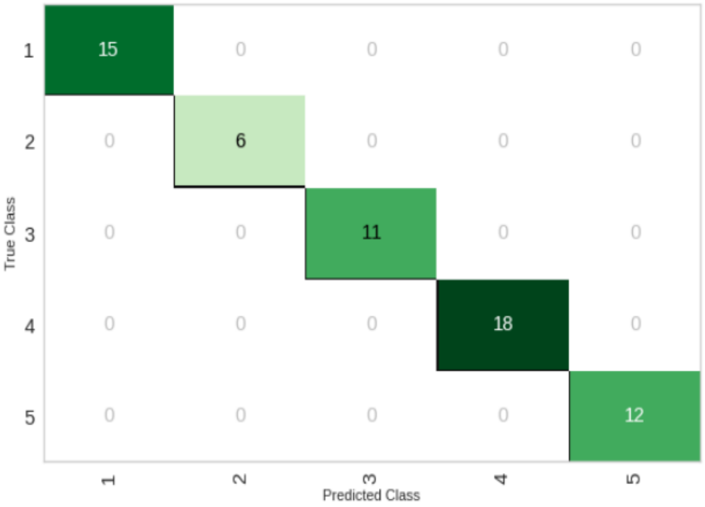
Results and discussion case study 2

Data Set 13 for 40 samples

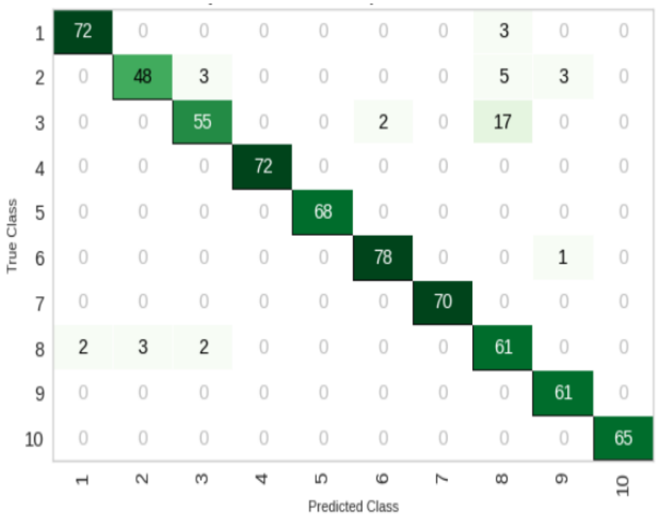
Light Gradient Boosting Machine is the most accurate predicting model; shown the Table below with an accuracy of 96.21%

M.L Model's	Acc.	A.U.C	Sensitivity	Prec.	F-1	Kappa	M.C.C
Light Gradient Boosting Machine	0.9621	0.9967	0.9625	0.9649	0.9622	0.9579	0.9582
R.F Classifier	0.9609	0.9966	0.9611	0.9633	0.9609	0.9565	0.9568
G.B Classifier	0.9565	0.9963	0.9567	0.9595	0.9569	0.9517	0.9519
E.T Classifier	0.9565	0.9977	0.9568	0.9593	0.9565	0.9517	0.952
D.T Classifier	0.936	0.9644	0.9362	0.9403	0.9361	0.9289	0.9294
Q.D.A	0.9298	0.9933	0.9306	0.9372	0.9294	0.922	0.9229
L.R	0.9124	0.9912	0.9134	0.9168	0.9119	0.9026	0.9032
Naive Bayes	0.8987	0.9904	0.9004	0.9282	0.8982	0.8874	0.8913
L.D.A	0.8968	0.9892	0.8979	0.9161	0.8962	0.8854	0.8878
K.N.N Classifier	0.8676	0.9718	0.8688	0.8681	0.8632	0.8529	0.8539
Ridge Classifier	0.6824	0	0.6852	0.7243	0.6602	0.6471	0.6605
SVM - Linear Kernel	0.6551	0	0.6583	0.6524	0.6066	0.6168	0.6418
Ada Boost Classifier	0.3219	0.7028	0.31	0.2309	0.2419	0.243	0.379

Results and discussion : Confusion Matrix

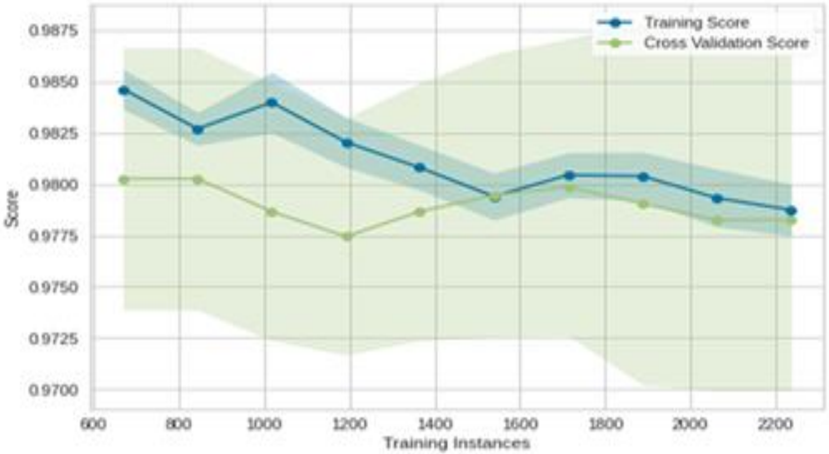


Case study 1

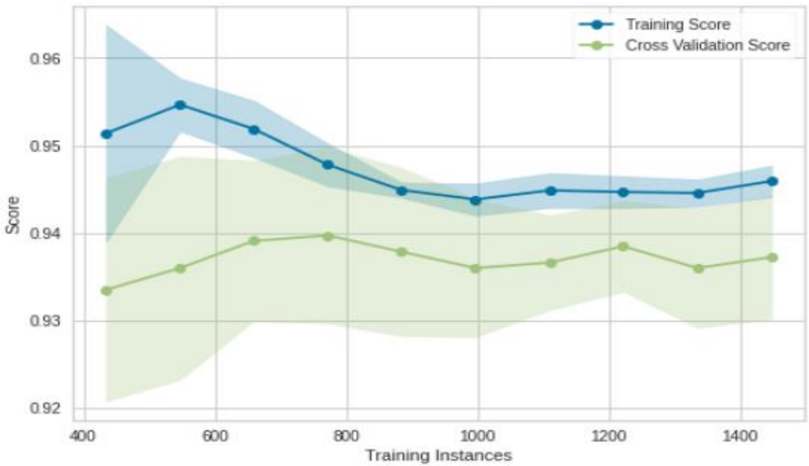


Case study 2

Results and discussion : Learning Curve

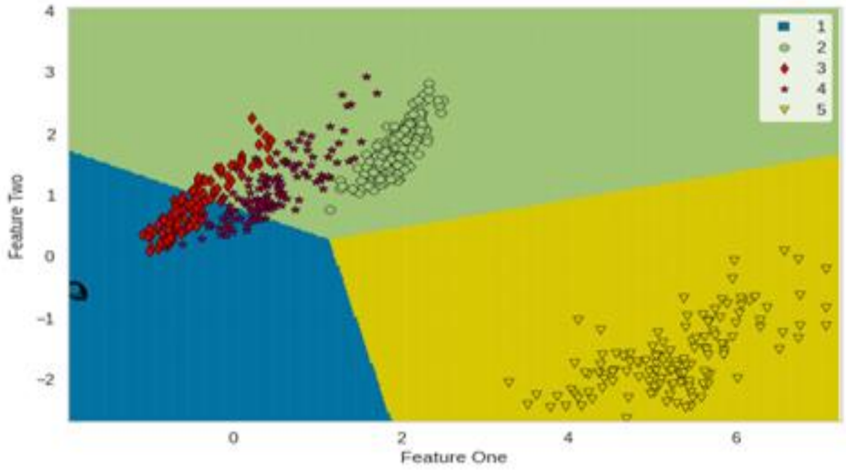


Case study 1

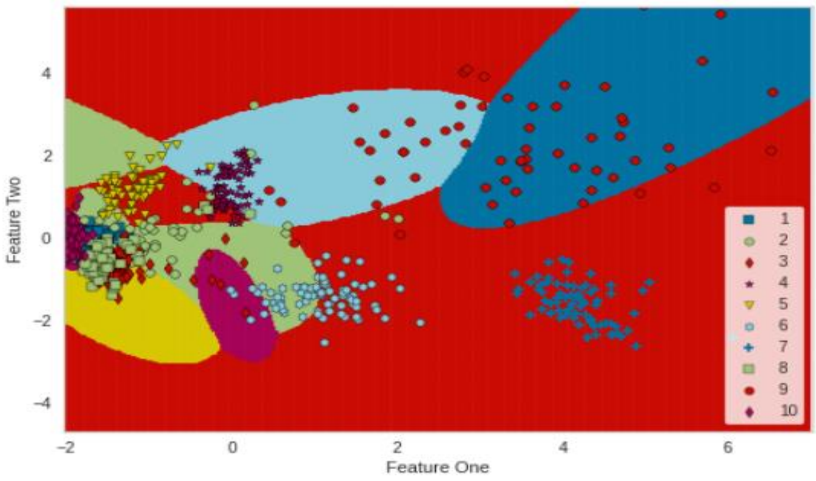


Case Study 2

Results and discussion : Decision Boundary

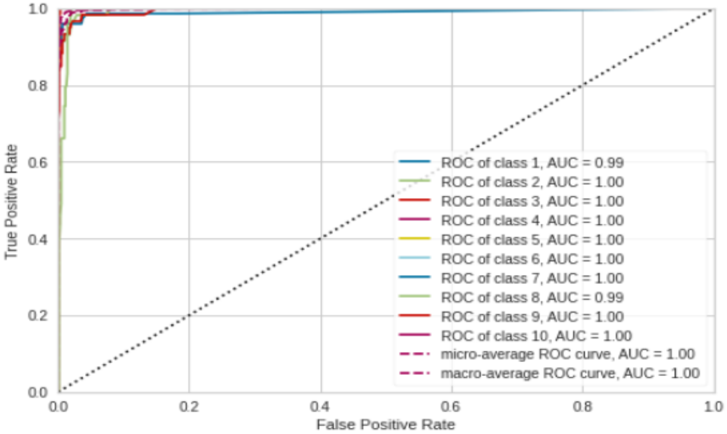


Case study 1

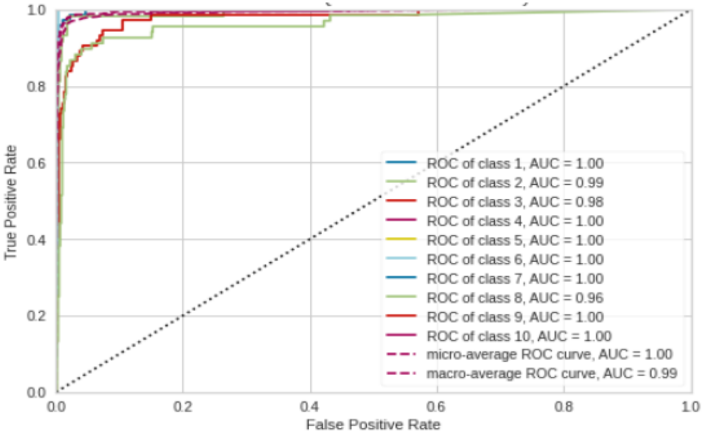


Case study 2

Results and discussion : R.O.C Curve

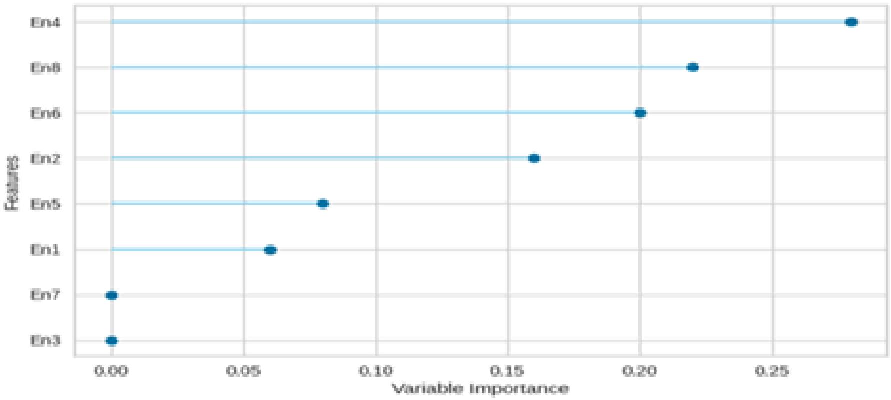


Case study 1

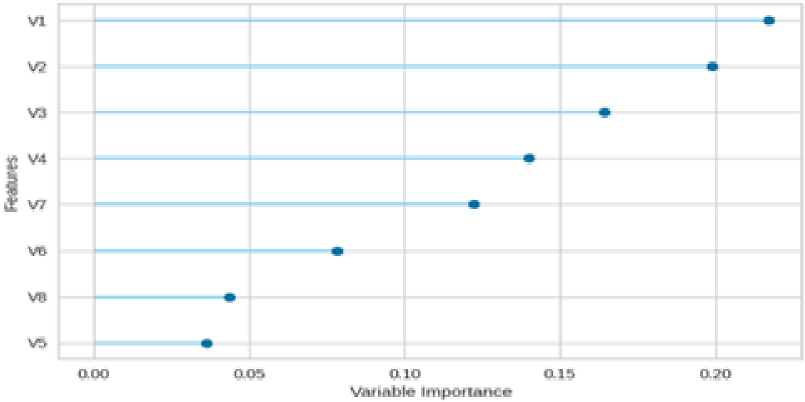


Case study 2

Results and discussion : Feature Importance

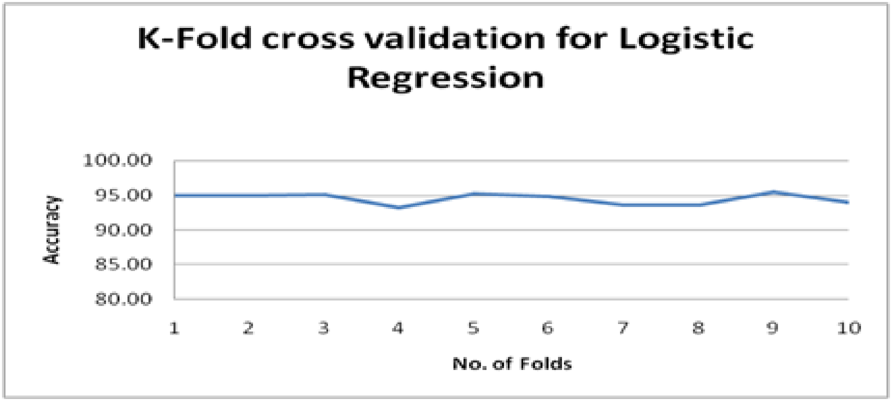


Case study 1

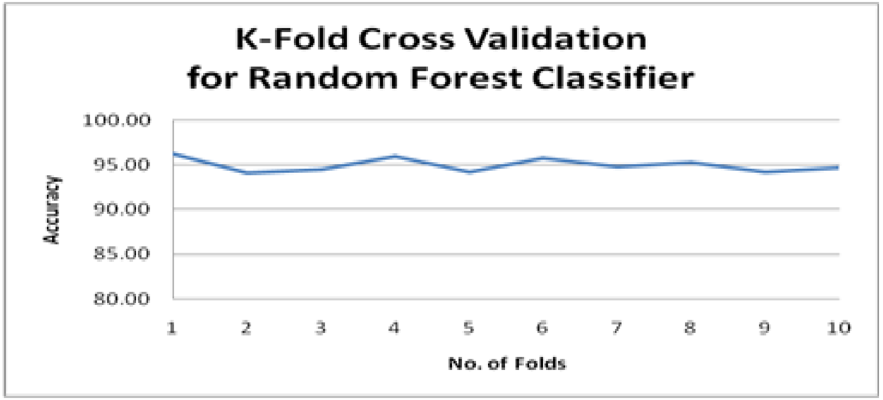


Case study 2

Results and discussion : K- Fold Cross Validation



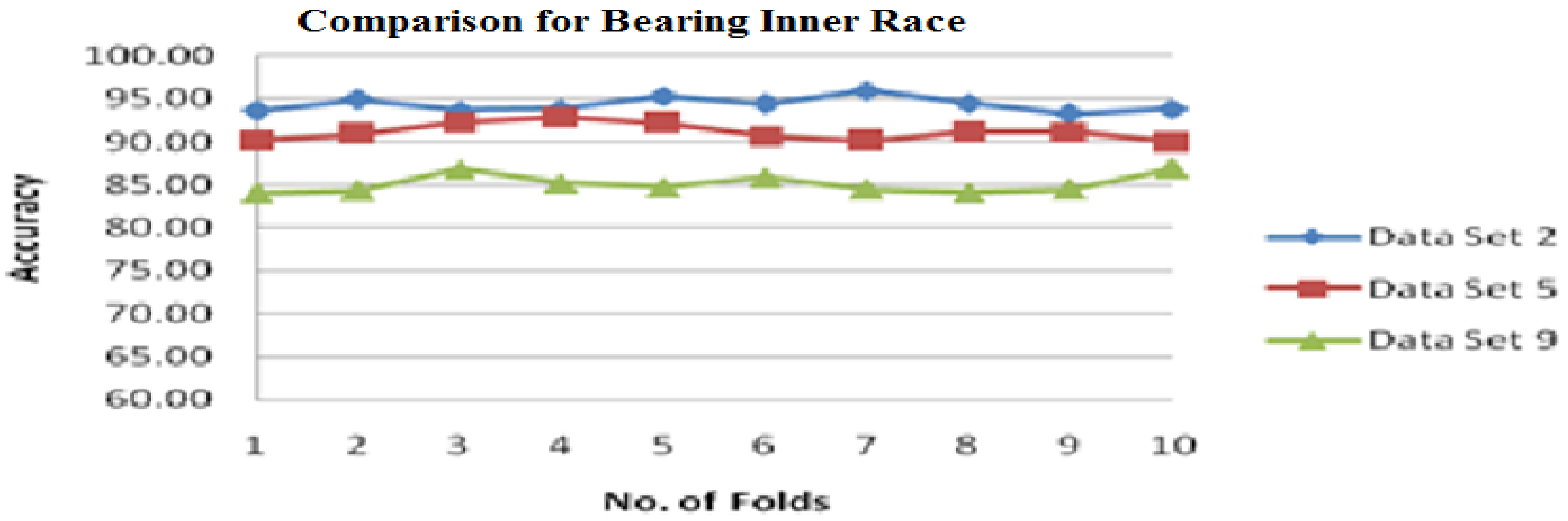
Case study 1



Case Study 2

Results and discussion for case study 1

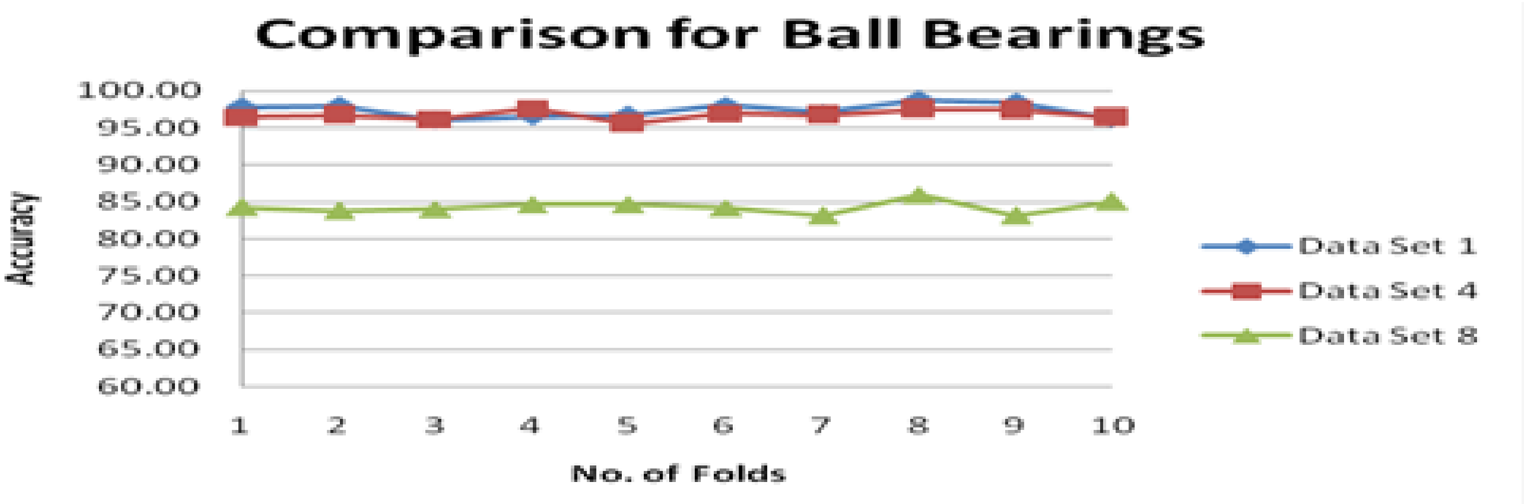
- Comparison of K-Fold Cross Validation for Bearing Inner Race



Comparison of K-Fold Cross validation of Accuracies for Bearing Inner Race

Result and discussion for case study 1

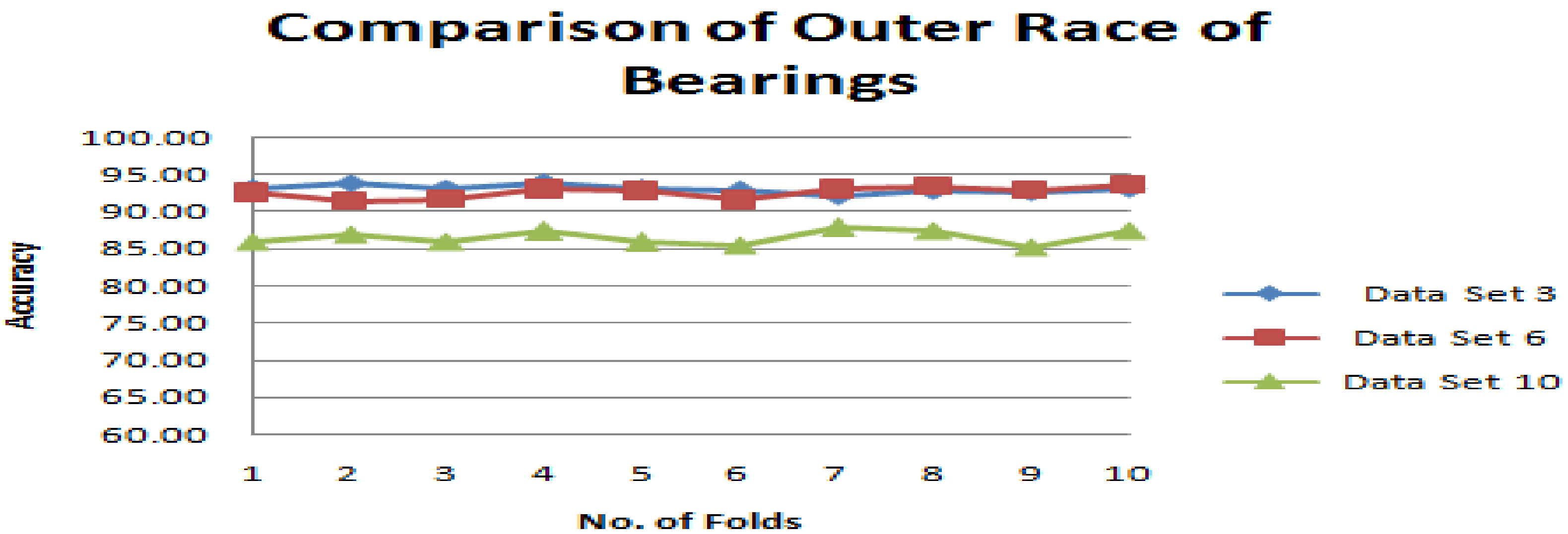
➢Comparison of K-Fold Cross Validation for Ball Bearing



Comparison of K-Fold Cross validation for Accuracies

Result and discussion for case study 1

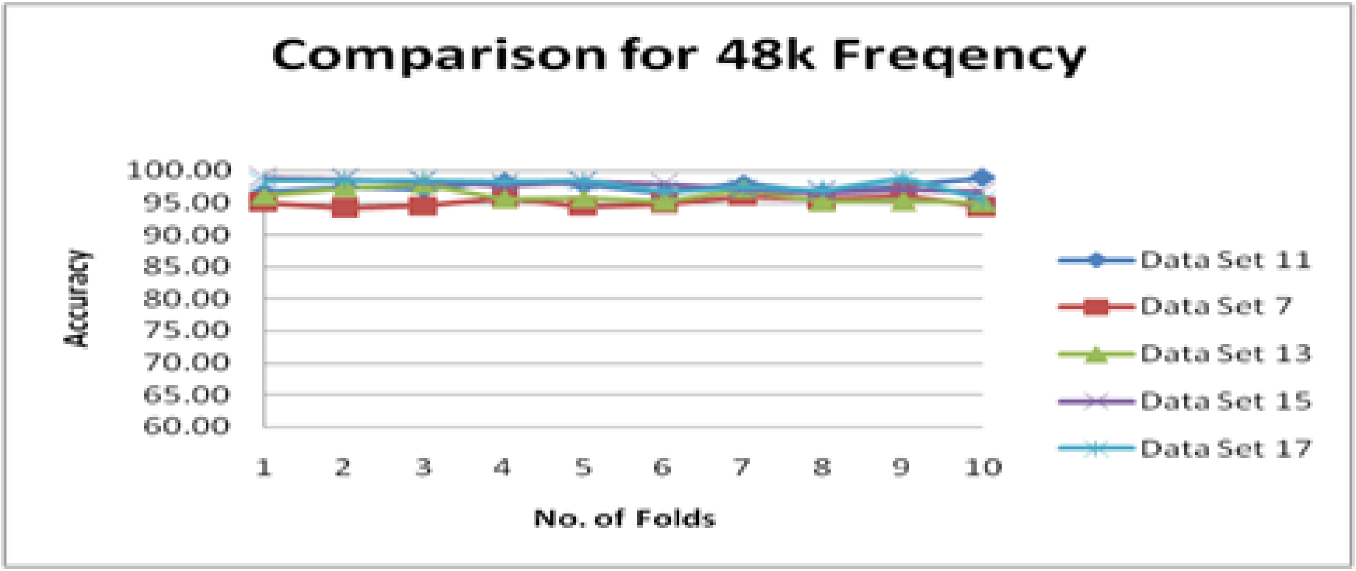
- Comparison of K-Fold Cross Validation for Bearing Outer Race



Comparison of K-Fold Cross validation for Accuracies

Result and discussion for case study 2

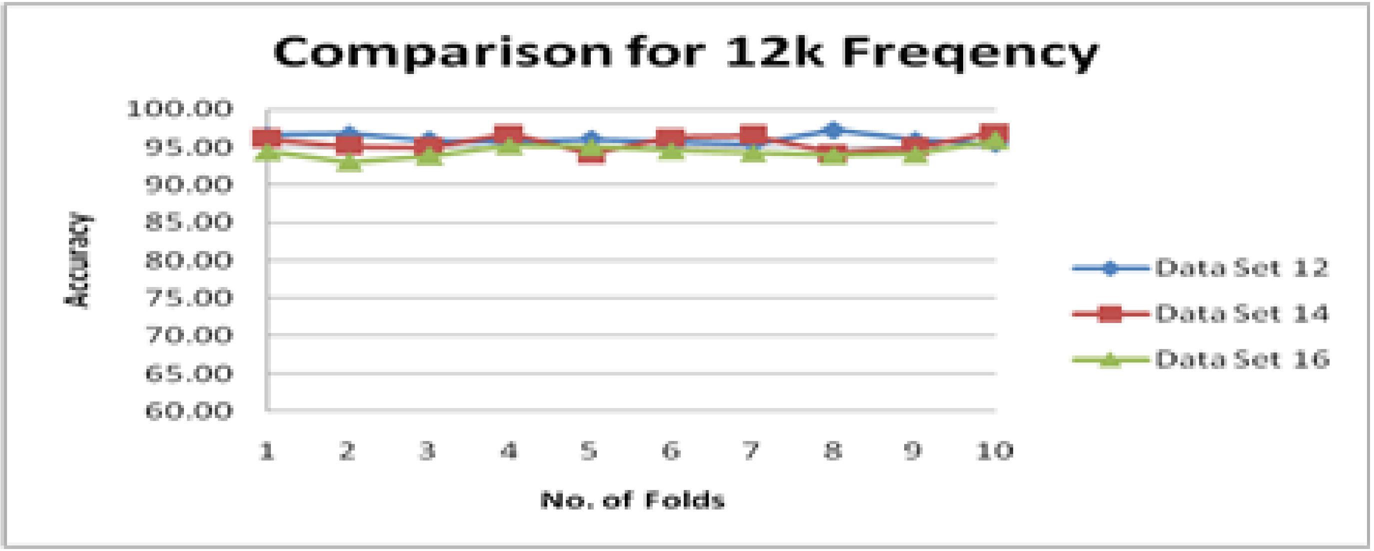
➢Comparison of K-Fold Cross Validation for different sample sizes at 48 k



Comparison of K-Fold Cross validation for Accuracies

Result and discussion for case study 2

➢Comparison of K-Fold Cross Validation for different sample sizes at 12 k



Comparison of K-Fold Cross validation for Accuracies

Concluding Remarks for case study 1

- Machine learning algorithm performed with respect to the load.
- The best performance seemed to be with the 0hp curve but this ambiguity leads to a dual check in the studies done with respect to the effect of frequency and location.
- Overall the results show that there is a proportional effect on the classification accuracy due to load variation.

Concluding Remarks for case study 2

- The performance of 12Khz curve was better than the 48khz when the sample size was small.
- But as the sample size increases performance of 48khz curve becomes better.
- 60 samples can be accurately be used to measure the sample size.
- A large sample size is always recommended.
- The results show that the sample size has a proportional effect on classification accuracy.

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Thank You