# B. TECH. PROJECT REPORT

**On**

# Development of Novel Algorithms for Prognostics


BY

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**DISCIPLINE OF MECHANICAL ENGINEERING**

**INDIAN INSTITUTE OF TECHNOLOGY INDORE**


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# Development of Novel Algorithms for Prognostics

**A PROJECT REPORT**

*Submitted in partial fulfillment of the requirements for the award of the degrees*

***of***

**BACHELOR OF TECHNOLOGY**

**in**

**MECHANICAL ENGINEERING**

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**INDIAN INSTITUTE OF TECHNOLOGY INDORE**

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## CANDIDATE’S DECLARATION

We hereby declare that the project entitled **“Development of Novel Algorithms for Prognostics”** submitted in partial fulfillment for the award of the degree of Bachelor of Technology in ‘Mechanical Engineering’ completed under the supervision of **Dr. B. K. Lad, Associate Professor, Discipline of Mechanical Engineering,** IIT Indore is an authentic work.

Further, we declare that we have not submitted this work for the award of any other degree elsewhere.

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## SUPERVISIOR’S CERTIFICATE

It is certified that the above statement made by the students is correct to the best of my knowledge.

**Dr. Bhupesh K. Lad**

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# PREFACE

This report on "Development of Novel Algorithms for Prognostics" is prepared under the guidance of Dr. B. K. Lad. It explores the employment of sensor-based condition monitoring techniques for Prognostics and Health Management (PHM) of a Fused Deposition Modelling type 3D-Printer.

It proposes a methodology for collaborative diagnostics and prognostics of the machine enabling autonomous data-driven decision making, therefore contributing towards industrial automation, Industry 4.0, and improving machine intelligence. The proposed methodology detects incipient machine component or system fault, performs machine diagnostics, failure prognostics, and health management.

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# ABSTRACT

Today’s manufacturing industries aims at reducing tie and cost for maintenance for production. Additive Manufacturing (AM) refers to a process by which the Computer-Aided Design (CAD) software directs the hardware to build up a model an object in layers by depositing material. Even though AM seems new to many, it has been around since the 1980s.

Current additive manufacturing techniques have meager techniques to monitor process conditions. In order to increase the levels of machine intelligence, machine conditions need to be monitored more precisely. In this study, a novel technique for the condition monitoring of a 3D-printer is proposed, where an accelerometer installed on the extruder assembly is used to capture the vibration signal to determine the health state of the machine. The process errors encountered with the printer were the worn-out timing belts driving the extruder assembly.

We have developed two Diagnostic Models for the 3D printer. The first model can classify the state of the machine as healthy or aberrant. The second model can classify the state as healthy or faulty as well as two intermediate states. We attempted to obtain data for the prediction of the Remaining Useful Life(RUL) of the machine. The diagnostics model can then be integrated with a prognostics model.

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# ABBREVIATIONS

| | |
|---|---|
| SM | Smart Manufacturing |
| CM | Condition Monitoring |
| CPS | Cyber-Physical System |
| RUL | Remaining Useful Life |
| AM | Additive Manufacturing |
| AE | Acoustic Emission |
| DAQ | Data Acquisition |
| CI | Condition Indicator |
| RMS | Root Mean Square |
| ANN | Artificial Neural Network |
| SVM | Support Vector Machine |
| RBF | Radial Basis Function |
| ML | Machine Learning |
| DL | Deep Learning |
| RF | Random Forest |
| KNN | K-Nearest Neighbours |
| SVC | Support Vector Classifier |
| RNN | Recurrent Neural Network |
| LSTM | Long Short Term Memory |
| GRU | Gated Recurrent Unit |

# Chapter 1

## INTRODUCTION

### 1.1 Smart Manufacturing

Smart Manufacturing enterprises are the systems that are "fully-integrated, collaborative manufacturing systems that respond in real-time to meet fluctuating demands and conditions in the factory, in the supply network, and customer needs."

Smart Manufacturing is the Fourth Industrial Revolution, which involves the use of embedded systems, sensor technology, and artificial intelligence to make machines intelligent. These machines can make decisions autonomously by taking into consideration the physical environment and the operating parameters.

The goal of SM is to recognize opportunities for automating operations and use data analytics to improve manufacturing performance. It draws upon specialized knowledge and skill from simulation, modeling, optimization, and machine learning, together with the understanding of industrial systems to improve and optimize processes.

### 1.2 Condition Monitoring

Condition monitoring is the process of monitoring a parameter of condition in machinery (vibration, temperature, etc.), to identify a significant change which is indicative of a developing fault. It is a principal component of predictive maintenance. The use of condition monitoring allows maintenance to be scheduled, or other actions to be taken to prevent consequential damages and avoid its consequences. The integration of condition monitoring is vital in developing a robust, condition-based maintenance strategy or predictive maintenance approach for machinery used in industrial applications.

Condition monitoring starts with installing sensors to collect data, which is then used to analyze changes in the performance or condition of a machine component while it is in operation. Any difference in the health of the component that differs from its standard parameters can be an indication of early-stage wear and deterioration. Condition monitoring not only describes the present state of a component but also provides information that can be interpreted to predict its RUL while in operation.

## 1.3 Prognostics and Health Management (PHM)

Prognostics and Health Management (PHM) is an integrated technique of condition monitoring for improving the availability and efficiency of high-value industry equipment and reducing the maintenance cost. It is the process of predicting the future reliability of a product by evaluating the extent of deviation or degradation of the product from its expected normal operating conditions. PHM methodologies monitor the health state in real-time and renew the reliability function based on measurements and evolution models obtained from past data. This technique is represented in Fig 1.1.

## 1.4 Cyber-Physical Systems

Cyber-Physical Systems (CPS) are integrations of computation, networking, and physical processes. Over the Internet of Things, cyber-physical systems communicate and cooperate and in real-time. In our research, we have integrated the Diagnostic Model of the machine to the cyber-twin of the machine. Cyber-Twin is the intelligence system installed outside a machine, linked through a data acquisition system. It acts as a virtual replica, which

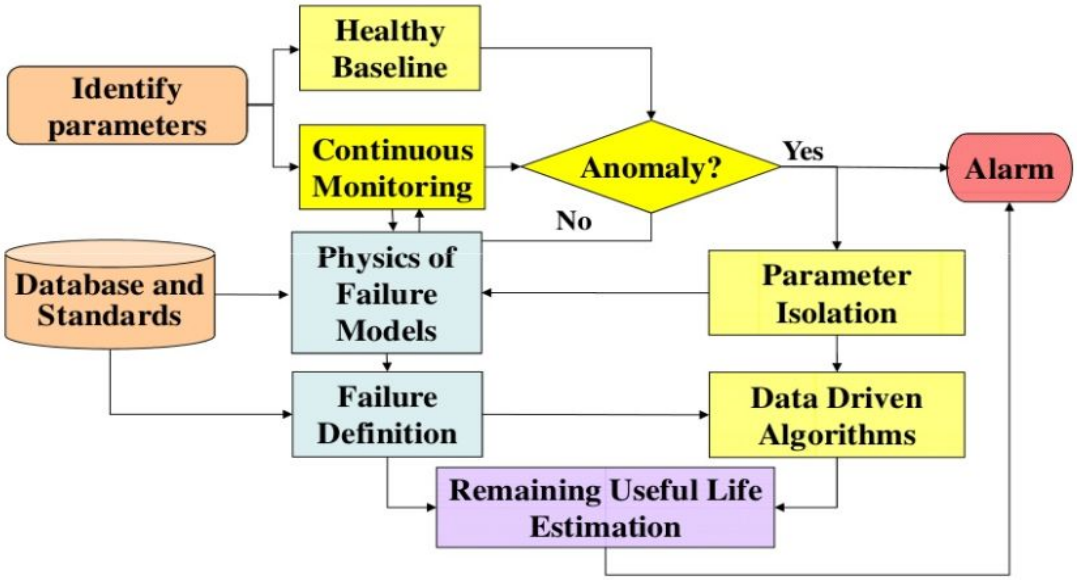



**Fig 1.1: PHM Methodology**

considers all the features of the physical machine, including job production, machine failure, etc. These features of the machine give rise to different conditions in which it exists.

An advanced cyber-twin may have a social aspect using which it can interact with other similar systems, inform others about its physical twin's conditions, know about other machines' conditions, and make collective decisions.

# Chapter 2

# PROBLEM DESCRIPTION

## 2.1 Introduction

Additive Manufacturing (AM) is an appropriate name to describe the technologies that build 3D objects by adding a layer-upon-layer of materials. With the advent of new technologies, a wide range of materials from plastics to even human tissues can be used in additive manufacturing (AM). The term AM encompasses many technologies including subsets like 3D Printing, Rapid Prototyping (RP), Direct Digital Manufacturing (DDM), layered manufacturing, and additive fabrication. 3D printing technologies have the potential to improve science, technology, and engineering as well as to enhance manufacturing technology. While the applications of additive manufacturing have been increasing over time, many challenges continue to impede its widespread adoption. The significant challenges to AM are more manufacturing time in comparison to standard processes, dimensional accuracy, nonlinearity (various resolutions for X, Y and Z axes, wall thickness), material properties, and system cost. The machine manufacturers are addressing these issues through improvement in the manufacturing process. Therefore, the development of a health monitoring and diagnostics system for 3D-Printers is necessary.

The prime objective of this research is to develop a real-time diagnostic model and consequently a prognostics model for condition monitoring of the machine, in order to detect and preclude breakdowns and process failures. The comprehensive goal is to achieve better process reliability, dimensional accuracy of the product and automation of AM. In particular, the focus is on the health condition of the belts driving the extruder. In our work, an investigation into the feasibility of PHM based vibration signal analysis technique is presented, and based on the observations from the signal, two diagnostics models for a 3D printer fault detection are developed.

## 2.2 Literature Review

Even though the 3D printing technology is available since the 1980s, it was not until recently that 3D printing was used in commercial manufacturing. Limited studies have been conducted on 3D printer health monitoring and prognostics to date. Yoon, Jae et al. (2014) used the Acoustic Emission (AE) sensor to differentiate between healthy and faulty states of the belt of a 3D-Printer. In their study, they found that the AE sensor manifested changes in the RMS and P2P (Peak to Peak) value of the AE signal for the healthy and worn-out states. Therefore, a diagnostics model could be built for a 3D printer in case of failure of timing belts. Acoustic emissions of 3D printers were also studied by Wu, Haixi et al. (2016). The printer was run at various nozzle temperatures. The experiments were carried out for three states of the nozzle (normal, semi-blocked, blocked). Tlegenov, Yedige et al. (2017) investigated the condition monitoring of the nozzle through the use of a vibration sensor.

# Chapter 3

## EXPERIMENTATIONS AND ANALYSIS

### 3.1 Methodology

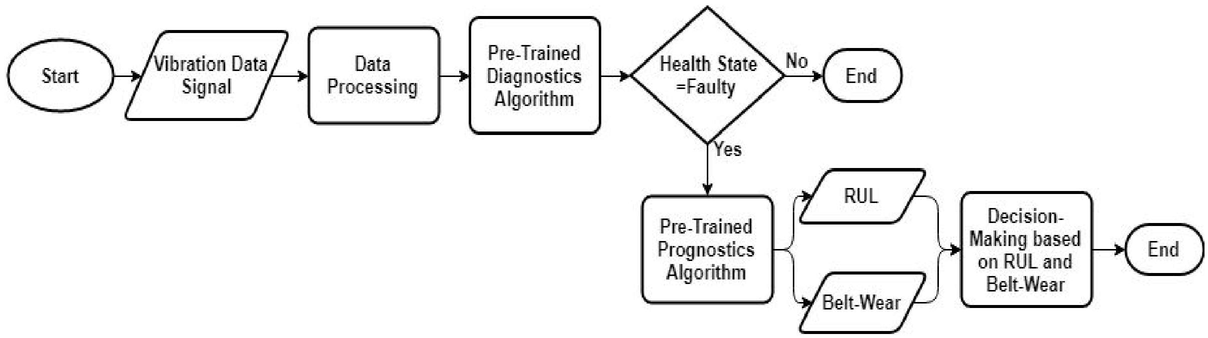



**Fig 3.1: Flowchart of Prognosis and integrated Diagnostics**

The flowchart represents the developed technique where when one wants to employ predictive maintenance the data flows in the shown manner. At first, the diagnostic model is triggered which diagnoses the machine in real-time and predicts it's current health state. This health state, if found aberrant, then triggers the prognostics model, which will predict the RUL of the machine and also provide optimized maintenance plans.

#### 3.1.1 Diagnostics Methodology

The field of machinery diagnostics is broad, covering everything from a skilled mechanic's inspection to programmed expert systems. In this report, we explored the use of vibration sensors for fault diagnosis of the machine following the methodology in Fig 3.2. For developing the diagnostic model the vibration signal was acquired, this raw data was converted into valuable features, studying the importance of each feature and finally training our learning algorithm.

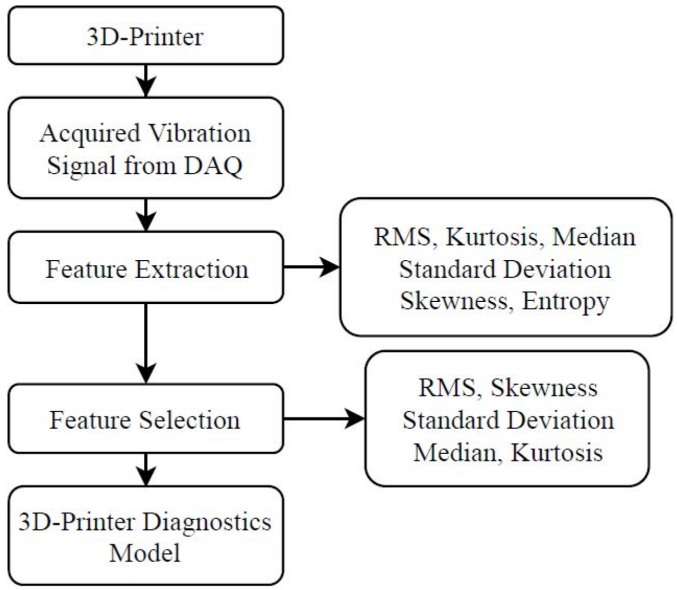



**Fig 3.2: Diagnostics Flowchart**

We developed two Diagnostics Model for this purpose. The first one differentiates between the completely healthy and completely faulty state. This model also takes into consideration the number of belts in the faulty state and the position of the faulty belts. Therefore, a binary classifier and a multi-class classifier with six states, both are integrated into this model. The second diagnostic model differentiates between the healthy state, faulty state, and two intermediate states (D1 and D2). Therefore, this model consists of a multi-class classifier with four outputs. We have made use of Deep Learning algorithms to build this multi-stage diagnostic model.

### 3.1.2 Prognostics Methodology

Machinery Prognostics deals with the prediction of the RUL of a machine or its components. The development of prognostics model requires destructive testing methods where the machine is operated tills its failure and the time to failure is recorded which is then used to predict the RUL. In this study, we operated our 3D-Printer from one simulated intermediate state until its failure.

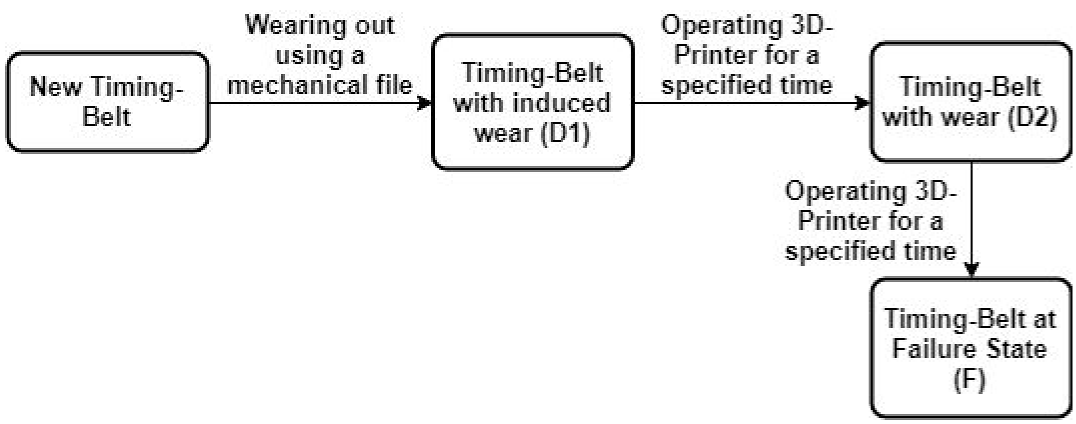



**Fig 3.3: Prognostics Flowchart**

## 3.2 Critical Component Analysis

During our study, we found out that the most prominent areas of failure of a 3D-Printer are the belts that drive the extruder assembly of the printer and the nozzle through which the fused material is dispensed. The timing-belts drive the extruder assembly, therefore, are an essential factor in determining the quality of the prototype. According to the troubleshooting maintenance document of the machine, one potential problem is the looseness of the belt driving the motion of the extruder nozzle. Thus, a malfunctioned toothed belt scenario was artificially created and simulated in the experiment. The teeth of the belt worn out and start slipping over the stepper motors, thus disrupting the motion of the assembly and the subsequent print quality of the object. We observe that there is a perceptible difference in the movement of the extruder assembly when it is operated under two extreme belt assembly conditions.

## 3.3 Sensor Selection

The next step is selecting appropriate sensors that can manifest the variation between the different states of the critical components already identified. In the initial stages, Arduino based vibration sensors were employed but they failed to manifest any variation. We also employed an Acoustic Emission sensor, but that too was unable to display any discrepancy. Finally, IEPE powered piezoelectric vibration sensor was found to exhibit significant variations in the vibration signals for the different states of the critical component (Timing Belts) of our machine.

## 3.4 Experimental Setup

The 3D-printer (Fig 3.4) used has a built volume of 350*300*300 cubic millimeters with a layer resolution of 100 microns, positioning accuracy of 10 microns, three belts controlled by three stepper motors, and one stepper motor to control the motion of the heated bed in Z-direction and a nozzle of 0.4 mm. The experiment was performed at three different extruder assembly speeds i.e. 60 mmps, 80 mmps, and 100 mmps. The experiment was also performed at different nozzle temperatures (160℃, 180℃, and 200℃), which affect the amount of material that comes out of the nozzle. It was found that the vibration sensor exhibited the same outcome in all cases.

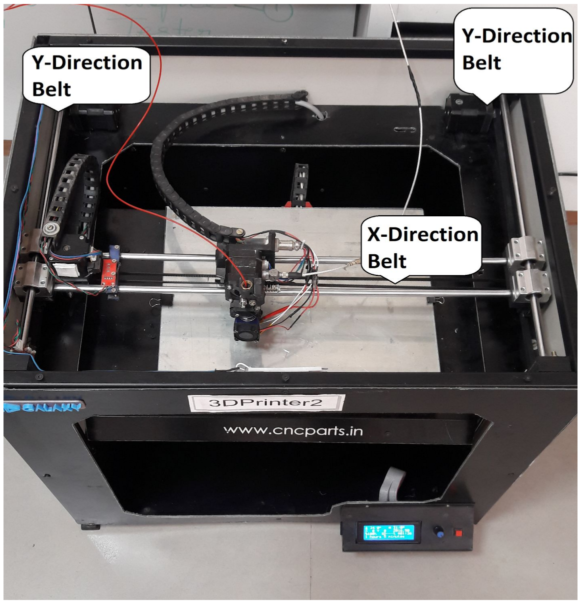



Fig 3.4: 3D-Printer

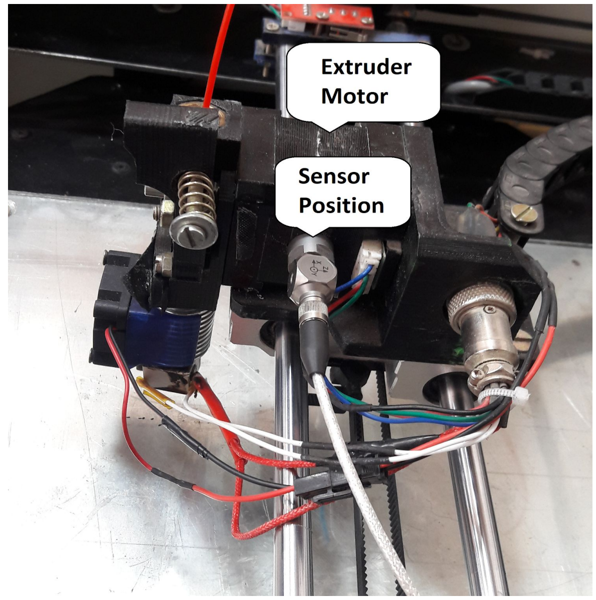



Fig 3.5: Sensor Positioning

### 3.4.1 Diagnostic Model- Ⅰ

For developing this model the Printer was operated at a speed of 60 mmps, nozzle temperature of 200℃ with the following timing-belt configurations:

1. All belts are new.
2. All belts are worn-out.
3. X belt is new; both Y belts are worn-out.
4. X belt is worn-out; both Y belts are new.
5. X belt and one Y belt is worn-out.
6. Only one Y belt is worn-out.

The condition of the used timing-belts is shown in Fig 3.6.

### 3.4.2 Diagnostic Model- Ⅱ

This model takes into account four health states of the printer as stated in Section 3.1.1. The dilapidated condition of the belts was simulated by smoothening the sharp teeth on the belts. The conditions of the different timing-belts used in this model are shown in Fig 3.7-3.10.

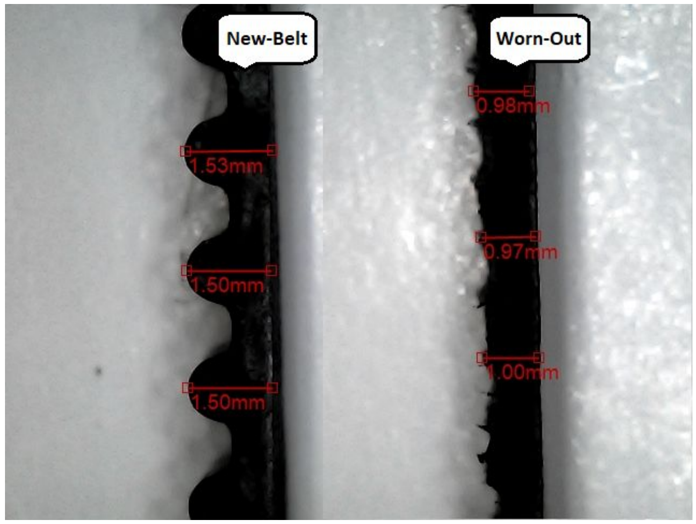
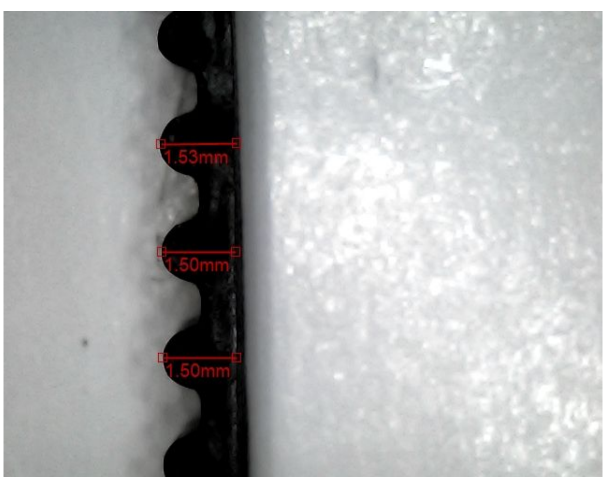



**Fig 3.6: Timing-Belts**



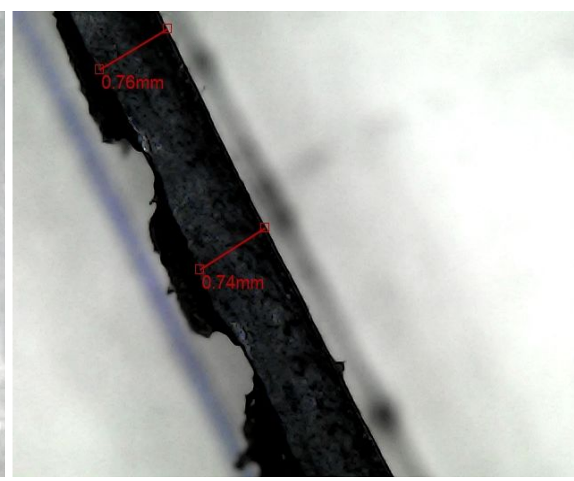




**Fig 3.7: Healthy Belt**

**Fig 3.8: Faulty Belt**

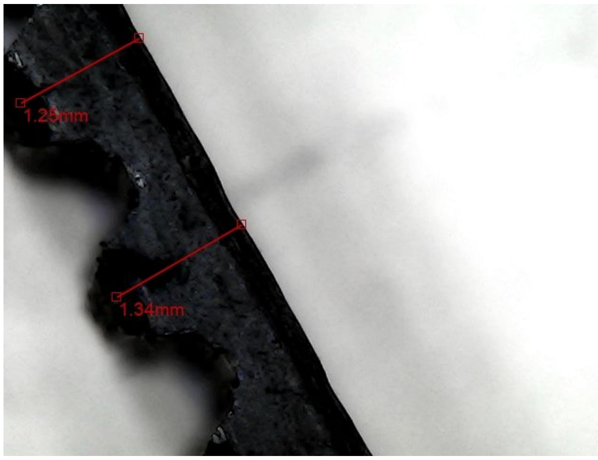



Fig 3.9: D1 Belt

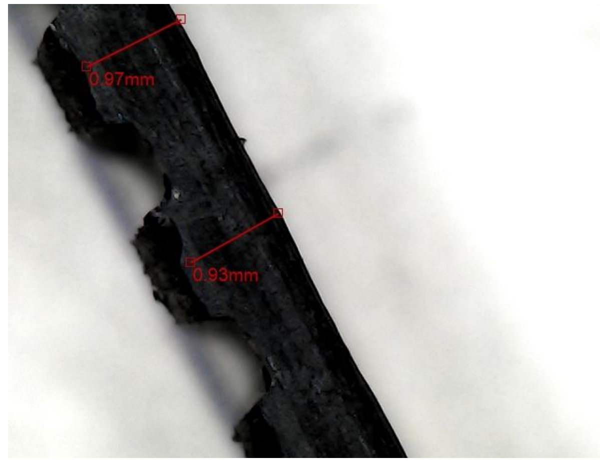



Fig 3.10: D2 Belt

## 3.5 Data Acquisition

The DAQ (Data Acquisition) (Fig 3.11) system includes a National Instruments' cDAQ-9188XT DAQ board with an analog input sampling rate of 1.65 MHz. Kistler 8763B IEPE Triaxial accelerometer is attached to the extruder head to get the vibration signal in X-direction. This sensor is connected to a TEDS piezotron coupler with an adjustable gain of 0.5-150 mV/g in increments of 0.01 mV/g. Fig 3.5 shows the mounting of the accelerometer on the extruder assembly. The signal coming from the coupler is sent to the DAQ board with the help of the c-series voltage input module by National Instruments. This signal is acquired and saved into a python readable file with .csv extension using the LabVIEW block-code (Fig 3.12).

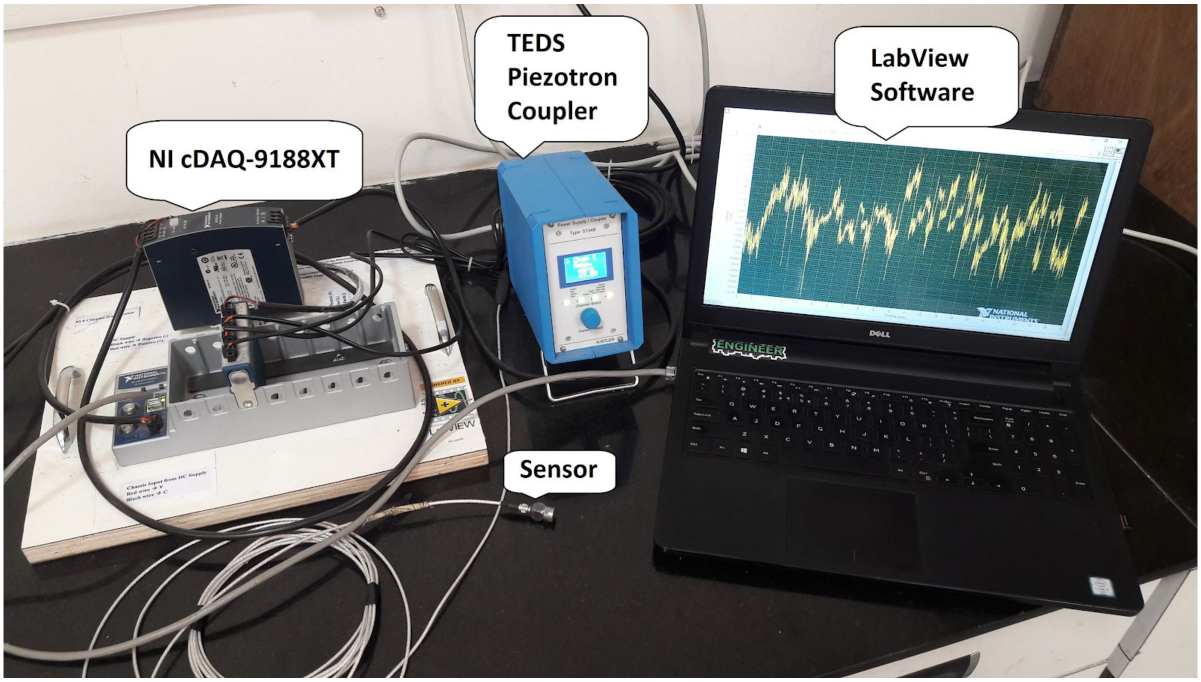



**Fig 3.11: DAQ System**

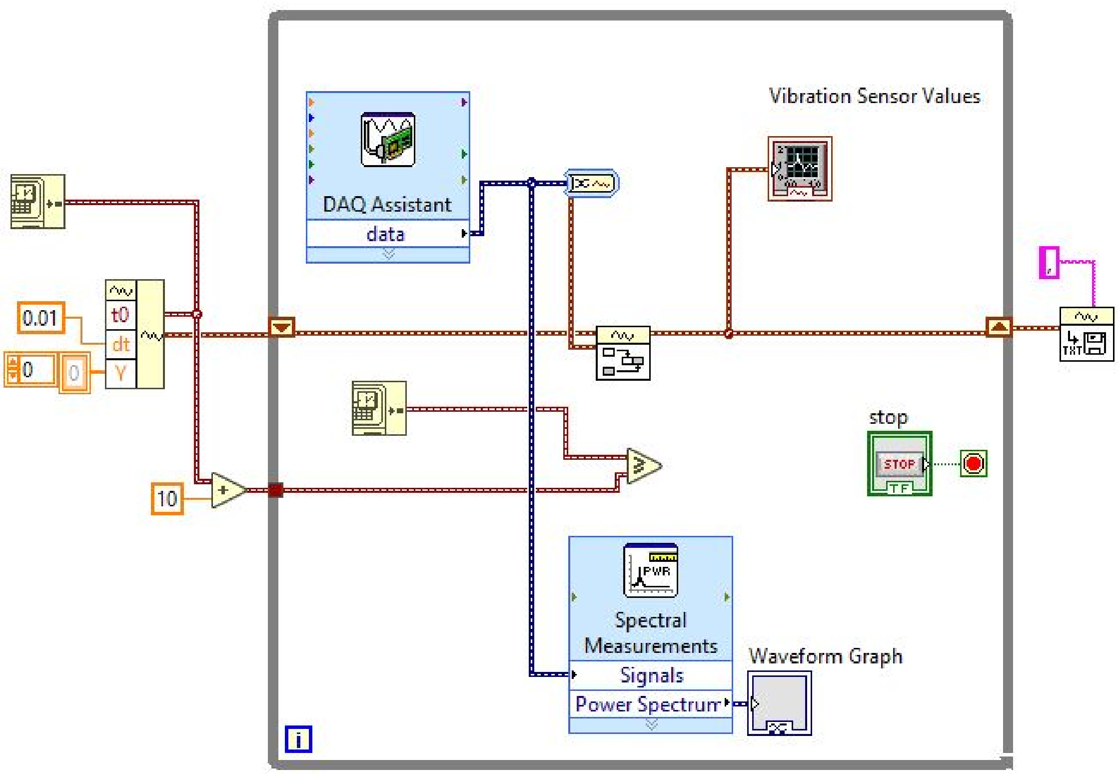



**Fig 3.12: LabVIEW Block-Code**

## 3.6 Data Processing and Feature Extraction

For Diagnostic Model-Ⅰ, the data-points from the raw data were divided into groups of 3500 data-points to obtain the useful features, each giving value of one individual processed feature or condition indicator(CI). This number was reached by a hit-and trial method such that it does not compromise the quality of the data, and we have sufficient data-points to train the diagnostics model. The following six CIs were investigated:

1. **RMS:** The RMS value of a set of values is the square root of the arithmetic mean of the square of the values.
2. **Standard Deviation:** Statistical measurement which depicts the dispersion of a data-set relative to its mean.
3. **Kurtosis:** Descriptor of the shape of a probability distribution curve.
4. **Entropy:** Information entropy is the average rate at which a stochastic source of data produces information.
5. **Median:** Value separating the higher half from the lower half of a data sample.
6. **Skewness:** Defined as the extent to which a distribution differs from a normal distribution.

For Diagnostic Model-Ⅱ we calculated only three CIs namely RMS, Kurtosis and Median as they proved to be the most important features for the learning algorithms. This was investigated with the help of feature importance techniques discussed in Section 3.6.1.

### 3.6.1 Feature Selection

Feature selection is necessary to identify the significant features and eliminate redundant features. The features which contribute the most to our diagnostic model can be manually or automatically selected by training a model and comparing individual accuracy of the six different algorithms trained on the six CIs, respectively. Techniques such as Univariate Selection (Select-K-Best) and Feature Importance can also be deployed to identify the features which have significant influence over the accuracy of the machine learning models. RMS, Kurtosis, Median, Skewness, and Standard Deviation were selected as features for the machine learning algorithms of diagnostic model-Ⅰ, neglecting entropy as can be seen from Table 3.1.

| Feature | Univariate Selection | Feature Importance |
|---|---|---|
| Kurtosis | 146.44 | 0.166 |
| RMS | 99.44 | 0.2685 |
| Skewness | 78.8 | 0.171 |
| Median | 41.24 | 0.2768 |
| Standard Deviation | 14.27 | 0.1174 |
| Entropy | 0.00 | 0.1053 |

**Table 3.1: Score of CIs**

For Diagnostic Model-Ⅰ, The remaining five CIs were fed as input to a multi-class classifier so that one can accurately discern the exact health state of each belt and identify the belts that need to be replaced. For the second model, three CIs were fed as input to the classifier.

# Chapter 4

## INTRODUCTION TO ALGORITHMS

### 4.1 Machine Learning Models

A brief description of a number of machine learning models is presented in this section. Python as a tool is utilized for implementing the various machine learning models. *sklearn* and *keras* libraries have been used to compile the models. For each model, 66.66% of data-points are used to train the model and 33.33% to test the model.

### 4.1.1 Random Forest Classifier

Random Forest is a flexible, easy to use machine learning algorithm that produces, even without hyper-parameter tuning, a great result most of the time. RF builds multiple decision trees and merges them together to get a more accurate and stable prediction. It brings extra randomness into the model while splitting the nodes. In our study, the classifiers have two hundred estimators or trees. It uses the default *gini* criterion. The maximum depth of the tree or the estimator is set to *none* and the minimum number of samples required to split a node is set to *two*.

### 4.1.2 Support Vector Classifier

The objective of the SVC is to find the hyperplane that classifies the data points. It chooses the hyperplane in such a way that the plane has the maximum margin, i.e., the maximum distance between data points of all the classes. Maximizing the margin distance provides some confidence so that future data points can be classified with more certainty. The SVC is developed with the *Radial Basis Function* kernel. Gamma, the kernel coefficient, is set to *auto*.

### 4.1.3 Artificial Neural Network

An ANN is based on a collection of connected units or nodes called artificial neurons which loosely model the biological neurons in a biological brain. An artificial neuron that receives a signal can process it and then signal additional artificial neurons connected to it. Keras is a powerful Python library for compiling and evaluating ANN models. The multi-class classifiers consist of an input layer, two hidden layers with ten and fifteen nodes respectively, and the output layer. The output layer uses the *sigmoid* activation function while the hidden layers use the *tanh* activation function. The algorithm uses *adam* optimization and *categorical crossentropy* loss function. The binary classifier has the same architecture except for the output layer. It uses the same activation functions and *adam* optimizer, and uses *binary crossentropy* loss function.

### 4.1.4 K-Neighbours Classifier

The KNN algorithm assumes that similar things exist close to each other. KNN captures the idea of proximity and calculates the distance between points on a graph. It is used in pattern recognition with a non-parametric method. The number of neighbors is set to *five* and the *auto* algorithm is used.

## 4.2 Deep Learning Models

Neural networks can be classified as recurrent or feedforward. Feedforward networks the ones that do not have any loops, or the connections between the cycle do not form a cycle. Recurrent Neural Network, as the name suggests, uses recursion in the network and maintains hidden states that are being used in every recursion. We have limited our study to only two types of architecture, LSTM, and GRU. We have used TensorFlow as the backend library for all our deep learning models. For all the DL models we have created arrays of time sequences of 50 data-points. Therefore, the input layer consists of 50 X 3 units and the output layer consists of four units for the four health state of the printer.

### 4.2.1 Long Short Term Memory (LSTM)

LSTM find its huge application in the field of Natural Language Processing because of its ability to use past information effectively. In LSTMs, the information flows through a mechanism known as cell states. They can selectively remember and forget things. The information at a cell state has three different dependencies. These dependencies are taken care of by the forget gate, output gate, and the input gate. Gates are a way of optionally letting the information through. We have tried to use this unique feature of LSTM to classify the health states in the multi-stage diagnostics model.

In this study, we have compiled three types of LSTM models:

1. Vanilla LSTM: Comprises the input layer, output layer, and one hidden layer of a hundred units. The output layer uses the *sigmoid* activation function.
2. Stacked LSTM: Comprises of three hidden layers with a hundred, seventy-five and fifty units respectively. The output layer uses the *sigmoid* activation function.
3. Bidirectional LSTM: It connects two hidden layers of opposite directions to the same output. It is capable of acquiring information from past and future states simultaneously. It comprises two hidden layers of a hundred

and fifty units respectively. The output layer uses the *sigmoid* activation function.

### 4.2.1 Gated Recurrent Unit (GRU)

The GRU is the newer generation of RNNs and is very similar to an LSTM. It consists of only two gates, a reset gate, and an update gate. The update gate is similar to the forget and input gate in LSTM. It decides what information to forget and what new information to add. The reset gate is used to decide how much past information to forget. The following three types of GRU models to identify the four health states of the machine:

1. GRU: Comprises the input layer, output layer, and one hidden layer of a hundred units. The output layer uses the *sigmoid* activation function.
2. Stacked GRU: Comprises of three hidden layers with a hundred, seventy-five and fifty units respectively. The output layer uses the *sigmoid* activation function.
3. Bidirectional GRU: Allows the use of information from previous time steps as well as later time steps to make predictions about the present state. It comprises two hidden layers of a hundred and fifty units respectively. The output layer uses the *sigmoid* activation function.

# Chapter 5

## OBSERVATIONS AND RESULTS

### 5.1 Data Comparison and Graphs

In this section, the graphs of data comparison obtained for both the diagnostic models are plotted and discussed. Even though we calculated multiple CIs, the graph for only RMS is presented. The states of the printer are compared individually two at a time as well as simultaneously at a time.

### 5.1.1 Diagnostic Model- I

Figures 5.1 to 5.6 show the comparison between the RMS of acquired vibration signal for the five faulty states and the RMS of acquired vibration signal for the healthy state of the 3D-Printer.

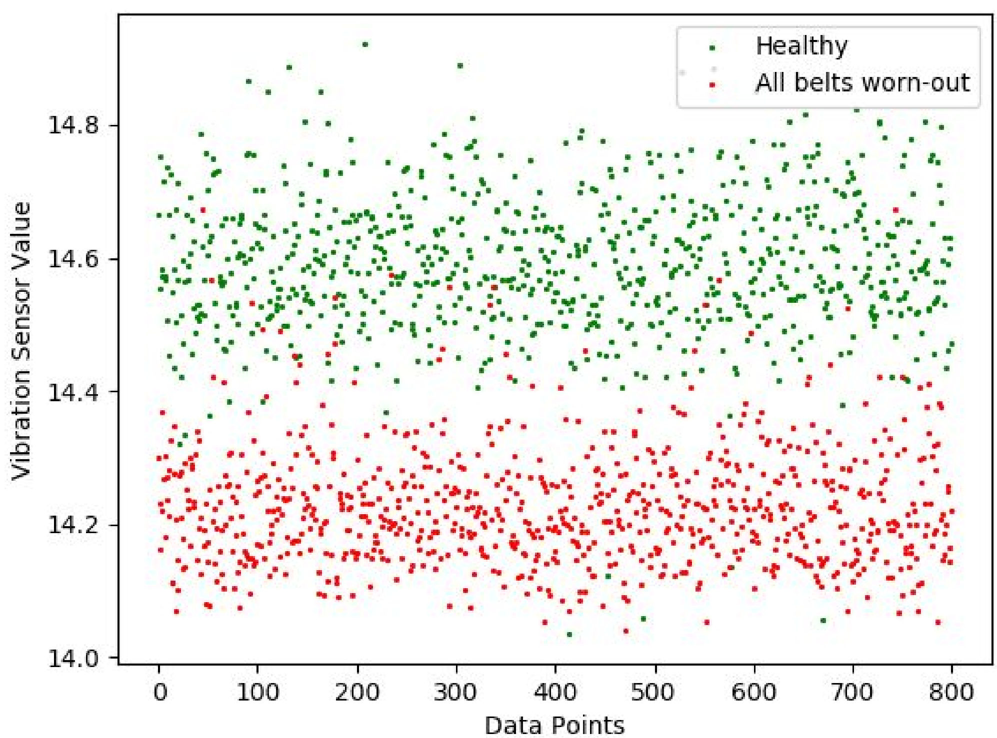



**Fig 5.1: Healthy vs All Belts worn-out**

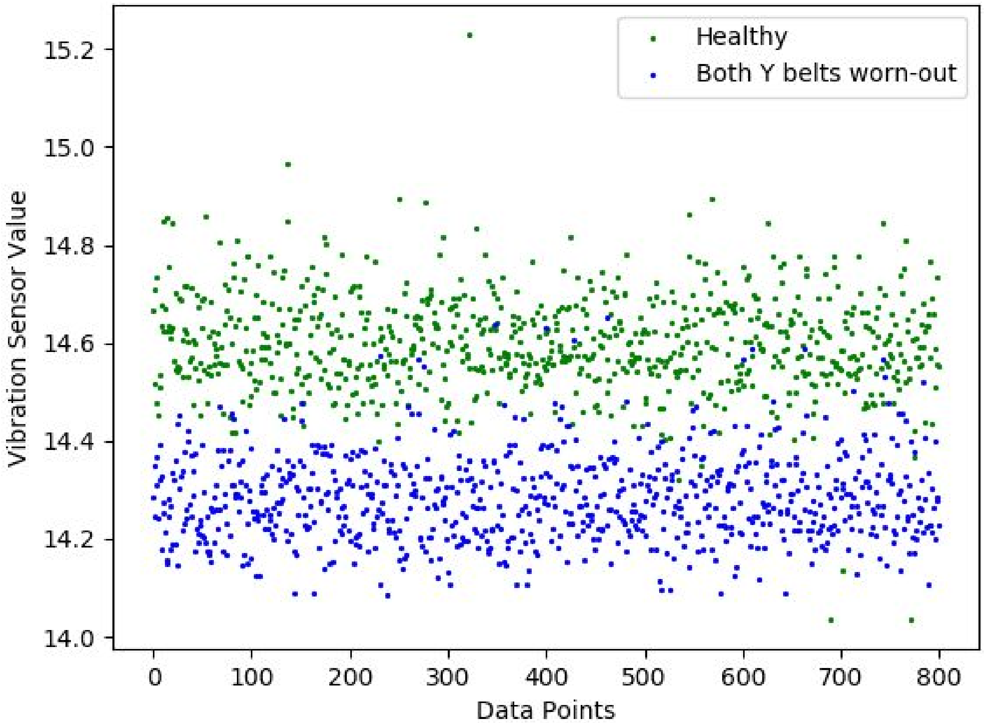



**Fig 5.2: Healthy vs Both Y Belts worn-out**

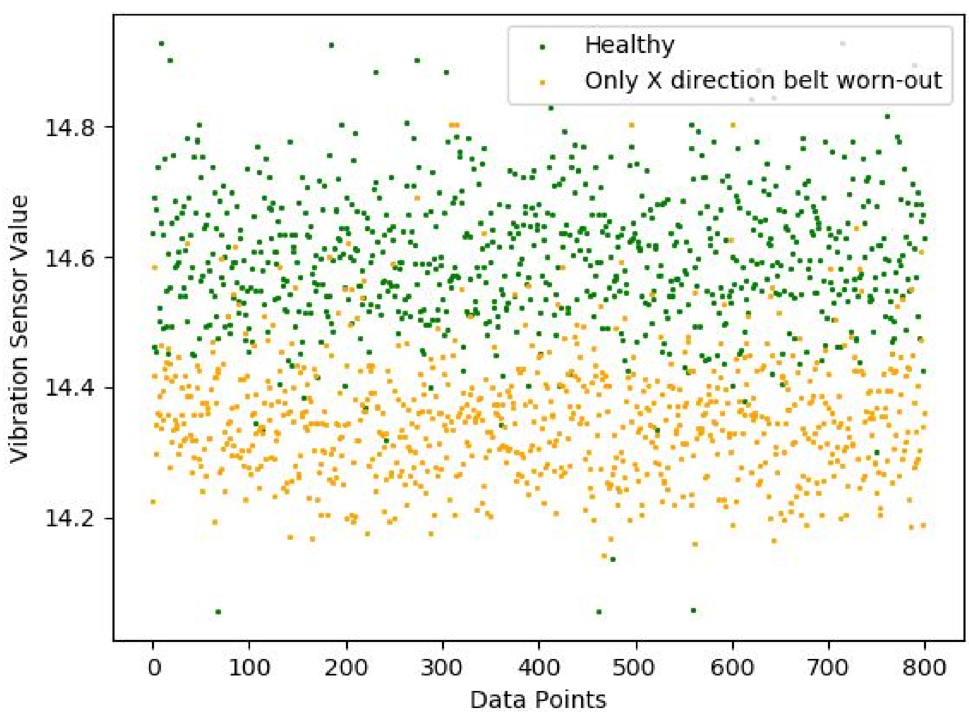



**Fig 5.3: Healthy vs Only X Belt worn-out**

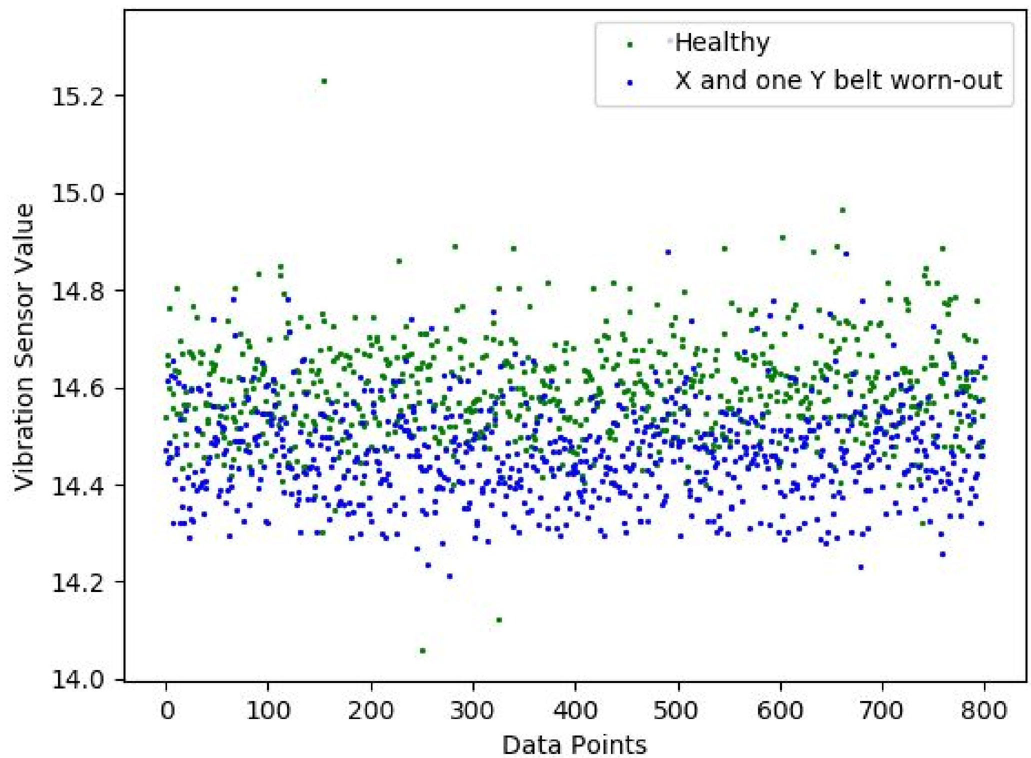



**Fig 5.4: Healthy vs X and one Y Belt worn-out**

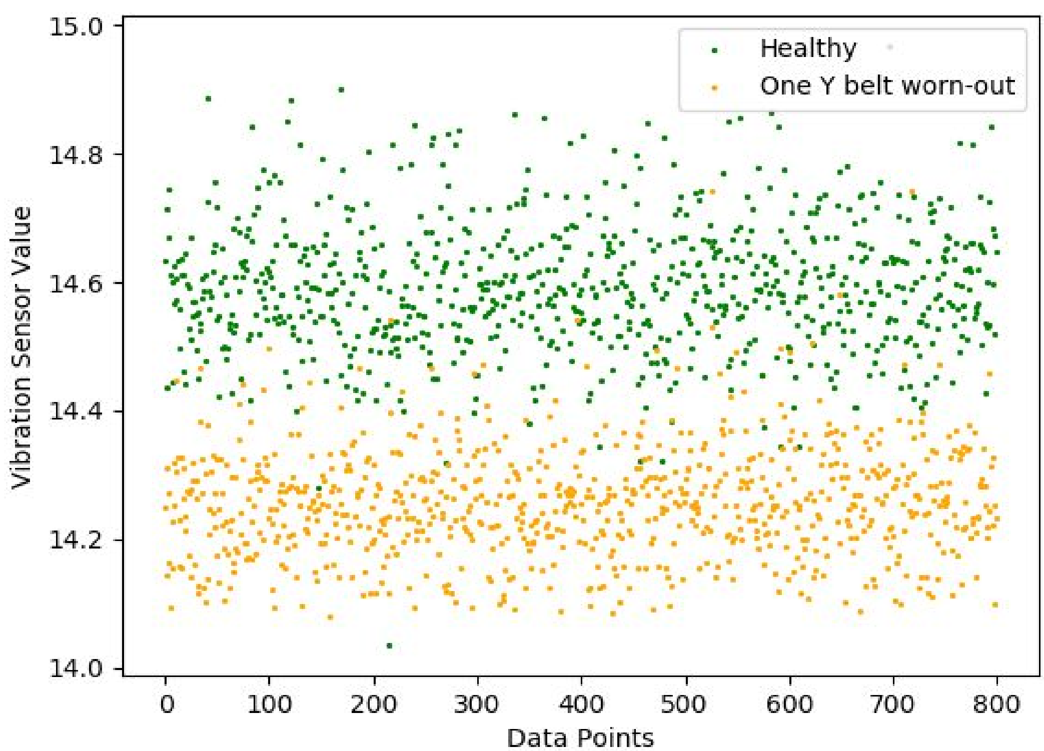



**Fig 5.5: Healthy vs One Y belt worn-out**

It is observed from figures 5.1 to 5.5 that the RMS of vibration readings differs the most in case of comparison between healthy and completely worn-out state. From Fig 5.2 and Fig 5.5, it can be observed that the difference in RMS of vibration readings is approximately the same independent of the number of Y belts in worn-out state. The difference in RMS is relatively lesser for the state when only the X belt is worn-out. This disparity can be observed from Fig 5.3 and Fig 5.5. Therefore, it can be inferred that the proposed method is the most accurate when all the timing belts are faulty, relatively less effective when only Y-Belts are faulty and the least effective when only X-Belts are faulty. The simultaneous comparison of all the states is shown in Fig 5.6.

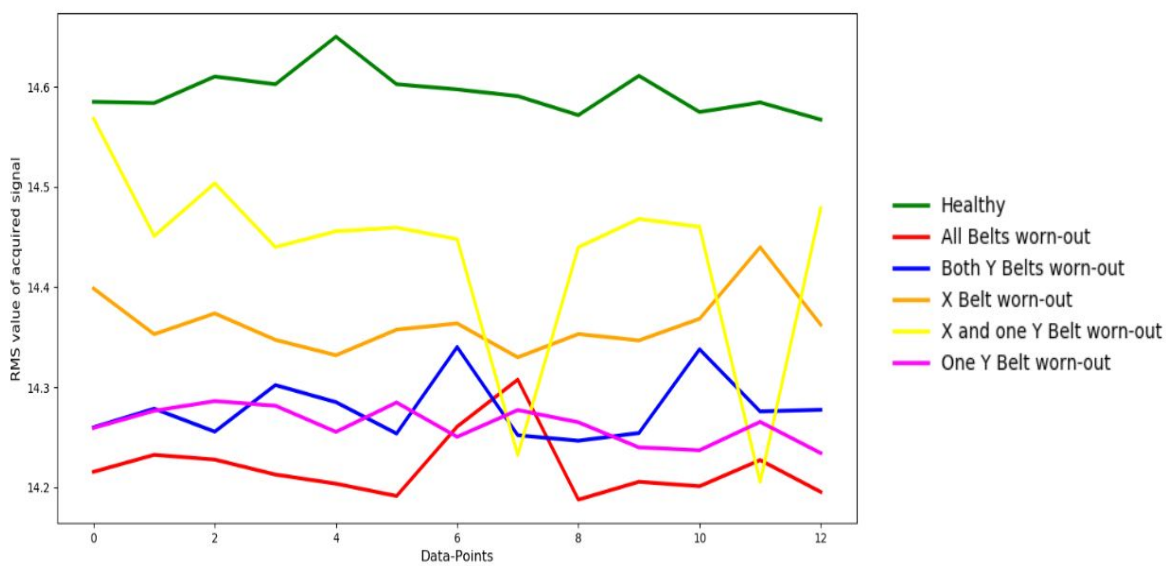



**Fig 5.6: Comparison of data from all states**

### 5.1.2 Diagnostic Model-Ⅱ

Figures 5.7 to 5.13 compare the RMS value of the raw data for the four health states of the printer. The graphs are plotted so as to compare two individual states at a time for clear visualization and simultaneously as well to see the overall trend.

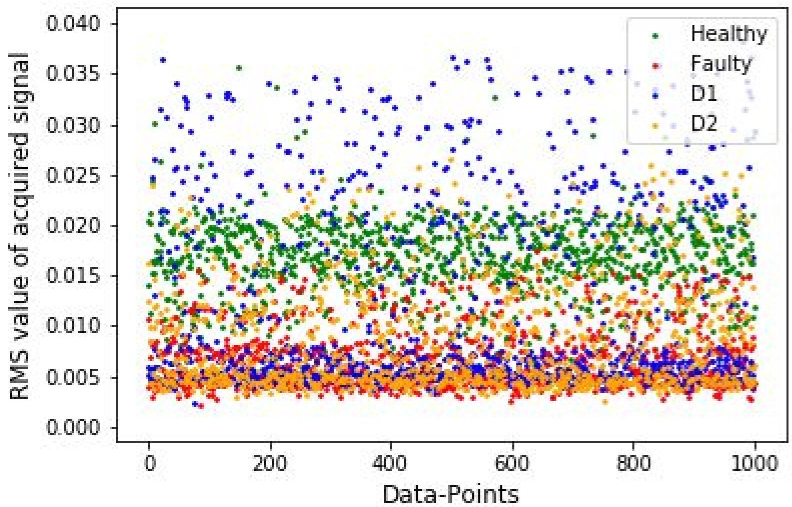



**Fig 5.7: Comparison of data of all States**

Fig 5.7 depicts the comparison of the RMS value of all the four health states of the printer.

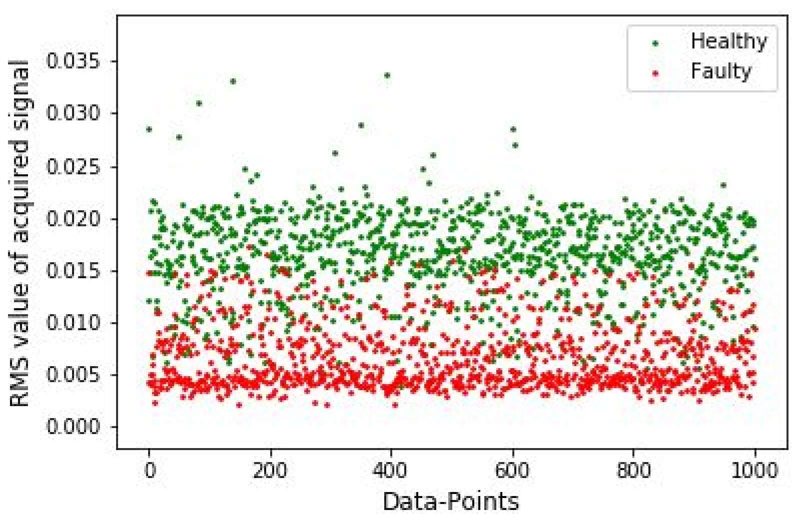



**Fig 5.8: Healthy vs Faulty State**

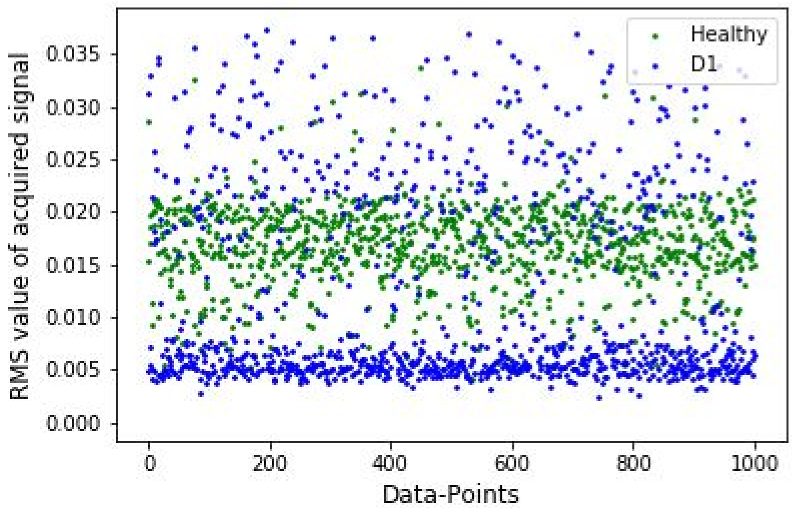



**Fig 5.9: Healthy vs D1 State**

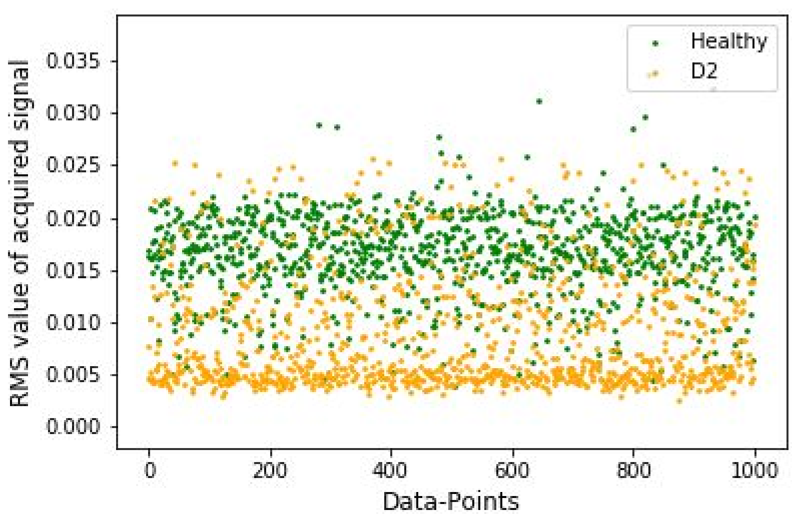



**Fig 5.10: Healthy vs D2 State**

Figures 5.8 to 5.10 show the comparison of the healthy state of the printer with the intermediate states (D1 and D2) and the faulty state individually. We see that maximum discrepancy is observed in the healthy and faulty states. Some parts of the D1 and D2 states overlap with the healthy state of the printer. More variance is seen in the comparison of the healthy state with the D2 state of the printer.

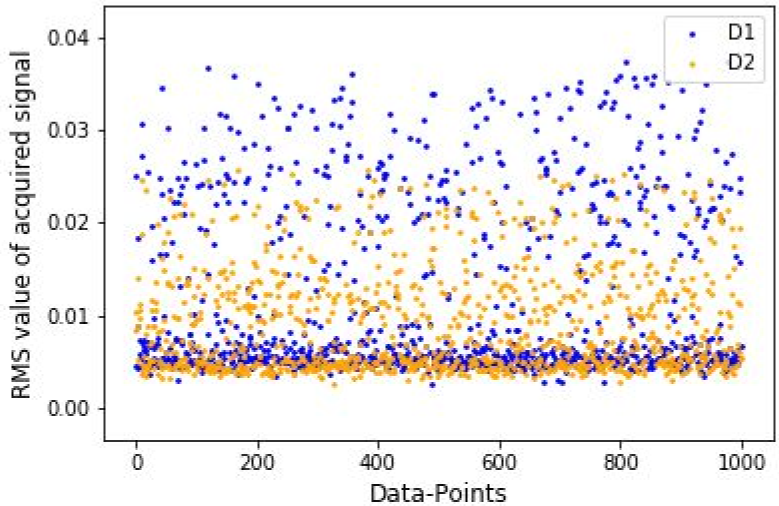



**Fig 5.11: D1 vs D2 State**

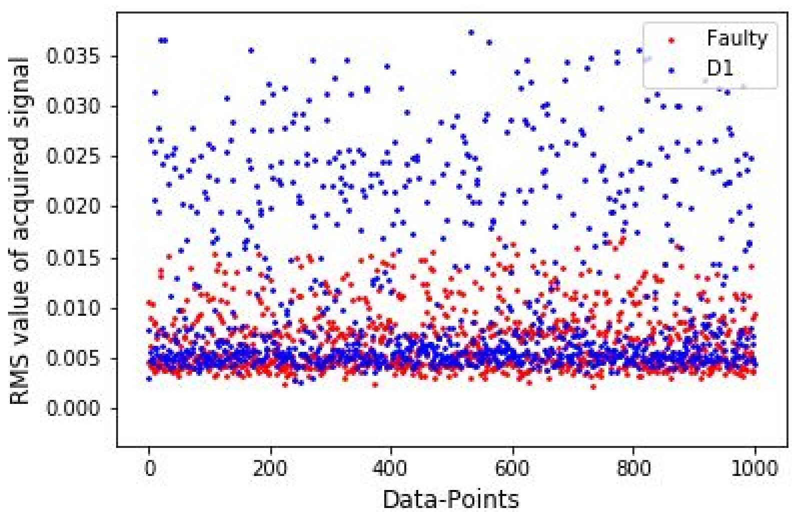



**Fig 5.12: D1 vs Faulty State**

Fig 5.11 and Fig 5.12 shows the comparison of the D1 state with the D2 state and the faulty state. We observe that maximum variation is seen in the D1 and the faulty state. Most of the RMS points of the D1 and the D2 state overlap each other.

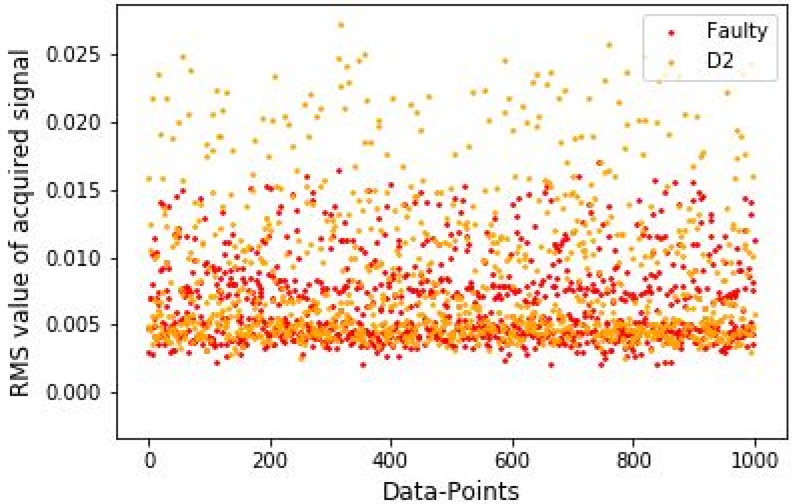



**Fig 5.13: D2 vs Faulty State**

Fig 5.13 plots the RMS points of the D2 state and the faulty state. Even though very little variation can be seen, most points of the faulty state fall in between 0.015 to 0.000, whereas the points in the D2 state have vibration values reaching up to 0.025.

## 5.2 Accuracy Tables

| Algorithms | Random Forest | | SVC | | ANN | |
|---|---|---|---|---|---|---|
| Healthy v/s | Train-Set | Test-Set | Train-Set | Test-Set | Train-Set | Test-Set |
| All Belts | 100% | 100% | 98.35% | 98.88% | 98.35% | 98.51% |
| Both Y-Belts | 100% | 98.76% | 99.18% | 98.76% | 98.57% | 99.59% |
| X Belt | 100% | 97.9% | 97.93% | 97.9% | 97.76% | 96.86% |
| X and Y-Belts | 100% | 94.11% | 95.63% | 94.48% | 91.45% | 88.6% |
| One Y-Belt | 100% | 99.59% | 99.19% | 99.59% | 98.6% | 98.37% |
| Multi-Class | 100% | 85.51% | 77.03% | 82.55% | 72.43% | 74.45% |

**Table 5.1: Accuracy Table of Diagnostic Model- I**

Table 5.1 provides the accuracy of the ML models developed for the first Diagnostic Model. Maximum accuracy is seen in the case of the binary classifiers. The multi-class classifier classifies between all the six states of the printer as described in Section 3.4.1. The binary classifiers classify between the five abnormal printer states taken one at a time and the healthy state.

| ML Algorithms | Accuracy | |
|---|---|---|
| | Train (%) | Test (%) |
| Random Forest | 97.88 | 58.86 |
| Support Vector Classifier | 56.99 | 58.41 |
| KNN | 71.23 | 60.36 |
| ANN | 60.88 | 61.23 |

**Table 5.2: Accuracy Table of ML Algorithms of Diagnostic Model- Ⅱ**

| DL Algorithms | Accuracy | |
|---|---|---|
| | Train (%) | Test (%) |
| Vanilla LSTM | 93.8 | 93.56 |
| Stacked LSTM | 97.54 | 97.3 |
| Bi-Directional LSTM | 97.56 | 97.29 |
| GRU | 97.66 | 97.2 |
| Stacked GRU | 97.01 | 96.7 |
| Bi-Directional GRU | 99.4 | 99.2 |

**Table 5.3: Accuracy Table of DL Algorithms of Diagnostic Model- Ⅱ**

Table 5.2 depicts the accuracy of the ML algorithms compiled for the second Diagnostic Model. It comprises ANN, SVC, RF, and KNN algorithms. ANN gives the highest accuracy for the test set followed by KNN. The average accuracy for all the algorithms is 60%.

Table 5.3 presents the accuracy of the DL algorithms compiled for the Diagnostic Model-Ⅱ. It comprises variations of LSTM and GRU. The highest accuracy for the test set is obtained in the Bidirectional GRU. The average accuracy for all the models is 96%. The accuracy of DL models is substantially greater than the classic ML algorithms.

# Chapter 6

## PROGNOSTICS MODULE

### 6.1 Experimentation and Analysis

For developing the Prognostics Module, the printer was operated from the simulated conditions (D1 and D2) as mentioned in Section 3.1.2. We recorded the vibration data for five minutes once in each hour of the operation. The other operating parameters (temperature and nozzle speed) were kept the same as in the Diagnostic Module.

### 6.2 Results

Fig. 6.1 shows the RMS values of the vibration signals obtained after the printer was operated from D1 state for nine hours continuously. The readings were recorded once each hour. We observed that the RMS values show no variation.

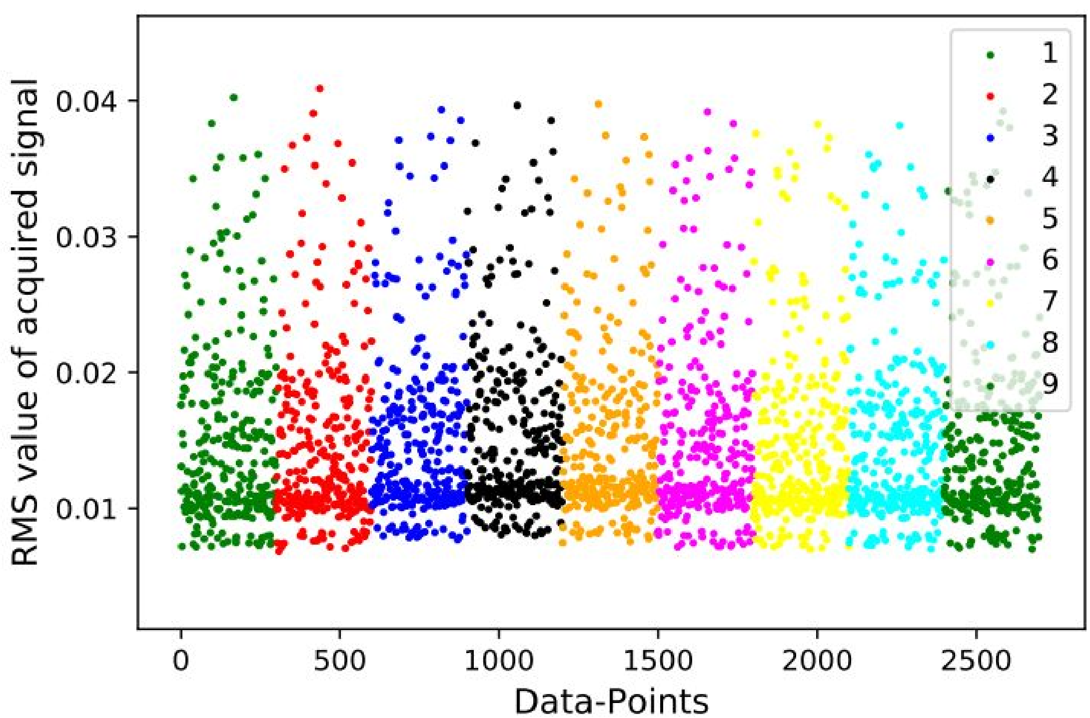



**Fig 6.1: Data comparison when operating the printer from D1**

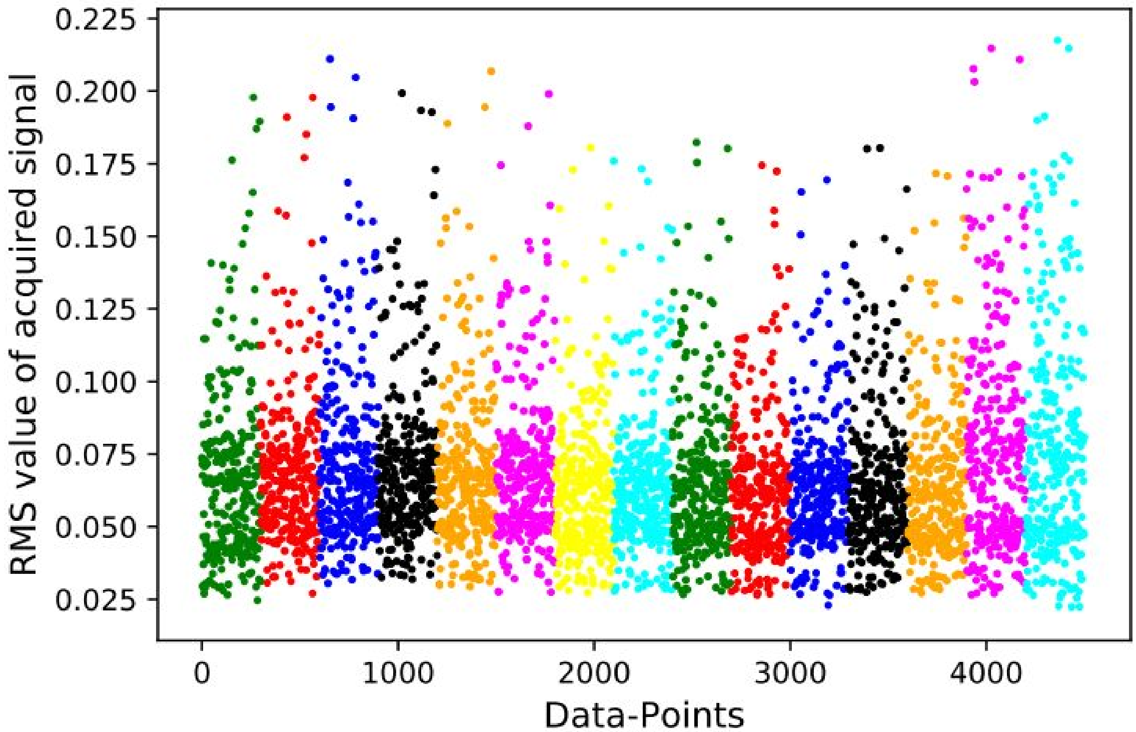



**Fig 6.2: Data comparison when operating the printer from D2**

Fig. 6.2 shows the RMS values of the vibration signals obtained after the printer was operated from D2 state for thirty hours continuously. The readings were recorded once every two hours. We observed that the RMS values started manifesting a minimal variation towards the end. Hence we are taking this investigation further and will continue to observe data till the time the vibration signal matches that of the faulty state observed in Diagnostic Model-Ⅱ mentioned in Section 3.4.2.

# Chapter 7

## CONCLUSION

### 6.1 Summary

Loosening and wear-out of belts are some of the most consequential process errors in 3D printers, which affect the quality of the prototype. In our current research work, a novel technique of application of an accelerometer to address this process error is presented. The time-domain features of the accelerometer were used to identify six different states of the machine. Normal and aberrant states were identified. The prominent features identified are RMS, Median, Kurtosis, Skewness, and Standard Deviation. These features were fed into Random Forest, SVM, and ANN classifier. The experimental results suggest vibration sensors prove to be reliable for condition monitoring of 3D printers.

Deep Learning Models were trained to identify the intermediate states of the printer. The results suggest DL algorithms provided better accuracy than the classic ML models.

### 6.2 Limitation and Future Scope of the Study

Further investigation needs to be done in order to increase the accuracy of the multi-class classifier. Mounting the sensor is very important to get accurate readings from the DAQ. In this study, the sensor is mounted on the extruder assembly. Various sensor positions can be explored for better data acquisition.

Other than the wear-out of the timing belts, other faults in the 3D printer can be investigated. For instance, nozzle clogging and deterioration of the stepper motors.

Various RNN models can also be developed to increase the efficiency of the diagnostics model. The diagnostics model can be integrated with a prognostics model to provide the RUL of the printer in real-time. For predictions in real-time, the module should be integrated with the cyber-twin of the machine.

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