DEVELOPMENT OF SENSOR-BASED MACHINERY VIBRATION ASSESSMENT SYSTEM FOR EFFECTIVE FAULTS DIAGNOSTIC IN CONDITION BASED MAINTENANCE USING MACHINE LEARNING

SYED MOHD SYAFIQ BIN SYED MAHMUD

FACULTY OF ENGINEERING
UNIVERSITI MALAYA
KUALA LUMPUR

2022

Universiti Malaya

DEVELOPMENT OF SENSOR-BASED MACHINERY VIBRATION ASSESSMENT SYSTEM FOR EFFECTIVE FAULTS DIAGNOSTIC IN CONDITION BASED MAINTENANCE USING MACHINE LEARNING

SYED MOHD SYAFIQ BIN SYED MAHMUD

RESEARCH REPORT SUBMITTED TO THE FACULTY OF ENGINEERING, UNIVERSITI MALAYA, IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER IN MECHANICAL ENGINEERING

DEPARTMENT OF MECHANICAL ENGINEERING
FACULTY OF ENGINEERING
UNIVERSITI MALAYA
KUALA LUMPUR

2022

Universiti Malaya

UNIVERSITI MALAYA

ORIGINAL LITERARY WORK DECLARATION

Name of Candidate: Syed Mohd Syafiq Bin Syed Mahmud

Matric No: S2030045

Name of Degree: Master's in Mechanical Engineering Title of Project Paper/ Research Report/Dissertation/Thesis ("this Work"): Development of sensor-based machinery vibration assessment system for effective faults diagnostic in Condition Based Maintenance using Machine Learning.

Field of Study: Mechanical Engineering

I do solemnly and sincerely declare that:

(1) I am the sole author/writer of this Work;
(2) This Work is original;
(3) Any use of any work in which copyright exists was done by way of fair dealing and for permitted purposes and any excerpt or extract from, or reference to or reproduction of any copyright work has been disclosed expressly and sufficiently and the title of the Work and its authorship have been acknowledged in this Work;
(4) I do not have any actual knowledge nor do I ought reasonably to know that the making of this work constitutes an infringement of any copyright work;
(5) I hereby assign all and every rights in the copyright to this Work to the University of Malaya ("UM"), who henceforth shall be owner of the copyright in this Work and that any reproduction or use in any form or by any means whatsoever is prohibited without the written consent of UM having been first had and obtained;
(6) I am fully aware that if in the course of making this Work I have infringed any copyright whether intentionally or otherwise, I may be subject to legal action or any other action as may be determined by UM.

Candidate's Signature　　　　　　　　Date: 19-july-2022

Subscribed and solemnly declared before,

Witness's Signature　　　　　　　　Date: 19 July 2022

Name: Ir. Dr. ALEX ONG ZHI CHAO

Designation: Assosiate Professor
Department of Mechanical Engineering
Faculty of Engineering
Universiti Malaya
50603 Kuala Lumpur

Universiti Malaya

ABSTRACT

Rotating machines such as turbines, motors, pumps, and fans generally generate the vibration when operate under normal condition. However, the presence of excessive force within the component of rotating machine can produce the high level of vibration. Without a systematic monitoring system, a high vibration can accelerate the machine wear, consume excess power, and damage the equipment. Consequently, the machine requires to shut down for maintenance and resulting unplanned downtime and increase the cost of maintenance. Furthermore, high level of vibration also can affect the machine performance and even worse affect the safety problems in engineered systems. High vibration caused by imbalance and misalignment become a major issue and leading to component damage such as shaft, seals, coupling and bearings in various rotating engineering application. Misalignments occurred when rotational centerlines are not collinear while imbalance is occurred when shaft geometric and mass centerline are not coincided. In a traditional way, the vibration data are present in plot such as orbit, time waveform, spectrum etc. However, to analysis and diagnose the vibration fault required a skilled worker who has vast experience, high technical knowledge, and expertise in vibration analysis. Furthermore, to diagnose the vibration fault would consume more time before final maintenance decision can be made. Therefore, the advance monitoring system that can diagnose the machinery fault is developed to supervise machine condition effectively. The system is build based on sophisticated deep learning program language by using modern python program to provide an assist and support in supervised the trend, performance of the machine and provide recommend decision. By using Convolutional Neural Network (CNN) method in deep learning offer a higher accuracy in prediction and detecting the vibration faults. The system is develop using 1D Convolutional Neural Network that can provide very simple in structure, easy to understand and flexible in design. Based on the validation result, the system successfully to achieve 100% accuracy

Universiti Malaya

in predict and detection each vibration faults correctly. In addition to this, the system is assessed with difference type of input data and the system achieve low accuracy when reducing the training data and using unprocessed data. However, this method required a huge number of training and validation dataset in order to get a better accuracy in predict and detecting the vibration faults. The fewer dataset could provide a result in a poor approximation and subsequently produce an incorrect interpretation of vibration faults.

Keyword: Vibration, Monitoring System, Failure, Deep Learning, Python

Universiti Malaya

ABSTRAK

Mesin berputar seperti turbin, motor, pam dan kipas biasanya menghasilkan getaran apabila beroperasi dalam keadaan normal. Walau bagaimanapun, kehadiran daya yang berlebihan dalam komponen mesin berputar boleh menghasilkan tahap getaran yang tinggi. Tanpa sistem pemantauan yang sistematik, getaran yang tinggi boleh mempercepatkan kehausan mesin, menggunakan lebihan kuasa dan merosakkan peralatan. Akibatnya, mesin perlu dimatikan untuk penyelenggaraan dan mengakibatkan masa henti yang tidak dirancang dan meningkatkan kos penyelenggaraan. Tambahan pula, tahap getaran yang tinggi juga boleh menjejaskan prestasi mesin dan lebih teruk lagi menjejaskan masalah keselamatan dalam sistem kejuruteraan. Getaran tinggi yang disebabkan oleh ketidakseimbangan dan salah jajaran menjadi isu utama dan membawa kepada kerosakan komponen seperti aci, pengedap, gandingan dan galas dalam pelbagai aplikasi kejuruteraan berputar. Penyelewengan berlaku apabila garis tengah putaran tidak berkolinear manakala ketidakseimbangan berlaku apabila garis tengah geometri aci dan jisim tidak bertepatan. Secara tradisional, data getaran hadir dalam plot seperti orbit, bentuk gelombang masa, spektrum dll. Walau bagaimanapun, untuk menganalisis dan mendiagnosis kerosakan getaran memerlukan pekerja mahir yang mempunyai pengalaman luas, pengetahuan teknikal yang tinggi dan kepakaran dalam analisis getaran. Tambahan pula, untuk mendiagnosis kerosakan getaran akan mengambil lebih banyak masa sebelum keputusan penyelenggaraan akhir boleh dibuat. Oleh itu, sistem pemantauan awal yang boleh mendiagnosis kerosakan jentera dibangunkan untuk menyelia keadaan mesin dengan berkesan. Sistem ini dibina berdasarkan bahasa program pembelajaran mendalam yang canggih dengan menggunakan program python moden untuk memberikan bantuan dan sokongan dalam mengawasi arah aliran, prestasi mesin dan memberikan keputusan yang disyorkan. Dengan menggunakan kaedah Convolutional Neural Network (CNN) dalam pembelajaran mendalam menawarkan ketepatan yang lebih tinggi dalam ramalan dan mengesan kerosakan getaran. Sistem ini dibangunkan menggunakan Rangkaian Neural Konvolusi 1D yang boleh memberikan struktur yang sangat mudah, mudah difahami dan reka bentuk yang fleksibel. Berdasarkan keputusan pengesahan, sistem berjaya mencapai ketepatan 100% dalam meramal dan mengesan setiap kerosakan getaran dengan betul. Di samping itu, sistem dinilai dengan jenis data input yang berbeza dan sistem mencapai ketepatan yang rendah apabila mengurangkan data latihan dan menggunakan data yang tidak diproses. Walau bagaimanapun, kaedah ini memerlukan sejumlah besar set data latihan dan pengesahan untuk mendapatkan ketepatan yang lebih baik dalam meramal dan mengesan kerosakan getaran. Set data yang kecil boleh memberikan hasil dalam anggaran yang kurang baik dan seterusnya menghasilkan tafsiran yang salah tentang kerosakan getaran.

Kata kunci: Getaran, Sistem Pemantauan, Kegagalan, Pembelajaran Mendalam, Python

Universiti Malaya

ACKNOWLEDGEMENTS

First and foremost, all praise to Allah for without His blessings this work would have never reached completion. I am ever grateful to Allah for His love, mercy, guidance, wisdom, strength and help in what has been an arduous academic and spiritual journey. The journey has taught me to put my trust and reliance in Allah, to be patient in all circumstances and to remain His humble servant.

Then, I express my deepest gratitude to my project supervisor, Ir. Dr. Ong Zhi Chao for his guidance, immense knowledge, constructive comments, and insightful suggestions that have significantly improved this research. I am thankful for his mentoring and teaching which has helped me grow and learn.

Next, thanks to my wife, Nurhaiza Bt Zaharrudin with her support and encouragement were definitely to be the major motivation for me to complete this research. I also would like to dedicate this project paper to my lovely child, Syed Amr Edruce and Syed Luth Hayden who is the happiness and delightful of my life.

Finally, my warmest thank to my employer, Malakoff Corporation Berhad for giving me the chance to do part-time master's degree and to my superior and colleagues in Engineering Department that have contributed directly and indirectly to the completion of this project paper. May Allah reward you all with the best in this life and the hereafter. Ameen.

Universiti Malaya

TABLE OF CONTENTS

Universiti Malaya

Universiti Malaya

Universiti Malaya

LIST OF FIGURES

Universiti Malaya

LIST OF TABLES

Universiti Malaya

LIST OF SYMBOLS AND ABBREVIATIONS

%	:	Percent
ANN	:	Artificial Neural Networks
CBM	:	Condition-based maintenance
FT	:	Fourier Transform
FFT	:	Fast Fourier Transform
IoT	:	Internet of Things
ISO	:	International Organization for Standardization
RMS	:	Root Mean Square
PM	:	Preventive Maintenance
Pdm	:	Predictive Maintenance
CM	:	Corrective Maintenance
IDE	:	Integrated Development Environment
pk	:	Peak
pp	:	Peak-to-peak
PIP	:	Pip Installs Packages
CNN	:	Convolutional Neural Network
RPM	:	Revolutions Per Minute
DE	:	Drive End
NDE	:	Non-Drive End
DCS	:	Distributed Control Systems
AI	:	Artificial Intelligence

Universiti Malaya

LIST OF APPENDICE

Universiti Malaya

INTRODUCTION

This section covers the explanation of the introduction, problem statement, objective, and scope of study.

1.1 Background

Recently, maintenance strategy has change dramatically due to the expanding of number in physical assets. The complex design of the assets together with new maintenance technique available and changing the view from management on the crucial maintenance make maintenance strategy become more important in order to ensure the reliability of the assets. The change in maintenance perspectives is also because of the evolution in awareness that equipment failure could give an impact to the safety and the environment, produce a product with a bad quality and increasing the pressure to reached high asset availability and maintainability and also to avoid a higher cost in maintenance. This demonstrated that the necessity of maintenance strategy with the objective to achieve highest level of machine reliability.

Over the time, maintenance strategy philosophy has evolved a lot over the decade. The maintenance evolution can be tracked since the period of World War Two. At that time, the equipment pattern was not much involved with complex mechanical design and simple to repair. The industry also was not highly automated and not very emphasis on the machine downtown time. As a result, the needs of systematic maintenance strategy are less crucial during this period.

The maintenance strategy has change significantly during World War Two where industry received high demand for goods production and supply while manpower dropped dramatically. Thus, more automated machine was introduced and the necessity for systematic maintenance strategy become a crucial part. This led the concept of Preventative Maintenance where the equipment overhaul at a fixed time interval.

Universiti Malaya

Then, in the mid-seventies, the development of industry in providing the goods and supply received even greater momentum. The demand and cost are high during this time. The design of assets equipment become more complex with increasing the cost. The competition between enterprise in providing the goods and supply also dramatically increased. In order to secure the maximum return of investment, the equipment needs to be operated at high level of performance with high reliability and maintainability. Thus, the equipment downtime and failure become priority and need to avoid with much better systematic maintenance approached. Hence, Condition-based monitoring was introduced where the equipment operates at maximum lifetime and only overhaul at a time before its failure.

In the recent times, a lot of technology based on condition-based monitoring maintenance were establish such as vibration, lubrication analysis, infra-red thermography monitoring, ultrasonic, acoustic emission etc. Condition-based monitoring is the process to monitor a condition of the machine, detection of fault development, trending of the faults and performance. It allows machine to operate at maximum lifetime before its failure and can prevent consequential damages thus can reduce of maintenance cost and repair downtime.

Nowadays, Condition-based monitoring has evolved to advanced diagnostic tool involving machine learning mechanism. The root cause of machinery fault can be identified further accurately with less dependency in human intervention. The capability of machine learning to handle multi-variety data and the ability to automate various decision-making tasks make it gain popularity especially with the approaching industry 4.0. With this technique, the equipment life cycle can be extended to the maximum lifetime and the maintenance actions can be optimize thus can reduce the maintenance cost.

Universiti Malaya

1.2 Problem Statement

Nowadays, numerous numbers of rotating equipment application commonly used in various mechanisms throughout the process in the industry sector. However, this application encounters many vibrations engineering problem. A range of vibration problems are regularly encountered in equipment such as steam turbine, motor, pump, fans etc. In the modern day, maintenance concept with systematic approach were introduced to overcome the problem in engineering. Furthermore, a comprehensive monitoring system is crucial to develop to monitor rotating equipment performance and to avoid inappropriate maintenance cost.

In general, vibration condition-based monitoring offers a capability to identify the root cause of vibration fault through the online and history of vibration data. Commonly, this data is present in plot such as orbit, time waveform, spectrum, shaft centerline, bode plot etc. Vibration faults such as misalignment and imbalance can be identified through details analysis and diagnose using all this data. However, these techniques required an expertise with capability to collect and handling the complex data, then to analyze with the high level of analysis and has the capability to interpret all thus trending into a root cause of failure. The misinterpretation will lead to inappropriate maintenance schedule and consequently increase the maintenance cost. Furthermore, to diagnose and analyze each of thus trending with complicated behavior of machine is not a straightforward and would consume additional time. This will be interrupted the production process and consequently caused an additional cost due to penalty from stakeholders. Due to this, Machine learning mechanism are introduced to assist in supervised the trend, support in technical decision-making in various type of machine failure and provide the improvement in the engineering system.

Universiti Malaya

1.3 Research Objective

Generally, this project is carried out to develop advanced vibration machinery diagnostic based on Machine learning approach using Python program language. The following objectives must be achieved along this project;

i. To investigate sensitive feature of raw vibration sensor data in time series from difference machinery faults.

ii. To develop machinery fault classification model using deep learning algorithm based on time series data.

iii. To validate machinery fault classification model in identifying difference machinery fault.

1.4 Scope of Research

In overall, this study focuses on the development of advanced machinery vibration assessment application program through data extraction, classification technique and machine learning processing to effectively diagnose and classify common machinery faults. Even though condition-based maintenance can used in difference application, in this study will focus on the application of vibration analysis and diagnose through vibration faults by using machine learning technology. Most Common causes of machine vibration which are misalignment and imbalance was used to simulate in this study. Other faults such as shaft crack, bent shaft, rotor rub, and oil whirl are excluded from this study due to prefabricated laboratory rotor kit that have been used to simulate the vibration faults is not equip with the capability to simulate all thus faults. On the other hand, this study focuses to identify and detect the misalignment and imbalance faults, healthy condition will exclude in this study in order avoid the misunderstanding between machine in good condition and others type of vibration faults that excluded from this study.

Universiti Malaya

Then, the machinery diagnostic will be developed by using Python software with the capacity to work as a machine learning tool in vibration fault interpretations. This is very useful in the implementation in the current condition-based maintenance programmed. At the end of this study, condition of the rotating machinery and vibration faults can be analyzed and identified through machine learning process. In order to analysis using this technique, the knowledge and interpretation of the program algorithm, type of vibration faults and the details about the machine condition is essential. The accurate root cause is crucial in identifying the perfect rectification work. The incorrect interpretation of the root cause will lead to the inappropriate rectification work and consequently can create another failure and increase the maintenance cost. On the other hand, by identify the accurate root cause, the correct rectification work can be performed and eliminate the failure thus the rotating equipment can operate and produce the desired output. Besides that, by rectify the failure, cost of maintenance can be reduced significantly and to can avoid recurrent failure.

Universiti Malaya

LITERATURE REVIEW

This chapter includes an overview information on previous studies and current research which are related to maintenance philosophy, condition monitoring, vibration analysis, machine learning and core outcome that are expected from the research.

2.1 Maintenance Methodology

Nowadays, maintenance strategy has become crucial part in most industries. The maintenance methodology needs to develop carefully to ensure equipment reliability and maintainability. According to Estefany Soares, Isabel da Silva Lopes and Juliana Pinheiro, maintenance strategies need to develop to meet the requirement in automotive manufacturing industry in order to identify the equipment that have an irregular rise in the number of failures. They successfully to prove that by implement the effective and efficient maintenance program can reduce significant number of failure rate and machine downtime (Soares, Lopes, & Pinheiro, 2021).

In addition, Ruey Huei Yeh and Wen Liang Chang has proved that failure rate of the equipment can be reduce significantly by implement an effective maintenance strategy. They also proved by implement a good maintenance strategy can minimized the total maintenance cost (Yeh & Chang, 2006).

Çaglar Karatug and Yasin Arslanoglu in their paper has shown that by implement an effective maintenance strategy, can enhances the efficiency of marine vessels performance. They suggest the implementation of condition-based maintenance strategy in maritime industry that can produce more efficient in marine vessels operations, embracing a more successful maintenance strategy, and decreasing operating costs (Çaglar & Arslanoglu, 2022).

Universiti Malaya

Maintenance can be described as a strategic or unprepared repair work that are performed with the objective to expand the lifecycle of the asset. There are various types of maintenance systems that consist of variety type of philosophy that can be implement in the industry such as preventive maintenance, breakdown maintenance, predictive maintenance, and Condition-Based Maintenance (Özgür-Ünlüakın, Türkali, Karacaörenli, & Aksezer, 2019).

Based on BSI Standards Publication, maintenance can be described as a sequence of administrative, technical, and organize the action to retain or restore the asset during the life cycle to perform the required function. It also stated that the objective of maintenance is to assign and accept a target such as cost reduction and machine availability, (BSI Standards Publication, 2010). In addition to this, the overall view of maintenance can illustrate as a Figure 2.1.

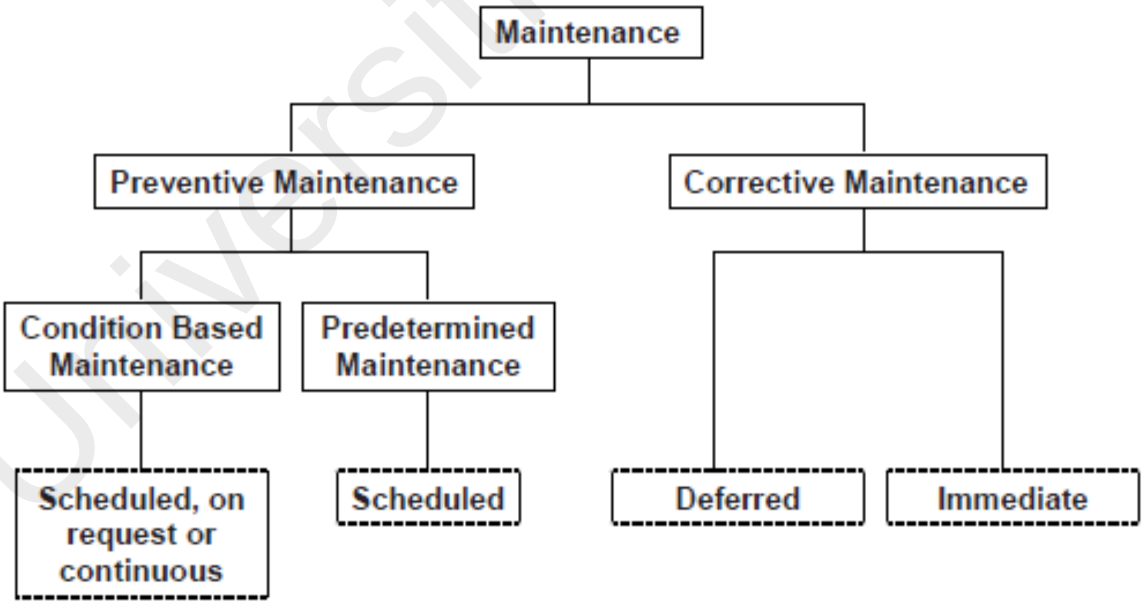

Figure 0.1: Maintenance Overall View

Adapted from BSI Standards Publication BS EN 13306 (2010).

Universiti Malaya

On the other hand, according to ISO 14224, maintenance need to carry out in order to restore the asset from the failure and to prevent the failure from occurring. In addition to this, maintenance can be categories into two type of maintenance which are preventive maintenance and corrective maintenance. Preventive maintenance is the action of work that needs to perform before the failure happen while Corrective maintenance is the work that perform after the failure happen (ISO 14224, 2006).

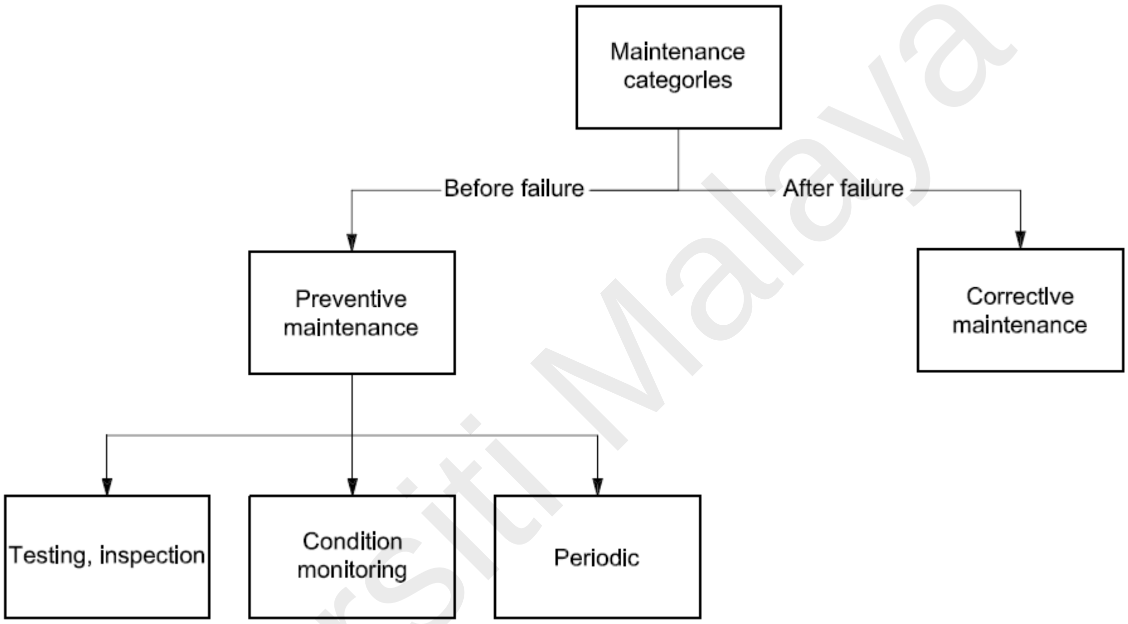

Figure 0.2: Maintenance Categorization

Adapted from ISO 14224, 2006

Moreover, Konsta Mikael Sirvio in his research define the maintenance management system is the application and principle of asset maintenance management. He also stated the definition of reactive maintenance is the unplanned maintenance that need to conduct until the asset back to operational again while proactive maintenance is maintenance that conduct before the failure occurs. In addition to this, corrective maintenance is the maintenance conduct after system failure while preventive maintenance is a proactive approach in identify the possible failure (Sirvio, 2017). The timing condition of the asset can be determine as shown in Figure 2.3.

Universiti Malaya

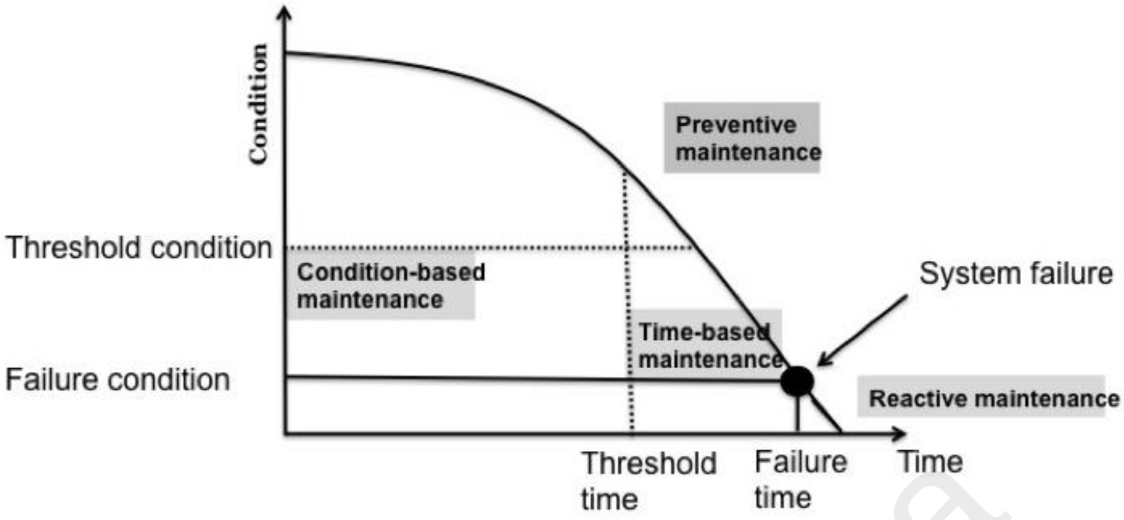

Figure 0.3: Maintenance Condition Over Time

Adapted from (Konsta Mikael Sirvio, 2015).

Besides that, according to ISO 14224 stated that there are two major period during the maintenance work which are active maintenance time and down time. Active maintenance time is the actual time of maintenance work being performed while down time is the time from the equipment stop until the equipment back to perform their function (ISO 14224, 2006). The difference between these two categories is shown in Figure 2.4.

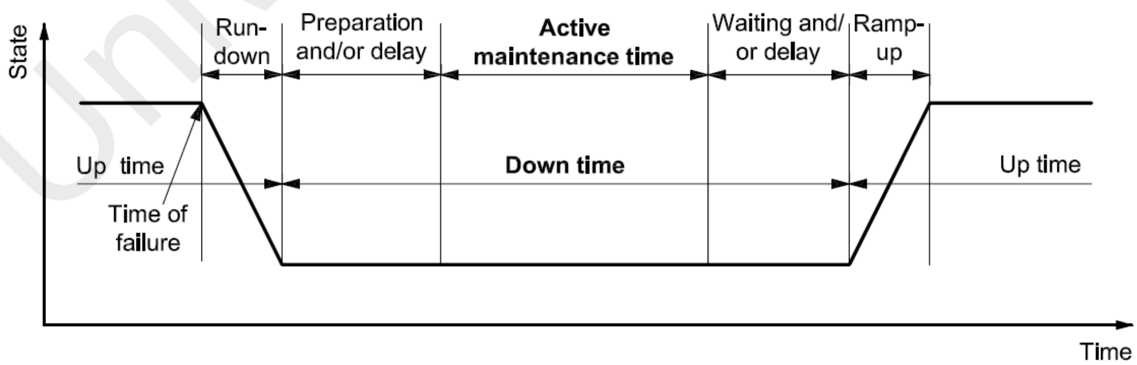

Figure 0.4: Maintenance times

Adapted from ISO 14224 (2006)

Universiti Malaya

On the other hand, the current digital transformation has influenced the way maintenance approach in industrial world especially the approaching of industry 4.0. According to Irene Roda and Marco Macchi in their research concluded that the world industrial is expecting evolving toward artificial intelligent in their maintenance management such as deep learning and machine learning, etc. (Roda & Macchi, 2021).In addition to this, Jay Lee et al. in their research has concluded that toward the industrial smart revolution, the objective of maintenance has transformed from cost reduction and reliability of the asset perspective and to maintenance scheduling approaches that can offer more flexibility in operations. They added that the research achievement for decade has transform the world industrial to modern and intelligent maintenance concept (Lee, et al., 2020).

2.2 Reactive Maintenance

Reactive maintenance is the maintenance that conduct after the failure occur and aimed to put the asset return to operate with same function performance (BSI Standards Publication, 2010). This type of maintenance suitable for the asset that less critical and give less impact to the whole engineering system if failure occur. In addition to this, reactive maintenance application can maximum the utilization of the asset value before the failure occurs.

Furthermore, reactive maintenance is simple and easy to manage and not required systematic and complex planning. The maintenance only needs to perform when the asset is failure, or the performance of the asset does not reach the desire output. In addition, this type of maintenance required a lower initial cost and less manpower needed which make suitable for management with less capital budget for maintenance. The relationship between repair cost and maintenance cost for three maintenance concepts can illustrated as in Figure 2.5.

Universiti Malaya

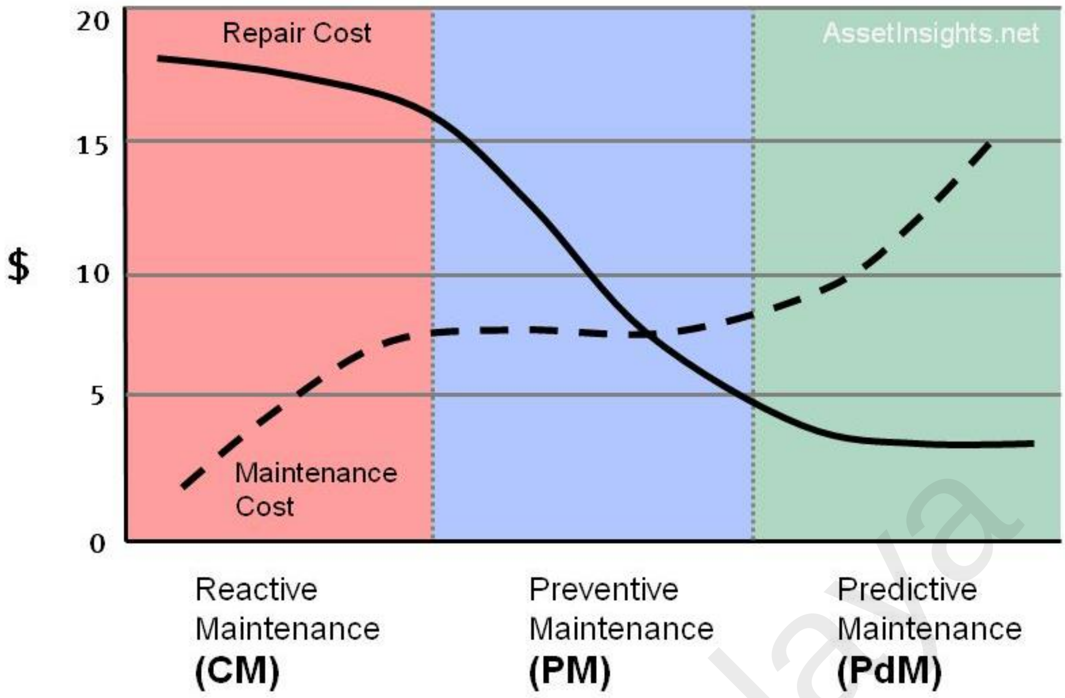

Figure 0.5: The correlation maintenance cost and repair cost

Adapted from (Asset Insights, 2013)

On the other hand, Ozgur et al. has define reactive maintenance as unplanned and planned maintenance that carried out in order to extend useful life of the asset. They also stated that in their research has suggest the necessity of systematic reactive maintenance at thermal power plant event though an efficient preventive maintenance is planned for such systems (Özgür-Ünlüakin, Türkali, Karacaörenli, & Aksezer, 2019).

2.3 Preventive Maintenance

Preventive maintenance can be defined as the maintenance activities that conducted regularly based on the planned schedule in order to prevent unpredicted failure in the future. This type of maintenance suitable for the critical equipment that can give terrible impact to the whole engineering system if failure. Currently, this type of maintenance concept has been widely applied and become major component in most facility in various industry.

Universiti Malaya

Furthermore, preventive maintenance offers more systematic and efficient maintenance management in order to prevent unexpected failure. The schedule plan of this type of maintenance relies on the historical failure rate especially the critical equipment. According to Hao Peng et al. in their research has successfully develop a reliability modelling for nuclear safety-class DCS using preventive maintenance concept based on failure rate evolution curve. (Peng, Wang, Zhang, Hu, & Xu, 2022).

However, the implementation of preventive maintenance required high capital upfront costs due to the maintenance activity need to regularly conduct. This kind of maintenance also required more labor worker and there is potential that over-maintenance. Rosmaini Ahmad and Shahrul Kamaruddin in their research has compare the maintenance concept between CBM and preventive maintenance. They have concluded that the application of CBM is more realistic compared to preventive maintenance. This is based on the 99% of machine failure will indicated some failure signature. They also stated that CBM has the advantage because its offer the vast data availability and the good accuracy (Ahmad & Kamaruddin, 2012).

Preventive maintenance application is developed based on bathtub curve. Bathtub curve is a common graphic presentation to demonstrate the failure rate of the asset. Currently, this curve has been widely used as a reference in reliability concept for engineering system. The bathtub curve can divide into three region which are early failure or infant mortality, asset useful life, and wear out as shown in Figure 2.6.

Universiti Malaya

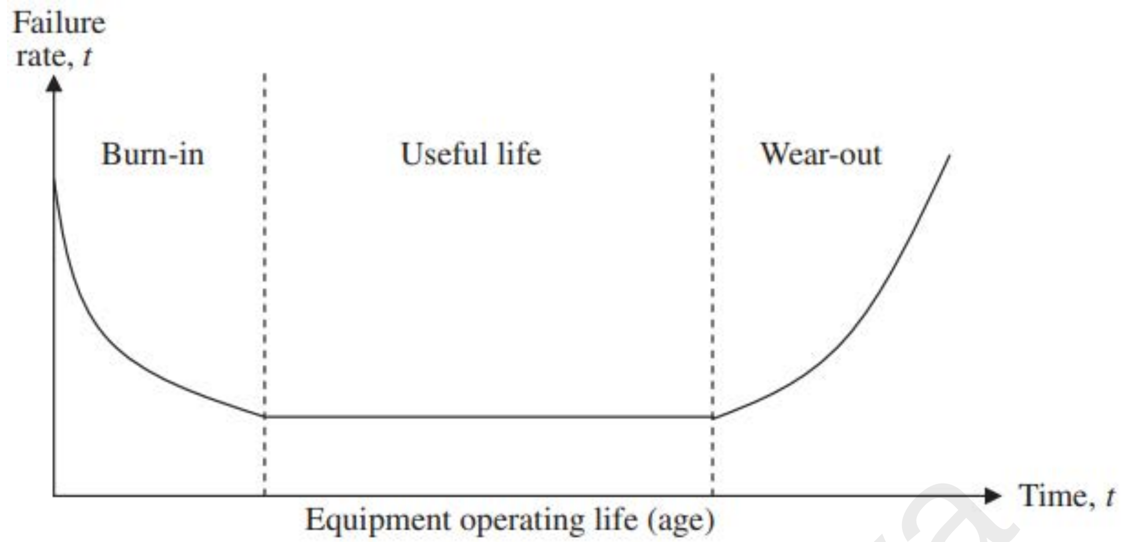

Figure 0.6: Bathtub Curve

Adapted from (Ahmad & Kamaruddin, 2012)

The first region is the period where a new commissioning machine in operate. Under this region, the failure rate decreases along the time. Then followed with normal life of operating in the second region. Under this period the failure rate is relatively constant and stagnant. Then, at the end of the product life, the failure rate exhibits the increment. Under this region, it is suggested to conduct the maintenance.

2.4 Condition-Based Maintenance (CBM)

CBM methodology can be described as a maintenance that conducted based on condition and degradation of the equipment. According to BSI Standards Publication, CBM is the action of work to perform repeated analysis, prepare the prediction and evaluate for certain parameter about the degradation of the asset performance (BSI Standards Publication, 2010). Generally, CBM application required a sensor device to collect and compile the real time measurement. Then the details analysis needs to conduct to identify the asset condition. Thus, the asset can shut down for maintenance and can schedule properly.

Universiti Malaya

Recently, Condition-Based Maintenance (CBM) has commonly been practiced in numerous industry such as military, aerospace, and power generation. Various research has been conducted to evaluate the effective of CBM in the industry. Analysis has showing that by applying the CBM into critical equipment in power plant in United Stated will result saving over $1 billion per year (Bond, et al., 2011). In critical facilities such as nuclear industry, the application of CBM technique is not just to sustain the assets performance but to ensure the safety related matters (Ayo-Imoru & Cilliers, 2018).

Besides that, CBM application can reduce the total cost of maintenance and repair. This can be achieved by collecting the real-time data, perform an analysis and interpret the data for asset condition. According to Ali Rastegari, the objective of CBM is to reduce the work of preventative maintenance that subsequently can reduce the maintenance cost while keeping the asset at high performance and availability. In addition to this, CBM is also the most effective maintenance strategy compared to the others due to the capability of this technique to predict and gives warning prior to the impendent failure (Rastegari, 2017).

Furthermore, the effective of implementation of CBM technology in industry can give a lot of benefit. Based on Taboada et al. on their research has demonstrated the capability of CBM to reduce the maintenance cost and to remove potential risks of any failure. In addition to that, they also stated that the objective of CBM is not to avoid the failure that will take place in first place, but CBM is the process of action that need to perform before the failure happen in order to avoid the asset not able to perform the functionality within cycle time. Therefore, CBM methodology can reduce the time for repair and maintenance activities and subsequently reduce the logistic and labor cost (Taboada, Diaz-Casas, & Yu, 2021).

Universiti Malaya

However, the CBM implementation in the industry comes with a wide variety of challenge. Emilia Ingemarsdotter et al. in their research has listed 19 challenges and 16 solutions in order to implement an effective CBM technology. One of the major challenges is limited experience and expertise in handling data analytics in CBM. They recommend developing awareness among employers and provide the easy tools to support (Ingemarsdotter, Kambanou, Jamsin, Sakao, & Balkenende, 2021).

Furthermore, a systematic approach needs to develop to address the challenge in implement an effective CBM technique. Based Humberto Nuno Teixeira et al in their research has suggest the needs and essentially of appropriate procedure and guideline in order to facilitate the effectiveness in CBM. They argue that the effectiveness of CBM implementation is relies on the experience of personnel expertise in handling the data, analyze the trend and making a vast recommendation and decision. They recommend developing a comprehensive methodology in order to support the personnel in making the decision (Teixeira, Lopes, & Braga, 2020).

In overall, condition-based maintenance is part of predictive maintenance. The concept and approach are almost similar with preventive maintenance. However, the difference between this two is predictive maintenance is the maintenance that conceptualized the condition of the system can be mapped based on system condition. The maintenance activities and machine shutdown can be properly planned before failure happen (Sirvio, Intelligent Systems in Maintenance Planning and Management, 2015).

Generally, condition-based maintenance concept can be demonstrated based on P-F curve as shown in Figure 2.7. Based on P-F curve, the asset condition and performance deteriorate over time and leading toward to the asset failure. Potential failure (P) point is the point that equipment is about to failed. During this interval, any necessary action is should be plan and conduct. This approach allows a window to shut down the system and

Universiti Malaya

perform a proper maintenance before the Functional failure (F) point is occurs (Mandreoli & Emilia, 2021)

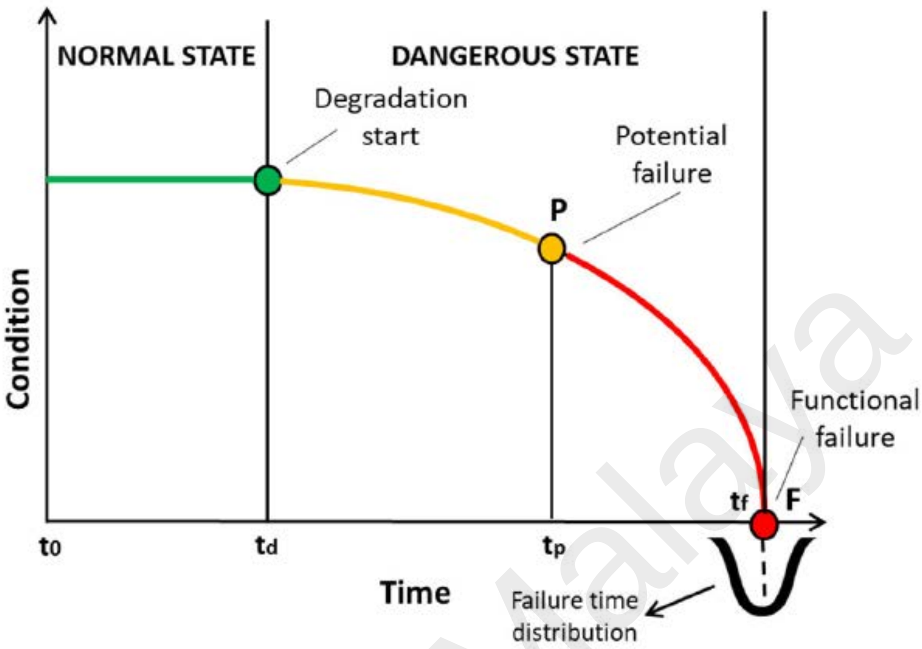

Figure 0.7: P-F Diagram

Adapted from Federica Mandreoli, Reggio Emilia, (2021).

Besides that, the advantage of condition-based maintenance is the data can collect using real-time data without necessary to shut down the system. Any deviation in asset performance can be determine and necessary action can plan properly. Currently, there are several CBM technology available such as vibration analysis, lube oil analysis, infrared thermography, ultrasonic analysis etc.

2.5 Vibration analysis

Vibration analysis is one of the components in CBM technology that normally used in rotating equipment such as gas turbine, steam turbine, and pump. Based on Mobius institute, vibration can be defined as an oscillation of the object at a fixed reference in complex way where it can vibrate at different frequencies and amplitudes (Mobius Institute, 2020).

Universiti Malaya

According to ISO 13373-1, the objective of vibration condition monitoring is to monitor and obtain the operating condition of the machine for the purpose of protection and predictive maintenance. The primary part of this process is to get the vibration condition of the machine over the operating time. Furthermore, the vibration monitoring can provide the essential information in order to increase equipment protection, improve safety and maintenance procedure, avoid catastrophic failure and extend equipment life (International Standard ISO 13373, 2002).

Failure in rotating equipment normally related with vibration issue. Based on research conduct by Al-Tekreeti Watban Khalid Fahmi et al., they listed 5 common phenomena on vibration issue in gas turbine. The five common are unbalancing and misalignment, rubbing, flow fluctuations, the critical rotor speed, and shorted-turns. They also stated that most of the failure in vibration are relating each other between the failure such as unbalancing and misalignment relate to the rubbing (Fahmi, Kashyzadeh, & Ghorbani, 2022).

Moreover, machinery equipment such as gas turbine, steam turbine and pump generally will produce a warning sign and symptom before its failed. In this case, early detection is crucial to prevent any further failure which can suffered with additional cost. With the implementation of vibration analysis, the failure assessment and accuracy of the vibration faults can be determined (Bovsunovsky, 2018).

Rotating equipment such as gas turbine has complicated design system where the structure can be vulnerable to dynamic centrifugal forces which can cause the failure in turbine component. The failure could continue for long time and the catastrophic failure can occur in the turbine. (Elsevier B.V, 2017). On the other hand, there is various form of typical vibration failure in gas turbine such as Shaft Cracks, Rotor imbalance, and Misalignment, which can happen at any gas turbine (Ahmed, Islam, Sarkar, & Haq, 2015).

Universiti Malaya

Furthermore, to improve the reliability in rotating equipment, various technique of vibration analysis was introduced. Xiaodong Zhu1, Xiu Tan, Wei Jiang and Yuanyue, has develop a machinery vibration based on fault tree analysis (Zhu, Tan, Jiang, & Bu, 2017). In addition to that, Jay Prakash Kumar, Premanand S. Chauhan and Prem Prakash Pandit has demonstrated by using time domain to analyze the vibration symptom by using statistical parameters (Kumar, Chauhan, & Pandit, 2022). Recently, Bently Nevada has develop more advance and sophisticated diagnostic tools which is system 1 monitoring system where the vibration analysis and monitoring are much simpler to detect the vibration faults (Bently Nevada, 2021).

In vibration analysis, measuring the vibration and collect the data is the essential element in vibration analysis. The analysis in advance machinery diagnostic relies on a good data in order to produce an accurate result. Based on the ISO 13373-2, vibration data a measured using a transducer that install at rotating equipment. Then, the transducer will generate an analog electrical signal that proportional with vibration motion. This signal can be measured and recorded in acceleration, velocity, and displacement unit depending on the transducer type and desired parameter (International Standard ISO 13373, 2002),

On the other hand, vibration signal can be analysis either in time domain or frequency domain. The relationship between time and frequency domain shown in the Figure 2.8. Based on the figure below, there are four overlapping signals that combine simultaneously to generate time domain waveform. Then, this signal divided into four distinct frequency components through Fourier process. Currently, most vibration analysis use frequency domain to identify the root cause of vibration problem. However, there also valuable to involved time domain history in analyze the vibration signal (International Standard ISO 13373, 2002)

Universiti Malaya

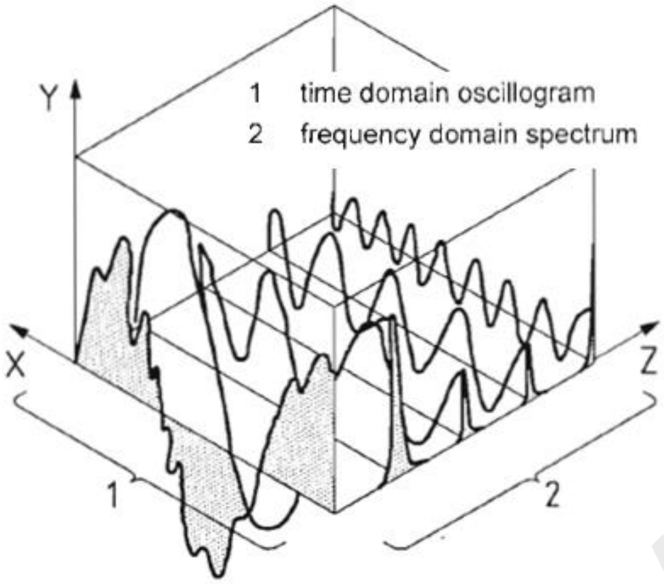

Figure 0.8: Time and Frequency domain

Adapted from ISO 13373,2002

Nowadays, a lot of research has conduct to analyze vibration using time domain. Time domain normally use in statically the trend on machine performance. Jay Prakash Kumar et al. has applied time domain in their vibration analysis on rolling element bearing. In their study, they use statistical parameter method to identify high vibration on rolling element bearing (Kumar, Chauhan, & Pandit, 2022).

2.6 Vibration Standard

In vibration analysis, diagnose the vibration faults and evaluation of vibration level should follow a several standard. ISO 7919 is international standard that provide the general guideline in estimate the vibration characteristic on various type of machine. Under this standard, the measurement of vibration will be capture directly on rotating shaft as illustrated in the Figure 2.9.

Universiti Malaya

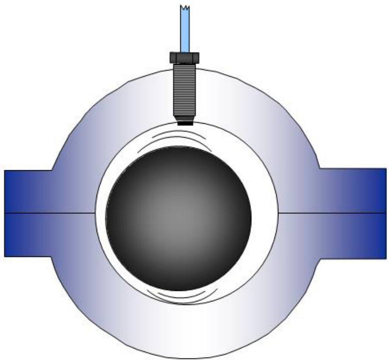

Figure 0.9: Diagram of a vibration measurement on directly at rotating part.

On the other hand, ISO 10816 is international standard that provide the general procedures in evaluation the vibration behavior on different type of machine. Under this standard, the measurement of vibration will be capture directly on non-rotating part as illustrated in Figure 2.10.

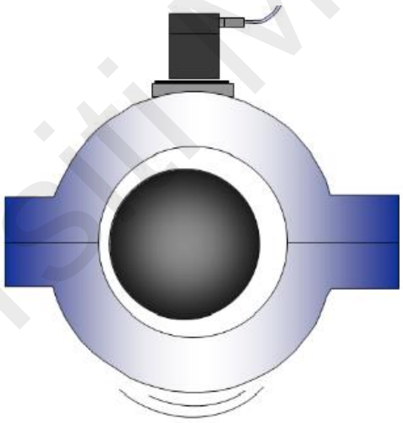

Figure 0.10: Diagram of vibration measurement on non-rotating part

In general, vibration measurement needs to determine at rotating parts and non-rotating part. Then, vibration analysis should be conducted in order to determine the machine condition at various machine operating mode. Next the evolution of vibration level should follow the evaluation zones standard. If the level reached the unsafe level of vibration, the machine needs to shut down and rectification work are necessary to conduct immediately.

Universiti Malaya

Zone A: The vibration of newly commissioned machines normally falls within this zone.

Zone B: Machines with vibration within this zone are normally considered acceptable for unrestricted long-term operation.

Zone C: Machines with vibration within this zone are normally considered unsatisfactory for long-term continuous operation. Generally, the machine may be operated for a limited period in this condition until a suitable opportunity arises for remedial action.

Zone D: Vibration values within this zone are normally considered to be of sufficient severity to cause damage to the machine.

On the other hand, ISO 10816-3 has explained the general requirement for measuring and evaluate vibration for industrial machine. This standard describes a specific guidance for assessing the vibration measurement at bearings, bearing pedestals and housing of the machine. Furthermore, vibration severity level has described specifically for different type of machine in industry either in velocity unit or displacement unit as shown in Figure 2.11 and 2.12.

Universiti Malaya

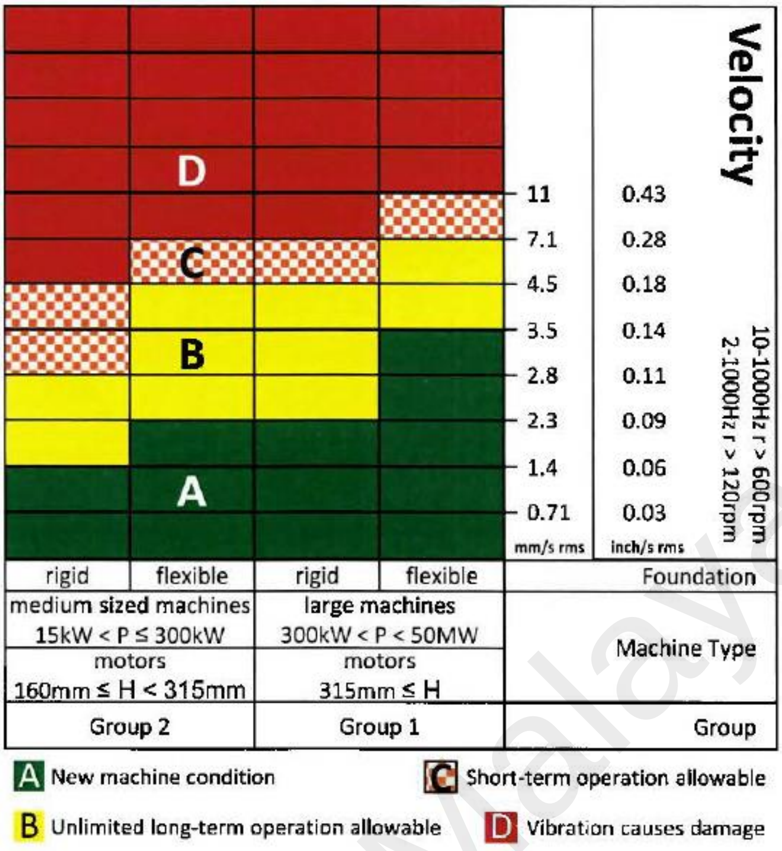

Figure 0.11: ISO 10816-3 Vibration Severity Chart (Velocity)

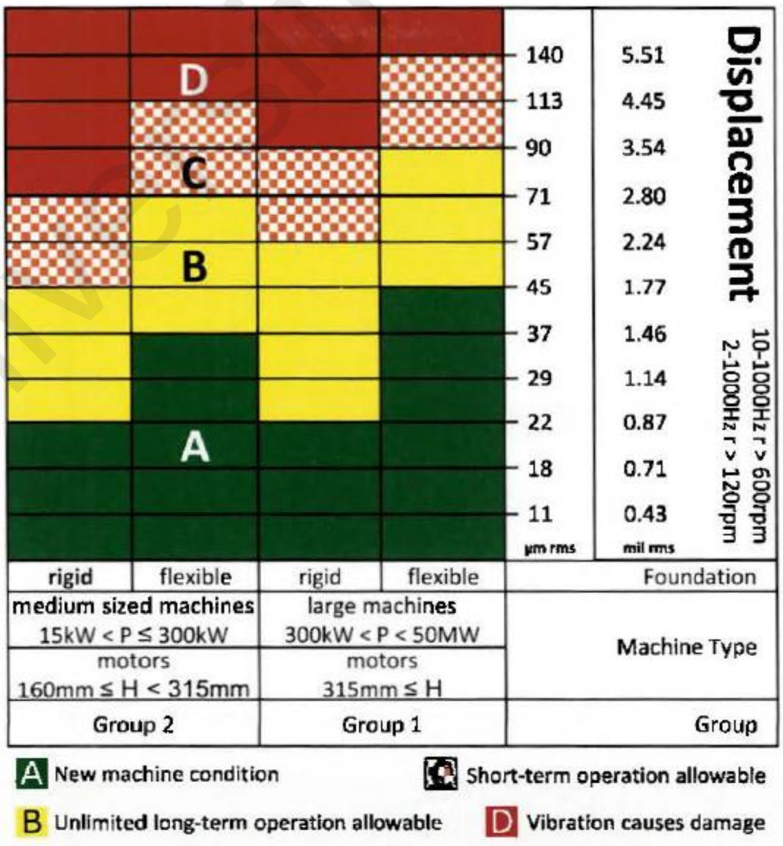

Figure 0.12: ISO 10816-3 Vibration Severity Chart (Displacement)

Universiti Malaya

2.7 Artificial Intelligence (AI)

Artificial intelligence is the concept of development a computer system that can perform a task that normally requiring human intelligence skill. The concept of Artificial intelligence emerged in the first time in Dartmouth Conference in 1956 by group of computer scientist. Then this concept has expended significantly over the past few years especially the development of GPUs that can provide the computer processing faster (Nada & Berchane, 2018).

Recently, artificial intelligence application had growth dramatically into an advance tool to imitate the human thinking in variety of industry. Furthermore, the growth of technology cloud platform and mobile application has attracted many industries to develop a system based on artificial intelligence. Basically, artificial intelligence consists of machine learning and deep learning. The relationship between these can illustrated as in Figure 2.13.

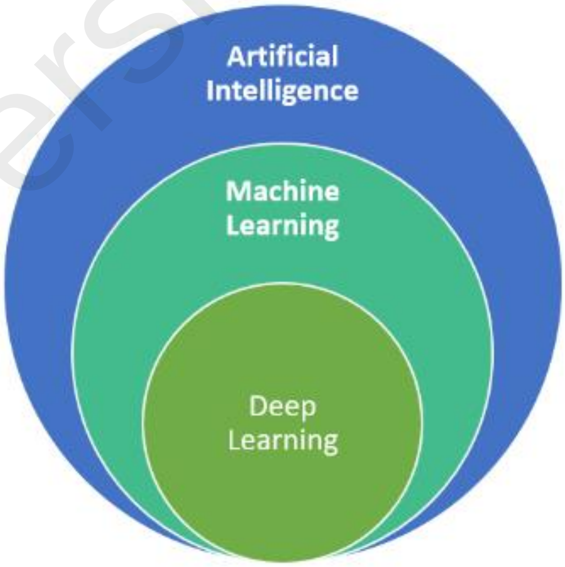

Figure 0.13:Artificial Intelligence, Machine Learning and Deep Learning Relationship

Adapted from (Berchane, 2018)

Universiti Malaya

According to Nvidia, artificial intelligence is the computer program capacity to learn, adapt and develop a necessary action automatically (Nvdia, 2021). The relationship between artificial intelligence, machine learning and deep learning can illustrate as in Figure 2.14.

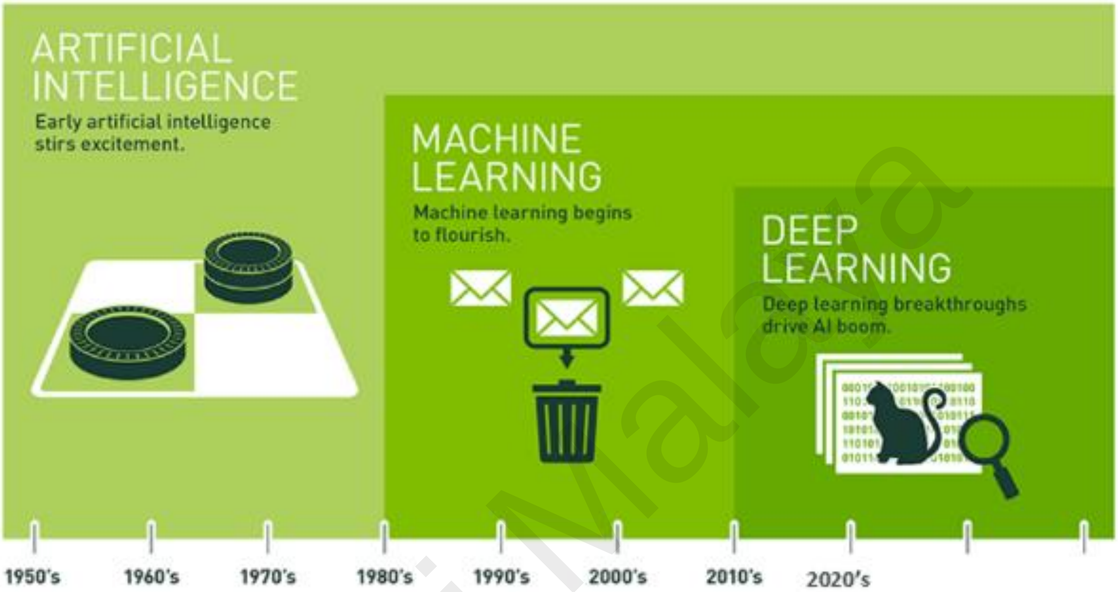

Figure 0.14: Artificial Intelligence, Machine Learning and Deep Learning Relationship

Adapted from (Nvdia, 2021)

Moreover, Artificial intelligence has a good potential to growth and implement in variety of current industry especially the approaching of industry 4.0. It has the capability to make engineering system become more efficient, flexible, and more reliable. Based Y.P. Tsang and C.K.M. Lee in their research, AI technology has the capacity and potential to be implement in industrial design especially with the approaching of industry 4.0. The AI technology can support and assist in technical decision making, provide the improvement in the engineering system and can optimize the function (Tsang & Lee, 2022).

Universiti Malaya

Furthermore, AI technology can become a vital part in application at various sector in industry. AI can be applied to develop a sophisticated system that can support human intelligence and skill. Based on research conducted by K.K. Ramachandran et al., AI has the capability to break the dependency on human skill, decreased the labor cost and increased work efficiency. They also stated that the industry can improve their performance by exploiting the use of massive data in machine learning and AI (Ramachandran, et al., 2022).

2.8 Machine Learning

According to ISO/IEC DIS 22989, Machine learning is defined as a process of optimization the model of computer system through computational techniques that have the capacity to learn and adapt reflected to the model algorithm and statistical models (International Standard ISO/IEC DIS 22989, 2021). On the other hand, ISO/IEC 2382-31 stated that machine learning is the process by which a functional unit improves its performance by acquiring new knowledge or skills, or by reorganizing existing knowledge or skills (International Standard ISO/IEC 2382-31, 1997).

In maintenance management, machine learning could support the management by predict the failure and provide the recommendation for rectification action. The high accuracy in machine learning in identify the root cause of failure could increase the reliability of the machine thus reduce maintenance cost. Based on the research done by Alexandre S.Roque at el., machine learning could provide 90% of accuracy, correctness and precision on decision making for maintenance. However, they emphasized the needs of carefully the way and verification to obtaining the dataset due to the needs to obtain the sufficient historical data for training and testing (S.Roque, W.Krebs, Figueiro, & Jazdi, 2022).

Universiti Malaya

Furthermore, machine learning has the capacity to produce a reliable forecast based on the history data that could improve the performance of the asset in the future. In addition to this, history data should be kept in database for long period of time in order to train the machine learning. Based on Syed Muhammad Tayyaba et al. research, machine learning could forecast the anomalies and failure by analyze the component degradation thus maintenance can carry out timely with systematic schedule (Tayyaba, Asghar, Pennacchi, & Chattertond, 2020).

On the other hand, Mohsen Nikfar et al. in their study on machine learning at low voltage industries motor has showed the strong performance from machine learning in detecting the faulty conditions that could assisted the management in detecting abnormal behavior on time. The installation of automatic system based on machine learning could prevent the accidents and stop the system before failure occurs. In addition to this, they also stated that the biggest challenge on their research was the lack of the data that representing each type of failure (Nikfar, Bitencourt, & Mykoniatis, 2022).

Currently, machine learning technology has widely used in many industries. Bosubabu Sambana et al. in their research has shown that the implementation of machine learning technology in wind turbine has improve in detection the vibration faults. They stated that by using anomaly detection produce more accurate in detection the fault (Sambana, P., Jarabala, & V.N.S.L, 2021). Furthermore, based B. Cui et al. in their research has utilized the machine learning to perform fault diagnostic in wind turbine. Their experiment has successfully demonstrated that machine learning can effectively extract the features from nonstationary signals and achieving good result in the fault diagnosis of wind turbine bearings (Cui, Weng, & Zhang, 2022).

In general, machine learning techniques consist of two types of categories. The first category is machine learning based on unsupervised learning. This type of machine

Universiti Malaya

learning is based on task driven where group and interpret data based only on input data. Under this category, machine learning system will be learn based on pattern of untagged data algorithm. The second category is supervised learning. This category of machine learning is based on the data driven where predictive model is develop based on the input and output data.

In machine learning, the data that being used as input will play a big role to produce accurate result. The accuracy of the data will depend on the amount of data and the applicability of the data for the good result. In general, machine learning models rely on four primary data types such as Categorical data, Numerical data, Time series data and Text data. In develop the machine learning model, the data should carefully validate to obtaining the dataset due to the needs to obtain the sufficient historical data for training and (S.Roque, W.Krebs, Figueiro, & Jazdi, 2022).

2.9 Deep Learning

Deep learning is part or subset to machine learning application. The concept of deep learning is to emulates the way human gain the information with the consideration of multiple levels of parameter and condition. In addition to this, deep learning facilitates the multiple processing of layer in computer system programming to process multiple layers of decision condition (LeCun, Bengio, & Hinton, 2015).

Universiti Malaya

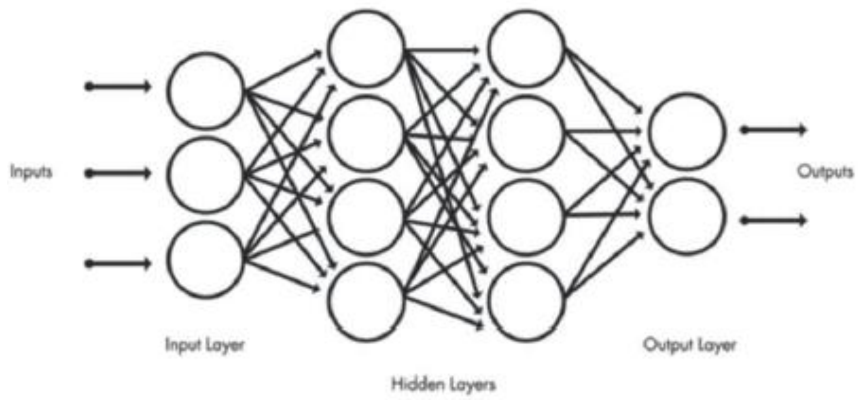

Figure 0.15: Concept of Deep Learning

Adapt from (Kongari, 2017)

Furthermore, deep learning is developed by a variety of architectures that can expand to provide the solution for a range of problem areas. The difference between deep learning and machine learning is deep learning is part of machine learning skill with the ability to provide the system that can imitate the human intelligence skill by processing the data. On the hand, machine learning is use data analysis to programs the analytical model (Khan, Hossain, Mozumdar, Akter, & Ashique, 2022).

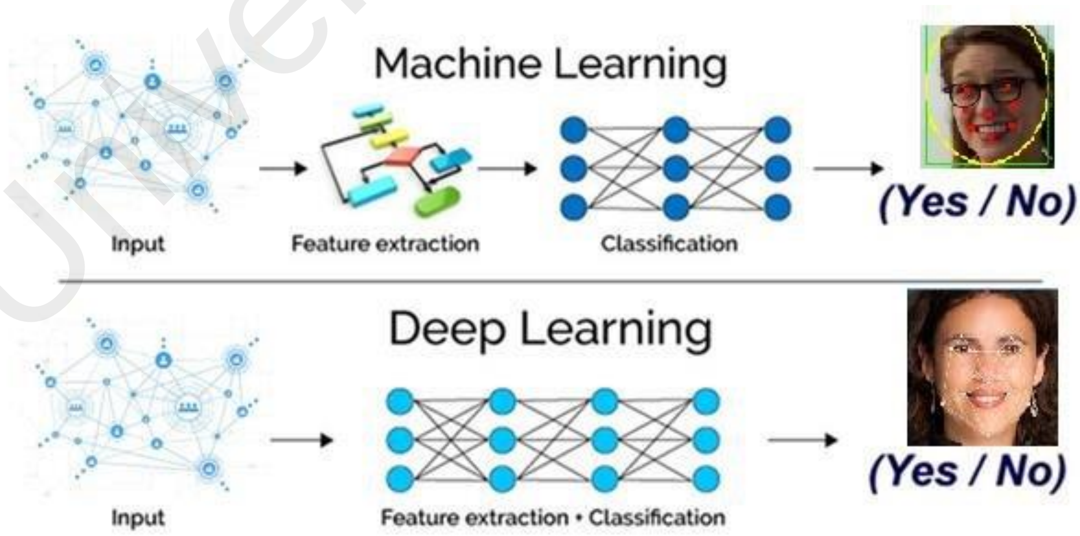

Figure 0.16: Difference between Machine Learning and Deep Learning

Adapted from (Ansaf, Najm, Atiyah, & Hassen, 2019)

Universiti Malaya

On the other hand, deep learning has been extensively used in industry for many applications. It can be used to support in decision making on engineering problem based on historical data and multiple layers of parameter. Fangyu Liu at al. in their research has develop a deep learning model to classify asphalt pavement crack severity. The result from this study shows that CNN model has the capability to get high deep learning accuracy based on fusion image and visible image for transfer learning (Liu, Liu, & Wang, 2022).

Furthermore, the application of deep learning also used as a safety system in construction industry. In this industry, precaution in safety is always become a vital element that need to consider in every construction work. Site safety is importance to protect the worker and public from any hazard accident. It also importance to ensure the project can running smoothly and complete on time. Based on Jiajing Liu et al. in their research has develop the deep learning system for construction safety. They emphasize that to focus on multi-layer of data and extracting the knowledge in order to make a decision for safety (Liu, Luo, & Liu, 2022).

Moreover, deep learning application also has potential and capability to apply in healthcare sector. It can be used to identify and detecting a pattern and algorithm for several disease condition. In addition to this, deep learning also has the potential to provide an assist and support in analyzing the disease data with exceptional speed without compromising the accuracy. Based on Harish Kongari, the application of deep learning in healthcare sector could provide the healthcare access to individual in rural and urban area at lower cost and emergency situations. It can assist and support in making a crucial decision by providing the immediate preventions recommendation for disease or accident (Kongari, 2017).

Universiti Malaya

2.10 Convolutional Neural Network (CNN)

Convolutional Neural Network is one of artificial neural network methods in deep learning methodology. Its use deep learning architectural to analyze and identify the input in image or object recognition and make a classification to produce the desire output. It designs and develops based on architectural that consist of multiple layer such as pooling layer, convolutional layer, and hidden layer as shown in the Figure 2.17 (Gaba, et al., 2022).

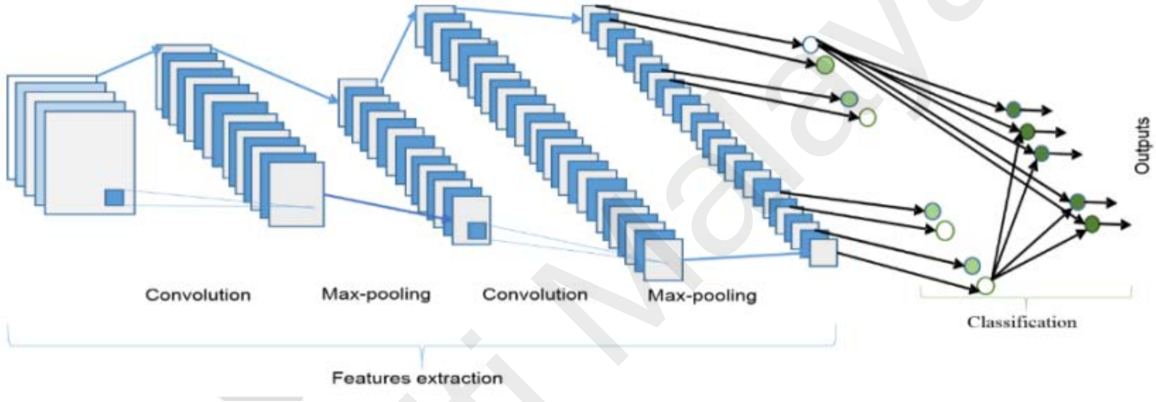

Figure 0.17: Architecture of Convolutional Neural Network

Adapted from (Gaba, et al., 2022)

Furthermore, CNN generally use to processing the image and grid-like topology. It used to make a classification and categorization based on the object characteristic and performances in the image. The basic architectural of CNN consist of 2 stage which are extraction stage and classification stage. Extraction stage applied to extract the data from the source and input signal while classification stage is the phase with the objective to connect all the layer in CNN in order to train the model and making a future prediction (Yeh & Chen, 2018).

Universiti Malaya

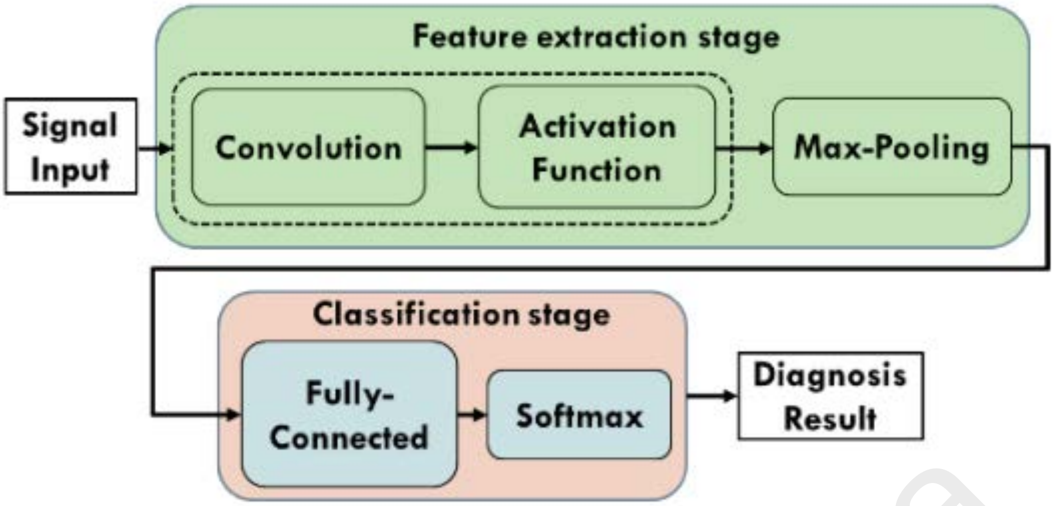

Figure 0.18: CNN basic Structure

Adopted from (Yeh & Chen, 2018)

Currently, Convolutional Neural Network has been used frequently in medical sector due to its ability and capability to perform effectively in handling and processing the medical imaging. According to Selene at al. in their research, CNN application in medical sector could provide a significant influence in diagnostic the lung cancer by offering an accurate diagnostic and provide a recommendation in a short time. They also stated that the CNN application required a large amount of labeled data in order to produce and generate an effective analysis (Tomassini, Falcionelli, Sernani, Burattini, & Dragoni, 2022).

Furthermore, CNN also have been widely used in engineering application in detection the machinery problem. Yongjian Sun & Shaohui Li has conducted a study relating with bearing faults analysis using an optimal convolution neural network. Based on their study, their CNN model successfully to produce average accuracy of 98.8%. Their calculation has shown that CNN model with three convolutional layers will produce the best result in identifying bearing faults (Sun & Li, 2022).

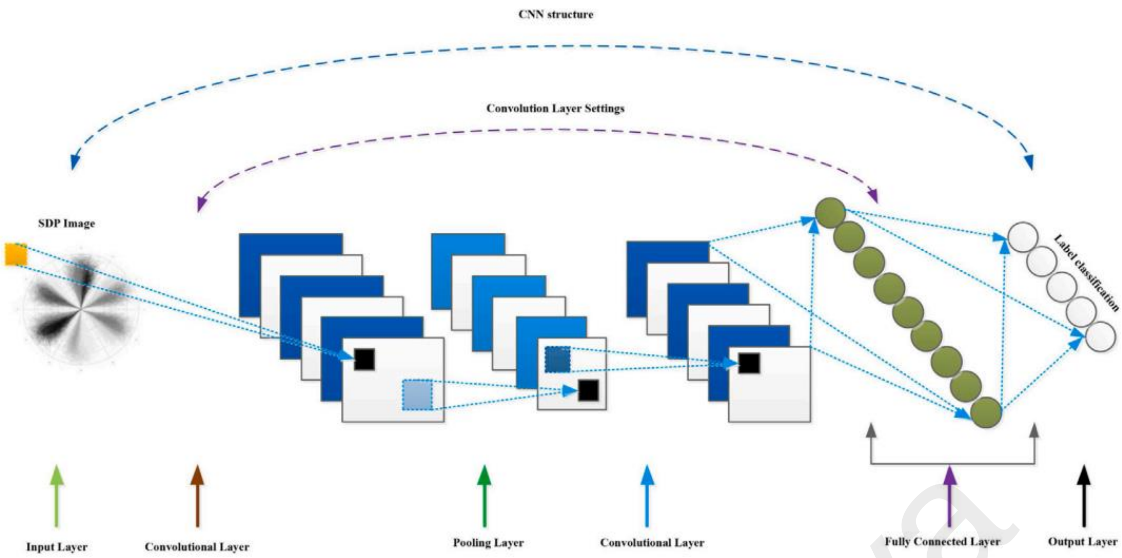

Figure 0.19: CNN model in Determine Bearing Faults

Adapted from (Sun & Li, 2022)

Currently, CNN application has expanded and widely used in vibration analysis application. CNN has the capacity to effectively produce a classification by detecting the vibration faults. Chiao Wei Yeh and Rongshun Chen has conducted research of using CNN in identifying the vibration fault. In their research, the input CNN model is develop based on time domain of bearing fault signals. They successfully to develop the model based on CNN algorithm with accuracy can reach above 96% and diagnosis time in 0.42 seconds (Yeh & Chen, 2018).

Furthermore, Han-Yun Chen and Ching-Hung Lee has conducted research to analyze a deep learning approach in vibration signal application. In the beginning, they stated that there are three basics of operation in CNN which are convolutional layers, pooling layers, and fully connected layers. Convolutional layers and pooling layers are applied for automatic feature while fully connected layers are act as classification. Then at the end of the research, they successfully to develop the CNN model with 100% accuracy in detecting the vibration faults (Chen & Lee, 2021).

Universiti Malaya

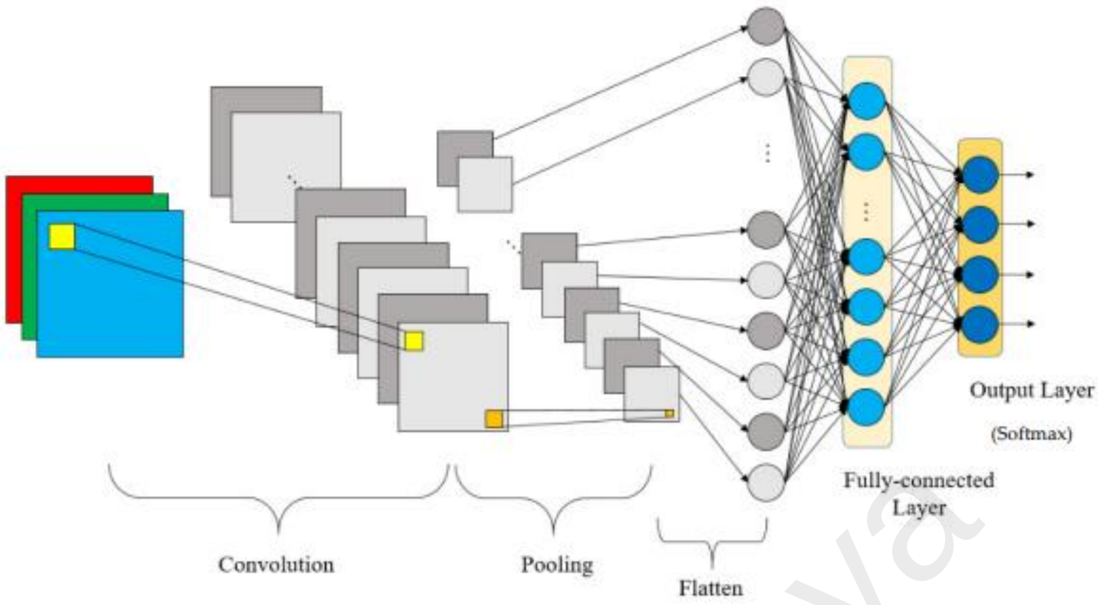

Figure 0.20: CNN Structure

Adapted from (Chen & Lee, 2021)

2.11 Summary

In summary, the increasing demand of high-level asset reliability in modern era has accelerated the growth of machinery fault diagnosis assessment as the solution for longer life-span and higher cost-efficiency machine in industry. The type of maintenance strategy such as reactive maintenance, preventive maintenance and Condition-Based Maintenance are reviewed. It is concluded that the vibration condition-based maintenance is a best option with the advantages of continuous examination of the machine's condition and high accuracy in identification of machinery defects.

As discussed, in conventional way, the accuracy of machinery faults is strongly relied on trained and experienced personnel analysis to make fault identification based on the data and signal pattern. However, the misinterpretation of the vibration faults will lead to the improper maintenance activities and subsequently increase the maintenance cost. Furthermore, to perform the analysis and diagnosis the complex vibration fault with complicated engineering system will required some additional time to ensure the correct interpretation of vibration faults and appropriate rectification work. This will cause further additional maintenance cost due to the assets unable operate and produce the desired output.

Therefore, the introduction of deep learning technology in rotating machinery fault diagnostic could reduce the reliance to the human skill and experience in interpreted the vibration fault. Deep learning technology offered an improvement in diagnostic of the rotating machinery fault by simplify the process and further enhance the accuracy of fault diagnosis of rotating machines. This technology also can use at wide range of applications in the engineering system especially when approaching industry 4.0 where a lot of rotating equipment designed with complex engineering structure.

Universiti Malaya

METHODOLOGY

This section discussed the methodology to develop an advanced machinery vibration assessment using machine learning program that can effectively diagnose vibration faults in rotating equipment.

3.1 Overview Flowchart

In overall, the methodology of this study can be illustrated as in the Figure 3.1. Based on the figure, the study begins with a discussion involving with a technique used to accomplish the first objective where the sensitive feature of raw vibration sensor data in time series is discussed. To achieve that, the method used for acquisition and extraction the data from the rotating equipment is explained appropriately. Then the data need to process and prepare to remove irrelevant data and to ensuring data is correct, consistent, and usable is also being discuss in this chapter. Next, the discussion continues with the method to achieve the second objective where machinery fault classification model is develop using deep learning algorithm based on time series data. The deep learning model in this study is develop using python program that applied as a tool for design the coding and coordinated the system algorithm. Then, the code editor platform is described specifically as part as an important element in the programming. After that, several libraries in python programming that used in this study is discussed and explained about the function and advantage of these library. Then, the deep learning method that applied is this system is also being describe intensely to show the advantage and the suitability of this method with the system that will develop. Lastly, the discussion continues with the method to accomplish the third objective which is to validate machinery fault classification model in identifying difference machinery fault. To achieve this, the method and the number of training data and validation data applied is this study is explained appropriately in order to get system with a better performance and accuracy.

Universiti Malaya

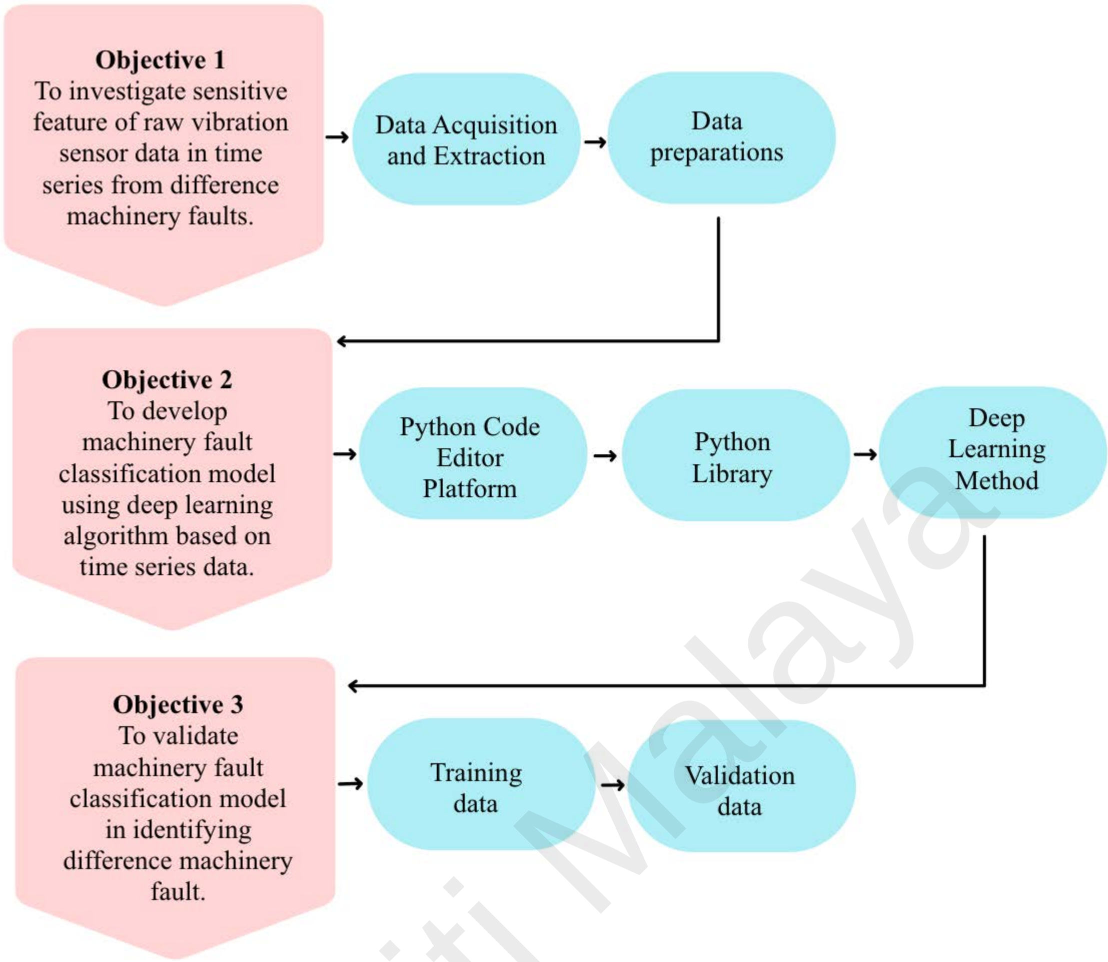

Figure 0.1: Overview Flowchart

3.2 Investigating the sensitive feature of raw vibration sensor data in time series from difference machinery faults.

As mentioned in the chapter 1, the first objective of this study is to investigate sensitive feature of raw vibration sensor data in time series from difference machinery faults. To accomplish this objective, the vibration data is extracted from the sensor that mounted at rotating equipment. Then, the data is processed to eliminated undesired and irrelevant data. Next, the data is readjusted and modified in order to increase the number of datasets.

Universiti Malaya

3.2.1 Data Acquisition and Extraction

In measuring the vibration, the data will be collected from transducers that mounted at the rotating equipment. This transducer needs to select correctly depending on the measurement unit in acceleration, velocity, and displacement. The environment and condition of the machine also need to take into consideration in determining a correct vibration transducer. Then, the transducer changes the vibration motion into electrical signal and stored the data in database for plotting, trending, and analysis. There is an option where data can be extracted to spreadsheet format for preprocessing data phase. The data will carefully be examined to eliminate the risk of unintended data being included in the results. In traditional method, these data value then presented in different form of formats and plot such as orbit, waterfall, cascade, time-based plot, shaft centerline etc. by using machinery diagnostic software.

However, in this study, the vibration data for training and testing machine learning model is taken from simulation that conduct in laboratory. The test was conducted using prefabricated laboratory rotor kit that have the capability including variable speed motor, two balancing discs, roller bearings and rubber type coupling. Then, the misalignment and unbalance were simulate using this setup and save the recording data in spreadsheet format.

Recently, vibration issue become a major concern as its encountered in industry in many engineering applications. In analyze the vibration, there a different type of vibration faults that can be identified based on faults signature. In this study, 4 type of vibration faults is selected as this is common issue in rotating equipment. The first type of vibration faults is unbalance. According to ISO 1925, unbalance is the condition of the rotor when vibration force and motion applied to the bearing as a result of centrifugal forces. Table 3.1 and 3.2 shows a dataset used as training and testing machine learning model.

Universiti Malaya

Table 0.1: Vibration data for Dynamic Imbalance

Vibration faults	Filename	Measurement location
Dynamic Imbalance	IMB_DY_PT1	NDE motor
	IMB_DY_PT2	DE motor
	IMB_DY_PT3	DE bearing
	IMB_DY_PT4	NDE bearing
	Set 3 IMB_DY_PT1	NDE motor
	Set 3 IMB_DY_PT2	DE motor
	Set 3 IMB_DY_PT3	DE bearing
	Set 3 IMB_DY_PT4	NDE bearing
	Set 4 IMB_DY_PT1	NDE motor
	Set 4 IMB_DY_PT2	DE motor
	Set 4 IMB_DY_PT3	DE bearing
	Set 4 IMB_DY_PT4	NDE bearing

Table 0.2: Vibration data for Static Imbalance

Vibration faults	Filename	Measurement location
Static Imbalance	IMB_ST_PT1	NDE motor
	IMB_ST_PT2	DE motor
	IMB_ST_PT3	DE bearing
	IMB_ST_PT4	NDE bearing
	Set 1 IMB_ST_PT1	NDE motor
	Set 1 IMB_ST_PT2	DE motor
	Set 1 IMB_ST_PT3	DE bearing
	Set 1 IMB_ST_PT4	NDE bearing
	Set 2 IMB_ST_PT1	NDE motor
	Set 2 IMB_ST_PT2	DE motor
	Set 2 IMB_ST_PT3	DE bearing
	Set 2 IMB_ST_PT4	NDE bearing

On the other hand, the second type of vibration faults is misalignment. Misalignment is occurred when the rotor rotational centerlines are not collinear when machine operating under normal condition. There are 2 types of misalignments which is Angular Misalignment and Parallel Misalignment. The vibration data that will use for training and test the machine learning model as shown in Table 3.3 and 3.4.

Universiti Malaya

Table 0.3: Vibration data for Angular Misalignment

Vibration faults	Filename	Measurement location
Angular Misalignment	MIS_AN_PT1	NDE motor
	MIS_AN_PT2	DE motor
	MIS_AN_PT3	DE bearing
	MIS_AN_PT4	NDE bearing
	Set 7 MIS_AN_PT1	NDE motor
	Set 7 MIS_AN_PT2	DE motor
	Set 7 MIS_AN_PT3	DE bearing
	Set 7 MIS_AN_PT4	NDE bearing
	Set 8 MIS_AN_PT1	NDE motor
	Set 8 MIS_AN_PT2	DE motor
	Set 8 MIS_AN_PT3	DE bearing
	Set 8 MIS_AN_PT4	NDE bearing

Table 0.4: Vibration data for Parallel Misalignment

Vibration faults	Filename	Measurement location
Parallel Misalignment	MIS_PA_PT1	NDE motor
	MIS_PA_PT2	DE motor
	MIS_PA_PT3	DE bearing
	MIS_PA_PT4	NDE bearing
	Set 5 MIS_PA_PT1	NDE motor
	Set 5 MIS_PA_PT2	DE motor
	Set 5 MIS_PA_PT3	DE bearing
	Set 5 MIS_PA_PT4	NDE bearing
	Set 6 MIS_PA_PT1	NDE motor
	Set 6 MIS_PA_PT2	DE motor
	Set 6 MIS_PA_PT3	DE bearing
	Set 6 MIS_PA_PT4	NDE bearing

Normally, two transducers are required for a single rotating equipment and need to mount consistently in order to capture the vibration trend. In addition to this, the vibration data needs to record using same method consistently at same location and same operating condition to ensure the repeatability and get accurate vibration response.

Universiti Malaya

In this study, the vibration data are recorded using a single-axis accelerometer and a triaxial accelerometer. The single-axis accelerometer used as a reference input signal while triaxial accelerometer used to capture three orthogonal directions. Then, the signal is transferred to the laptop through National Instruments signal conditioner and Ni-DAQ is used as the acquisition of vibration data. Specification for both single-axis accelerometer and a triaxial accelerometer as shown in Table 3.5 and 3.6.

Table 0.5: Single-Axis Accelerometer Specification

Parameter	Value
Model	786C, General purpose accelerometer
Brand	Wilcoxon
Sensitivity	100 mV/g
Sensitivity tolerance	±5 %
Frequency range	0.5 Hz - 14,000 Hz
Mounting Thread	1/4-28 UNF tapped hole
Temperature range	-50°C to +120°C

Table 0.6:Triaxial Accelerometer Specification

Parameter	Value
Model	604B31
Brand	PCB Piezotronics
Sensitivity	100 mV/g
Sensitivity tolerance	±20%
Frequency range	0.5 to 5000 Hz
Mounting Thread	1/4-28 Male
Temperature range	-54°C to +121°C

In traditional way, vibration measurement needs to take at three orthogonal directions separately. However, this will lead consuming more time hence increase the maintenance cost. On the other hand, triaxial accelerometer has the capability to capture the vibration measurement at three orthogonal directions simultaneous by mount the transducer at 1 location. This make triaxial accelerometer convenience to use, cost savings, and can improved tangential sensitivity.

Universiti Malaya

In measuring the vibration, the capacity of data need to adequate in order to detect changes in machine conditions and to identify specific machine faults. However, collect too much data will increase the cost and consume much time to collect while collect less data make lacking information to act on vibration issue. The data need to collect repeatable data for better trending and to ensure a good quality data. In this study, the vibration data consist of three orthogonal directions which are vertical, horizontal, and axial direction in order to record the vibration movement. This is following the recommendation by ISO 10816 for vibration measurement as shown in the Figure 3.2.

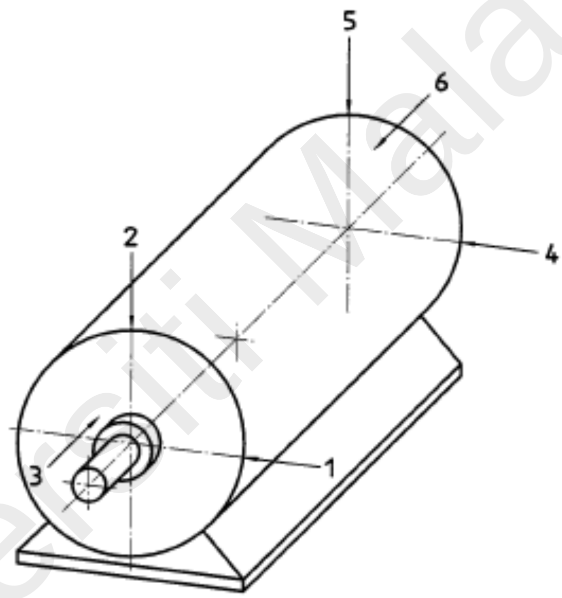

Figure 0.2: Vibration Measuring Point

Adapted from ISO 10816 (1995)

Based on the Figure 3.2, position 1 and position 4 indicate a vibration point at horizontal directions and position 2 and position 5 indicate vibration point at vertical directions. While position 3 and position 6 indicate vibration point at axial directions. In this study, the three orthogonal directions were writing in the spreadsheet as in the Table 3.7.

Universiti Malaya

Table 0.7: Orthogonal Directions

Reference point	Write 0 [g]
Axial direction	Write 1 [g]
Horizontal direction	Write 2 [g]
Vertical direction	Write 3 [g]

On the other hand, each series of data consist of four measurement point located at different locations as shown in the Figure 3.3. Two of the measurement points are allocated at the drive end and non-drive end of the motor while another 2 points are set at the roller bearing. Then, the simulation is conduct by adjusting the coupling position in order to generate misalignment. While for unbalance simulation, the additional weight is added at balancing disc to generate unbalance condition. The illustration simulation arrangement is illustrated at Figure 3.4, 3.5, 3.6 and 3.7.

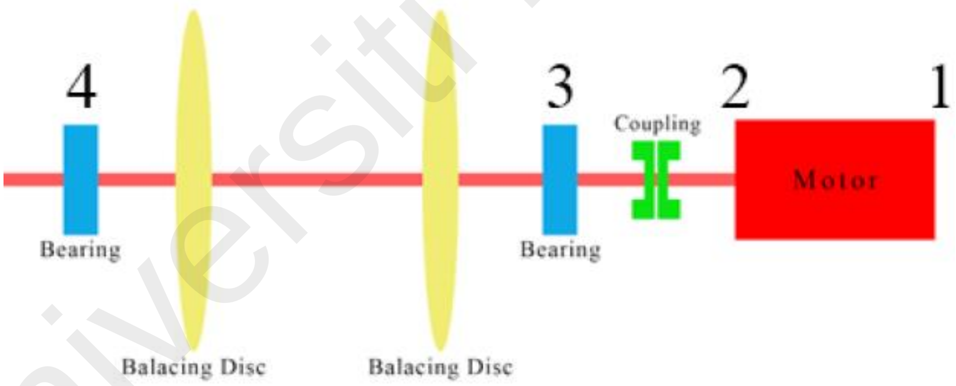

Figure 0.3: Illustration for Laboratory Setup

Adapted from (Quan, 2021)

Parallel Misalignment is occurred when shaft centerlines are parallel between shafts but not coincident. This kind of vibration fault can generate shear force and bending moment on the coupled end of each shaft. The shaft position is 180° degrees out of phase across the coupling in the radial and axial directions. The arrangement of the simulation illustrated as Figure 3.4.

Universiti Malaya

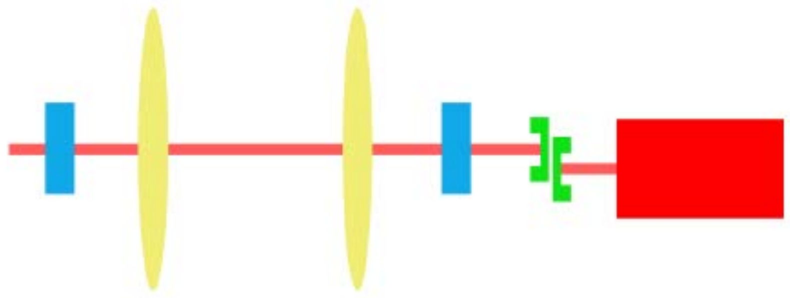

Figure 0.4: Illustration of Parallel Misalignment

Adapted from (Quan, 2021)

On the other hand, Angular Misalignment occur when shaft meet at a point between shaft but are not parallel. This kind of vibration fault generate a bending moment at each shaft. The shaft position is 180° degrees out of phase across the coupling in the axial direction and in-phase in radial direction. The arrangement of the simulation illustrated as Figure 3.5.

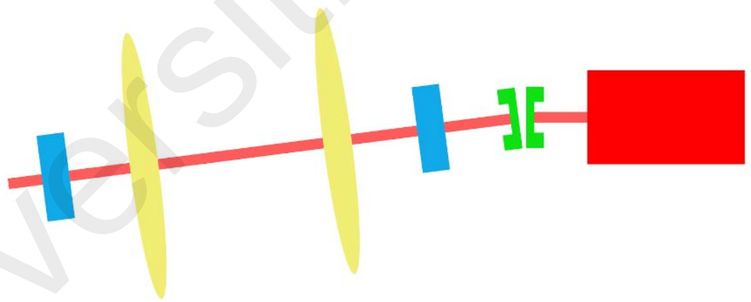

Figure 0.5: Illustration of Angular Misalignment

Adapted from (Quan, 2021)

Static Imbalance occur when there are heavy spot at a single point in the rotor. This kind of vibration fault will show up even the shaft not running. Static Imbalance generate sinusoidal time waveform with frequency of running speed. The arrangement of the simulation illustrated as Figure 3.6.

Universiti Malaya

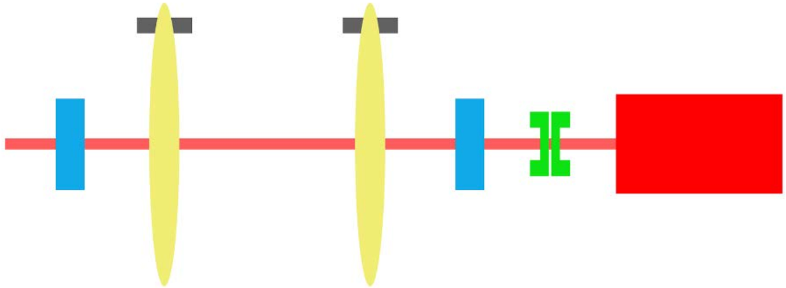

Figure 0.6: Illustration of Static Imbalance

Adapted from (Quan, 2021)

Similar to the Static Imbalance, Dynamics Imbalance occur when there are heavy spot along the shaft. The imbalance happens when the shaft geometric centerline and mass centerline does not coincide each other. However, Dynamics Imbalance is combination of couple imbalance and static imbalance. The arrangement of the simulation illustrated as Figure 3.7.

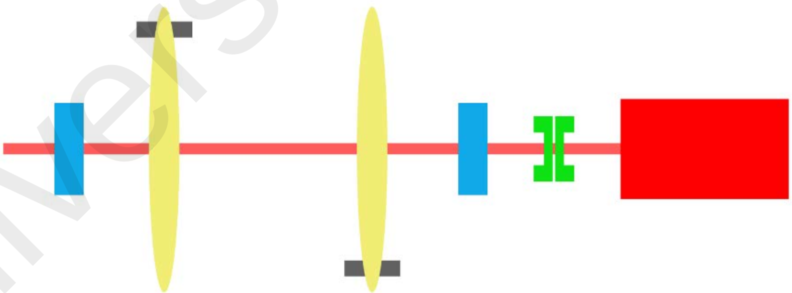

Figure 0.7: Illustration of Dynamics Imbalance

Adapted from (Quan, 2021)

Normally, vibration fault can be analysis at difference type of machine operating condition such as steady state operation, transient operating, or slow roll condition. Steady state operation is the condition where machine operate at constant speed but change in load based on the demand. In traditional way, vibration under this condition can be

Universiti Malaya

analysis based on time-based plot, waterfall plot and spectrum plot. Then, for transient operating condition is the data that collected during machine start-up and shutdown. For this condition, shaft-centerline, cascade plot, polar plot, bode plot are suitable to use. Meanwhile, Slow roll condition is which machine operate at very low speed with no dynamic forces also can be analyze. Analysis at this condition is essential to identify the precision the vibration measurement. Plot that will use for analysis at this condition is shaft-centerline, cascade plot, polar plot, bode plot. In this study, the vibration fault is collected in the condition where machine operate at constant speed and using time-based plot

3.2.2 Data preparations

The acquired raw data then proceed with the process to clean up the data by detecting and identify an unusable data, make a correction and modification, and remove an irrelevant part of the data. This is essential component in deep learning in order to get a quality data, increase the overall model accuracy and allow higher correctness in detecting the vibration faults. In this study, time-based series data is used to analyze the vibration faults. Time-based data offer and provide additional insight in detecting vibration faults and can be used to enhancing the vibration analysis.

Then, the acquired raw data is readjust and modified to ensure adequate of dataset for training and testing deep learning model. This is crucial part in deep learning because without enough dataset, the model is train and test prematurely that can subsequently produce the bad performance and affecting the accuracy in determine the vibration faults. Hence, in this study each of dataset is to readjust so that each dataset will represent two datasets since the time-based series have steady trend and the level of amplitude for each fault are consistent along the time.

Universiti Malaya

In the simulation lab, the vibration faults are simulated up until 17 second for each type of vibration faults. Time-based waveform has shown that there are 21 cycles with period of 0.82 second for each cycle in total 17 second as shown in Figure 3.8. Hence, the first 10 cycle which is equivalent to 8.2 second is represent the first part of dataset and the next 10 cycle represent the second part of the dataset. To ensure each dataset is uniform, the last cycle of the waveform is eliminated.

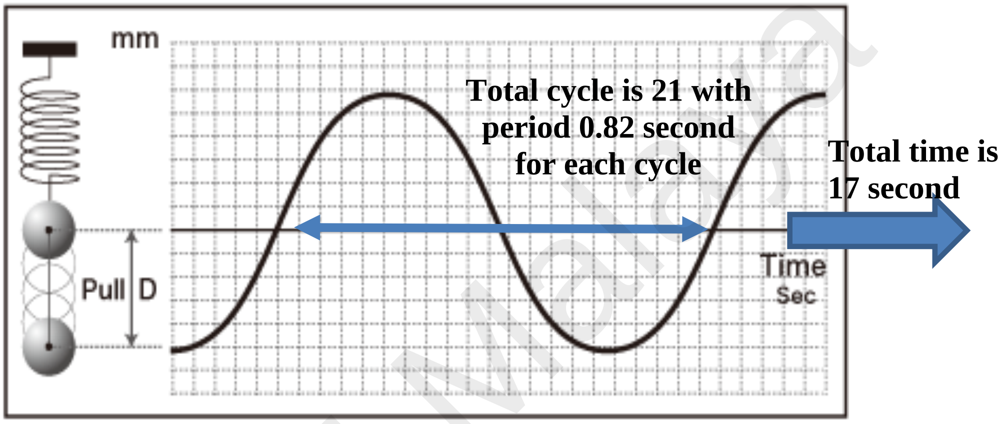

Figure 0.8: Graphical Explanation of time-base waveform

3.3 Developing machinery fault classification model using deep learning algorithm based on time series data.

The second objective of this study is to develop machinery fault classification model using deep learning algorithm based on time series data. In this study, the advance machinery diagnostic is developed by using python program with capacity to work as deep learning sophisticated tools. Nowadays, python become one of most popular computer languages and grow rapidly in the world. Python is a computer programming language that used to develop variety of difference kind of program with capability to control, manage, testing, and in many other ways. Furthermore, python is a powerful tool, flexible and very easy to use and consumed less computer memory. Its free and open-source package which make it available to access and learn to anyone.

Universiti Malaya

3.3.1 Python Code Editor Platform

Python code editor is application of software that is designed specifically to assist the developer to develop the python model, manage the coding and debug the program language. It offers a convenient platform to developer to open multiple and variety coding files, improve the speed of coding, develop code more efficiently and can manage a large codebase. The source of this software can be either from individual program or part of an integrated development environment (IDE). In python, several code editors are applicable to use to develop python model such as:

i. Jupyter Notebook
ii. Visual Studio Code
iii. Sublime Text
iv. Atom
v. Vim
vi. PyCharm

In this study, Jupyter Notebook will be use as code editor for developing the python model. Jupyter Notebook is a modern and powerful web application from open-source software that develop to support the data science and scientific computing through all programming languages. It offers a simple and convenient platform for developer to design and create a coding model in python. On the hand, the installation of Jupyter Notebook is available to install through the Python Package Index by using PIP coding as shown in the Figure 3.9.

Shell

```
$ pip install jupyter
```

Figure 0.9: Jupyter Notebook Installation Code

Universiti Malaya

Jupyter Notebook is modern program and latest web-based software that develop with the sophisticated and advance features, environment interactive and flexible interface capability. It allows a developer and programmer to arrange and organize the workflow appropriately with the flexibility to develop, design and configure in developing the advance program. Figure 3.10 is an example of Jupyter notebook interface with variety tools programming.

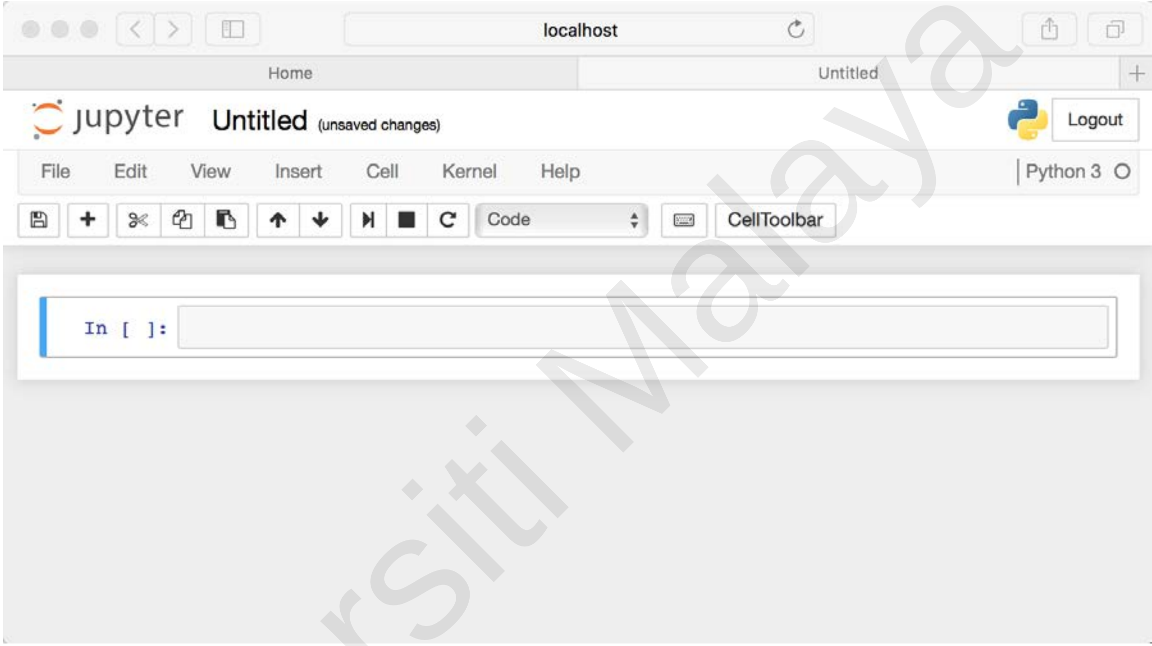

Figure 0.10: Jupyter Notebook Interface

3.3.2 Python Library

Besides that, python come with vast libraries support that consist of a collection of related programs. It contains package of coding code that can be used repeatedly in different kind of programs. This eventually makes python programming become simpler to design, convenient to use and easy to understand for the programmer. In this study, several libraries have been used in order to develop deep learning program for vibration assessment.

Universiti Malaya

The first library that use in this study is Pandas library. It is a library tools that written using python programming language. It's used for data manipulation and analysis and offers data structures and operations for manipulating numerical tables. Furthermore, pandas have capacity to provide excellent data presentations and capability handle a large data efficiently.

On the other hand, Scikit-learn library is a platform that used to develop the machine learning and deep learning based on processing the data from Pandas and provide the statistical modelling. It can use to apply variety machine learning model for classification, clustering, and regression. Scikit-learn offer a concise and reliable result with simplicity on complex algorithms and versatile workflows that stand behind the machine learning.

Tensor flow is a library in python that primarily used for deep learning applications. It has the capability to enabled to build a design much complex applications with great accuracy. It allows multi-layer neural network that can contains more than one layer of network thus can produce much accurate result for complex applications.

The next library that used in this study is Numpy library. In general, number library offers the python model to work with mathematical function and multidimensional array object such as linear algebra, Fourier transform, and matrices. Furthermore, it has the capability to perform a high-level functioning tools and work with various type of math operations.

The installation of all the library that involved in study are install through the Python Package Index by using PIP coding. Python Package Index is the repository software and consist of a variety of library program in Python. It uses for many developers and data scientist in order to make simpler in coding and easy to understand.

Universiti Malaya

3.3.3 Deep Learning Method

Nowadays, deep learning has gained a popularity in developing the algorithm and model based on machine learning due to its capability to work with high level of performance through a massive amount of input data. In addition, deep learning is subset to machine learning technique that representing the learning of the program system similar like human intelligent ability and skill. In this study, the method in deep learning that will be use in developing the advance machinery system is Convolutional Neural Network (CNN).

Convolutional Neural Network is a method and technique in deep learning that design in particularly to analysis and processing structured arrays of data. It has the capacity to work with input image that have binary representation of visual such as circles, lines, gradients and even faces. It also consists multiple of layer that has the difference parameter and work differently based on the input data.

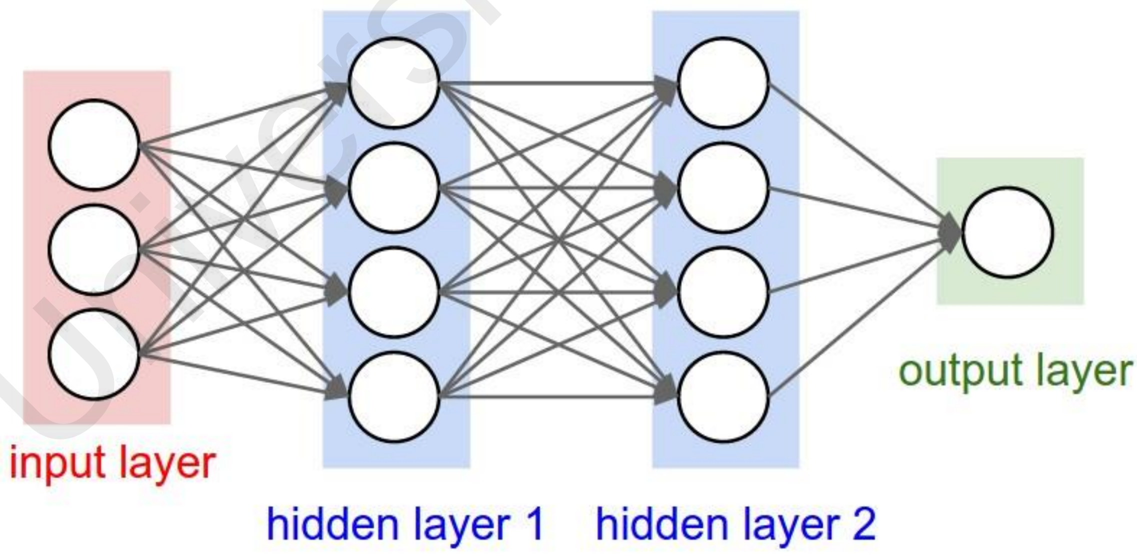

Figure 0.11: Multiple Layer in Deep Learning

Universiti Malaya

In this study, the model is developed based on 1D Convolutional Neural Network and its details are furnished by Keras library. This method offers and provide a very simple in structure, easy to understand, flexible and computationally cheap. Furthermore, it consists of compact architecture configuration rather than complex deep architectures like other type of Convolutional Neural Network. It also suitable to applied to real-time fault detection and monitoring due to it only involve with 1D convolutions. In addition to this, this method suitable to use as sequence classification as it can learn from the raw time series data directly and in turn do not require domain expertise to manually engineer input features. The model can learn an internal representation of the time series data and ideally achieve comparable performance to models fit on a version of the dataset with engineered features. Moreover, the cost involved for implementation of hardware is cheaper due to its simple and compact configuration.

In general, 1D Convolutional Neural Network used primarily on 1D signals such as audio and text. Due to this, it's widely and commonly use on time-series data with the objective to perform a recognition and classification task. The model will be train and learns an internal representation of the data or object in one-dimensional input and process as feature learning. The model then to learns to obtain a variety of component and parameter from sequences of interpretations and develop a mapping with different activity types.

On the other hand, 1D Convolutional Neural Network will be applied together with Keras Library in Python. Keras is a free open-source Python library that simple and powerful in developing and evaluating the deep learning models. It covers the efficient numerical computation libraries Theano and TensorFlow and allows to define and train neural network models in just a few lines of code.

Universiti Malaya

3.4 Validation of Machinery fault classification model

The third objective of this study is to validate machinery fault classification model in identifying difference machinery fault. To accomplish this, the data need to split into two subsets which are training and test data. The objective of this dataset is determined and measured the performance and the accuracy of the model. The measurement of accuracy in python is essential in order determine the correctness and precision of the model in identify the vibration faults and to provide the more accurate recommendation of the rectification work. In this study, a variety sets of training and validation dataset was applied in order to determine and verify the effect of the input to the model algorithm performance and accuracy.

3.4.1 Training Data

The first portion of dataset were used as a training data. Training data is the segment of the actual data that use to applied in python model in order to determine the pattern of the vibration faults. Generally, the training dataset involved with the huge amount of dataset that subsequently vital in appropriately train and prepare the model design. Its essential element in every model of machine learning and deep learning to provide the accurate prediction and perform any required and desired task. If the inaccurate dataset is uses in training, it would badly affect the model accuracy and subsequently become a major reason the failure of machine learning and deep learning model. Therefore, in order establish and determine the pattern of vibration fault in time series data, 20 datasets with 5 datasets for each vibration faults are used for training the model. The training dataset is as listed in the Table 3.8, 3.9, 3.10 and 3.11.

Universiti Malaya

Table 0.8: Dynamic Imbalance Training Dataset

Vibration faults	Filename	Measurement location
Dynamic Imbalance	IMB_DY_PT1 (2)	NDE motor
	IMB_DY_PT2 (2)	DE motor
	IMB_DY_PT3 (2)	DE bearing
	IMB_DY_PT4 (2)	NDE bearing
	Set 3 IMB_DY_PT1 (1)	NDE motor
	Set 3 IMB_DY_PT1 (2)	NDE motor
	Set 3 IMB_DY_PT2 (1)	DE motor
	Set 3 IMB_DY_PT2 (2)	DE motor
	Set 3 IMB_DY_PT3 (1)	DE bearing
	Set 3 IMB_DY_PT3 (2)	DE bearing
	Set 3 IMB_DY_PT4 (1)	NDE bearing
	Set 3 IMB_DY_PT4 (2)	NDE bearing
	Set 4 IMB_DY_PT1 (1)	NDE motor
	Set 4 IMB_DY_PT1 (2)	NDE motor
	Set 4 IMB_DY_PT2 (1)	DE motor
	Set 4 IMB_DY_PT2 (2)	DE motor
	Set 4 IMB_DY_PT3 (1)	DE bearing
	Set 4 IMB_DY_PT3 (2)	DE bearing
	Set 4 IMB_DY_PT4 (1)	NDE bearing
	Set 4 IMB_DY_PT4 (2)	NDE bearing

Table 0.9: Static Imbalance Training Dataset

Vibration faults	Filename	Measurement location
Static Imbalance	IMB_ST_PT1 (2)	NDE motor
	IMB_ST_PT2 (2)	DE motor
	IMB_ST_PT3 (2)	DE bearing
	IMB_ST_PT4 (2)	NDE bearing
	Set 1 IMB_ST_PT1 (1)	NDE motor
	Set 1 IMB_ST_PT1 (2)	NDE motor
	Set 1 IMB_ST_PT2 (1)	DE motor
	Set 1 IMB_ST_PT2 (2)	DE motor
	Set 1 IMB_ST_PT3 (1)	DE bearing
	Set 1 IMB_ST_PT3 (2)	DE bearing
	Set 1 IMB_ST_PT4 (1)	NDE bearing
	Set 1 IMB_ST_PT4 (2)	NDE bearing
	Set 2 IMB_ST_PT1 (1)	NDE motor
	Set 2 IMB_ST_PT1 (2)	NDE motor
	Set 2 IMB_ST_PT2 (1)	DE motor
	Set 2 IMB_ST_PT2 (2)	DE motor
	Set 2 IMB_ST_PT3 (1)	DE bearing

Universiti Malaya

Table 3.9 Continued

	Set 2 IMB_ST_PT3 (2)	DE bearing
	Set 2 IMB_ST_PT4 (1)	NDE bearing
	Set 2 IMB_ST_PT4 (2)	NDE bearing

Table 0.10: Angular Misalignment Training Dataset

Vibration faults	Filename	Measurement location
Angular Misalignment	MIS_AN_PT1 (2)	NDE motor
	MIS_AN_PT2 (2)	DE motor
	MIS_AN_PT3 (2)	DE bearing
	MIS_AN_PT4 (2)	NDE bearing
	Set 7 MIS_AN_PT1 (1)	NDE motor
	Set 7 MIS_AN_PT1 (2)	NDE motor
	Set 7 MIS_AN_PT2 (1)	DE motor
	Set 7 MIS_AN_PT2 (2)	DE motor
	Set 7 MIS_AN_PT3 (1)	DE bearing
	Set 7 MIS_AN_PT3 (2)	DE bearing
	Set 7 MIS_AN_PT4 (1)	NDE bearing
	Set 7 MIS_AN_PT4 (2)	NDE bearing
	Set 8 MIS_AN_PT1 (1)	NDE motor
	Set 8 MIS_AN_PT1 (2)	NDE motor
	Set 8 MIS_AN_PT2 (1)	DE motor
	Set 8 MIS_AN_PT2 (2)	DE motor
	Set 8 MIS_AN_PT3 (1)	DE bearing
	Set 8 MIS_AN_PT3 (2)	DE bearing
	Set 8 MIS_AN_PT4 (1)	NDE bearing
	Set 8 MIS_AN_PT4 (2)	NDE bearing

Table 0.11: Parallel Misalignment Training Dataset

Vibration faults	Filename	Measurement location
Parallel Misalignment	MIS_PA_PT1 (2)	NDE motor
	MIS_PA_PT2 (2)	DE motor
	MIS_PA_PT3 (2)	DE bearing
	MIS_PA_PT4 (2)	NDE bearing
	Set 5 MIS_PA_PT1 (1)	NDE motor
	Set 5 MIS_PA_PT1 (2)	NDE motor
	Set 5 MIS_PA_PT2 (1)	DE motor

University Malaya

Table 3.11 Continued

	Set 5 MIS_PA_PT2 (2)	DE motor
	Set 5 MIS_PA_PT3 (1)	DE bearing
	Set 5 MIS_PA_PT3 (2)	DE bearing
	Set 5 MIS_PA_PT4 (1)	NDE bearing
	Set 5 MIS_PA_PT4 (2)	NDE bearing
	Set 6 MIS_PA_PT1 (1)	NDE motor
	Set 6 MIS_PA_PT1 (2)	NDE motor
	Set 6 MIS_PA_PT2 (1)	DE motor
	Set 6 MIS_PA_PT2 (2)	DE motor
	Set 6 MIS_PA_PT3 (1)	DE bearing
	Set 6 MIS_PA_PT3 (2)	DE bearing
	Set 6 MIS_PA_PT4 (1)	NDE bearing
	Set 6 MIS_PA_PT4 (2)	NDE bearing

As shown in Table 3.8, 3.9, 3.10 and 3.11., each dataset consists for 2 segment of the data that represent the first 10 cycle of time-waveform and the next 10 cycle of the time-waveform. This is to increase the number of datasets for training so the model can learn with variety type of trend and pattern for future prediction and detection in vibration faults.

3.4.2 Validation Data

The second portion of the data is use for validation the model. After effectively build and train the model, the validation is required to evaluate and validate the performance and accuracy of the algorithm and to optimize improving the result. During the stage where the model is train with the input data, the huge amount of data is involved. Hence, the validation part will give the opportunity to the improve the quality of data and model. In this study, to evaluate the performance of model, 4 set of data with 1 set data for each vibration fault is use. The dataset that uses and applied for validation is shown in Table 3.12.

Universiti Malaya

Table 0.12: Validation Data Set

Vibration faults	Filename	Measurement location
Dynamic Imbalance	IMB_DY_PT1 (1)	NDE motor
	IMB_DY_PT2 (1)	DE motor
	IMB_DY_PT3 (1)	DE bearing
	IMB_DY_PT4 (1)	NDE bearing
Static Imbalance	IMB_ST_PT1 (1)	NDE motor
	IMB_ST_PT2 (1)	DE motor
	IMB_ST_PT3 (1)	DE bearing
	IMB_ST_PT4 (1)	NDE bearing
Angular Misalignment	MIS_AN_PT1 (1)	NDE motor
	MIS_AN_PT2 (1)	DE motor
	MIS_AN_PT3 (1)	DE bearing
	MIS_AN_PT4 (1)	NDE bearing
Parallel Misalignment	MIS_PA_PT1 (1)	NDE motor
	MIS_PA_PT2 (1)	DE motor
	MIS_PA_PT3 (1)	DE bearing
	MIS_PA_PT4 (1)	NDE bearing

Universiti Malaya

RESULTS AND DISCUSSIONS

This chapter represent the outcome of the developing of machine learning for machinery diagnostic using python program language. In this section, the data acquisition and extraction including outcome from developing model program language were discussed. At the end of the section, the validation of the program was perform using several primary machinery faults and compare with variety type of quality data.

4.1 Raw vibration sensor data in time series from difference machinery faults.

All the recorded measured vibration data are saved appropriately in spreadsheet format and tag with the name of each vibration fault. The full path of spreadsheet file stored need to capture and carefully referred. The data then need to cleanup and adjusting to ensure the quality of data. In order to increase the number of data set, each file is represented as 2 set of data with same start point in time-based waveform at difference time. The first set is the first 10 cycle of waveform and second part is the next 10 cycle of waveform. Then spreadsheet file is load directly into python system by using Pandas library. Next, the spreadsheet file is converted into the data frame in python algorithm by using Pandas library. Data frame format in Python is 2-dimensional data structure that use for organizing the data into rows and columns as shown in the Figure 4.1.

	Measurement time[hh:mm:ss]	Write 0 [g]	Write 1 [V]	Write 2 [V]	Write 3 [V]	Fault	Point
0	1	-0.047676	0.005500	-0.005011	0.002934	Static Imbalance	Point 1
1	2	0.007571	0.006824	-0.003498	0.002574	Static Imbalance	Point 1
2	3	-0.051359	0.012677	0.002524	0.009712	Static Imbalance	Point 1
3	4	-0.073711	0.002766	-0.008909	-0.001599	Static Imbalance	Point 1
4	5	0.054630	0.012658	0.002585	0.008937	Static Imbalance	Point 1

Figure 0.1: Spreadsheet file convert to Data Frame

Universiti Malaya

Then the data represent in time-based waveform as shown in the Figure 4.2, 4.3, 4.4 and 4.5 to visualize the data points at intervals of time and to observe the pattern of raw vibration data from the sensor. Each point on the data corresponds to both a time and a quantity that is being measured. Time-based plot is useful to represent an actual information from the rotating equipment about the forces being generated. It tracks every moment of vibration force occur within the rotating equipment. Based on the figure, each vibration faults showing a difference vibration pattern that can be used in deep learning model in identifying the vibration faults.

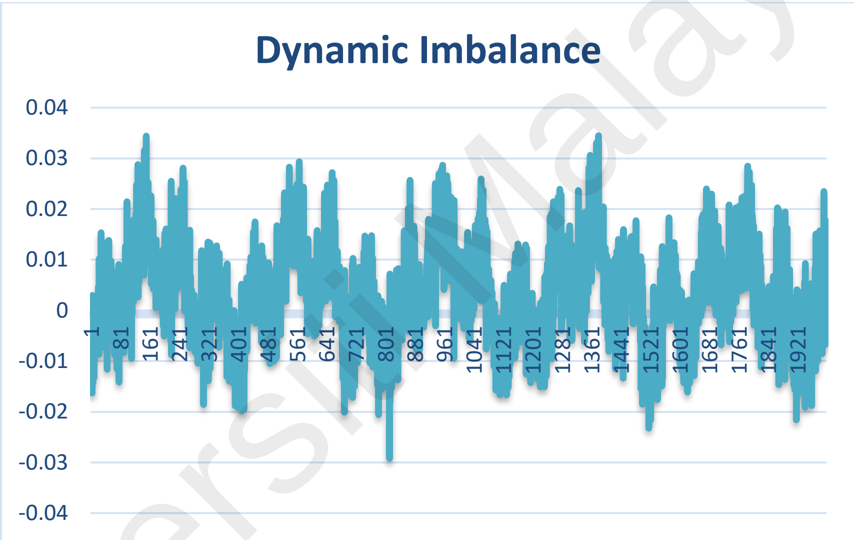

Figure 0.2: Dynamic Imbalance Time-Based Plot

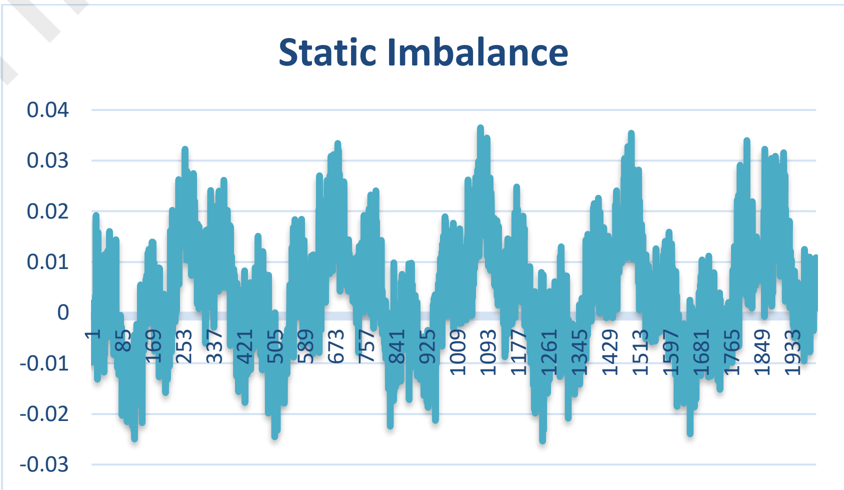

Figure 0.3: Static Imbalance Time-Based Plot

Universiti Malaya

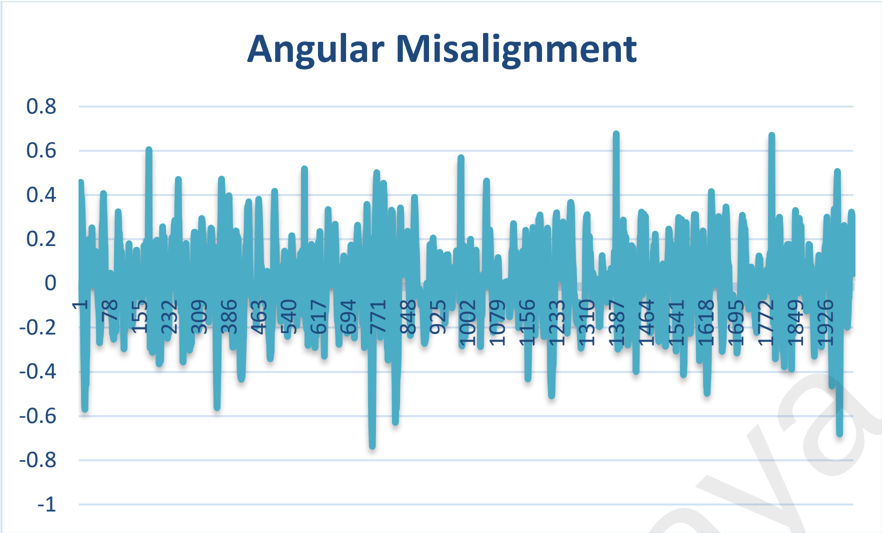

Figure 0.4: Angular Misalignment Time-Based Plot

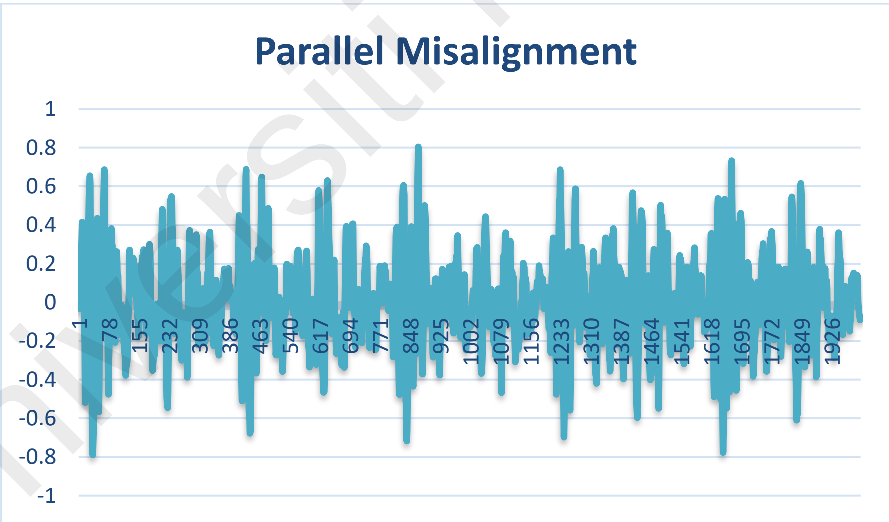

Figure 0.5: Parallel Misalignment Time-Based Plot

Universiti Malaya

4.2 Training the Machinery Fault Classification Model

Then, each data needs to reorganize and rearrange in row and column to ensure all the data are in uniform state and suited to merge in python environment as a model training data. This is the process to transform the raw data into the data that can run through in machine learning algorithm in order to identify and detecting the pattern and to build a prediction. In general, there is total of 6,553,600 rows of data that use to train the model algorithm with 1,638,400 rows for each vibration faults. The data after reorganizing and rearrange is shown in Figure 4.6.

	Write 0 [g]	Write 1 [V]	Write 2 [V]	Write 3 [V]	Fault
0	-0.047676	0.005500	-0.005011	0.002934	Static Imbalance
1	0.007571	0.006824	-0.003498	0.002574	Static Imbalance
2	-0.051359	0.012677	0.002524	0.009712	Static Imbalance
3	-0.073711	0.002766	-0.008909	-0.001599	Static Imbalance
4	0.054630	0.012658	0.002585	0.008937	Static Imbalance
...	...	...	...	...	...
6553595	0.200719	0.008084	0.047136	-0.035153	Dynamic Imbalance
6553596	0.025491	0.010073	0.024564	0.040435	Dynamic Imbalance
6553597	-0.033677	0.018678	0.012460	-0.034671	Dynamic Imbalance
6553598	0.199177	0.004978	0.023465	-0.059867	Dynamic Imbalance
6553599	-0.001355	-0.002193	0.029078	0.002415	Dynamic Imbalance

Figure 0.6: Training Dataset After modification

Next, label of each set of data is constructed based on every vibration fault that are used as a training data are shown in Figure 4.7. In machine learning, labeled dataset is used to support the machine learning models to learn and understand the pattern of the input data and produce an accurate output in identifying vibration faults. It is the process where machine learning algorithm used to identify the raw data that used as a training data so model can learn from it.

Universiti Malaya

As shown in Figure 4.7, the model algorithm of this design is train based on the total 5 dataset that represent each vibration fault which are static imbalance, angular misalignment, parallel misalignment, and dynamic imbalance. Each of the dataset involve with difference kind of pattern and shape in time waveform that can apply in interpretation and detection the future vibration faults.

```
['Static Imbalance',
 'Static Imbalance',
 'Static Imbalance',
 'Static Imbalance',
 'Static Imbalance',
 'Angular Misalignment',
 'Angular Misalignment',
 'Angular Misalignment',
 'Angular Misalignment',
 'Angular Misalignment',
 'Parallel Misalignment',
 'Parallel Misalignment',
 'Parallel Misalignment',
 'Parallel Misalignment',
 'Parallel Misalignment',
 'Dynamic Imbalance',
 'Dynamic Imbalance',
 'Dynamic Imbalance',
 'Dynamic Imbalance',
 'Dynamic Imbalance']
```

Figure 0.7: Dataset Label for Training

Then, the data is prepared and modify according to python program format to ensure the data is suited with python system environment. After all the program and dataset is ready for training, then the program is prepared to run at multiple steps in order to develop and build the model algorithm. This running program is iterative process that generate the sequence of solution for specific vibration faults criteria. The program is fully run and completed when the model has ultimately reached the stage at upon final solution at the end of the process.

Universiti Malaya

As shown in Figure 4.8, the model training achieves 95% accuracy, and the model takes 299 steps of training before the model is fully converged. This mean that at step 299 the model algorithm is achieves a state where the loss remains in within an error range. Furthermore, at step 299, any additional and further training of the model will no longer useful to help and improve the model.

```
Epoch 279/500
4/4 [==============================] - 73s 18s/step - loss: 0.4022 - sparse_categorical_accuracy: 0.8000
Epoch 280/500
4/4 [==============================] - 75s 19s/step - loss: 0.3214 - sparse_categorical_accuracy: 1.0000
Epoch 281/500
4/4 [==============================] - 72s 18s/step - loss: 0.4084 - sparse_categorical_accuracy: 0.8500
Epoch 282/500
4/4 [==============================] - 72s 18s/step - loss: 0.3385 - sparse_categorical_accuracy: 0.9500
Epoch 283/500
4/4 [==============================] - 73s 18s/step - loss: 0.3700 - sparse_categorical_accuracy: 0.9000
Epoch 284/500
4/4 [==============================] - 76s 19s/step - loss: 0.3475 - sparse_categorical_accuracy: 0.9000
Epoch 285/500
4/4 [==============================] - 76s 19s/step - loss: 0.5759 - sparse_categorical_accuracy: 0.8500
Epoch 286/500
4/4 [==============================] - 72s 18s/step - loss: 0.3462 - sparse_categorical_accuracy: 0.9000
Epoch 287/500
4/4 [==============================] - 73s 19s/step - loss: 0.3986 - sparse_categorical_accuracy: 0.9500
Epoch 288/500
4/4 [==============================] - 74s 19s/step - loss: 0.5474 - sparse_categorical_accuracy: 0.7500
Epoch 289/500
4/4 [==============================] - 77s 18s/step - loss: 0.3625 - sparse_categorical_accuracy: 0.9500
Epoch 290/500
4/4 [==============================] - 72s 18s/step - loss: 0.4187 - sparse_categorical_accuracy: 0.8000
Epoch 291/500
4/4 [==============================] - 72s 18s/step - loss: 0.3599 - sparse_categorical_accuracy: 0.9000
Epoch 292/500
4/4 [==============================] - 74s 19s/step - loss: 0.4255 - sparse_categorical_accuracy: 0.8000
Epoch 293/500
4/4 [==============================] - 80s 20s/step - loss: 0.3721 - sparse_categorical_accuracy: 0.9000
Epoch 294/500
4/4 [==============================] - 75s 18s/step - loss: 0.3523 - sparse_categorical_accuracy: 0.9500
Epoch 295/500
4/4 [==============================] - 72s 18s/step - loss: 0.3480 - sparse_categorical_accuracy: 0.8500
Epoch 296/500
4/4 [==============================] - 76s 18s/step - loss: 0.3723 - sparse_categorical_accuracy: 0.9000
Epoch 297/500
4/4 [==============================] - 75s 19s/step - loss: 0.4220 - sparse_categorical_accuracy: 0.8500
Epoch 298/500
4/4 [==============================] - 76s 19s/step - loss: 0.5461 - sparse_categorical_accuracy: 0.9000
Epoch 299/500
4/4 [==============================] - 77s 19s/step - loss: 0.3523 - sparse_categorical_accuracy: 0.9500
Epoch 00299: early stopping
```

Figure 0.8: Training Simulation Progress

Universiti Malaya

4.3 Machinery Fault Classification Model Validation

Next the dataset is label according to the vibration faults as shown in the Figure 4.9. In figure shown that there is total 4 dataset use for validation with 1 dataset use to validate each vibration faults. Similar like in training data process, the data then need to readjust and rearrange to fit into python environment system. In general, the total rows use for validation is 1,310,720 rows with 327,680 rows for each vibration faults.

```
['Dynamic Imbalance',
 'Static Imbalance',
 'Angular Misalignment',
 'Parallel Misalignment']
```

Figure 0.9: Data Label for Validation

After the completion of structured the data for validation, the program was run to determine the performance and accuracy. The accuracy in machine learning is a system of measurement that generally illustrate the model performance across all the input data. This is the measurement of how well the model in identify and detecting the vibration faults based on trending and pattern in time-based waveform. In this study, the model algorithm is run and simulate, and the result of validation shows the model successfully to get 100% accuracy. This means that the model is successfully to detect and identify each vibration fault correctly. This also shows that the model is perfectly fit to any learning dataset and capable to interpret the dataset.

Then, the confusion matrix is constructed as shown in the Table 4.1. Confusion matrix is the table or matrix that used to determine the performance of a classification algorithm for a given set of test data. It is crucial to visualize the predictive analytics and provide direct comparison between each vibration faults. In this study, each validation set data is successfully to be recognize correctly for each vibration faults.

Universiti Malaya

Table 0.1: Validation Confusion Matrix

	Angular Misalignment	Dynamic Imbalance	Parallel Misalignment	Static Imbalance	
Angular Misalignment	1 25%	0 0.0%	0 0.0%	0 0.0%	**100%** **0.0%**
Dynamic Imbalance	0 0.0%	1 25%	0 0.0%	0 0.0%	**100%** **0.0%**
Parallel Misalignment	0 0.0%	0 0.0%	1 25%	0 0.0%	**100%** **0.0%**
Static Imbalance	0 0.0%	0 0.0%	0 0.0%	1 25%	**100%** **0.0%**
	100% **0.0%**	**100%** **0.0%**	**100%** **0.0%**	**100%** **0.0%**	**100%** **0.0%**

4.4 Model assessment using different type of input data.

After completing to develop an effective model with the capability to detect each vibration fault correctly, next, the model program is test and validate using variety combination of difference input to observe the impact of the data to the output and to observe the performance and accuracy. This is vital element in order to verifying the model prediction in detecting the machinery faults toward to actual condition in industry.

4.4.1 Assessment by reduce training dataset and increase validation dataset.

Firstly, the model program is test and validate by using different number of training and validate dataset to observe the impact. The first case in verifying the model is by reduce the number of datasets for training and increase the number of datasets for validation. Under this case, 16 dataset is used for training the model with 4 datasets represent each vibration faults. The label of dataset for each vibration faults is shown in the Figure 4.10. Based on the figure, there is 4 datasets assign for each vibration faults which are dynamic imbalance, static imbalance, angular misalignment, and parallel misalignment. Then training model is run and takes 440 step to completed and achieved 100% accuracy as shown in Figure 4.11.

Universiti Malaya

```
['Dynamic Imbalance',
 'Dynamic Imbalance',
 'Dynamic Imbalance',
 'Dynamic Imbalance',
 'Static Imbalance',
 'Static Imbalance',
 'Static Imbalance',
 'Static Imbalance',
 'Angular Misalignment',
 'Angular Misalignment',
 'Angular Misalignment',
 'Angular Misalignment',
 'Parallel Misalignment',
 'Parallel Misalignment',
 'Parallel Misalignment',
 'Parallel Misalignment']
```

Figure 0.10: Label for Training Data

```
4/4 [==============================] - 68s 16s/step - loss: 0.2992 - sparse_categorical_accuracy: 1.0000
Epoch 429/500
4/4 [==============================] - 71s 15s/step - loss: 0.3020 - sparse_categorical_accuracy: 1.0000
Epoch 430/500
4/4 [==============================] - 65s 15s/step - loss: 0.3580 - sparse_categorical_accuracy: 1.0000
Epoch 431/500
4/4 [==============================] - 62s 14s/step - loss: 0.2895 - sparse_categorical_accuracy: 1.0000
Epoch 432/500
4/4 [==============================] - 67s 16s/step - loss: 0.3623 - sparse_categorical_accuracy: 1.0000
Epoch 433/500
4/4 [==============================] - 63s 14s/step - loss: 0.2997 - sparse_categorical_accuracy: 1.0000
Epoch 434/500
4/4 [==============================] - 66s 15s/step - loss: 0.3032 - sparse_categorical_accuracy: 1.0000
Epoch 435/500
4/4 [==============================] - 68s 16s/step - loss: 0.2796 - sparse_categorical_accuracy: 1.0000
Epoch 436/500
4/4 [==============================] - 65s 15s/step - loss: 0.3125 - sparse_categorical_accuracy: 1.0000
Epoch 437/500
4/4 [==============================] - 65s 15s/step - loss: 0.2900 - sparse_categorical_accuracy: 1.0000
Epoch 438/500
4/4 [==============================] - 65s 14s/step - loss: 0.2963 - sparse_categorical_accuracy: 1.0000
Epoch 439/500
4/4 [==============================] - 65s 15s/step - loss: 0.3158 - sparse_categorical_accuracy: 1.0000
Epoch 440/500
4/4 [==============================] - 63s 15s/step - loss: 0.3307 - sparse_categorical_accuracy: 1.0000
Epoch 00440: early stopping
```

Figure 0.11: Training Simulation Progress

Universiti Malaya

Then to observe the impact to the model, the number of validations dataset is to increase. In this case, there is total 8 dataset is used with 2 datasets represent for each vibration faults. As shown in Figure 4.12, the label for each vibration faults indicate 8 datasets used for validating the model with each vibration faults which are dynamic imbalance, static imbalance, angular misalignment, and parallel misalignment assign with 2 datasets.

```
['Static Imbalance',
 'Static Imbalance',
 'Dynamic Imbalance',
 'Dynamic Imbalance',
 'Parallel Misalignment',
 'Parallel Misalignment',
 'Angular Misalignment',
 'Angular Misalignment']
```

Figure 0.12: Label for Model Validation

Then, after the model is properly prepared, the model is run and simulate to observe the performance and accuracy. Based the measurement in python system, the model is producing 50% accuracy. This mean that some of vibration fault are wrongly detecting the correct vibration faults. Next, the confusion matrix is constructed as shown in Table 4.2 in order to visualize the accuracy.

Table 0.2: Confusion Matrix

	Angular Misalignment	**Dynamic Imbalance**	**Parallel Misalignment**	**Static Imbalance**	
Angular Misalignment	2 25%	2 25%	0 0.0%	2 25%	**33.3%** **66.7%**
Dynamic Imbalance	0 0.0%	0 0.0%	0 0.0%	0 0.0%	**0.0%** **0.0%**
Parallel Misalignment	0 0.0%	0 0.0%	2 25%	0 0.0%	**100%** **0.0%**
Static Imbalance	0 0.0%	0 0.0%	0 0.0%	0 0.0%	**0.0%** **0.0%**
	100% **0.0%**	**0.0%** **0.0%**	**100%** **0.0%**	**0.0%** **0.0%**	**50%** **50%**

Universiti Malaya

Based on the table, the model program is incorrectly detecting dynamic imbalance and static imbalance to other vibration faults while the model is successfully to recognize angular misalignment and parallel misalignment accurately. This is bringing the accuracy 50% accuracy in detecting the vibration faults.

4.4.2 Assessment using unprocessed data.

Then, the model is test and validate by using unprocessed data. Unprocessed data is the raw data that directly collected from the transducer without any modification, analysis, cleaning and organized. Under this case, 8 datasets are used as a training data with 2 set for each vibration faults. As shown in Figure 4.13, the model is assigning with 2 datasets for each vibration faults which are 2 datasets for dynamic imbalance, static imbalance, angular misalignment, and parallel misalignment.

```
['Dynamic Imbalance',
 'Dynamic Imbalance',
 'Static Imbalance',
 'Static Imbalance',
 'Angular Misalignment',
 'Angular Misalignment',
 'Parallel Misalignment',
 'Parallel Misalignment']
```

Figure 0.13: Label for Training Data

Then the model is training by run the simulation. This is important to observe the training accuracy. Based on the Figure 4.14, the model achieves to reach accuracy to 87.5% with the total step taken is 223 before it fully converged.

Universiti Malaya

```
Epoch 209/500
2/2 [==============================] - 28s 10s/step - loss: 0.4735 - sparse_categorical_accuracy: 0.7500
Epoch 210/500
2/2 [==============================] - 28s 11s/step - loss: 0.5005 - sparse_categorical_accuracy: 0.7500
Epoch 211/500
2/2 [==============================] - 28s 11s/step - loss: 0.3968 - sparse_categorical_accuracy: 0.8750
Epoch 212/500
2/2 [==============================] - 28s 11s/step - loss: 0.4296 - sparse_categorical_accuracy: 0.8750
Epoch 213/500
2/2 [==============================] - 28s 10s/step - loss: 0.4382 - sparse_categorical_accuracy: 0.7500
Epoch 214/500
2/2 [==============================] - 28s 10s/step - loss: 0.4600 - sparse_categorical_accuracy: 0.8750
Epoch 215/500
2/2 [==============================] - 28s 10s/step - loss: 0.4273 - sparse_categorical_accuracy: 0.8750
Epoch 216/500
2/2 [==============================] - 28s 11s/step - loss: 0.4860 - sparse_categorical_accuracy: 0.7500
Epoch 217/500
2/2 [==============================] - 28s 10s/step - loss: 0.4256 - sparse_categorical_accuracy: 0.8750
Epoch 218/500
2/2 [==============================] - 28s 10s/step - loss: 0.4973 - sparse_categorical_accuracy: 0.7500
Epoch 219/500
2/2 [==============================] - 29s 11s/step - loss: 0.4279 - sparse_categorical_accuracy: 0.7500
Epoch 220/500
2/2 [==============================] - 28s 11s/step - loss: 0.4478 - sparse_categorical_accuracy: 0.7500
Epoch 221/500
2/2 [==============================] - 28s 11s/step - loss: 0.4320 - sparse_categorical_accuracy: 0.7500
Epoch 222/500
2/2 [==============================] - 31s 13s/step - loss: 0.4636 - sparse_categorical_accuracy: 0.7500
Epoch 223/500
2/2 [==============================] - 31s 11s/step - loss: 0.4004 - sparse_categorical_accuracy: 0.8750
Epoch 00223: early stopping
```

Figure 0.14: Training Simulation Progress

Then the model is validated by using remaining dataset. For this, 16 datasets are used with 4 datasets for each vibration faults. As shown in the Figure 4.15, the model has assigned the label to 4 datasets for each vibration faults which are 4 datasets for dynamic imbalance, static imbalance, angular misalignment, and parallel misalignment.

```
['Dynamic Imbalance',
 'Dynamic Imbalance',
 'Static Imbalance',
 'Static Imbalance',
 'Angular Misalignment',
 'Angular Misalignment',
 'Parallel Misalignment',
 'Parallel Misalignment',
 'Static Imbalance',
 'Static Imbalance',
 'Dynamic Imbalance',
 'Dynamic Imbalance',
 'Parallel Misalignment',
 'Parallel Misalignment',
 'Angular Misalignment',
 'Angular Misalignment']
```

Figure 0.15: Label for Validation data

Universiti Malaya

Next, after the training and validation data is ready and prepared properly, the model is run and simulate to observe the impact to the performance and accuracy. Based on the result shows that the model has the accuracy only 6.25% in detecting the vibration faults. The confusion matrix then is constructed to visualize the output as shown in Table 4.3. Based on the table, there are only 1 type of vibration fault that correctly recognized by the model which is static imbalance while the others vibration faults are incorrectly interpret by the model.

Table 0.3: Confusion Matrix

	Angular Misalignment	**Dynamic Imbalance**	**Parallel Misalignment**	**Static Imbalance**	
Angular Misalignment	0 0.0%	0 0.0%	0 0.0%	0 0.0%	**0.0%** **0.0%**
Dynamic Imbalance	2 12.5%	0 0.0%	0 0.0%	3 18.75%	**0.0%** **100%**
Parallel Misalignment	0 0.0%	0 0.0%	0 0.0%	0 0.0%	**0.0%** **0.0%**
Static Imbalance	4 25%	0 0.0%	6 37.5%	1 6.25%	**100%** **0.0%**
	0.0% **100%**	**0.0%** **0.0%**	**0.0%** **100%**	**100%** **0.0%**	**6.25%** **93.75%**

4.5 Summary

The machinery vibration assessment system developed in Python has successfully classified and detecting each vibration faults through the application of deep learning. The validation process has shown 100% accuracy in detection each vibration faults. Primary machinery faults such as rotor imbalance and misalignment are effectively analyzed with the assistance of application of deep learning hence the objective has been met. This is beneficial for the future work to develop an accurate and time-saving assessment system for any untrained personnel to diagnose the problems. Yet, the system still possesses plenty of opportunities to improve by the future workers on it.

Universiti Malaya

Then, the machinery vibration assessment system developed has successfully tested and validate with different type of input to observe the impact to the model performance and accuracy. Based on the model testing, the model algorithm produces 50% accuracy when it uses 66% of dataset for training and 33% dataset for validation. The model then reached 100% level of accuracy when the training data used is 83% and 17% for validation. This result is shows the important of the huge number in training dataset to the accuracy in prediction the vibration faults. In a real situation in industry, the history data for each vibration faults are essentially to keep properly in order to train the deep learning algorithm and use for future faults prediction.

Then the model is tested with unprocessed raw data that collected directly from transducer. The result shows the accuracy is only 6.25% which is unacceptable in deep learning. This is show that the important of data to process correctly, analyze and organized to ensure the quality of the data. Therefore, based on this the objective is achieved to observe the variety of input that can impacting model output. The comparison of difference type of input is shown in the Table 4.4.

Table 0.4: Accuracy Comparison Between Input Data

Case	Number of training data	Training accuracy	Number of validation data	Accuracy
1	20	95%	4	100%
2	16	100%	8	50%
3	8	87.5%	16	6.25%

Universiti Malaya

CONCLUSION

This chapter concludes and summarizes the overall results, which also answers research objective. The limitation and recommendation of future work is also described briefly in this section.

5.1 Conclusion

In summary, advanced machinery vibration assessment application program are successfully to be develop using one of deep learning technique which is convolutional neural network (CNN). The program is develop using modern python program where it offers an advance technique and method in deep learning algorithms with vast library support for easier and simply the program. Additionally, the program is formed by using time series data that are extracted from simulation test rig at laboratory with 4 type of vibration faults.

The model then is validated by using the 83% of this measured data to training the deep learning model. The run and simulation required 299 steps before the model fully converged and the training accuracy achieved 95%. Next, the deep learning model is using another 17% of data with 4 type of vibration faults to validate the model. Based on the result, the model successfully to achieve 100% of accuracy in determine and detecting each vibration faults correctly.

At the end of the study, the model is successfully tested and evaluated with variety type of input in order to observe the impact to the model performance and accuracy. The deep learning model is assessed and tested by reducing the training data and use unprocessed raw data in time series as an input. Based on the result, both type of input data produces and achieve a low accuracy which are 50% and 6% respectively that impacting the accuracy of model.

Universiti Malaya

5.2 Limitations of the research

However, a few limitations have been encountered along the process of completing this research. Firstly, the insufficient set of vibration data for training the model and validation affect the accuracy and could produce unreliable result in detecting the vibration fault. Insufficient data also increases the margin of error, which can represent the study irrelevant. Consequently, it could produce the misleading in providing the recommendation and decision. A very huge of vibration data with multiple type of vibration faults are required in order to perform better and to achieve a better accuracy in determine the vibration faults.

Besides that, the lacking in computer power system creates a limitation to process a various coding algorithm. To handle the complex coding and sophisticated model with additional of complicated architecture in python required a power computer with an extremely good in processor and GPUs. Furthermore, the huge data input needs to process and simulate through multi-layer algorithm computer system that too large to fit with standard computer system. Subsequently, slow processing in data simulation will consume a substantial time to complete the model design and making harder to developer to improve the model algorithm.

Furthermore, the limitation in skill and knowledge in python has restricted to achieve a good modelling. Machine learning and Python is a broad topic with complex process and algorithm to understand and required a vast experience in order to get better in machine learning modelling. In python program, each modelling and algorithm has various components and advance function that need to understand in detail before it can use appropriately.

Universiti Malaya

5.3 Recommendation of Future Work

Machine learning relies on data to analysis the algorithms of pattern and continuously improve the model over time. The quality of data is vital in order this model to produce and operate efficiently. Due to this, the amount of meaningful data is crucial in order to get a better in accuracy, it is recommended to increase the number of set data for each type of vibration fault. This could improve the model prediction in detection the vibration fault and reduce the margin of error thus increase the accuracy with resulted in better decisions making. This is essential in industry since machine learning is developed to assist and support in providing a decision and recommendation in each vibration fault. Incorrect interpretation of vibration fault could lead improper maintenance activities thus increase maintenance cost.

Furthermore, future study could be conducted by including more type of vibration fault such as bending shaft, mechanical looseness, cocked bearing and rub. In real situation, there are many types of vibration faults that are encounter by rotating machinery in industry. This is essential element to determine the real root cause of vibration issue to avoid any unnecessary maintenance. On the other hand, the machine learning model also can be enhanced by upgrading the data using real-time data that collect directly from the machine. This could provide continuous monitoring and precise assessment in the rotating equipment.

Universiti Malaya

REFERENCES

Asset Insights. (2013). Retrieved from https://assetinsights.net/Glossary/G_Maintenance_Mix.html

Ahmad, R., & Kamaruddin, S. (2012). An overview of time-based and condition-based maintenance in industrial application. *Computers & Industrial Engineering*.

Ahmed, I., Islam, R., Sarkar, M., & Haq, Z. (2015). Vibration Monitoring and Condition Analysis of a 210MW Steam Turbine. *International Conference on Mechanical, Industrial and Materials Engineering 2015 (ICMIME2015).*

Ansaf, H., Najm, H., Atiyah, J. M., & Hassen, O. A. (2019). mproved Approach for Identification of Real and Fake Smile using Chaos Theory and Principal Component Analysis. *Journal of Southwest Jiaotong University*.

Ayo-Imoru, R., & Cilliers, A. (2018). A survey of the state of condition-based maintenance (CBM) in the nuclear power industry. *Annals of Nuclear Energy*.

Bently Nevada. (2021). Retrieved from https://www.bakerhughes.com/bently-nevada

Berchane, N. (2018). Artificial intelligence, machine learning and deep learning. *M2 IESCI*.

Bond, L.J., Ramuhalli, P., Tawfik, M.S., . . . N.J. (2011). Prognostics and life beyond 60 years for nuclear power plants. *Prognostics and Health Management (PHM)*, 1–7.

Bovsunovsky, A. (2018). Estimation of efficiency of vibration damage detection in stepped shaft of steam turbine. *Electric Power Systems Research*.

BSI Standards Publication. (2010). Maintenance - Maintenance terminology. *BS EN 13306:2010*.

Çaglar, K., & Arslanoglu, Y. (2022). Development of condition-based maintenance strategy for fault diagnosis. *Ocean Engineering*.

Chen, H.-Y., & Lee, C.-H. (2021). Deep Learning Approach for Vibration Signals Applications. *Sensors*.

Cui, B., Weng, Y., & Zhang, N. (2022). A feature extraction and machine learning framework for bearing fault diagnosis. *Renewable Energy*.

Fahmi, A.-T. W., Kashyzadeh, K. R., & Ghorbani, S. (2022). A comprehensive review on mechanical failures cause vibration in the gas turbine of combined cycle power plants. *Engineering Failure Analysis*.

Gaba, S., Budhiraja, I., Kumar, V., Garg, S., Kaddoum, G., & Hassan, M. M. (2022). A Federated Calibration Scheme for Convolutional Neural Networks: Models, Applications and Challenges. *Computer Communications*.

Universiti Malaya

Ingemarsdotter, E., Kambanou, M. L., Jamsin, E., Sakao, T., & Balkenende, R. (2021). Challenges and solutions in condition-based maintenance implementation - A multiple case study. *Journal of Cleaner Production*.

International Standard ISO 13373. (2002). Condition Monitoring and Diagnostics of Machines - Vibration Condition Monitoring.

International Standard ISO/IEC 2382-31. (1997). Artificial intelligence — Machine learning.

International Standard ISO/IEC DIS 22989. (2021). Information technology — Artificial intelligence — Artificial intelligence concepts and terminology. *ISO/IEC DIS 22989*.

ISO 14224. (2006). International Standard ISO 14224.

Khan, M. M., Hossain, S., Mozumdar, P., Akter, S., & Ashique, R. H. (2022). A review on machine learning and deep learning for various antenna design applications. *Heliyon*.

Kongari, H. (2017). Deep Learning: The Answer to Future Healthcare Systems. *International Healthcare Vision 2037. New Technologies, Educational Goals and Entrepreneurial Challenges*, (pp. 88-89).

Kumar, J. P., Chauhan, P. S., & Pandit, P. P. (2022). Time domain vibration analysis techniques for condition monitoring of rolling element bearing: A review. *Materials Today: Proceedings*.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*.

Lee, J., Ni, J., Singh, J., Jiang, B., Azamfar, M., & Feng, J. (2020). Intelligent Maintenance Systems and Predictive Manufacturing. *Journal of Manufacturing Science and Engineering*.

Liu, F., Liu, J., & Wang, L. (2022). Deep learning and infrared thermography for asphalt pavement crack severity classification. *Automation in Construction*.

Liu, J., Luo, H., & Liu, H. (2022). Deep learning-based data analytics for safety in construction. *Automation in Construction*.

Mandreoli, F., & Emilia, R. (2021). Enterprise Integration and Interoperability for Big Data-Driven Processes in the Frame of Industry 4.0. *Information Management Unit (IMU), School of Electrical and Computer Engineering, National Technical University of Athens*.

Mobius Institute. (2020). Retrieved from https://www.mobiusinstitute.com/

Nada, & Berchane, N. (2018). Retrieved from https://master-iesc-angers.com/artificial-intelligence-machine-learning-and-deep-learning-same-context-different-concepts/

Universiti Malaya

Nikfar, M., Bitencourt, J., & Mykoniatis, K. (2022). A Two-Phase Machine Learning Approach for Predictive Maintenance of Low Voltage Industrial Motors. *3rd International Conference on Industry 4.0 and Smart Manufacturing*, (pp. 111–120).

Nvdia. (2021). Retrieved from www.nvdia.com

Nvidia. (2022). *Artificial Intelligence*. Retrieved from https://www.nvidia.com/en-us/glossary/data-science/artificial-intelligence/

Özgür-Ünlüakın, D., Türkali, B., Karacaörenli, A., & Aksezer, S. Ç. (2019). A DBN based reactive maintenance model for a complex system in thermal. *Reliability Engineering and System Safety*.

Özgür-Ünlüakin, D., Türkali, B., Karacaörenli, A., & Aksezer, S. Ç. (2019). A DBN based reactive maintenance model for a complex system in thermal power plants. *Reliability Engineering and System Safety*.

Peng, H., Wang, Y., Zhang, X., Hu, Q., & Xu, B. (2022). Optimization of preventive maintenance of nuclear safety-class DCS based on reliability modeling. *Nuclear Engineering and Technology*.

Quan, K. G. (2021). *DEVELOPMENT OF MACHINERY VIBRATION ASSESSMENT SYSTEM FOR EFFECTIVE FAULTS DIAGNOSTIC IN CONDITION BASED MAINTENANCE.*

Ramachandran, K., Mary, A. A., Hawladar, S., Asokk, D., Bhaskar, B., & J. P. (2022). Machine learning and role of artificial intelligence in optimizing work performance and employee behavior. *Materials Today: Proceedings*.

Rastegari, A. (2017). Condition Based Maintenance in the Manufacturing Industry From Strategy to Implementation. *Mälardalen University Doctoral Dissertation*.

Roda, & Macchi, M. (2021). Maintenance concepts evolution: a comparative review towardsAdvanced Maintenance conceptualization. *Computers in Industry*.

S.Roque, A., W.Krebs, V., Figueiro, I. C., & Jazdi, N. (2022). An analysis of machine learning algorithms in rotating machines maintenance. *IFAC PapersOnLine*, (pp. 252–257).

Sambana, B., P., A. N., Jarabala, R., & V.N.S.L, N. (2021). Performance validation of wind turbines using machine learning methodologies. *Materials Today: Proceedings*.

Sirvio, K. M. (2015). Intelligent Systems in Maintenance Planning and Management.

Sirvio, K. M. (2015). Intelligent Systems in Maintenance Planning and Management. *Intelligent Systems Reference Library*.

Sirvio, K. M. (2015). Intelligent Systems in Maintenance Planning and Management. *Intelligent Systems Reference Library*.

Universiti Malaya

Sirvio, K. M. (2015). Intelligent Systems in Maintenance Planning and Management asacascascascsaccsasasc. *Intelligent Systems Reference Library*.

Sirvio, K. M. (2017). Intelligent Systems in Maintenance Planning and Management.

Soares, E., Lopes, I. d., & Pinheiro, J. (2021). Methodology to Support Maintenance Management for the Identification and Analysis of the Degradation of Equipment Reliability. *IFAC-PapersOnLine* (pp. 1272-1277). Elsevier.

Sun, Y., & Li, S. (2022). Bearing fault diagnosis based on optimal convolution neural network. *Measurement*.

Taboada, J. V., Diaz-Casas, V., & Yu, X. (2021). CBM challenges and opportunities for O&M of the Johan Sverdrup Oil and Gas Field. *Journal of Petroleum Science and Engineering*.

Tayyaba, S. M., Asghar, E., Pennacchi, P., & Chattertond, S. (2020). Intelligent fault diagnosis of rotating machine elements using machine learning through optimal features extraction and selection. *30th International Conference on Flexible Automation and Intelligent Manufacturing (FAIM2021)*, (pp. 266–273).

Teixeira, H. N., Lopes, I., & Braga, A. C. (2020). Condition-based maintenance implementation: a literature review. *Conference on Flexible Automation and Intelligent Manufacturing (FAIM2021)*, (pp. 228–235).

Tomassini, S., Falcionelli, N., Sernani, P., Burattini, L., & Dragoni, A. F. (2022). ung nodule diagnosis and cancer histology classification from computed tomography data by convolutional neural networks: A survey. *Computers in Biology and Medicine*.

Tsang, Y., & Lee, C. (2022). Artificial intelligence in industrial design: A semi-automated literature survey. *Engineering Applications of Artificial Intelligence*.

Yeh, C. W., & Chen, R. (2018). Using Convolutional Neural Network for Vibration Fault Diagnosis Monitoring in Machinery. *2018 IEEE International Conference on Advanced Manufacturing (IEEE ICAM 2018).*

Yeh, R. H., & Chang, W. L. (2006). Optimal threshold value of failure-rate for leased products with preventive maintenance actions. *Mathematical and Computer Modelling*, 730–737.

Zhu, X., Tan, X., Jiang, W., & Bu, Y. (2017). Fault Diagnosis of Steam Turbine Vibration Based on Fault Tree Analysis. *7th International Conference on Education, Management, Information and Mechanical Engineering (EMIM 2017).* Advances in Computer Science Research (ACSR).

Universiti Malaya