

# **Condition Based Monitoring of Ball Bearings Using Machine Learning**



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PROJECT REPORT**

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Learning**

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## **Abstract**

Ball bearings are used in rotary machines such as turbines, generators, automobiles, and electric motors just to name a few. They operate in harsh conditions, heavy loads and shocks which deteriorate their health and if not monitored timely, can lead to costly damage. With the advancements in technology, various sensors are integrated to monitor machines' health. An important health indicator of such machines is vibration signal data which provides meaningful insight into a variety of mechanical faults. Traditionally, bearing faults are analyzed in time-frequency domain which is incapable to classify the types of faults accurately. In this project, we used vibration signal data acquired by Korean Advanced Institute of Technology and ourselves and coupled it with machine learning algorithms to classify bearing faults. Additionally, we developed a Convolutional Neural Network that classifies these faults solely based on raw vibration signal data unlike machine learning algorithms that rely on an extensive number of features for greater accuracy.

## **Sustainable Development Goals**

Goal eight aims to promote sustained, inclusive, and sustainable economic growth, full and productive employment, and decent work for all. It focuses on enhancing global resource efficiency, fostering innovation, and encouraging entrepreneurship. By improving working conditions and access to jobs, this goal seeks to reduce poverty and inequalities.

Goal nine emphasizes building resilient infrastructure, promoting inclusive and sustainable industrialization, and fostering innovation. It aims to enhance scientific research, upgrade technological capabilities, and support small-scale enterprises. Ensuring equitable access to information and financial services is crucial for economic growth and bridging the technological divide in developing regions.

Goal twelve focuses on ensuring sustainable consumption and production patterns. It promotes efficient resource use, waste reduction, and recycling. Encouraging businesses and consumers to adopt sustainable practices is key. This goal aims to decouple economic growth from environmental degradation, ensuring a healthy planet for future generations.

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## CHAPTER 1: INTRODUCTION

Rotatory machines constitute a large portion of machines under use by the industry. Power generation plants, automotive industry, mining plants, agricultural equipment, material processing, and product manufacturing industries depend on electric motors, generators, pumps, and turbines for operation. For smooth transfer of power and motion, bearings are deployed in these machines, and they undergo heavy loads operating in harsh environments. Consequently, 41 percent of the failures occur in bearings (Figure. 1) [1]. Hence, it is of utmost importance to monitor the health of these machines.

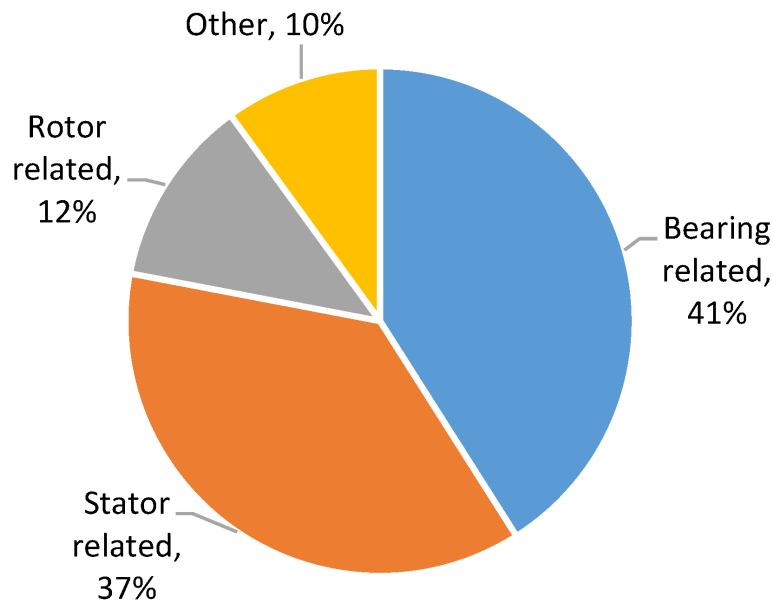


Figure 1. Percentage of failures by rotating machine components

Predictive maintenance and condition monitoring go hand in hand for machine maintenance and these two methods have proven to be the most useful ones for increasing reliability and life of the machines. Sensors provide data in real time which is analysed using model-based diagnosis systems and computer software. Microcomputer systems have decreased the footprint of the monitoring systems making health monitoring of the machines a less tedious procedure. Industry 4.0 has brought in the technical advancements of artificial intelligence coupled with traditional data acquisition techniques to modernize condition monitoring and fault diagnosis [2].

Industries across the globe rely on numerous integrated sensors which provide useful insights into the optimal operation and health of the machine. This raw data coming straight out of the machine contains rich information and features which can be processed and analysed using AI for accurate fault diagnosis. Organizations are now turning towards AI for less cost, better performance, and future proof solutions [3].

The primary goal of this project is to devise a system to study raw vibration signal data acquired from the bearings using a custom hardware and propose an efficient, modern artificial intelligence based system for fault classification of ball bearings. These enhancements are

expected to bring maintenance costs down, reduce downtimes, increase both machine and worker safety, extend life and improve reliability of the machines. The objectives of the project are stated below.

- Develop a test rig for data acquisition from faulty ball bearings
- Preprocess and extract features from the data for training of machine learning algorithms
- Compare the performance of various machine learning algorithms such as Random Forest Classifier, Logistic Regressor, KNN, Support Vector Machine [4], and Multi Layer Perceptron and to validate the performance of the selected algorithm

Initially, to understand the behaviour of the machine learning algorithms, vibration signal data from Korea Advanced Institute of Science and Technology will be used for training and validation of the model. Then, vibrational data will be acquired from an experimental setup developed by us and accuracy of the previously trained models will be tested. If the models fail to classify faults at an acceptable rate, the new data acquired from our setup will be used to retrain the model and the performance shall be reevaluated.

The thesis focuses specifically on the classification of the 6205 ball bearing faults that occur at the inner and outer races of the bearings using vibration signal data. The research includes the design and implementation of the experimental setup, feature extraction from vibration signals, and training, validation and evaluation of machine learning models.

## CHAPTER 2: LITERATURE REVIEW

### 2.1 Bearing

A bearing is a mechanical device that constrains the relative motion of parts in a machine to only one desired direction. Bearings also help in reducing friction between moving parts. Their design help in free rotatory or linear motion along some fixed axis. They might also help in minimizing motion by controlling acting forces on parts of the machine. The name is derived from “to bear,” as they allow one part to bear another.

By relative motion, bearings allow:

- Linear motion (drawers)
- Radial rotation (shafts)
- Spherical rotation (ball and socket joints)
- Hinge motion (doors)

There are several types of bearings plain bearings being the most common of them. Other types include rolling element, jewel, fluid, magnetic, and flexure bearings.

Rolling element bearings are classified into two categories by the element used for rotation:

- Roller bearings
- Ball bearings

Ball and roller bearings have two races, outer and inner with the rolling elements in between them along a grooved path known as raceways.



Figure 2. Types of bearings

Bearings are named according to a set of specified rules showing their series, type, dimensions, design, and seal types. For example, for our project, we have decided to use 6205-2RS ball

bearings as they are used more commonly than other types with their vibrational signal data available readily in substantial amounts. The digit six represents deep grooved ball bearings, digit two representing diameter series 2, 05 indicating a diameter of 25mm and 2RS showing that the bearing is sealed with rubber on both sides. Figure below helps in understanding the nomenclature better.

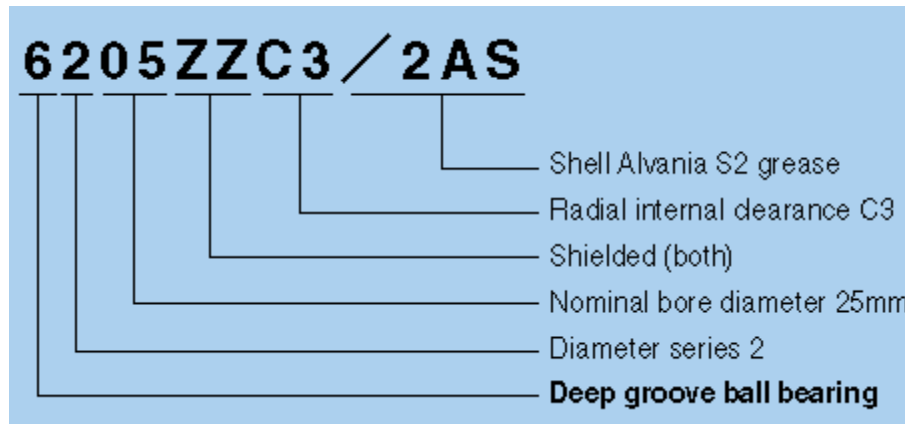


Figure 3. Nomenclature of bearings

To minimize friction, bearings are lubricated with oil or grease. Friction is a major factor governing the life cycle of a bearing and if timely lubrication is neglected, friction can cause severe thermal and mechanical degradation of the bearing. Lubrication can help in:

- Prolonging bearing fatigue life
- Reducing friction and wear
- Carrying heat away from within bearing due to friction
- Preventing corrosion and contamination by dirt

Grease, highly refined mineral oils, and synthetic oils are used to lubricate bearings. Mineral and synthetic oils generally have a wider operating temperature range as compared to greases. Oils are also combined with additives to enhance their rust preventive and oxidation inhibiting properties.

## 2.2. Types of maintenance strategies

A machine is a physical system that uses energy or forces, manipulates or converts them into other forms of energy to perform actions on the environment. From a wheel to combustion engines, motors to automobiles, airplanes, ships, rockets, robots, and computers, all these machines have proved to be the backbone of modern technology and advancements.

Machine maintenance is the act of keeping machines running smoothly with minimal downtimes. Machine maintenance can be done at regular intervals at scheduled times or in emergencies which are caused randomly and are out human control.

Maintenance can be categorized distinctively based on the approach used.

### **2.2.1. Reactive Maintenance**

Reactive maintenance refers to emergency repairs as this sort of maintenance is done after the machine has failed and is one of the oldest approaches. This maintenance is rushed, unplanned, and unscheduled and is often referred to as “fighting fires.”

Run-to-fail maintenance is like reactive maintenance, with just the difference that the machine is let run to failure deliberately. There is usually contingency for such machines and skilled labour along with spare parts are ready to get the machines up and running again as soon as possible. Run-to-failure approach can be useful when the repairs are cheaper in comparison to scheduled maintenance plans. 61 percent of the manufacturing facilities used run-to-failure method for maintenance [5].

### **2.2.2. Routine Maintenance**

Routine maintenance, as the name implies, is a regular, scheduled maintenance done at regular intervals and ongoing basis. Worn out parts might be tested, replaced, and lubricated based on their condition.

### **2.2.3. Corrective Maintenance**

Corrective maintenance usually consists of smaller, non-invasive inspections only fixing parts, such as realignment of a shaft, before a complete failure occurs.

### **2.2.4. Preventive Maintenance**

Preventive maintenance is a regular, scheduled maintenance done to avoid unexpected failures before they occur. Preventive maintenance can be split into time-based and usage-based maintenance. Time-based maintenance is done after regular intervals, for example at last day of every month. Usage-based maintenance is carried out after certain units consumed, like checking engine oil viscosity after every five hundred miles. 78 percent of the manufacturing facilities deploy a preventive maintenance plan.

### **2.2.5. Condition-Based Maintenance**

Condition-based maintenance carried based on real-time data collected from the machine using sensors indicating actual health and condition of the machine. Condition-based monitoring is discussed in detail later in this report and lays the foundation for this project.

### **2.2.6. Predictive Maintenance**

Predictive maintenance builds on the foundation laid by condition-based monitoring for predicting failures in real-time. Remaining useful life prediction is a major benefit of predictive maintenance.

### **2.2.7. Prescriptive Maintenance**

Artificial Intelligence and Machine Learning techniques can be used to automate maintenance process. AI can prescribe optimal solutions against failures in real-time using data acquired from sensors.

A combination of above-mentioned plans can also be used for better and more efficient maintenance according to our needs and applications.

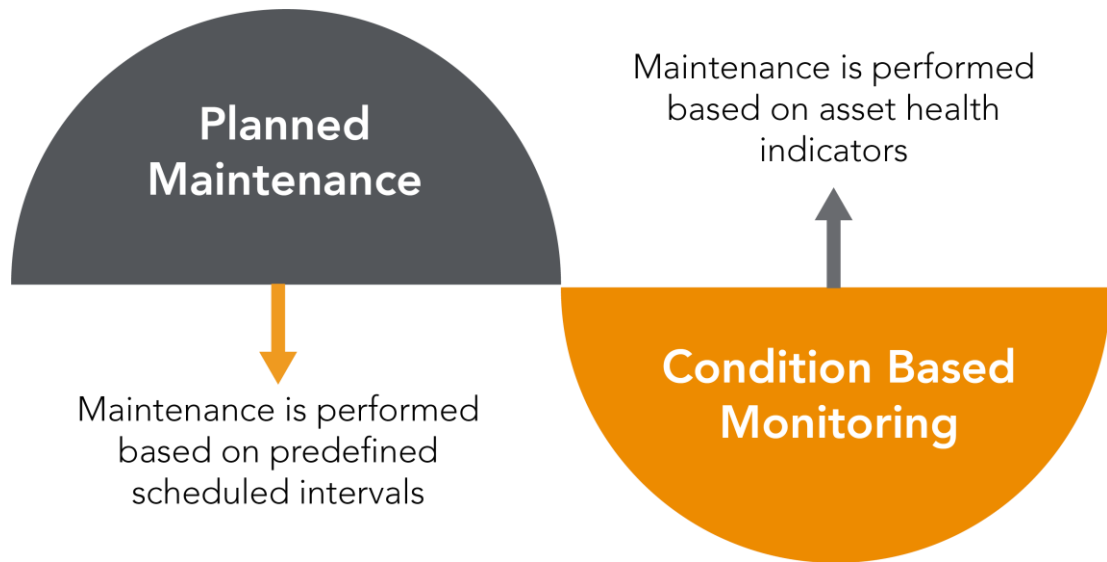


Figure 4. Difference between planned and condition based maintenance

### 2.3. Condition-Based Monitoring

Condition-based monitoring is deployed to prevent downtime, asset failures, and unnecessary practices by monitoring machine performance metrics in real-time by integration of various sensors with the machine itself. Progress made in the field of microcontrollers and other computer systems have made it even more practical to acquire and analyse data for predictions with the help of not only traditional mathematical models, software, artificial intelligence, and machine learning algorithms [6]. Condition-based monitoring ensures maintenance is carried out only when required above a certain threshold avoiding unnecessary costs and downtimes in the wake of routine checkups.

A big advantage of this monitoring technique is its non-invasive nature as sensors are mounted on the outer surface of the machine saving time by avoiding disassembly and giving health indicators merely by sensory data. This data can also be used to study randomness, repeatability and abnormality in the operating nature of the machine.

### 2.4. Fault Diagnosis of Ball Bearings

Fault diagnosis of ball bearings is critical in determining the health and performance of rotatory machines. Various methods can be used for fault diagnosis of the bearings making use of sensors, signal processing [7], and artificial intelligence. Some commonly used methods are stated below.

#### 2.4.1. Ultrasonic Testing

Ultrasonics have been used in marine technology for deep sea exploration [8], in medical field for non-invasive diagnosis [9], and detection of cracks which is helpful in not only fault diagnosis of the bearings but also in estimating the size of the crack [10].

#### **2.4.2. Acoustic Emission Analysis**

Acoustic emission analysis is the analysis of the high-frequency sound waves produced by the initiation and growth of cracks or defects in bearings [11]. These acoustic signals are captured using highly sensitive, high-frequency, MEMS based microphones.

#### **2.4.3. Thermal Analysis**

Worn out or defective bearings generate excessive heat due to friction that is higher than a normal and healthy bearing. Temperature sensors mounted on the bearing bracket can be used for temperature monitoring or infrared thermography can be used for detecting abnormal hotspots on the surface of the bearings which might indicate potential faults [12].

#### **2.4.4. Model-Based Estimation**

Model-based estimation uses mathematical modelling like state estimation techniques or Finite Element Analysis (FEA) [13] of the bearing system to estimate the life and health. FEA enables detailed simulation of the bearing under varying loads and conditions predicting stress distribution, deformation and potential failures. Multibody Dynamics analyses interaction of components of the machinery with the bearing, thus providing a comprehensive overview of the operational environment.

#### **2.4.5. Vibration Analysis**

Vibration analysis is the most effective and commonly used technique for fault diagnosis in bearings. Accelerometers are mounted on the bearing bracket and vibrations are recorded and analysed using mathematical models, computer software, or machine learning techniques. The data obtained gives useful insight into features and patterns produced by the faults which are incredibly useful in successful diagnosis and classification. Vibrational analysis can be done in time, frequency, time-frequency domains and using wavelet techniques.

Raw data obtained from the sensors is in time domain by default and it can be transformed into frequency domain by using Fourier transform. Hilbert Huang Transform (HHT) transforms the time domain data to intrinsic mode functions which are capable of analysing non-linear and non-stationary signals [14].

#### **2.4.6. Machine Learning**

Machine learning has become a supportive tool and tends to replace traditional fault diagnosis methods as it is data-driven, requires less extensive knowledge of the domain, and less experience. It is also less time consuming as the algorithms monitor the data in real time with minimal interference with the operation of the machine.

A combination of vibrational analysis and machine learning algorithms is a very viable solution for fault diagnosis, especially fault classification as some machine learning algorithms are far better at classifying data than traditional model-based and signal processing techniques [15].



## **CHAPTER 3: METHODOLOGY**

The methodology section describes the systematic approach to research the faulty bearings, the methods to classify these faults and developing machine learning techniques to classify the faults. The chapter is divided into two sections: hardware and software. Hardware will expand on the design and development of the test rig used for data acquisition and software section shall describe the data preprocessing, machine learning algorithms and Convolutional Neural Network architecture created for robust classification of the faults.

Hardware description will delve deep into the details of each component, the reason for choosing such components, and the design philosophy and criteria behind the test rig. Following this, data collection process will be explained, detailing the types of faults and how these faults were induced. Feature extraction techniques applied on the data will also be detailed, highlighting the rationale behind selection of specific features. Finally, the chapter will conclude by giving an overview of the machine learning algorithms used for classification, along with training and evaluation procedures opted for performance assessment.

### **3.1 Test Rig Hardware**

The hardware for this project was designed to simulate the rotatory motion of the bearings in keeping the conditions as close to real world as possible. The test rig comprises of the following components:

#### **3.1.1. DC Motor**

A DC motor is an electric device that converts electrical energy to mechanical energy in the form of rotatory motion. DC motors operate on direct current and usually have high speed but low torque. They must be coupled with a gearbox to increase their capability of handling higher loads, but it decreases their speed limit. Most DC motor operate north of 3,000 RPM at just 12 volts and can go up to 20,000 RPM at 24 volts. To keep track of their speeds, an encoder is coupled with the motor mounted on the back of the rotor shaft. The encoder generates pulses which can be counted by means of electronic devices and using simple mathematical relations, speed can be calculated.

In addition to voltage supply, to provide the flexibility of controlling the speed, 3.3 volts or 5 volts Pulse Width Modulated signal is applied to the motor. The duty cycle of the signal determines the speed.

For our project, we are using 24 volts, brushless DC DSE38BE27-001 motor. It comes with a 100 Pulses per Revolution GP1A30R optical encoder. At 24 volts, its rated speed is 4,400 RPM. It has a good balance of torque and speed.

#### **3.1.2. BTS7960 Motor Driver:**

A motor driver is an electronic circuit that is used to control and manage the operations of a motors. It plays the role of an interface between low-power control signals of a microcontroller and high-power requirements of the motor. It supplies power and pulse-width modulated signal to precisely control the speed and direction of the motor. To ensure safe and efficient operation, they include features such as thermal shutdown, overcurrent protection, and fuses. The circuit

is built using high power transistors or MOSFETs, logic controllers, diodes and other electronic components.

BTS7960 is a powerful and versatile dual H-Bridge configuration motor driver. Due to its high current capabilities of up to 43 amperes, it is widely used in robotics and even electric vehicles as well. It operates in the range of 6 volts to 27 volts and supports up to 25kHz pulse-width modulated signals. It has built in protections against overtemperature, undervoltage, overcurrent, short circuit, and has an overvoltage lockout. For schematic of the driver, refer to the datasheet.

### 3.1.3. Shaft:

A shaft is a mechanical component used for transmission of torque and rotational motion between other components of the machine. Typically cylindrical in shape, shafts are designed to support and transfer torque while maintaining structural integrity under loads and stresses in wide ranges. Shafts are commonly found in engines, gearboxes, differential systems, axle-wheel pairs, etc. They are made from high-strength materials like aluminium and steel to withstand high loads. Shafts may include features like splines, keyways, and tapers to secure gears, pulleys, and other components to facilitate effective and precise mechanical connections.

The design of the entire test rig is built around the shaft, its length and critical speed of the shaft resulting due to its length. Critical speed of the shaft is defined as the speed beyond which it tends to vibrate transversely. First critical speed of the shaft can be calculated using the equation below.

$$\omega = \left(\frac{\pi}{l}\right)^2 \sqrt{\frac{EI}{A\rho}}$$

Since we are concerned with the vibrations produced by the bearings only, any vibrations produced by other components, especially the shaft, would add unwanted noise to the data acquired. So, to avoid whirling of the shaft following critical speeds for a steel shaft of 8 millimetres diameter with various lengths were calculated which are listed in Table 1 below.

Table 1. Lengths and critical speeds for the shaft

Length (mm)	Critical Speed (RPM)
150	2670
175	1957
200	1499
225	1184
250	955
275	792
300	668

A length of 250 millimetres seems suitable as it would provide us a reasonable cushion of 955 RPM and a moderate length of the shaft.

### 3.1.4. Coupling:

Motor couplings are mechanical devices used to connect two shafts together and transmit power between them. They compensate for misalignments, axial movement, and dampen vibrations.

The DC motor used in this project is coupled with the 8 millimetres diameter shaft using a 5x8 millimetres flexible coupling as shown in Figure below.

### 3.1.5. 6205-2RS Ball Bearing:

6205-2RS belongs to the family of deep grooved ball bearings as evident by the digit six. It has a bore of 25mm, outer diameter of 52mm and width of 15mm to 19mm. The suffix 2RS shows that it is sealed with rubber on both sides. These bearings find their application in transmissions, motors, bikes, pumps, etc.

This bearing has been used by several universities for research purposes such as CASE Western Reserve University (CWRU), Paderborn University, Korean Advanced Institute of Science and Technology (KAIST), Huazhong University of Science and Technology (HUST) to name a few. As a result, this bearing has large datasets available openly for researchers all over the world.

### 3.1.6. Bearing Bracket:

Bearing brackets, also called bearing housings, are used to hold and support the bearings within an assembly or machinery. These brackets ensure proper alignment and stability by providing a secure mounting surface for the bearing. They are tailored to accommodate different types and sizes of bearings. They are made from highly durable and strong materials such as cast iron or steel to ensure stability and integrity of the bearing assembly.

The bracket for 6205 bearing used in this project is modular in nature, that is, bearings can be replaced easily by merely taking off the top half of the bracket. The bracket is shown in Figure. Below.

### 3.1.7. ADXL345 Accelerometer:

An accelerometer is a sensor used to measure acceleration forces in various directions. It senses changes in velocity or orientation of the object, giving data on movement, vibration and tilt. Accelerometers are being used in smartphones, fitness trackers, automotive systems, industrial equipment and navigation. Accelerometers are usually based on Micro Electro-Mechanical Systems Technology (MEMS), but modern accelerometers use piezoelectric materials as sensing element as well for better frequency response.

ADXL345 is a MEMS-based accelerometer provided by Analog Devices. It is used in modern smartphones and fitness trackers for measuring vibration patterns (single-tap, double-tap gestures, etc.) and tracking workout activity, respectively. For its well-crafted specifications, which are listed in Table 2 below, it used in this project as the sensor to measure the vibrations from faulty bearings. For more details refer to the datasheet.

Table 2. Specifications of the ADXL345 accelerometer

Specification	Value
---------------	-------

Acceleration Range	$\pm 2g, \pm 4g, \pm 8g, \pm 16g$
Sensitivity	Adjustable (4 mg/LSB to 256 mg/LSB)
Output Data Rate (ODR)	Selectable up to 3200 Hz
Resolution	Up to 13-bit
Operating Voltage	2.0V to 3.6V (Typical 3.3V)
Supply Current (Measurement)	25 $\mu A$ at 100 Hz ODR
Supply Current (Standby)	0.1 $\mu A$
Digital Interface	SPI, I2C
Operating Temperature Range	-40°C to +85°C
Package	Small, low-profile LGA or LCC
Features	Tap/double-tap detection, free-fall detection, low power consumption

Although the range is shown to be up to 16g, the accelerometer is capable of handling shocks of up to 10,000g. The output data rate of 3200 Hz means that 3200 data points are being output every second and the sensor can pick up mechanical frequencies of up to 1600 Hz.

### 3.1.8. ESP32 Microcontroller:

ESP32 is a versatile and feature rich System-on-Chip (SOC) developed by Espressif Systems providing a dual-core processor, a rich set of peripherals with wireless Wi-Fi and Bluetooth communication capabilities making it ideal for Internet-of-Things, home automation and even industrial monitoring applications. With its low power consumption, high processing power, low cost, and extensive and highly supportive development ecosystem, ESP32 enables rapid prototyping and deployment of connected devices. Some main specifications of ESP32 are listed in the Table 3.

For high-speed applications like data logging, ESP32 makes an excellent candidate as it supports speeds up to 80 Mega bits per second (80 MHz) for Serial Peripheral Interface (SPI), 1 Mega bits per seconds (1 MHz) for Inter-Integrated Circuit protocol (I2C) and 5 Mega bits per second (5 MHz) for Universal Asynchronous Receiver-Transmitter (UART). Since the ADXL345 accelerometer outputs data at a rate of 3200 Hz or 3.2 kHz, the I2C protocol is speedy enough to log data without any hiccups.

Table 3. ESP32 specifications

Specification	Value
CPU	Dual-core Xtensa LX6, up to 240 MHz
Memory	520 KB SRAM 4 MB Flash
Connectivity	Wi-Fi 802.11 b/g/n Bluetooth v4.2 + BLE
Interfaces	UART (up to 5 Mbps) SPI (up to 80 MHz) I2C (up to 1 Mbps) I2S, ADC, DAC, GPIO
Operating Voltage	2.2V to 3.6V
Operating Temperature	-40°C to +125°C
Power Consumption	Low-power modes available

### **3.1.9. SD Card Module:**

A Secure Digital card, commonly known as SD card, is a permanent, non-volatile memory device that can provide up to 1 Terabyte of storage space these days. For this project, an SD card module is interfaced with the ESP32 microcontroller through SPI protocol for high-speed data logging. The SD card can store up to 16 Gigabytes of data.

### **3.1.10. Potentiometer:**

A potentiometer is a variable resistor that is used for precise control of electrical resistance. It comprises of a resistive element and a slider, or wiper, which adjusts the output voltage based on the position of the slider. Potentiometers are broadly used in electronics for dimming, volume control, and even position sensing.

A 10 kilo ohm potentiometer is used to control the speed of the motor in this project.

### **3.1.11. OLED Display:**

An Organic-Light Emitting Diode (OLED) is a display that uses organic compounds to emit light and produce vivid graphics and text on a display screen. A 0.96-inch OLED display is being used in this project to display motor speed and other useful information. The OLED display is shown in Figure.

### 3.2. KAIST 6205 Ball Bearing Vibration Dataset

The dataset used for the training and validation of the machine learning is acquired from Korea Advanced Institute of Science and Technology by Jung et al. Their hardware comprised of a SIEMENS three phase, four pole, three horsepower induction motor driven at 380 volts and 60 Hz at 1770 rated rpm, torque meter, gearbox, rotors, hysteresis brake, bearing housing A and bearing housing B. A total of four PCB35234 accelerometers were installed on two housings, in x and y directions.

The bearings were damaged artificially by means of fault seeding method with fault sizes of 0.1 mm, 1 mm and 3 mm, each on inner and outer races of the bearings. This gives us a total of seven classes, six of which are faulty and one is a healthy bearing. The vibration data was logged at a rate of 25.6 kHz. The vibration data is saved in MATLAB file format in measure of g-forces, which is the force equivalent to gravitational pull of the Earth ( $1g = 9.8 \text{ m/s}^2$ ).

This dataset uses standardized NSK bearing (NSK 6205 DDU) with a ball diameter ( $d$ ) of 7.90 mm, a pitch diameter ( $D$ ) of 38.5 mm, contact degree angle ( $\theta$ ) of zero degrees, and the number of balls ( $N$ ) is 9. Therefore, the shaft frequency ( $f_s$ ) is 50.17 Hz, fundamental train frequency (FTF) is 19.94 Hz, ball pass frequency inner (BPFI) is 272.07 Hz, ball pass frequency outer (BPFO) is 179.43 Hz, and ball spin frequency (BSF) is 234.19 Hz [16].

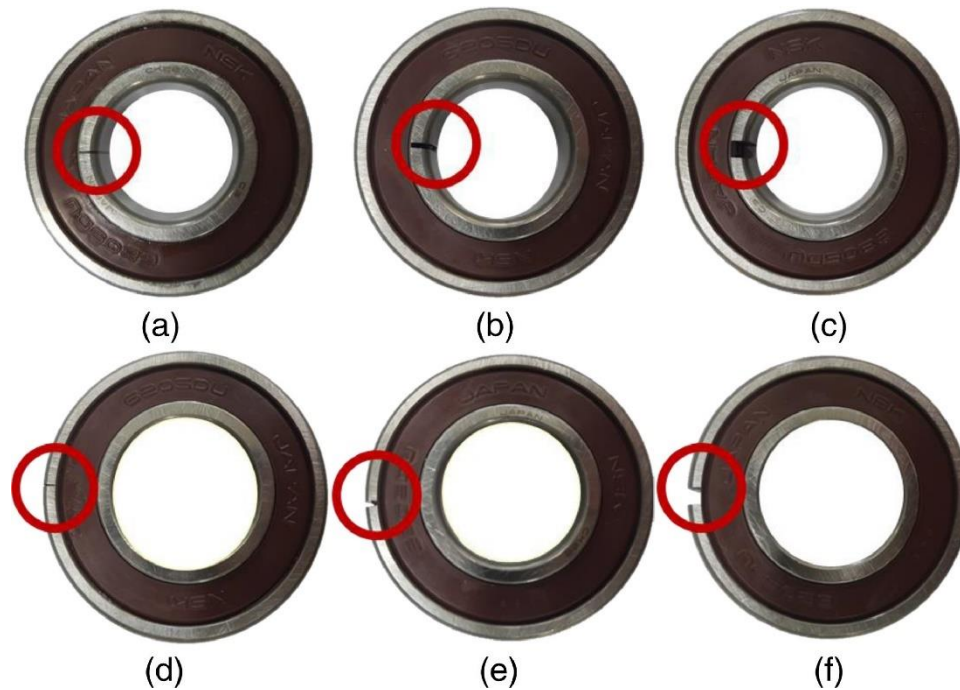


Figure 5. Bearing by crack size: (a) inner race 0.3 mm, (b) inner race 1.0 mm, (c) inner race 3.0 mm, (d) outer race 0.3 mm, (e) outer race 1.0 mm, and (f) outer race 3.0 mm

### 3.3. Feature Extraction

Feature extraction techniques [17] are essential in providing extensive and structured information about the data to the machine learning algorithms for effective usage. The feature extraction techniques we used in our project are detailed next and they are all in time domain.

We decided to extract following six features from two data channels, x and y axes which gives us a total of twelve features.

### 3.3.1. Mean

The most, normally known as the average, is a statistic that gives an image of the middle or common value in a collection. The absolute deviation is the total of values in the dataset divided by the total number of the values in the dataset. The mean is often used to compute how the data that was examined is centrally located while comparing different groups or samples.

$$Mean(\mu) = \frac{1}{n} \sum_{i=1}^n x_i$$

Where:

- $\mu$  is the mean.
- $n$  is the number of observations in the data set.
- $x_i$  represents each individual value in the data set.

### 3.3.2. Kurtosis

Kurtosis sets out the shape of a distribution for the dataset's value. It is an indicator if a curve is pointed or even or flat compared to the normal distribution curve. The high kurtosis means a lot of data in the distribution, and this implies that the statistics are skewed and there are more outliers among the frequency. The kurtosis coefficient lower than 1 implies that the distribution has fewer points around the mean, and therefore, there are fewer outliers. Curtailment can help you get the fact that variability and data are homogeneously distributed. Kurtosis is regarded as one of the most important feature in classifying faulty bearings [18].

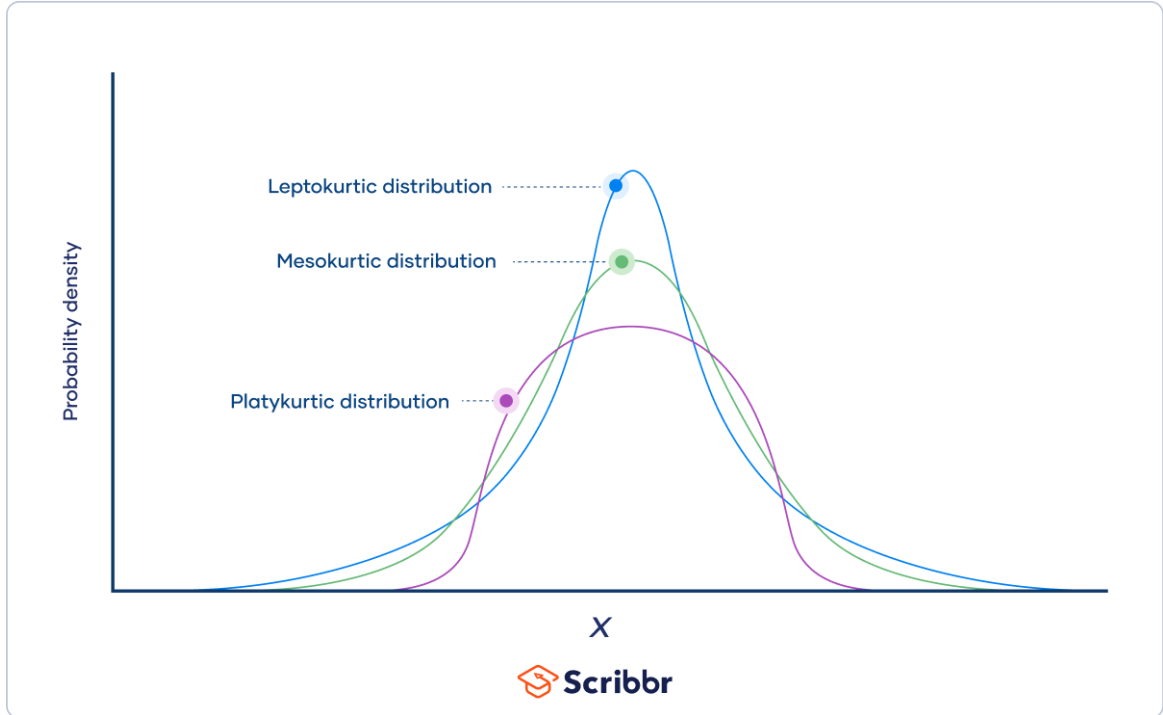


Figure 6. Kurtosis

### 3.3.3. Skewness

Skewness, which is a factor that indicates the degree of the dataset's value distribution, is a concept that measures the asymmetry of data's value in a set. A greater number of positive scores for skewness implies that the data have been skewed to the right, and this is characterized by a larger tail at the end of the distribution on the right of the data line. However, if the coefficient is less than zero, it implies that the distribution is left skewed, since a longer tail is located on the left side of the distribution. Skewness helps our determination about whether our data is skewed or no skewed when around the mean.



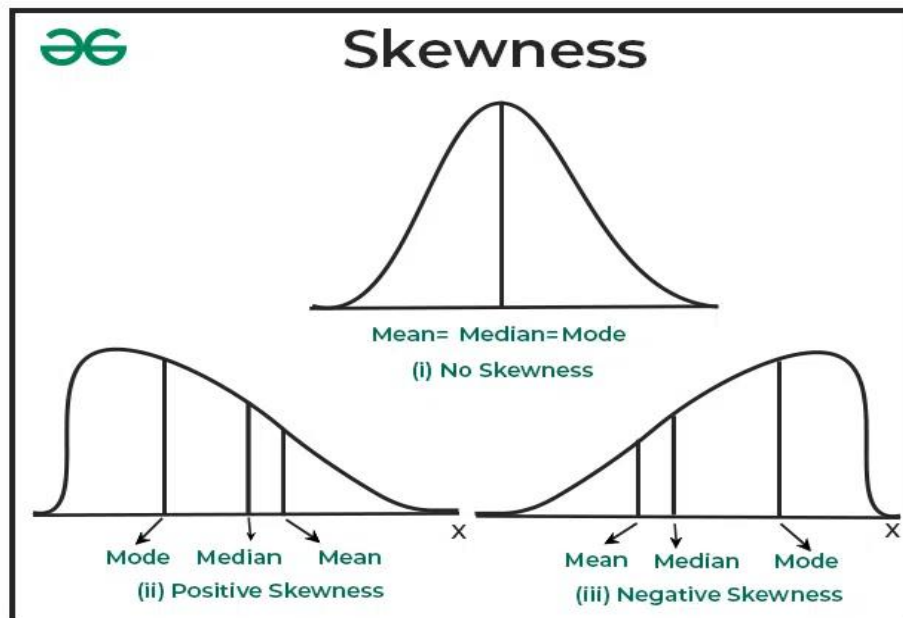


Figure 7. Skewness and its leaning tendencies

### 3.3.4. Root Mean Square (RMS)

Determining the RMS of a dataset, which is simply the square root of the squares' average values, is a fundamental operation in statistics. Within the subject areas of engineering and physics, it is often associated with this "effective" value of a variable quantity, which would account for both positive and negative values. On the one hand, RMS finds its application in data processing and analytical tasks. It provides the measure of either total magnitude of the data, or simply the total intensity.

### 3.3.5. Minimum and Maximum Values

Data set shows the highest value by being represented as max value, and lowest value could be represented as min value. These values are the extremes, and they show where the highs and lows are saved in the data. These limits define the boundaries or limits of the data. By this fact, we can identify the outliers or the data points that are out of the range of the normal statistics that can give out some misleading results or analysis.

### 3.4. Machine Learning Algorithms

Machine learning is the technique through which computer systems learn to predict real world phenomenon based on the data collected. These machine learning algorithms are better performant when they are provided with rich data features. Features can be defined as the description of a data point which explain characteristics of the said data point with more detail. Machine learning algorithms can predict continuous as well as classify data into distinctive types. We have decided to use five machine learning algorithms which are best for classification purposes as our application requires classification of faulty bearings. Classification is simply categorization of data based on previously provided information. The input to a machine learning algorithm consists of the data features and its output is a prediction. The algorithms are explained in detail below for better understanding.

### 3.4.1 Random Forest

Random Forest - a machine learning method, works by linking a variety of decisions trees during the training phase and forming a powerful prediction model [19]. At any tree in the forest the data and type of characteristics will be selected in random way for the tree's training that will help to reduce overfitting and at the same time improve the performance of the generalization. A variety of methods such as taking statements or averages of the trees' findings are used in making predictions - the algorithm can either work for classification problems or it can determine the probabilities of certain events occurring. Random Forest becomes a good choice for many applications involving multidimensional data and noise and/or with missing values. Besides calculating feature importance that can unveil feature relevance and thus key elements that influence the prediction a model finds. They usually take part in such activities like assigning items to classes, regression, and simple data analysis.

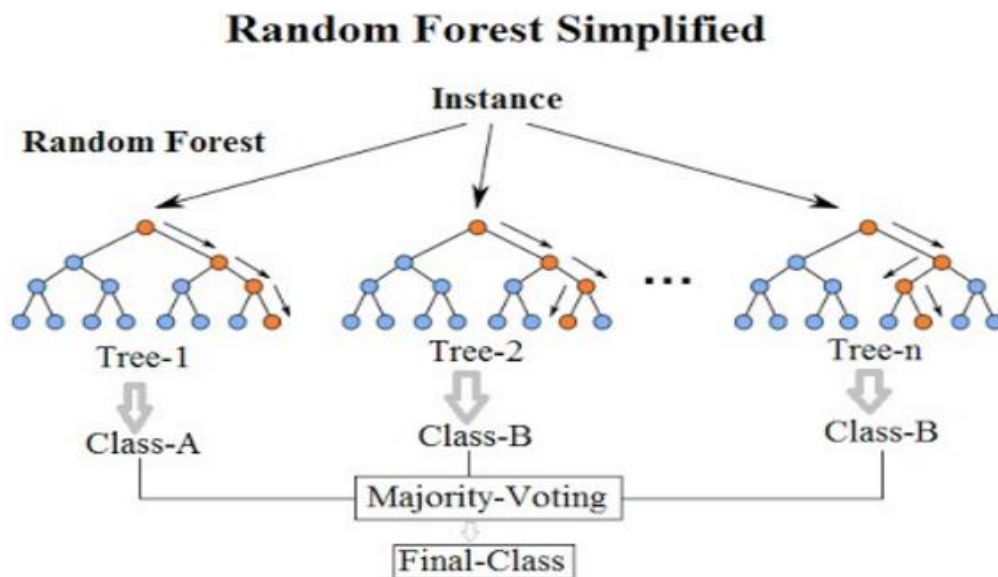


Figure 8. A simple representation of Random Forest

### 3.4.2. Support Vector Machines (SVM)

Support Vector Machines (SVM) are one type of transversal learning models, which belong to the supervised learning branch and are used for classification and regression tasks [20]. SVM is divided into the process whereby the optimal plane is found which divide points with different classes and maximum margin using it. To put it in another way, this margin is the space between the closest distances of these two different classes, which is necessary to make the decisions more effective. In doing so, it can deal with nonlinear as well as linear decision boundaries using kernel procedures, which thus projects the input data into higher-dimensional spaces. SVM is very suitable in the data that has high-dimensional spaces, particularly in those where the number of features is greater than the number of samples. It is perhaps never fitting too closely to the data and is very popular used in tasks such as images, texts, and spotting extraordinary items. One of the most cherished advantages an SVM has is that it fights the process of

overfitting and makes it more suitable for categories of complex data. SVMs are working across many domains as image classification, text sorting and differentiating of anomalies.

The decision boundary in SVM is given by the equation:

$$w^t \cdot x + b = 0$$

where 'w' is the weight vector, 'x' is the input vector, and 'b' is the bias term.

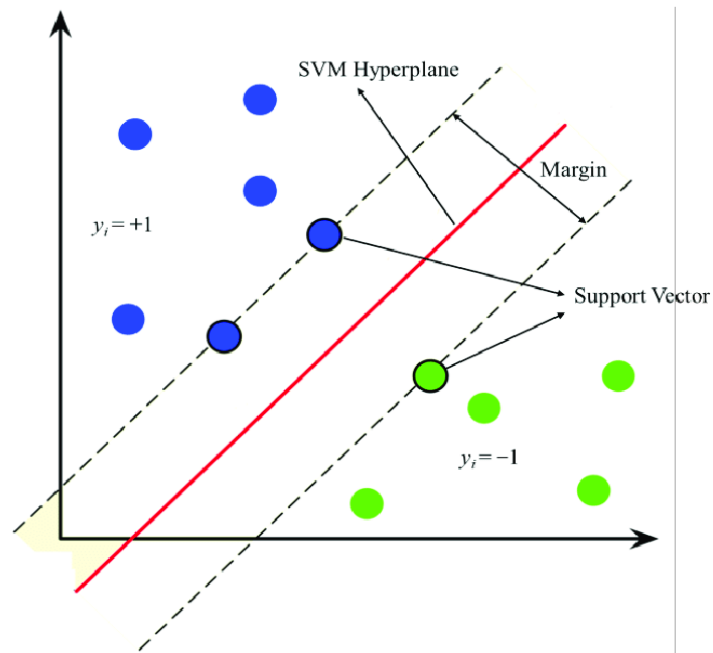


Figure 9. Support Vector Machine and their hyperplanes

### 3.4.3. Logistic Regression

Logistic Regression is a computational approach which is used for the sorting things into two groups, among the computing methods, it is a statistical method for the two category classification tasks, where the output variable exists in categories with only two possible results (yes or no). g., true/false, yes/no, 0/1). The logistic regression is a linear model, which uses the logistic (sigmoid) function to increase the saturation growth of inputs to the corresponding probabilities of a particular class [21]. It produces the likelihood by applying models on input data and select the highest threshold to make prediction. Logistical regression is easy to understand, runs on weak computing systems and works correctly when the decision line between groups is completely straight. It is good performance for the output features and feature input variables that are linear. Logistic Regression has been popular beyond the health sector as in it is applied in healthcare. g.), but also notaries (in document certificate issues), finance (so in project finance), microbiology (in infectious diseases), genetics (in clan research), insurance (in risk assessments) and tourism (in mapping activities). g. Here, the specific competencies clearly state case evidence assessment, credit risk assessment), marketing (as well as others). g. In the coming months, the AI funnel will not only nurture leads but will along with and social sciences. g., survey analysis). On the other hand, binary logistic regression presents the constraint of performing binary classification tasks and a linear decision boundary supposition.

In logistic regression, probability of the positive class is given by the logistic function:

$$p(y = 1 | x) = \frac{1}{1 + e^{-z}}$$

where 'w' is the weight vector, 'x' is the input vector, and 'b' is the bias term.

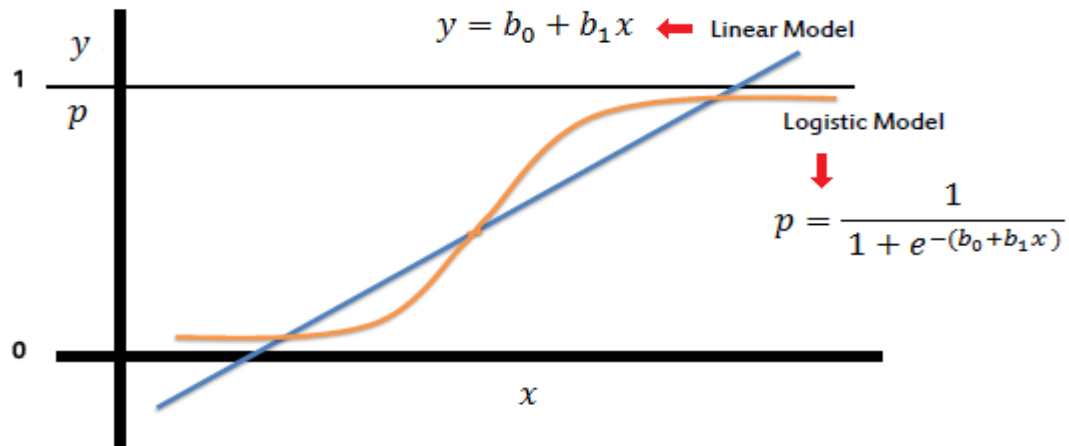


Figure 10. Logistic regression model

#### 3.4.4. K-Nearest Neighbours (KNN)

One of the simplest and powerful methods of classification and regression is KNN (k-Nearest Neighbour) algorithm [22]. In KNN, the prediction is based on the majority class (for classification) or the average value (for regression) of the K nearest neighbours in the training dataset. Therefore, there is a lack of data to train the model when you have a large amount of data from several categories simultaneously. Distance as used in this context refers to the magnitude of how far two points are from each other using the Euclidean metric to determine how equally points go as similar points. And K adds the nuance of the model weighting between proportionality to the data versus not falling into overfitting. KNN doesn't concern any suppositions about how the information is spread out it only considers the nearby point for a future prediction. It is within the scale of medium to large data sets and effective with derailed data. KNN is a quite easy to grasp and work with algorithm which is probably one of the main canons produced for being a basic machine learning task and baseline model. Though, in contrast, the KNN model slowdown in terms of prediction time—as compared to the model-based approaches, KNN algorithm is sensitive to the choice of distance metric and can suffer from the curse-of K.

## K Nearest Neighbors

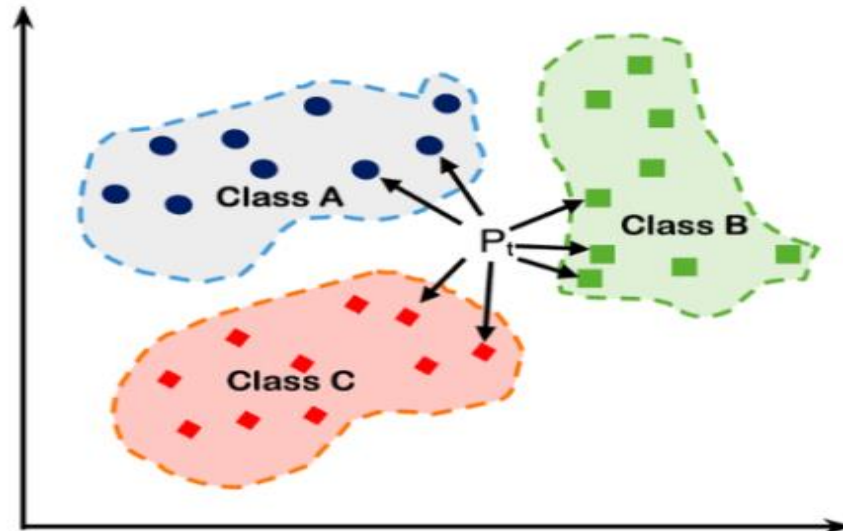


Figure 11. A visual representation of K- Nearest Neighbours

### 3.4.5. Multi-Layer Perceptron (MLP)

The Multilayer Perceptron (MLP) is one of the most widespread types of neuro networks which have several hidden layers in addition to the input layer. Without rules, there would be no picture. Each "thinking unit" or which is exactly called "neuron" then performs a weighted sum of inputs. But, after this, a special rule (like a light switch turning on or off) is used to decide how active it should be. In this way, the data are passed through the layers head to tail, thereby, MLP finds relations in multi-layered, complex data. MLP functions well if it is to be applied in a sort to organize into categories, make predictions, or spot the patterns. MLPs (Multi-layer Perceptron) are used for supervised learning problems such as classification & regression [23]. Every MLP neuron accumulates DA with various weights and adds them with a special function that indicates how much it needs to be activated. g., we want to build neural networks with layers of nodes (sigmoid, ReLU, etc.), and feed the obtained result as input for the subsequent layers. Using MLPs, one can learn different complex non-linear relationships in data. Because of this, the function can be approximated by a single hidden unit if there are enough of them. These algorithms work by backpropagating the error through all the layers to the input layer, and by using the gradient descent optimization algorithm the increase in accuracy and decrease in errors is achieved. They can approximate any continuous function by means of a network even the data and training if they have enough. MLPs researchers have gained success in domain such as image recognition, natural language processing and financial forecasting. On the contrary, the training and using of MLPs require substantially large amounts of computational resources, and they could easily get fitted if not properly developed.

The output of a neuron in an MLP is calculated using the formula:

$$y = f(w^t \cdot x + b)$$

where 'f' is the activation function (e.g., sigmoid or ReLU), 'w' is the weight vector, 'x' is the input vector, and 'b' is the bias term.

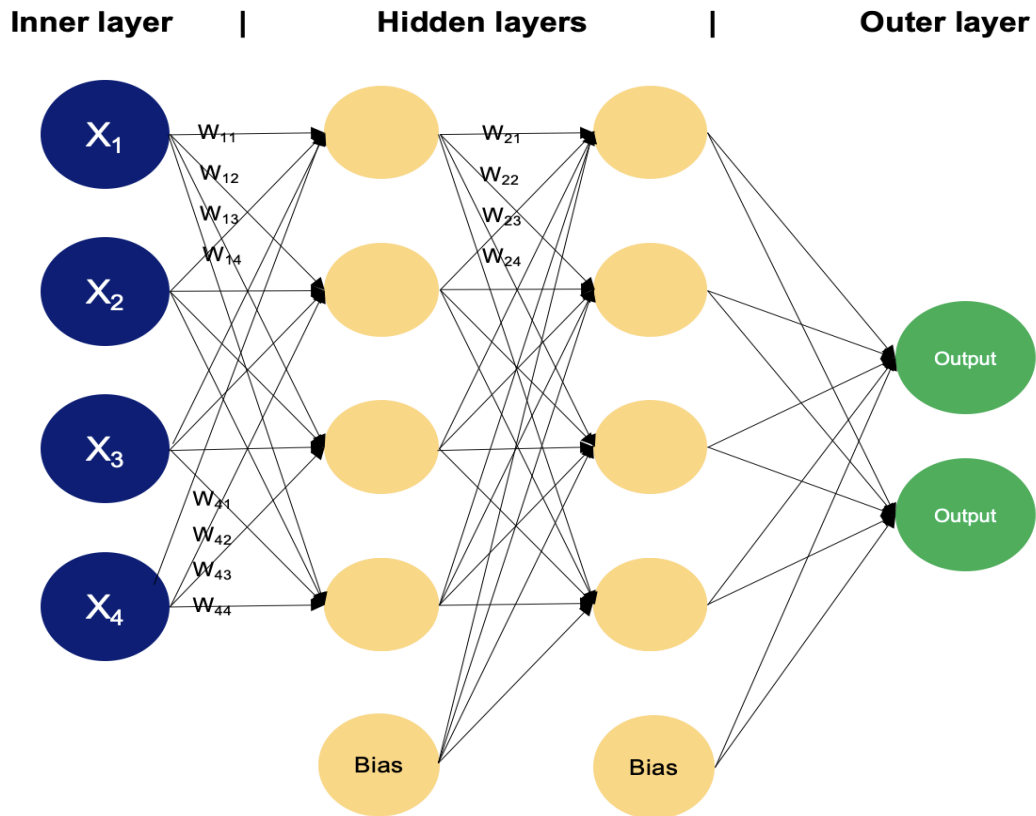


Figure 12. Multi-Layer Perceptron and their hidden layers

## **Chapter 4: Results**

The five machine learning algorithms were trained on the KAIST dataset, and their performance was judged based on the accuracy of classification. Classification reports and confusion matrix of the respective models are also provided to give more meaningful insights into performance of the algorithms.

Confusion matrix provides detailed information about the number of data points the model has managed to classify correctly. The algorithms are trained to classify the bearings into seven categories, six of them being faulty bearings and one being healthy. The fault types have been stated earlier in section 3.2.

Machine learning algorithms are implemented using Scikit-learn's python library. Data was manipulated using Pandas, Numpy, and Scipy and Seaborn was used for generating confusion matrices.

## 4.1. Random Forest Classification

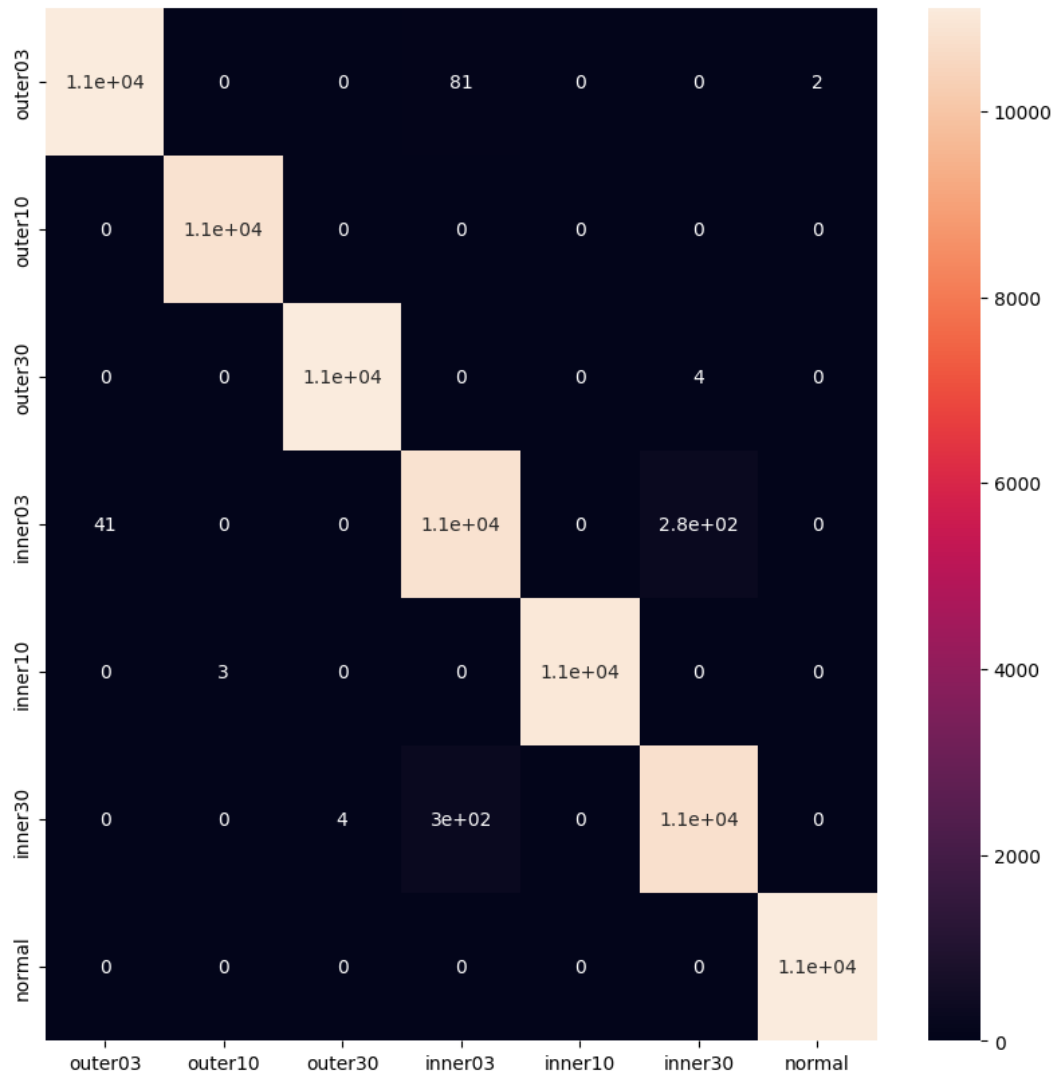


Figure 13. Confusion matrix of the Random Forest classifier



```
Accuracy: 0.9906845138117264

Classification Report:
      precision    recall  f1-score   support

0         1.00      0.99      0.99     11187
1         1.00      1.00      1.00     10823
2         1.00      1.00      1.00     11071
3         0.97      0.97      0.97     11145
4         1.00      1.00      1.00     10992
5         0.97      0.97      0.97     11088
6         1.00      1.00      1.00     11092

 accuracy          0.99      77398
 macro avg         0.99      0.99      0.99      77398
 weighted avg      0.99      0.99      0.99      77398

Cross Validation: [0.99086353 0.9905313 0.99172181 0.99039287 0.99042029]

Mean accuracy: 0.9907859598565245
```

Figure 14. Random Forest classification report

Random Forest classified the bearing faults with an accuracy of 99.07 percent and was the best performant model.

## 4.2. Logistic Regression Classification

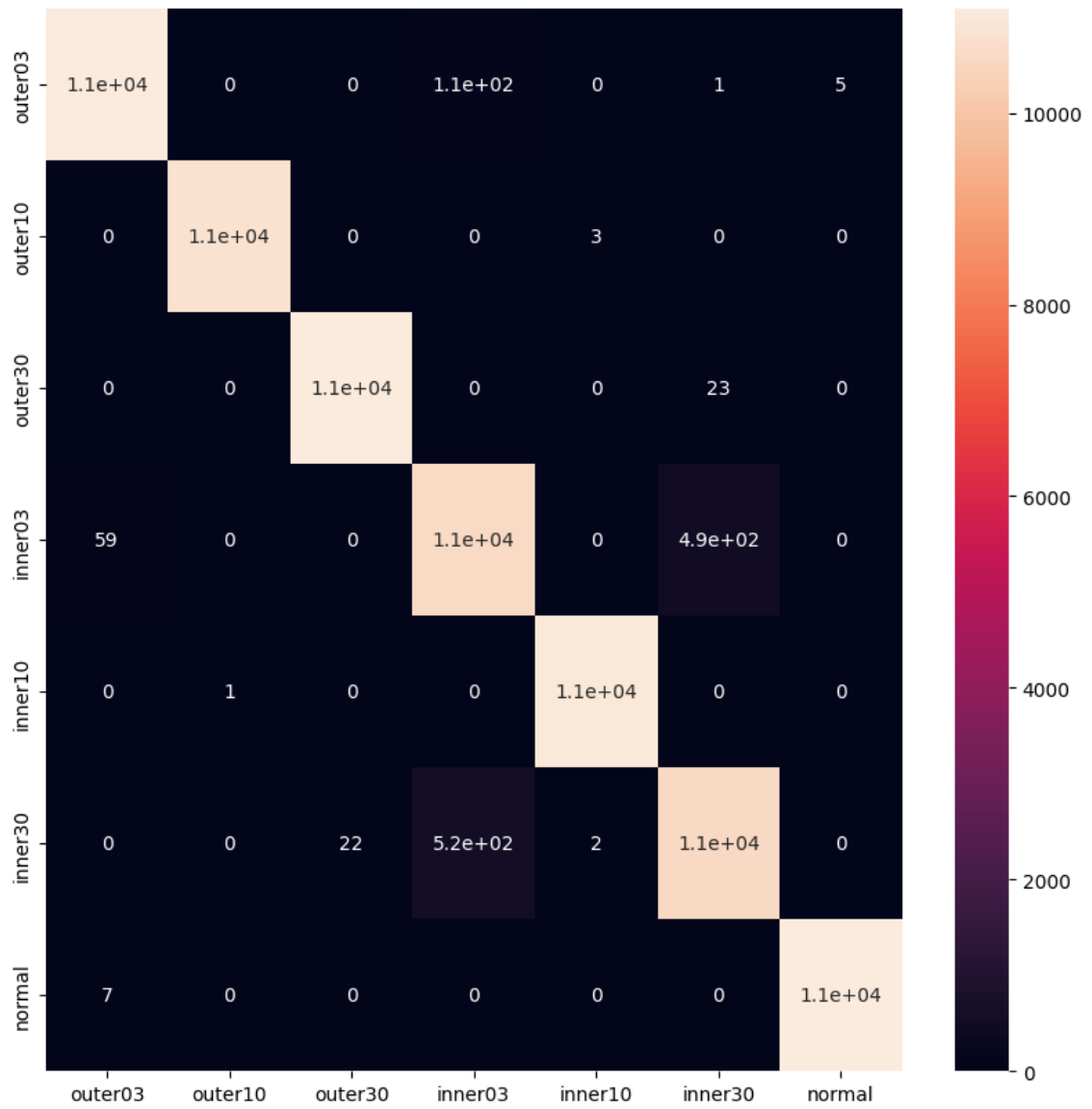


Figure 15. Logistic Regressor's confusion matrix

Accuracy: 0.9839272332618414

Classification Report:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	11187
1	1.00	1.00	1.00	10823
2	1.00	1.00	1.00	11071
3	0.94	0.95	0.95	11145
4	1.00	1.00	1.00	10992
5	0.95	0.95	0.95	11088
6	1.00	1.00	1.00	11092
accuracy			0.98	77398
macro avg	0.98	0.98	0.98	77398
weighted avg	0.98	0.98	0.98	77398

Cross Validation: [0.98455107 0.98399734 0.98482793 0.98341593 0.98308323]

Mean accuracy: 0.9839750994392269

Figure 16. Logistic Regression classification report

Logistic regressor managed to classify at a rate of 98.39 percent.

### 4.3. K-Nearest Neighbour Classification

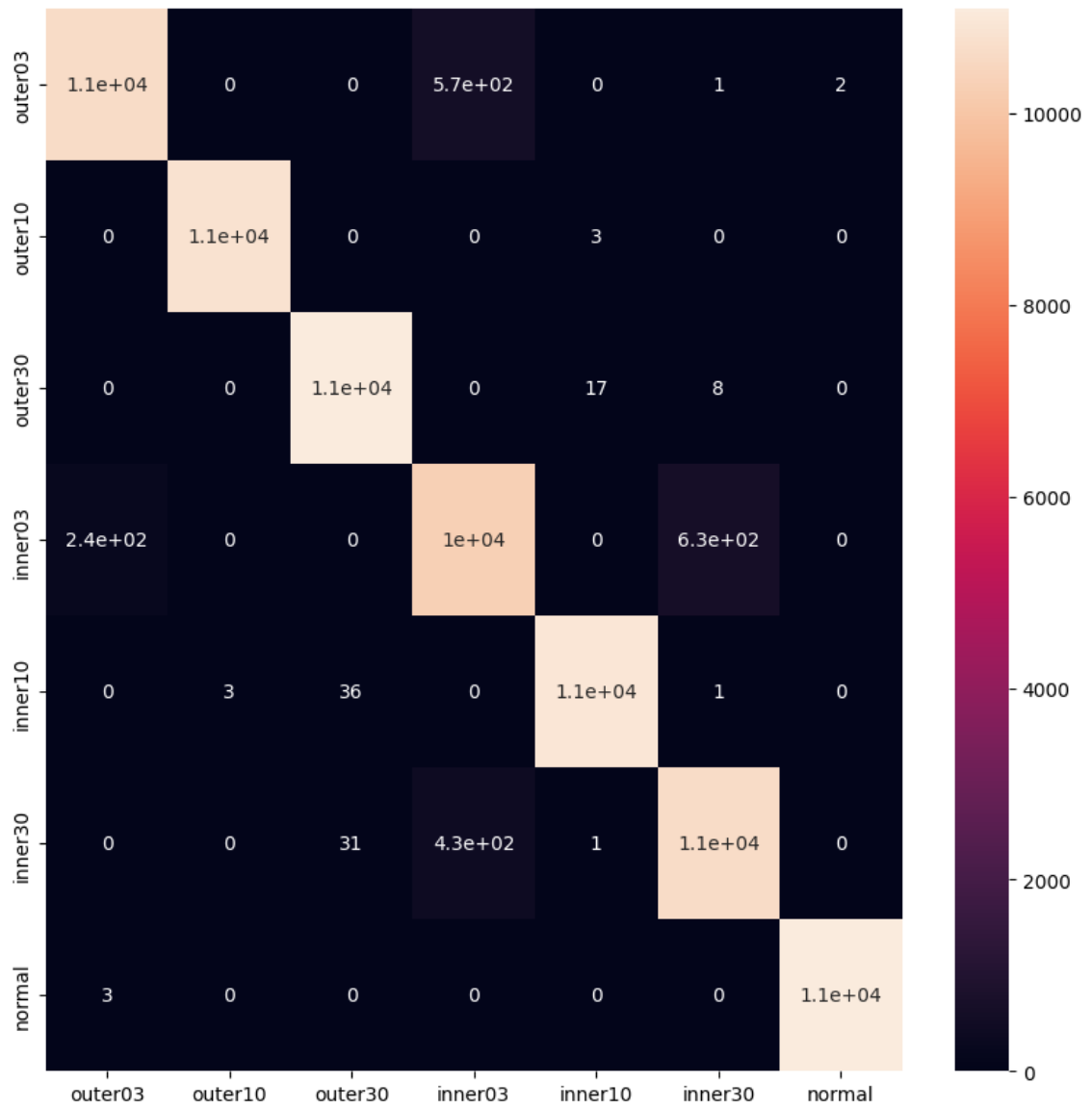


Figure 17. KNN confusion matrix

```
Accuracy: 0.9745600661515802

Classification Report:
      precision    recall  f1-score   support

0         0.98        0.95        0.96     11187
1         1.00        1.00        1.00     10823
2         0.99        1.00        1.00     11071
3         0.91        0.92        0.92     11145
4         1.00        1.00        1.00     10992
5         0.94        0.96        0.95     11088
6         1.00        1.00        1.00     11092

 accuracy          0.97     77398
 macro avg         0.97     77398
weighted avg         0.97     77398

Cross Validation: [0.97436252 0.97422409 0.97563609 0.97355962 0.9731159 ]

Mean accuracy: 0.9741796457039115
```

Figure 18. K-Nearest Neighbour classification report

K-Nearest Neighbour algorithm managed to classify results faults with an accuracy of 97.41 percent.

#### 4.4. Multi-Layer Perceptron Classification

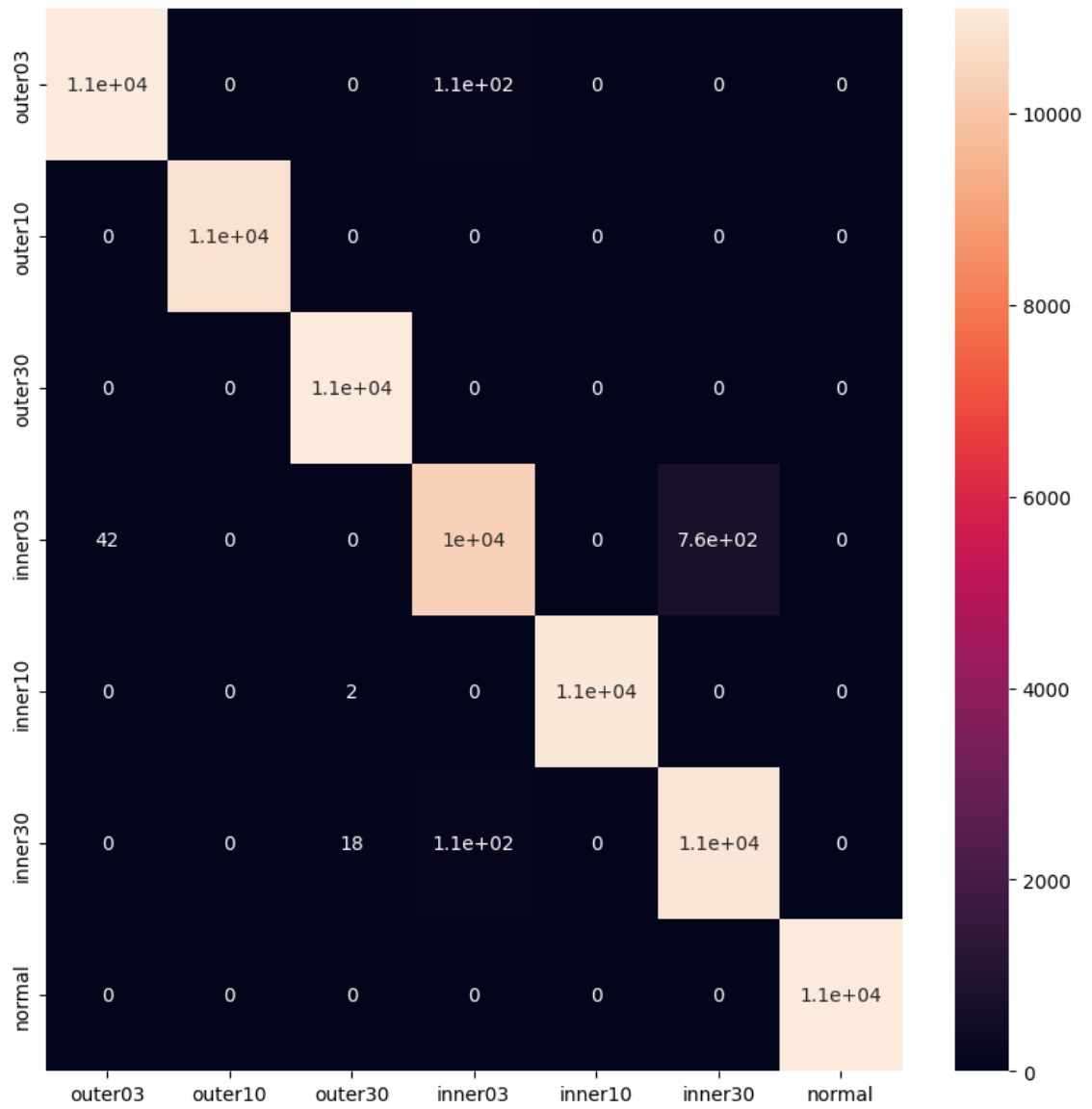


Figure 19. Multi-Layer Perceptron confusion matrix

```
Accuracy: 0.9865888007442053

Classification Report:
      precision    recall  f1-score   support

0         1.00      0.99      0.99     11187
1         1.00      1.00      1.00     10823
2         1.00      1.00      1.00     11071
3         0.98      0.93      0.95     11145
4         1.00      1.00      1.00     10992
5         0.94      0.99      0.96     11088
6         1.00      1.00      1.00     11092

 accuracy          0.99     77398
 macro avg         0.99     77398
weighted avg         0.99     77398

Cross Validation: [0.98958997 0.98731969 0.98986683 0.98848252 0.98571349]

Mean accuracy: 0.9881944999224489
```

Figure 20. Multi-Layer Perceptron classification report

MLPC classified at a rate of 98.81 percent.

## 4.5. Support Vector Machine Classification

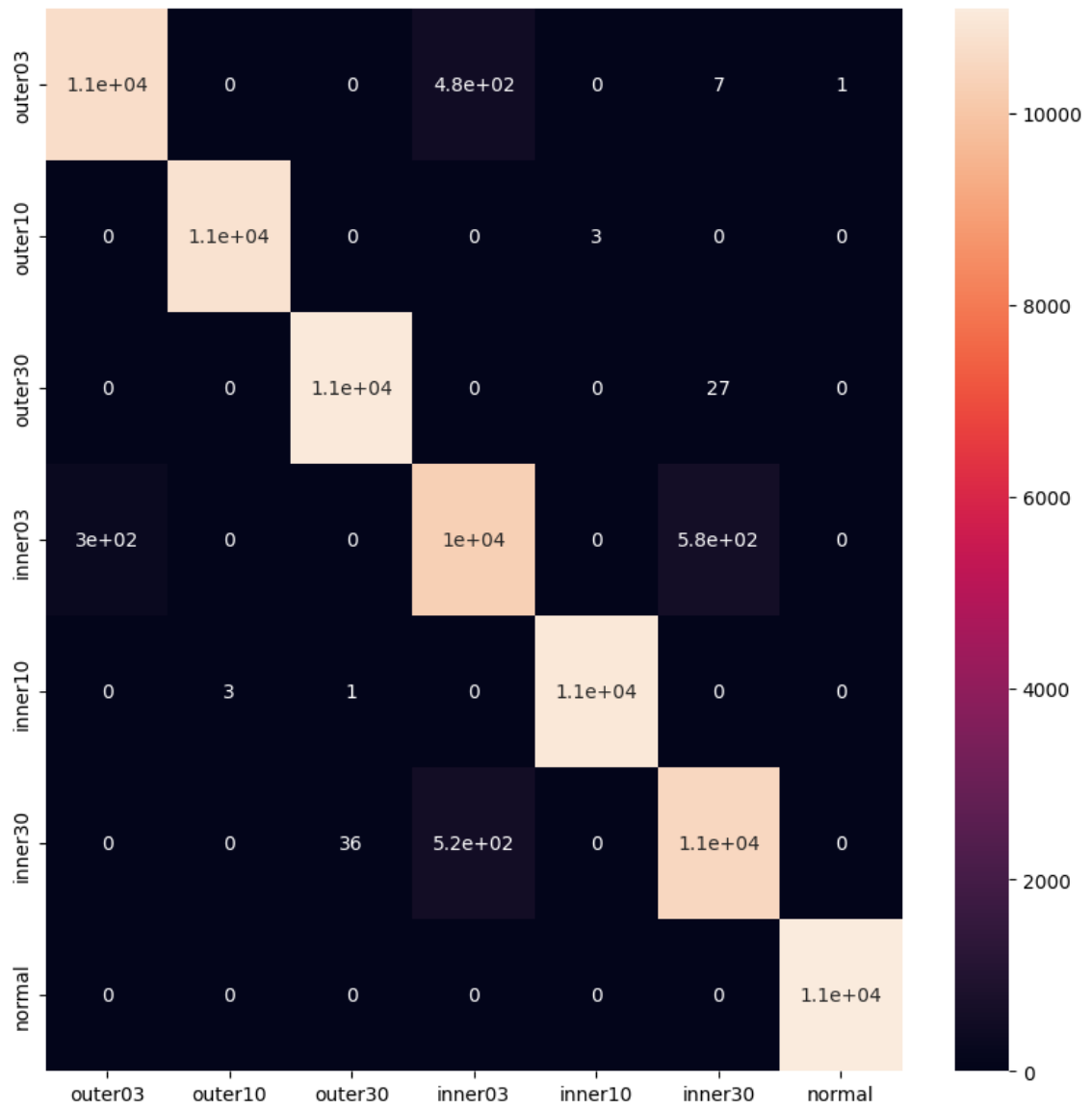


Figure 21. Support Vector Machine confusion matrix



```

Accuracy: 0.9746505077650586

Classification Report:
      precision    recall  f1-score   support

0         0.97      0.96      0.96     11187
1         1.00      1.00      1.00     10823
2         1.00      1.00      1.00     11071
3         0.91      0.92      0.92     11145
4         1.00      1.00      1.00     10992
5         0.95      0.95      0.95     11088
6         1.00      1.00      1.00     11092

 accuracy          0.97      77398
 macro avg         0.97      0.97      0.97      77398
 weighted avg     0.97      0.97      0.97      77398

Cross Validation: [0.9740026  0.97386417 0.97505468 0.97325507 0.97272828]

Mean accuracy: 0.9737809614235141

```

Figure 22. Support Vector Machine classification report

SVM predict faults with a mean accuracy of 97.37 percent which was the lowest performance out of all the five algorithms.

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