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COLLEGE OF SCIENCE AND TECHNOLOGY

AFRICAN CENTRE OF EXCELLENCE IN INTERNET OF THINGS

Monitoring Three Phase Induction Motor Performance for Predictive maintenance Using IoT and ML

A dissertation Submitted in partial fulfilment of the requirements for the award of

MASTERS OF SCIENCE DEGREE IN INTERNET OF THINGS: WIRELESS SENSOR NETWORKING

Submitted By

Romeo BYIRINGIRO (REF.NO: 221030486)

June, 2024

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Romeo BYIRINGIRO (REF.NO:221030486)

Supervised by:

- Dr. Gaspard HARERIMANA

- Dr. Martin KURADUSENGE

June , 2024

Declaration

I BYIRINGIRO Romeo, Master ‘student from African Center of Excellence in Internet of Thing, at University of Rwanda. I declare that this research thesis is my own original work and it has never been presented before anywhere in the world.

Names: BYIRINGIRO Romeo

Ref: 221030486

Signed: ………………………….

Date: ……/……/……

Bonafide certificate

This is to certify that this submitted Research Thesis work report is a record of the original work done by **Romeo BYIRINGIRO** (**Ref. Nu: 221030486**), MSc. IoT-WISNET Student at the University of Rwanda / College of Science and Technology / African Center of Excellence in Internet of Things, the Academic year 2021/2023.

This work has been submitted under the supervision of ***Dr Gaspard HARERIMANA*** and ***Dr Martin KURADUSENGE***

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Abstract

Fault detection and performance monitoring are vital on 3-phase induction motors for early detection and preventing serious infrastructure damage in manufacturing environments. They improve safety, credibility, and availability as well as lower the cost of maintenance for modern industrial systems. Despite the fact that it is affordable, dependable, and sturdy, 3-phase induction motors have been widely used in many industrial operations. However, monitoring and fault detection alone for 3 phase induction motor, may not be helpful on how to efficiently correct the fault and can result on long downtime for a technician to easily find solution. This system is a method for doing predictive maintenance by utilizing IoT sensors and ML to monitor the performance of a three-phase induction motor and provide possible quick solution when a certain fault is detected. The system is made up of sensors attached on the motor to detect temperature, vibration, speed, current, and voltage parameters. After sensing, they send the data to an Arduino Uno for real time analysis. The data is run through the ML algorithms to forecast the motor's performance and identify any irregularities or defects and provides a quick guide to correct it. This system makes it possible to identify potential motor problems before they escalate and require costly downtime and repairs. For potential areas for development, the data gathered by the sensors could be used to improve the performance of the motor. A three-phase induction motor was used to test the proposed system, and the findings was to demonstrate the effectiveness in tracking the motor's operation, spotting irregularities and suggest a solution. In conclusion, the method for tracking a three-phase induction motor's performance using IoT and ML was a used as a tool for predictive maintenance that saves maintenance expenses, increase motor longevity, increase accuracy, and decrease downtime.

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List of symbols

A: Amperes

Cm: Centimeter

GND: Ground terminal

I: Current

Khz: Kilohertz

Kw: Kilowatts

mA: Milliampere

Mm: Millimeter

^{o}c: Celicius Degree

Rx: Receiver

t: Temperature

Tx: Transmitter

V: Volt

List of Acronyms

AC: Alternative Current

AI: Artificial Intelligence

ARIMA: Auto Regressive Integrated Moving Average

DC: Direct current

IDE: integrated development environment

IM: Induction Motor

IoT: Internet of Thing

KNN: k-nearest neighbors

LED: Light Emitting Diode

MCU: Micro controller Unit

ML: Machine Learning

MLR: Multiple Linear Regression

MQTT: Message Queuing Telemetry Transport

OLED: Organic Light Emitting Diodes

PCB: Printed Circuit Board

RFID: Radio Frequency Identification Device

RPM: Revolution Per Minute

SCADA: Supervisory control and data acquisition

SLR: Simple Linear Regression

SVM: Support Vector Machine

USB: Universal Serial Bus

Wi-Fi: Wireless Fidelity

Chapter 1: INTRODUCTION

1.1 General overview

The most often utilized electrical machines are induction motors[1]. Despite the fact that induction motors are extremely dependable, require little maintenance, and have a reasonably high efficiency, they are prone to several electrical and mechanical failures[2]. However, their unanticipated downtime or sudden breakdown can result in significant output losses, elevated maintenance costs, and operational interruptions. It is then essential to find errors when they are still being developed. If a fault is not found early on, it could turn catastrophic and do serious harm to the machine[1] [2].

There are three general methods that industries employ to maintain their equipment, include: (1) Reactive maintenance, which is related to equipment failures and involves making repairs after an asset has already broken down; (2) Preventive maintenance, which is carried out at regular intervals to avoid equipment breakdowns and unplanned outages; it is based on knowledge of the asset's anticipated lifetime; and (3) Predictive maintenance, which is based on monitoring the performance and condition of the asset to determine the ideal time to maintain it before it breaks down[3]. Indeed, Predictive maintenance strategies have gained popularity as a solution to address these issues and move away from conventional reactive maintenance techniques. Predictive maintenance uses real-time data gathering and analysis to continuously monitor the health of the equipment, enabling the early identification of anomalies and probable problems.

Induction motor fault distributions between 0.75 kW and 150 kW have recently been identified through research, along with possible scenarios and diagnostic procedures[4]. Induction motor problems can generally be divided into four categories. 1: rotor bar (7%), stator winding (21%), bearing fault (69%), and shaft/coupling and others (3%). About two-thirds of problems were caused by bearings, and one-fifth by stator windings[5].

Numerous characteristics, including current, vibration, temperature, and speed, must be monitored in order to ensure the reliable and efficient operation of an electrical machine[6]. With temperature, vibration, current and speed sensors could be used to detect anomaly vibration, non-rated temperature, speed and current values, which are the source of some electrical such as short circuit that takes a place in stator windings, overloading, imbalance in speed and mechanical faults like rotating elements, such as bearings faults, gearboxes, or rotors that cause malfunctioning of machine and bad speed of three phase induction motor[5].

This study focuses on creating and implementing a predictive maintenance system for three-phase induction motors based on IoT and ML for usage in industrial settings. Data collection from sensors measuring vital characteristics like current, speed, temperature, and vibration is made easier by the incorporation of IoT. ML techniques, enable the simultaneous optimization of maintenance plans and the prediction of impending motor failures. It also aims to improve motor reliability, decrease downtime, and optimize maintenance costs by using the power of IoT and ML, thereby raising the general productivity and efficiency of industrial processes. Additionally, this research advances the use of IoT and ML in industrial maintenance, providing a chance for revolutionary advancements in predictive maintenance techniques and their widespread implementation across a range of industrial sectors.

1.2 Background and motivation

Industrial machinery and apparatus that were installed ten to twenty years ago are becoming archaic as technology advances into the twenty-first century[7]. Previously, the motor's performance was checked manually[7].

Internet plays a vital part in the advances in technology that have grown quickly over the last several years[8]. We are now capable to connect everything, including embedded elements and sensors, with the Internet of Things in order to share data via other systems and devices. The most recent technology to operate and monitor a motor from a distance is the Internet of Things (IoT) [8]. Practically speaking, the IoT connects machines and human beings. Data collection and distribution are beneficial. Each induction motor needs to be frequently inspected in order to avoid breakdowns[8].

Artificial intelligence (AI) approaches have replaced traditional methods for electrical machine monitoring and defect detection in recent years[9]. Predictive maintenance on induction motors in industrial settings will involve machine learning significantly. Machine learning algorithms are able to spot trends and anomalies which can be used to anticipate and stop motor failures before they happen by combining historical data, real-time monitoring, as well as advanced analytics[9].

Monitoring induction motor characteristics including the like of temperature, speed, vibration, and power consumption has always been a top priority in industries[8]. Since the analysis of data found can help in fault detection like electrical faults like stator winding fault as well as motor overloading, mechanical faults such as overheating and strong vibration that are present frequently on induction motor in industries[10] [11].

Currently the way used to monitor the induction motor performance is using SCADA system and manual checking which is very expensive, it does not allow online monitoring and it is complex to study and implement it easily. That is why using IoT sensors to monitor motor performance will be low cost and easily to deploy in smart factories[12].

Many research had conducted research on predictive maintenance of induction motor using IoT and ML[10] [11] [12]. However, there were no suggestion on how to quickly correct the fault, it leads to longtime of downtime which increase the cost of maintenance and leads to production loss. The proposed system will predict the fault based on real time data and suggest the way of fault healing to induction motor user.

1.3Problem Statement

Due to their reliability and efficiency, three-phase induction motors are frequently utilized in numerous industrial applications. However, as they age, their performance might deteriorate, which can cause sudden breakdowns and expensive downtime as well as repair costs. In order to enable predictive maintenance, it is necessary to establish an effective and trustworthy system for tracking the performance of three-phase induction motors.

The conventional method of motor maintenance focuses on planned maintenance or prompt repairs in the event of a failure. This strategy increases the possibility of unplanned downtime as well as production losses in addition to being time-consuming. Additionally, it ignores the motor's performance & condition in real time.

The development of machine learning (ML) as well as the Internet of Things (IoT) offers the chance to completely alter how three-phase induction motors are maintained. It is feasible to get real-time data on different motor properties, such as temperature, vibration, current, and power consumption, by utilizing IoT-enabled sensors. Then, ML systems can examine this data to find patterns, abnormalities, and trends connected to declines in motor function and then suggest the quick guidance to user on how to correct the issue.

The development of an integrated system that integrates IoT and ML methods for tracking three-phase induction motor performance would greatly improve industrial settings' maintenance procedures. A proactive and economical maintenance strategy would result, lowering unexpected downtime, boosting productivity, and extending the lifespan of important equipment.

1.4Study Objectives

An IoT and machine learning (ML) based predictive maintenance system for tracking three-phase induction motor performance is the goal of the project. The study's goals can be divided into two categories: general goals and specific goals.

1.4.1 General Objective

The main aim is to monitor the three phases of induction motor performance for predictive maintenance using IoT and ML for Enhancing operational efficiency and reducing downtime.

1.4.2 Specific Objectives

The objectives include:

1. Developing IoT performance monitoring system of three phase induction motor.
2. Acquiring data from the installed IoT platform.
3. Establishing predictive analysis.

1.5Study Scope

The purpose of this study is to create and deploy a predictive maintenance system based on IoT and ML for tracking three-phase induction motor performance in industrial environments. The study includes the collecting of data from sensors that measure current, speed, temperature, & vibration, as well as feature extraction with preprocessing. It entails developing and incorporating a model that can spot irregularities and forecast motor failures. To enable real-time data transfer and analysis, the system will be implemented in an IoT framework. The analysis also involves maintenance schedule optimization based on past performance data and anticipated failure probabilities. In order to increase motor dependability, save maintenance costs, and boost overall industrial output, experimental experiments on actual three-phase induction motors of between 0.75 kW and 150 kW rated power that will be used to validate and evaluate the system's performance.

1.6Significance of the Study

This study is essential because it addresses the urgent need for three-phase induction motors in industrial settings to have effective predictive maintenance. The created predictive maintenance system allows real-time monitoring of motor performance through the integration of IoT and ML technologies, enabling prompt detection of anomalies and probable failures.

The use of the system will improve motor dependability, decrease downtime, as well as optimize maintenance schedules, all of which can boost industrial output and save a lot of money. This research contributes to increased operational effectiveness, safety, and sustainability in industrial processes and paves the way for broader applications of IoT and ML-based predictive maintenance in various industrial sectors by having the potential to reduce unscheduled downtime and prevent critical motor failures.

1.7 Organization of the Study

The research thesis document is organized as follows:

Chapter one gives an introduction of the research which includes the general overview of the research, the background of the study and its motivation, study objectives, hypothesis of the study, significant of the study, problem statement, scope and the conclusion.

Chapter two discusses related researches that were carried out before, existing gaps and how this research is going to improve and fill the existing research.

Chapter three gives the research methodology. It gives an overview of the research methods that will be used in this work. Tools and steps used in the study are also outlined.

Chapter four presents the system analysis and design

Chapter five provide results and analysis and discussions.

Chapter six presents a conclusion and suggest some recommendation and outline suggestions for the future work.

1.9 Conclusion

The research has provided an overview of the study, the study's background and motivation, a detailed problem statement, the study's scope and limitations, the study's organizational structure, and the researcher's motivation for undertaking the study in this chapter.

CHAP II. Related Literature

2.1 Overview

The brief examination of relevant studies is covered in this chapter. This comprises the issue that was looked at by earlier researchers, the technical solution that was suggested, the methodology approach used, and the findings. After some time, the gaps in the prior similar and related studies were discovered, and these serve as both the justification and the driving force of the current investigation[13].

2.2 Introduction

Workhorses in many different industrial areas are induction motors. Pumps, conveying systems, machine tools, centrifugal machines, presses, elevators, and packing equipment are among the common uses for induction motors[14].Most of the Induction motors are susceptible to mechanical, thermal, and electromagnetic stressors during operation, much like any other electromechanical device. Examples of these stresses include vibration[15]. If the motor is not properly maintained, it will eventually wear down and have a disruptive failure[16]. Due to unscheduled corrective repairs and production downtime, failures result in significant financial and operational losses[17]. Consequently, induction motor maintenance receives a lot of attention.

The predictive maintenance strategy, also known as condition monitoring, has gained acceptance in the industry in recent years [18]. In order to assess the real state of the equipment, predictive maintenance necessitates constant sensors monitoring[19]. There are two ways to think about fault detection and diagnosis systems: model-based methods and data-driven methods[20]. According to the primary components of a machine, stator related faults, rotor related faults, bearing related faults, and other faults induction machine failure surveys have identified the most frequent failure mechanisms in induction machines[21]. Temperature, current, speed, as well as vibration are the main monitoring parameters that are examined in this literature review of the state-of-the-art approaches, technology, and critical parameters in predictive maintenance for three-phase induction motors[22]. In predictive maintenance, improved method of maintenance management that seeks to anticipate equipment breakdowns before they happen is the use of machine learning[23] . It is in the regards that three phase induction motors can benefit greatly from predictive maintenance when Internet of Things (IoT) sensors and machine learning (ML) are used.

In the following related works, the recent researches on IoT sensors with ML to predict the faults before they occur have been covered. Many ML learning models have been identified and studied, their methods have been elaborated as well as the gap in their findings.

2.3 Related works

In [24], AI Techniques for Three Phase Induction Motors Fault Detection were stated and studied on, where by the aim was to enhance the loss function, identify the induction motor failure, and amplify the less powerful vibration signal. The construction of an efficient classification ensemble was discussed in the work, and it was applied to situations that call for online monitoring as well as a subsequent diagnostic level[24]. Destructive tests were performed for various rotor severities in an induction motor that is fed through an inverter along the line while experimentation[25]. Data from the current signal was converted into pertinent data that helps to compile representative features of the motor status. However, real time performance monitoring and fault prevention model as well as faults recommender model in this work by using optimized IoT sensor were not worked on.

In [26], Approaches for vibration analysis along with motor current signature analysis have been utilized to detect and categorize defects in high-powered induction motors. Both the time-domain stator current signals as well as vibration signal of the induction motor have been subjected to the fast Fourier transform. The frequency spectrum of both vibration & motor current signals from healthy and ill motors has been compared[27]. The created system offered a realistic and reasonably priced replacement for the traditional off-line induction motor condition surveillance methods. However, there no preventive advise and the signal that were used to achieve the objectives were inefficient to optimize motor faults detection such as real time IoT sensor like current, voltage and temperature sensor which are essential for electrical fault detection for induction motor[28].

Using a case study from the manufacturing sector, IoT based predictive maintenance of Manufacturing Sector explores and puts into practice IoT based predictive maintenance [29]. The study talks about Industry 4.0 and a networked IoT-based sensor environment where devices can communicate and share data. Manufacturing companies can use sensor data to forecast the failure of their machines. However the data used are from historical data from machine operation and later on they applied certain model to predict some industrial fault in general[29]. So, the model to develop the real data performance monitoring should be effective to optimize fault detection and enables real-time fault correction by using preventive approaches maintenance.

The authors in the IoT Assisted Motor Monitoring System for Industries focused on observing the motor parameters for a total preventive maintenance [8]. The parameters such as temperature, RPM (Revolution per Minute), as well as vibration were continually tracked via various sensors. The inspected values were sent to the web application for preventive maintenance[8]. Nevertheless, the suggested model to correct the predicted faults for induction motor were not studied at all.

In [3], They researched and built an End-to-End Industrial IoT Platform with Actionable Predictive Maintenance, including its architecture, design, and practical execution. Numerous maintenance techniques were examined and described along with their various benefits. And given that Industry4.0's most well-known use case for smart manufacturing is predictive maintenance. The requirement to combine numerous fragmented data sources, conduct research on and use advanced predictive analytics, and close the loop to the field in order to give actionable intelligence make the development of predictive maintenance systems still difficult[3],. However the predictive model used is insufficient to real time enable fault correction. So, using preventive approaches should be effective for direct motor healing from faults[30].

The study in [31], Utilizing IoT Sensor Data in Machine Learning during Predictive Maintenance of Industrial Devices, it investigates the application of Auto Regressive Integrated Moving Average (ARIMA) forecasting on the time series data gathered from multiple sensors collected by a Slitting Machine, in order to identify potential failures as well as problems, enhancing the overall manufacturing process[31]. Thus, the use of machine learning in IoT shows to be an essential element, with applications in quality management and quality control, reducing maintenance costs, and enhancing the entire manufacturing process[32]. Even though the inexpensive model in machine learning were used, but still, the preventive model to advise what to do with corresponding fault were not developed and studied[33].

In order to determine the condition of the equipment in use and forecast when failure will occur or maintenance will be required on the single phase induction motor, predictive maintenance approaches have been explored and studied [34]. The operational efficiency of the machine being tested could be improved using the Simple Linear Regression (SLR) and Multiple Linear Regression (MLR) algorithms, which provide new statistical patterns that serve as the foundation of prediction analysis. The objective was to offer cost savings over unforeseen reactive repair or schedule-based preventative maintenance, which could leave machines inoperable at the crucial times[35]. While there are several methods for anticipating failures, in this project the voltage and current of the power that is provided to the motor were measured[34]. But by themselves, these approaches are unable to locate some critical faults on induction motor. However the other additional IoT sensors and preventive model should be used to optimize fault detection.

In [7], The study conducted presents the creation of an internet-of-things-based real-time condition monitoring system for controlling industrial low voltage motors. The device could track the temperature and vibration of an industrial motor and transfer the information to a data logging center wirelessly. The prototype, which could successfully recognize abnormal motor conditions from sensor input values that exceed predetermined set points, was created utilizing open source hardware and software. The system changes status and sends a mobile alert to the user when a motor is getting close to an abnormal state[7]. The user must conduct an RFID enforced inspection as required by the motor management system. Until authorized workers visited the device and scanned the specific RFID batch, the alarm system was in operation[36]. However in future they suggested to work on the way of providing the fault that is occurring and the way to come up with solution as preventive measure. Secondly, the sensors used were few to scan each and every fault on electrical motor.

The research in[37], provides an overview of current developments for gathering data from industrial motor inputs, outputs, loads, and parts, including temperature, vibration, and acoustics, utilizing a variety of industrial sensors to analyze the machine's state in real-time. Machine learning and transmission protocols like MQTT (Message Queuing Telemetry Transport) were used for predictive maintenance with the advent of the industrial internet of things by tracking the real-time operation of the machine to prevent unexpected breakdowns, prevent unpredictable losses, and reduce maintenance costs, extending the lifespan of the equipment[38]. Yet they suggested the preventive model to assign the user what to do in real time operation so that to prevent that fault.

3.3 Gaps Analysis

Author s/date	**Paper title**	**Problem Addressed**	**Methodology used**	**Outcomes**	**Gaps**
1. [24]	A State-of-Art Approach on Fault Detection in Three	Increase of dangers in choices involving computing	supervised classification method for Induction	method proposed achieves higher	Solution recommender approaches should have been addressed

	Phase Induction Motor using AI Techniques	device maintenance and decrease costs.	Motor (IM) faults that is based on the Logit boosting (Meta.logitboost) algorithm was used	performance metrics for the incipient identification and classification of IM faults than other classifiers used in this field	to effectively minimize the downtime that can last longer due to breakdowns
2. [34]	Predictive maintenance of single phase ac motor using IoT sensor data and machine learning (simple linear regression and multiple linear regression algorithms)	Costly over schedule based preventative maintenance or unexpected reactive maintenance.	An integrated network of PZEM-004T meter with a Node MCU ESP8266 -12E Module was used to monitor and collect data about the voltage, current, and active power of AC motor. And Regression ML was used	Test result was compared with obtained predicted result based on which the prediction accuracy of each machine learning algorithm was decided	Accuracy was less due to lack of more data while. low data in ML should decrease prediction accuracy increases and Fault correction approaches should have been addressed to effectively minimize the downtime

3. [39]	Real Time Monitoring IoT Based Methodology for Fault Detection in Induction Motor	Lack of safety and more cost-effective conditions of current automation method in industry	Hardware and Software was used too to design and implement circuit.	It showed how to monitor the start and stop of an induction machine using both automatic and manual methods.	Machine learning is lacking to be able to recommend a reduction downtime since the faults could be found early and corrected directly.
4. [25]	A Review of Artificial Intelligence Methods for Condition Monitoring and Fault Diagnosis of Rolling Element Bearings for Induction Motor	Increase in the cost of maintenanc e of modern industrial systems and applications due to lack of continuous monitoring	Extensive review of Condition Monitoring and Fault Detection and Diagnosis of the IM using.	IoT sensors were used	Fault correction recommendati on should have been addressed to effectively minimize the downtime
5. [37]	A REVIEW ON MAINTENAN CE TECHNIQUES FOR INDUSTRIAL	Lack of continuous evaluation of the health of the motor which	machine learning and transmission protocols such as MQTT (Message Queuing	the industrial motor inputs, outputs, and load and	Fault prediction and fault correction approaches should be effective to minimize the

	EQUIPMENT AND ITS MACHINE LEARNING ALGORITHMS	results on decrease of the lifetime of that equipment.	Telemetry Transport) was studied to predict maintenance by monitoring the real-time operation of the machine	parts data such as temperature , vibration, and acoustics using various industrial sensors for analyzing real-time state of the machine were used	breakdowns that still present in industries or factories sector.

Table 1: summary of gaps from related works

The analysis of gaps shows that, there were no recommendation suggested on how to quickly correct the fault using IoT sensors and machine learning, it leads to longtime of downtime which increase the cost of maintenance and leads to production loss. The proposed system will predict the fault based on real time data and suggest the way of fault healing to induction motor user.

Chap III: Research Methodology

1. Overview

The approach that was used to create real-time data acquisition for the three phase induction motor is described in this chapter. In general, the chapter under "Methodology" provides information on the specifics of how this study would be carried out.

2. Methods

2.1. Documentation

Documentation was essential in research protocol for locating facts relevant to my topic and serving as proof of concepts and data that have been copyrighted. Only secondary sources are used as evidence here. Some data came from papers, articles, books, web and the others came from Lab while testing the prototype.

3 Developing IoT performance monitoring system of three phase induction motor.

3.1. System process flow for sensors

The event flow from sensors is depicted in the following diagram.

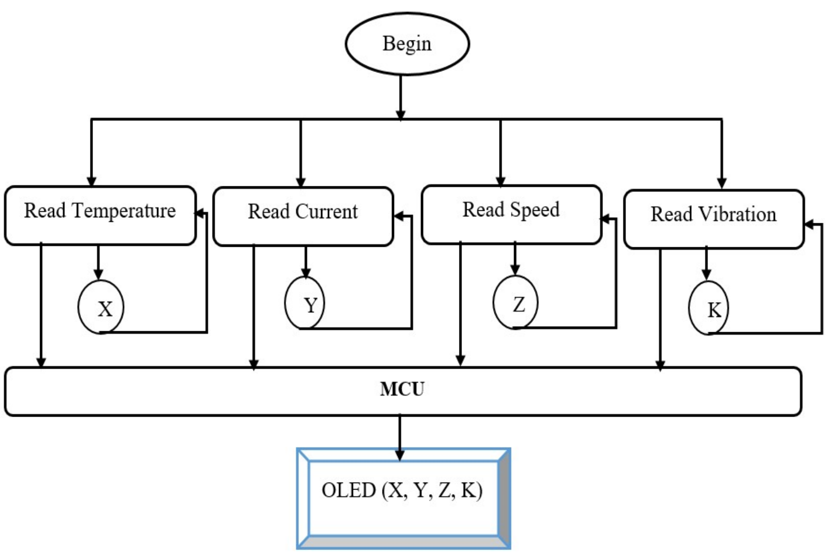


Figure 1: process flow for sensors

While the process is beginning with the data which are being gathered from a variety of sensors such as we considered the temperature data as X, Current data as Y, speed data as Z and Vibration data as

K, then the data are transferred to a microcontroller named MCU for processing before being presented locally on an OLED display, Current sensor will detect amperes or current intensity; temperature will detect Celsius degree; vibration will detect high and low vibration whereas speed will detect RPM value. In the following table we are going to find details of each and every components.

3.2. Components used

Sn	Types	Components	Commercial name	Description
1	Sensors	Current sensor	ACS712 Current Sensor Module	Measures both AC and DC current; Available as 5A, 20A and 30A module; Provides isolation from the load; Easy to integrate with MCU, since it outputs analog voltage; Scale Factor; ACS712 30A Getting a ±0.1A Current sensor accuracy[16].
		Temperature sensor	NTC100K Thermistor Sensor	Temperature measurement head cylinder diameter 3mm, length 15mm; temperature measurement range is increased from -50 ℃ +250℃ to -50 ℃ ~ +320 ℃[16] [17].
		Speed sensor	LM393 IR Motor Speed Sensor	Supply voltage: 4 to 26 V DC; Operating frequency: 0 to 12 KHz; Sensing Range: 30 cm; Operating Temperature: -40 to 125 Deg C; IP rating: IP54 Housing Material: PCB; Board size: 3.1 X 1.5 cm; Phase Type: Three Phase[18].
		Vibration sensor	LM393 chip	Dimension of the board: 3.2cm x 1.4cm; Adjustable potentiometer: To adjust sensitivity; SW-420 based sensor; Normally closed type vibration sensor; On-board LM393

				chip; On-board indicator LED to show the results; Digital output Supply voltage:3.3V-5V[18].
	Actuator	Buzzer	DC 3-24V Electronic Buzzer	Product Name: Electronic Buzzer; Model No. : SFM-27-I;Sound-making Type : Continuous Sound; Rated Voltage : DC 3-24V;Rated ; Current : 30mA;Sound Pressure : 80dB; Operating Temperature : -20°C to +80°C;Body Diameter : 30mm / 1.2″;Overall Size : 48 x 30 x 15mm / 1.9″ x 1.2″ x 0.6″ (L*W*H); Mounting Hole Diameter : 3.7 x 3.2mm / 0.14″ x 0.12″ (L*W);Wire Length : 11cm / 4.3″;External Material : Plastic; Color : White; Weight : 5g;Package Content : 1 x Electronic Buzzer
	MCU	Arduino Nano	Arduino Nano RP2040 Connect	Nano RP2040 Connect; Microcontroller: Raspberry Pi® RP2040; USB connector: Micro USB; Built-in LED pin:13; Digital I/O Pins:20; Analog Input Pins:8; PWM pins:20 (Except A6, A7); External interrupts:20 (Except A6, A7); Wi-Fi: Nina W102 uBlox module; Bluetooth: Nina W102 uBlox module; Secure element:ATECC608A-MAHDA-T Crypto IC; IMU:LSM6DSOXTR (6-axis); Microphone :MP3DT06JTR; UART: yes; I2C:yes; SPI: yes; Circuit operating voltage:3.3V; Input Voltage (VIN):5-21V; DC Current per I/O pin:4 mA; Clock speed Processor:133 MHz; AT25SF128A-MHB-T :16MB Flash IC; Nina W102 uBlox; module:448 KB ROM, 520KB ;SRAM, 16MB Flash; Weight:6g; Width:18 mm; Length:45 mm[17].

Table 2: components to be used

2.3 Acquiring data from the installed IoT platform.

2.3.1 Data gathering process

In this procedure, it is shown that after the data are captured from the sensors, and processed by MCU, the remaining is being sent to database and present to the dashboard.

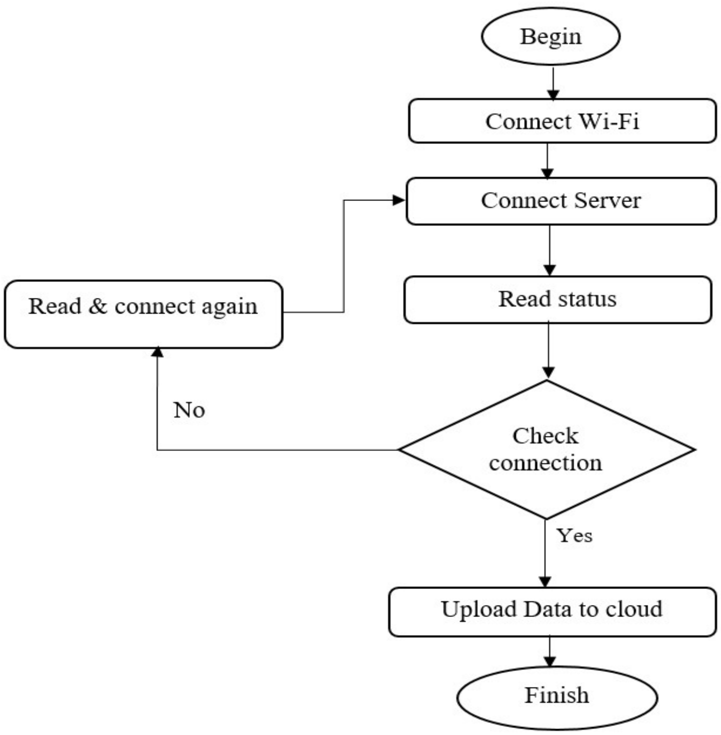


Figure 2: Data acquisition process flow

Arduino Nano was used to process several types of sensor data provided in objective 1, upload it to an IoT cloud, all of the data is uploaded to cloud using the esp8266 WIFI module. After that the data remains stored in database for further analysis.

2.3.2 Main components

- **Wi-Fi Module**

The Wi-Fi module that uses 3.3V as its operational voltage is known as an Esp8266. The Wi-Fi module can only receive a maximum voltage of 3.6V from us. The Esp8266 Wi-Fi has a total of 8 pins, one of which is the supply pin that receives power from an Arduino board or another external power source. The diagonal pin is GND. RX and TX pin are necessary for data transmission, as seen in the above diagram. The Reset and Enable pins are the only ones left. The LM317 can be used to control the voltage so that it can be altered based on the requirements [20].

- **Cloud platform**

A cloud-based IoT analytics platform service, enables the collection, visualization, and analysis of real-time data streams [21]. A group of technologies, instruments, and services collectively referred to as a "cloud platform" allow for the online distribution of cloud computing resources. Users can access and use a variety of computer resources, such as virtual machines, storage, databases, networking, and software applications, without the requirement for on-premises infrastructure thanks to cloud platforms, which offer a scalable and virtualized environment [22].

2.4 Establishing predictive analysis.

1. Overview on ML

Data can be analyzed using various machine learning methods, which enables computers to identify hidden insights without being explicitly programmed. Machine learning is a subfield of artificial intelligence that enables computers to learn from previous examples [23].

2. Predictive process via Machine Learning

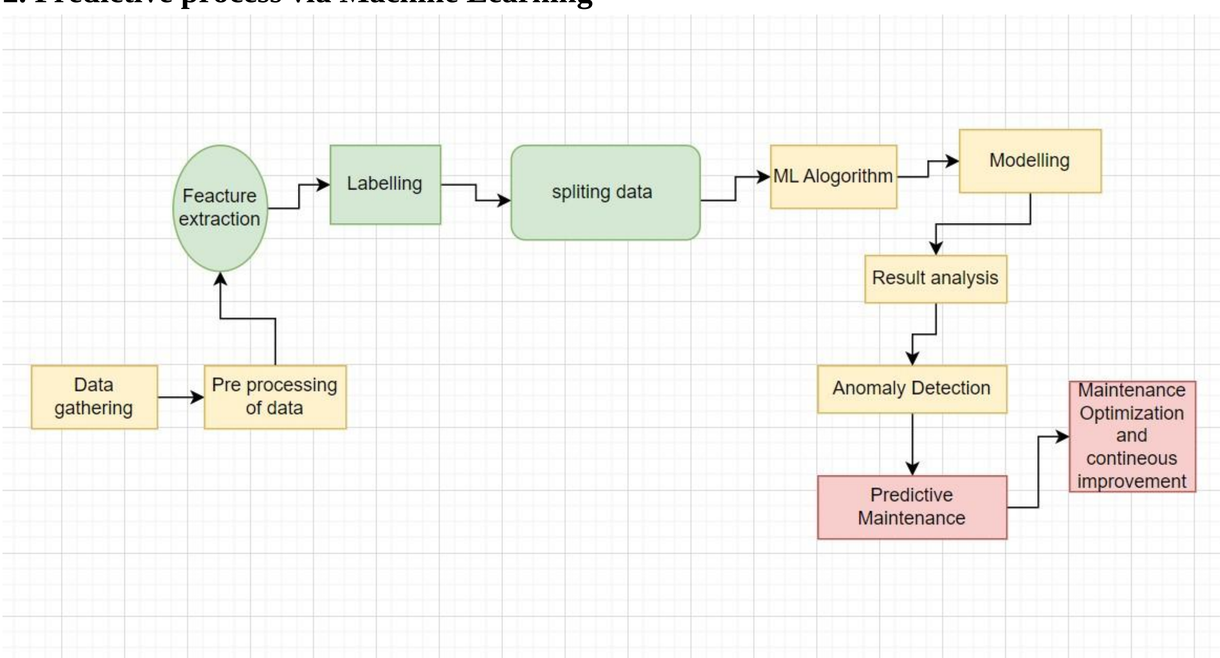


Figure 3: Process flow of motor faults prediction using machine learning

In the above figure, we have different stages important from them, we have Data gathering, in data gathering we gather current, speed, temperature, and vibration data in real time from sensors mounted on the induction motor. Secondly, we have Preprocessing of the data; this involves removing outliers, dealing with missing numbers, and doing any necessary data transformations on the obtained data. To make sure that all features are scaled similarly, normalize the data. After feature extraction we have Labeling to describe the operational state of the motor, such as normal functioning, pre-failure circumstances, or failure events[40].. We again have Training and Test Data split; which involves separating the labeled data into training and test sets. The ML Algorithm part enables us to do the predictive maintenance task. After that we have Data modelling and Anomalies detection: that plays important role in using the trained ML algorithm model to find abnormalities in real time motor data. The model forecasts the operational status of the motor using the retrieved attributes as inputs. An anomaly is found and an alert or warning is sent when the projected state diverges from normal operation[40].

Indeed the Predictive Maintenance and continuous improvement are done Based on the motor's present operating circumstances, apply the SVM model to forecast its remaining useful life. The model can forecast when maintenance or replacement is likely to be necessary by continuously monitoring the motor's performance.

3. Dataset Gathering

In this study it is effective to locate a whole dataset based on the factors that were desired to be included like temperature, current, speed and vibration. In order to generate fresh insights, it is possible to merge different open-source datasets using open source. An additional feature of these open-source datasets is their transparency; they typically include comprehensive documentation outlining the data collection and processing procedures, as well as assurances that ethical standards are fulfilled.

From kaggle.com, the dataset was found for a motor in numerical value and the dataset provides information on motor current, temperature, and vibration for faults under various speed settings, ranging from 680 RPM to 2460 RPM[41]

3.1 Nature of labeled dataset

Labels were done by labelling the data set in other to get analyzed in appropriate manner, the following logic was used for each of the parameter since the raw data format was numerical. So the change is based on normal range, pre failure range and failure to insure the condition of three phase induction motor. Briefly, the labels are classified into 3 categories such as normal, pre failure and failure whereby 1: normal, 2: pre failure and 3: failure.

1. Current

Current bellow 4 Amps then the motor is normal then the state is 1

Current is from 4.1 to 5 Amps then the motor is pre failure the state is 2

Current is above 5 Amps then the motor is failure then the state is 3

2. Temperature

Bellow 35 Celsius degree is normal then the state is 1

From 36 to 41 Celsius degree is pre failure then the state is 2

From 42 above send failure the state is 3

3. Vibration

If vibration is from 0.1 to 0.2 inches per second, it is normal then the state is 1

If vibration is from 0.21 to 0.3 inches per second, it is pre failure then the state is 2

If vibration is above 0.3 inches per second, it is failure then the state is 1

4. Speed

Speed bellow 600 rpm then the motor is in failure state then the state is 3

Speed between 600 to 900 rpm then the motor is in pre failure then the state is 2

Speed above 1200 rpm then the motor is in normal state then the state is 1

5. System condition

For a system condition logic, if from current1 labeling to vibration we have 1 for all then the output (system condition) is normal. If we have a mix of 1 and 2 only then the output is pre failure otherwise the output is failure. To conduct this research 1007 data were used to ensure the system stability. And their interpretation is given in the table below.

	current_1_lebelling	current_2_lebelling	current_3_lebelling	temperature	speed	vibration	system_condition
0	1	1	2	2	1	1	2
1	2	1	1	2	1	2	2
2	1	2	1	2	1	3	0
3	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1
...	...	...	...	...	...	...	...
1004	1	3	3	3	3	3	0
1005	2	2	2	2	2	1	2
1006	1	1	1	1	1	1	1
1007	3	3	3	3	3	3	0
1008	1	1	1	1	1	1	1

1009 rows × 7 columns

Table 3: Nature of the dataset

The above table shows the data sets after being labeled and the condition for system condition as provided above. The condition for system condition have been described above. The total data sets that was used is 1008 data to tests different models as we are going to see them in the following part

3.2 Graphs showing every single parameter of datasets

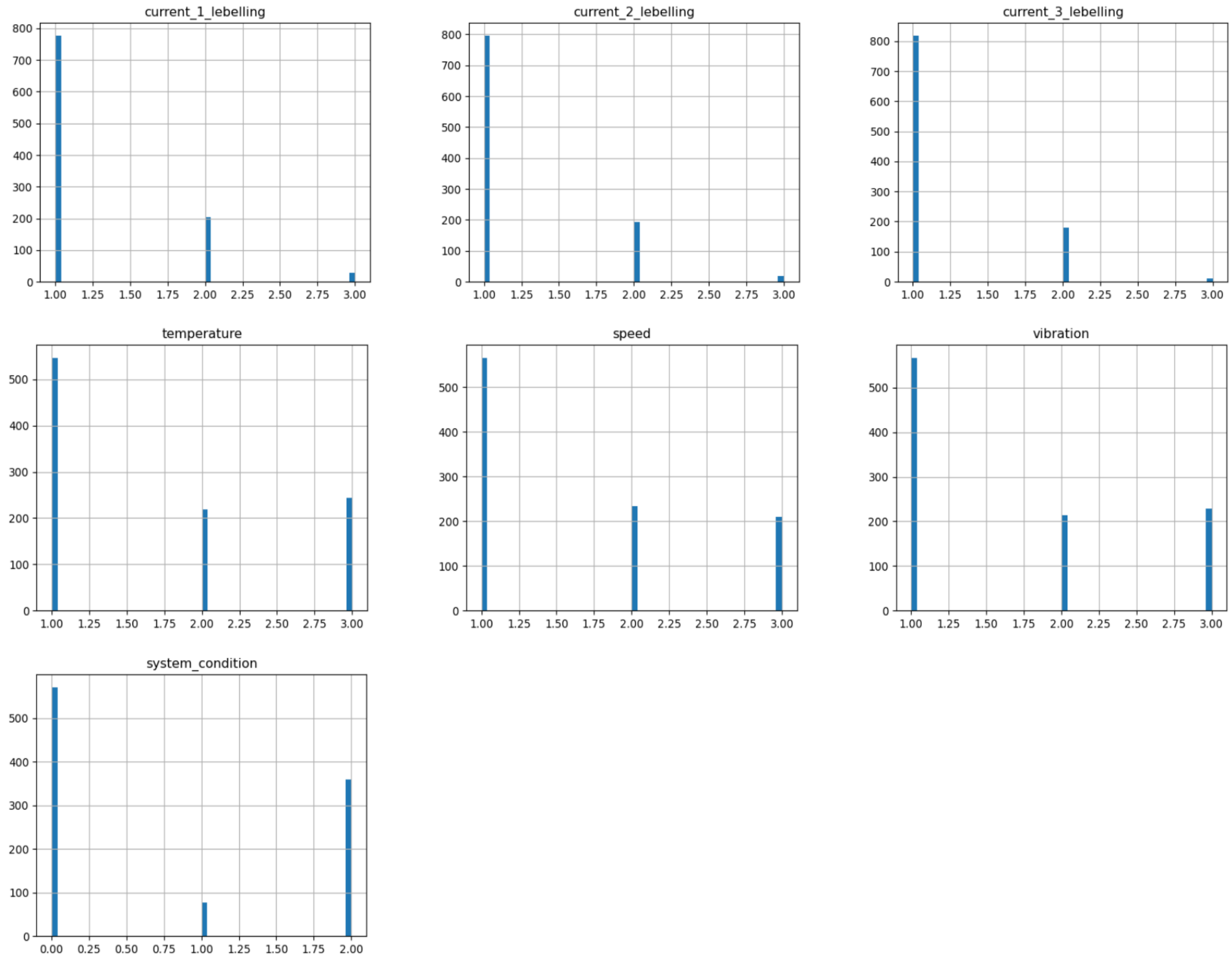


Figure 4: Graphs showing analysis every single parameter of datasets

In the above graphs, we have shown the presence of repetition for failure, normal and pre failure condition for each of the parameters such as current 1, current 2, current 3, vibration and speed. Taking into consideration that value 1 is presenting normal, 2, pre failure and 3 is failure condition. We have also shown the system condition presence in normal state, pre failure state and failure state that are interpreted in general.

3.3 Correlation and description of dataset

The correlation between two variables is displayed in each cell of the table. Usually, the value falls between -1 and 1

	current_1_lebelling	current_2_lebelling	current_3_lebelling	temperature	speed	vibration	system_condition
current_1_lebelling	1.000000	0.080710	0.081626	0.048087	0.076308	0.004905	-0.086988
current_2_lebelling	0.080710	1.000000	0.115582	0.055592	-0.019413	0.058933	-0.051836
current_3_lebelling	0.081626	0.115582	1.000000	0.018349	0.003242	0.041164	0.012494
temperature	0.048087	0.055592	0.018349	1.000000	-0.188029	-0.120540	-0.322192
speed	0.076308	-0.019413	0.003242	-0.188029	1.000000	-0.123279	-0.297506
vibration	0.004905	0.058933	0.041164	-0.120540	-0.123279	1.000000	-0.336963
system_condition	-0.086988	-0.051836	0.012494	-0.322192	-0.297506	-0.336963	1.000000

Table 4: Description of the dataset.

In the table above we have, Strong direct association with a high positive correlation is between: 0.7 to 1.0. While, Moderate Direct Relationship that associates with Moderate Positive Correlation is between: 0.4 to 0.69; Weak direct link with low positive correlation 0.1 to 0.39. Zero Correlation means that, there is no linear connection. We also have also Weak inverse connection with low negative correlation (-0.1 to -0.39).

3.4 Modelling methodology

To improve the predictive maintenance of three-phase induction motors, we used a variety of machine learning models in this work, including Random Forest, Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbors (KNN) and Logistic Regression Due to nature of dataset, size, feature and target.

The temperature, current, vibration, and speed data that were gathered from IoT sensors monitoring important parameters were used to train the models. These characteristics are essential for detecting problems including current imbalance, overloading, overheating, and poor vibration. At the end, SVM was the best option for this application since it showed the highest accuracy among the tested models in identifying abnormalities and forecasting motor failures.

3.3.1 ML models used in training datasets

In the following part we are going to see the reason why we chose the model, but as it is supervised ML models, we used classified one from the size, feature, target and nature of dataset we have [42].

1. SVM (Support Vector Machine): The reason why the SVM was used is it finds the ideal hyperplane that maximizes the margin between various Class using labeled training data[43].

2. Random Forest: The research used Random forest from the fact that it uses several data subsets, it constructs numerous decision trees and applies averaging to enhance prediction precision and manage overfitting. Labeled training data is used to build each decision tree[42].

3. Decision Tree: It was used because, It uses labeled training data to develop a model that predicts the value of a target variable by learning simple decision rules inferred from the data attributes[44]

4. Logistic Regression: It uses labeled training data to develop a model that predicts the value of a target variable by learning simple decision rules inferred from the data attributes[43].

5. KNN (K-Nearest Neighbors): By identifying the K-nearest neighbors in the training data and giving the new instance the label that is most common with them, it uses labeled training data to make predictions[42].

3.3.2 ML performance evaluation conditions

Let study and analyze the precision, Recall, F1 score and Accuracy for each and every chosen models. This was done basically using true positive, true negative, false positive and false negative values to help calculating the precision, accuracy, Recall and F1-score for each and every model. [45].

To calculate Precision, Recall, F1 Score and accuracy, the following formula have been used to ensure the best model.

1. Precision: $\frac{TP}{TP+FP}$……….Eq 1: precision[46].

Where:

TP: True Positive

FP: False Positive

The precision of a model is defined as the ratio of true positive predictions to all positive predictions.

2. Recall: $\frac{TP}{TP+FN}$……….Eq 2: Recall[46].

Where:

TP: True Positive

FN: False Negative

Recall quantifies the percentage of genuine positive predictions among all real positive occurrences; it is sometimes referred to as sensitivity or true positive rate.

F1-Score: $\frac{Precision*Recall}{Precision+Recall}$*2……………..Eq 3: F1-Score[46].

The F1 Score is a measure that is used to balance recall and accuracy. It is computed as the harmonic mean of recall and precision. It is helpful when trying to find a balance between strong recall and high precision because it penalizes excessive negative values of either component.

Accuracy: $\frac{TP+TN}{TP+TN+FN+FP}$………………Eq 4: Accuracy[46].

Where:

TP: True Positive

FN: False Negative

FP: False Positive

TN: True Negative

Accuracy shows what percentage of the model's total predictions were successful.

CHAPTER 4: SYSTEM ANALYSIS AND DESIGN (SAD)

4.1 Introduction

The primary duty of the system analysis and design process is to produce a building blueprint of a system that satisfies predefined needs. This section contains the system architecture as well as flowchart that are required.

4.2 Background

Within the broader trend of integrating Internet of Things (IoT) technologies into everyday objects. After a review of several Internet of Things (IoT) solutions, especially those pertaining to industry, three phase induction motor monitoring for predictive maintenance using IoT and ML is developed with the aim of minimizing motor failure along with downtime, as well as helping operators identify faults and know what to do about them.

4.3 System requirements

4.3.1 Functional requirements

Sensors, communication model, user interface, and security are integrated for practical needs.

4.3.2 Non-functional requirements

Performance, reliability, usability, and interoperability are the areas where the system addresses non-functional needs.

4.4 System architecture

The architecture is comprised of some components such as: 3 phase Induction motor sensors, MCU, Actuators, display (OLED). The following figure depicts the overall layout of the system.

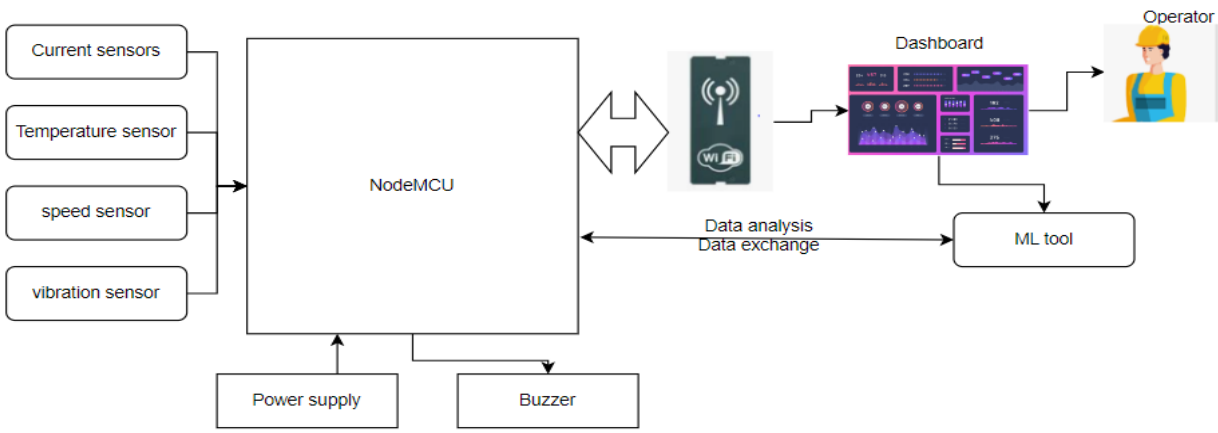


Figure 5: System architecture.

A vibration sensor, a current sensor, a speed sensor, and a temperature sensor was used to measure the input data produced by a three-phase induction motor. An Arduino Nano microcontroller unit was used for data processing, and the database was used as a data storage medium. With the aid of an ML tool, the real-time data gathered by the sensors were considered, analyzed and presented using dashboard. This involved tasks including reviewing component datasheets, journals, websites, and reference materials. All of these were crucial to the project's success.

4.5 Simulation Tools

1. Arduino IDE

With the aid of library functions, the Arduino IDE, which is integrated development software available for Arduino devices, enables programmers to connect sensors and other types of components with Arduino microcontrollers and to carry out operations on both the local and global levels [19]. This Arduino IDE helps to provide an algorithm in which microprocessor follow while sensor are providing data from external environment.

2. Django

It's a high-level Python web framework that makes it possible to create safe, scalable websites quickly. Because of its strong ORM (Object-Relational Mapping) architecture, which enables developers to connect with databases using Python code rather than SQL, it's a great option for creating database-driven applications[47]. In this work, it helped us to develop a database that is able to communicate with ML model programmed using Python language.

3. Python language

Python is a high-level interpreted programming language that is well-liked by both novice and seasoned programmers due to its ease of use and readability. It is compatible with several programming paradigms, such as functional, object-oriented, and procedural programming[48]**.** The development and analysis of ML learning modelling was done by usage of Python Language. It helped in analyzing them by finding which one is performing well.

CHAPTER 5: RESULTS AND ANALYSIS

5.1 Introduction

This presentation uses tables, graphs, and pictures to show the outcomes of the system design and data collection. This section's advantages include using data analysis and interpretation to generate new ideas and findings.

5.2 Results of developing IoT performance monitoring system of three phase induction motor.

5.2.1 Results of completed wired of prototype

In the photo bellow, there is a built circuit containing different internal parts where we observe the microcontroller, wiring and connections.

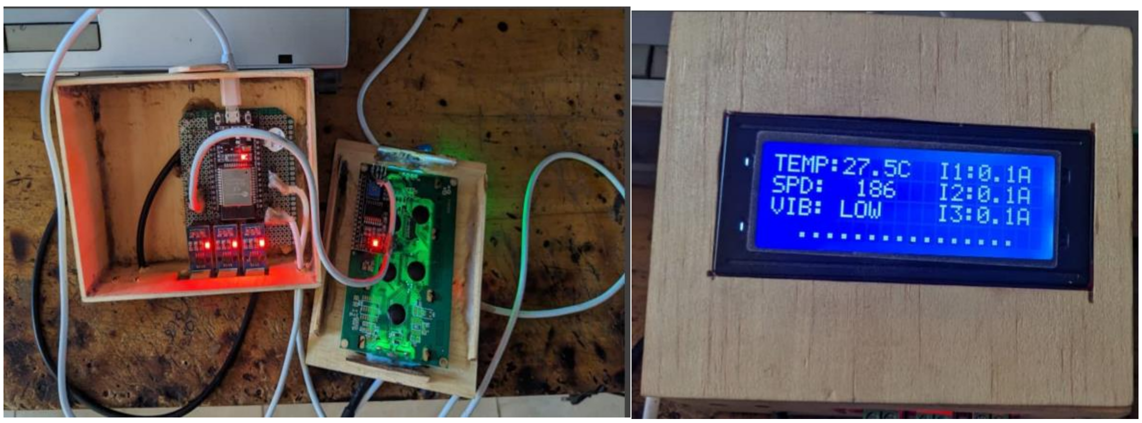


Figure 6: result of internal wiring

The Fig 17, is actually showing the internal wiring of the prototype and it also shows the display which is working properly. In internal wiring, we observe wires, MCU and enclosure to protect it against external environment.

5.3 Results of Acquired data from the installed IoT platform Data.

5.3.1 Results of data presentation on dashboard

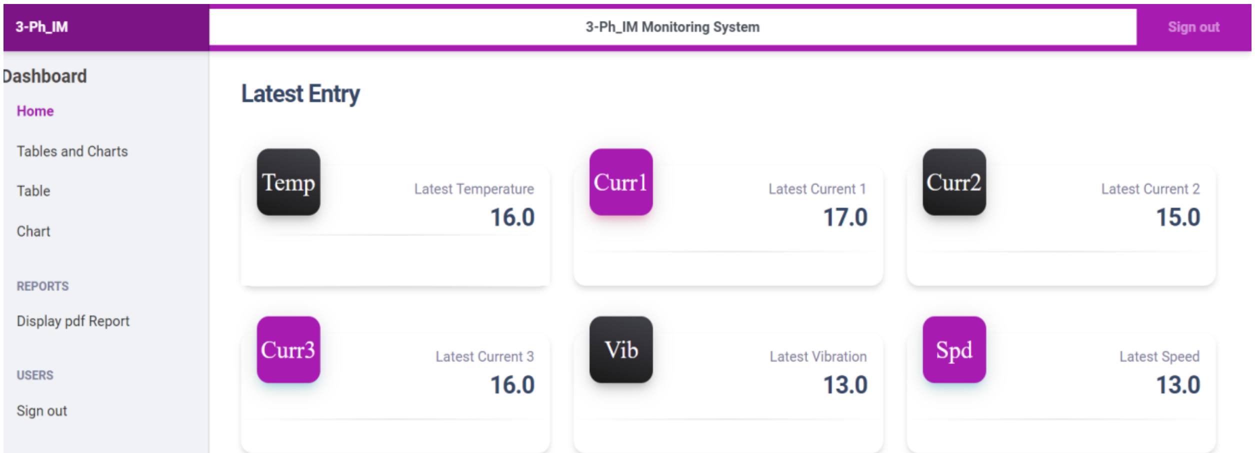


Figure 7: result of a dashboard

In the figure 20 temp as temperature is shown, curr1 as current one is observed, Curr2 as current 2 is shown, Curr3 as current 3 are shown, Vib as vibration is shown and spd as speed data are all present. It also has the Tables as well as Charts to help displaying each and every parameter results.

5.3.2 Results of displayed data in sinusoidal wave on dashboard

The following diagram shows the sinusoidal waveforms of different data taken from different time as it is indicated on it, we have temperature data, current1, current2, current3, vibration as well as speed data and the corresponding taken time.

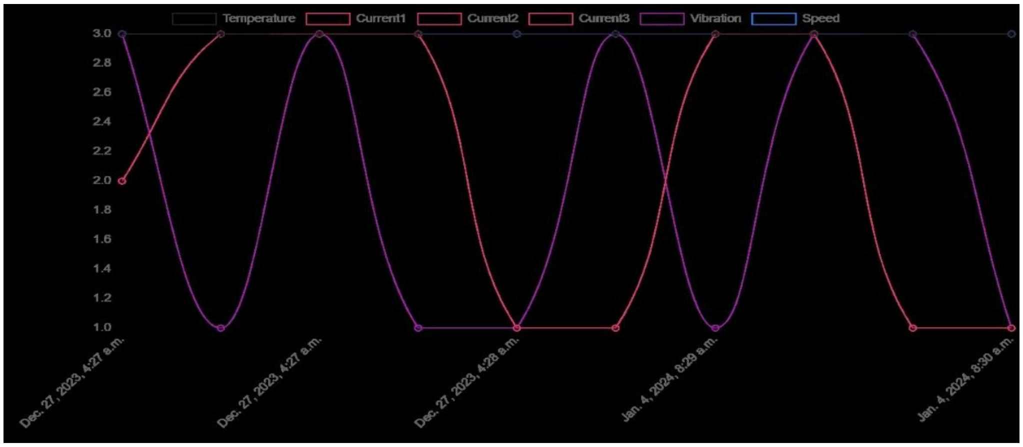


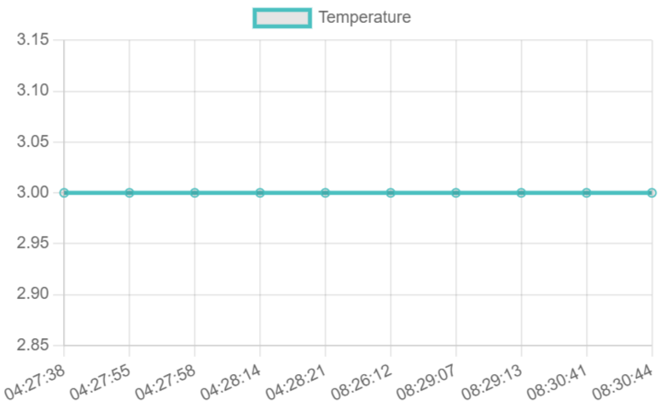
Figure 8: sinusoidal waveforms of taken real data.

In the Figure 9, it displayed data at different time line the ones taken Dec, 27/2023 the other ones taken from Jan 4, 2024 respectively. It is a sinusoidal wave signal that sum up every parameter when checking in it you observe different colors corresponding to every parameter, legend is provided in to Cleary find its details

5.3.3Table and charts from each of the feature on dashboard.

The following charts and tables shows the data presentation on both chart and tables which are displayed on dashboard to really help the user or operator to report and have historical data. The data appeared in the following manner:

5.3.3.1 Temperature charts and data

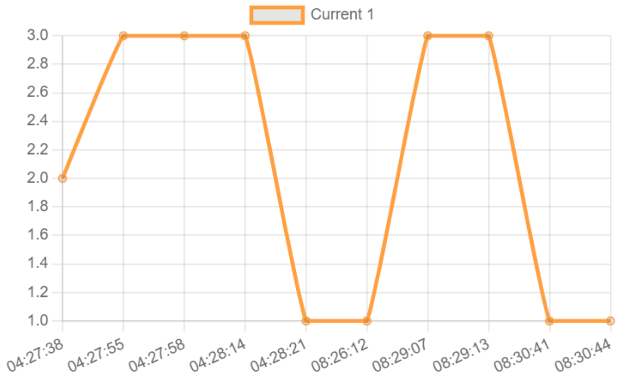


Timestamp	Temperature
04:27:38	3.0
04:27:55	3.0
04:27:58	3.0
04:28:14	3.0
04:28:21	3.0
08:26:12	3.0
08:29:07	3.0
08:29:13	3.0
08:30:41	3.0
08:30:44	3.0

Figure 9: temperature charts and data

Temperature data we are observing as provided in data analysis, it shows the abnormality due to the fact that the state is 3 which means the abnormal. From that overheating test have been carrying out. The results also observe the time stamp and the state of temperature as well.

5.3.3.2 Current1 charts and data

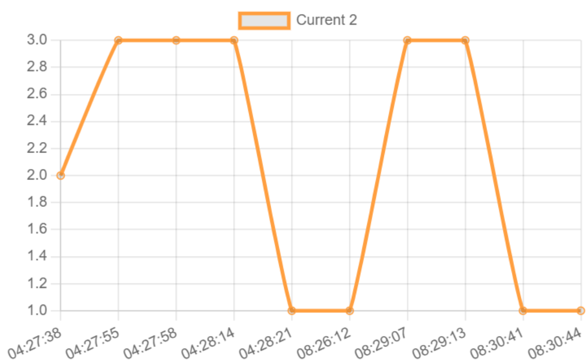


Timestamp	Current 1
04:27:38	2.0
04:27:55	3.0
04:27:58	3.0
04:28:14	3.0
04:28:21	1.0
08:26:12	1.0
08:29:07	3.0
08:29:13	3.0
08:30:41	1.0
08:30:44	1.0

Figure 10: current 1 and data

Current one data and charts are observed in fig 24 above, it shows different state of normal, pre failure and failure condition since it is varying from 1, 2, and 3 states as respectively. The time stamp that data were taken are also present in the fig above.

5.3.3.3 Current2 charts and data

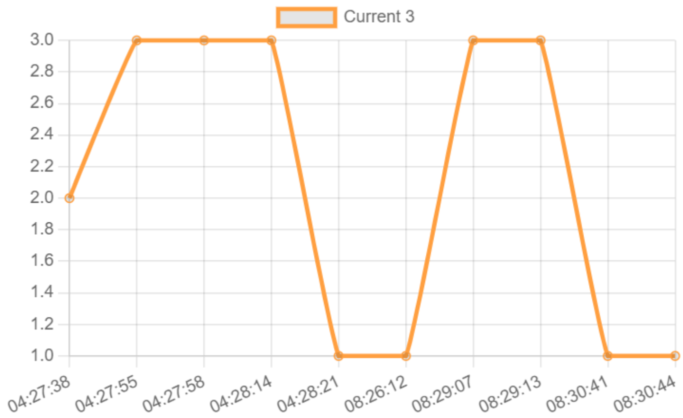


Timestamp	Current 2
04:27:38	2.0
04:27:55	3.0
04:27:58	3.0
04:28:14	3.0
04:28:21	1.0
08:26:12	1.0
08:29:07	3.0
08:29:13	3.0
08:30:41	1.0
08:30:44	1.0

Figure 11: current 2 and data

Current 2 data and charts are observed in fig 25 above, it shows different state of normal, pre failure and failure condition since it is varying from 1, 2, and 3 states as respectively. The time stamp that data were taken are also present in the fig above.

5.3.3.4 Current3 charts and data

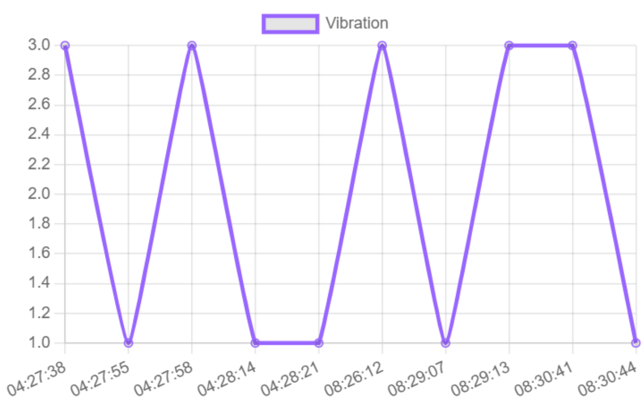


Timestamp	Current 3
04:27:38	2.0
04:27:55	3.0
04:27:58	3.0
04:28:14	3.0
04:28:21	1.0
08:26:12	1.0
08:29:07	3.0
08:29:13	3.0
08:30:41	1.0
08:30:44	1.0

Figure 12: current 3 and data

Current 3 data and charts are observed in fig 26 above, it shows different state of normal, pre failure and failure condition since it is varying from 1, 2, and 3 states as respectively. The time stamp that data were taken are also present in the fig above.

5.3.3.5 Vibration charts and data

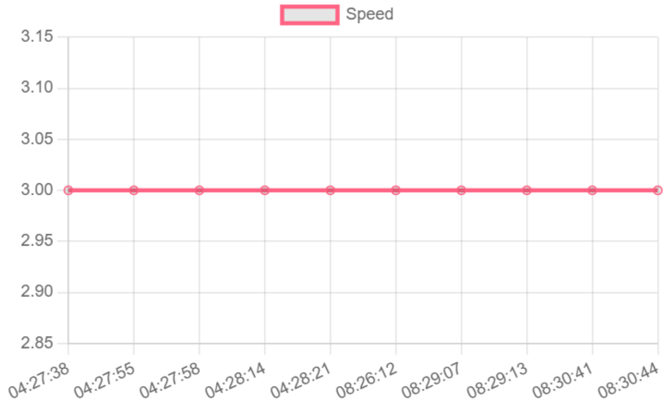


Timestamp	Vibration
04:27:38	3.0
04:27:55	1.0
04:27:58	3.0
04:28:14	1.0
04:28:21	1.0
08:26:12	3.0
08:29:07	1.0
08:29:13	3.0
08:30:41	3.0
08:30:44	1.0

Figure 13: vibration and data

Vibration in the figure above fig 27, shows only 2 state which are normal and failure tests done and the results are shown above depending on the timestamp that the data taken.

5.3.3.6 Speed charts and data



Timestamp	Speed
04:27:38	3.0
04:27:55	3.0
04:27:58	3.0
04:28:14	3.0
04:28:21	3.0
08:26:12	3.0
08:29:07	3.0
08:29:13	3.0
08:30:41	3.0
08:30:44	3.0

Figure 14: speed chart and data

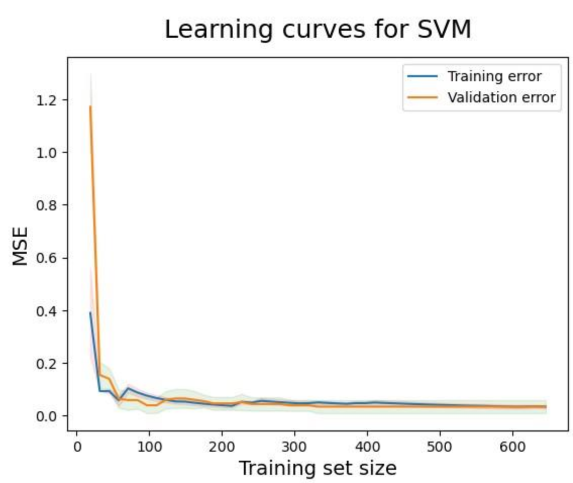
Here the speed was in failure state due to the fact that a motor was running without the load during tests. That is why it is displayed 3 state only which means failure but practically it shows that there is no load. Just to alert the user or operator that the motor is running on off load.

5.4 Results of Prediction of motor Faults using Machine learning.

5.4.1 Modelling Results

In the following part we are going to see the results of model and the relationship between validation error and training error for each and chosen models to study and evaluate our data set.

1. SVM (Support Vector Machine)



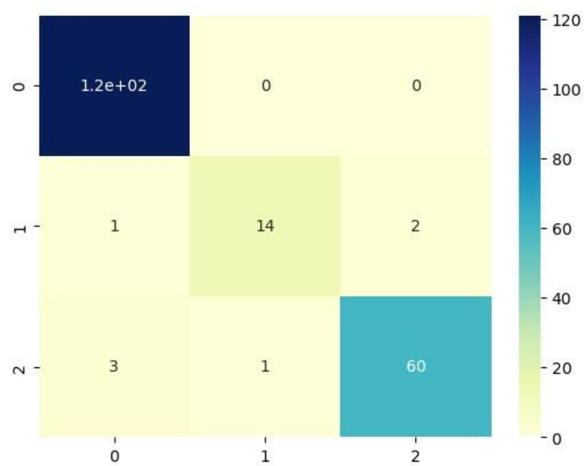


Figure 15: Learning curves for SVM

The results with high accuracy show that there is a good fit, as indicated by the low training and low validation errors.

- **SVM Performance Evaluation**

Class	TP	FN	FP	TN	Precision	Recall	F1-Score	Accuracy
0	121	0	4	77	0.97	1	0.98	0.97
1	14	3	1	184	0.93	0.82	0.87	
2	60	4	2	136	0.97	0.94	0.95	

Table 5: SVM Performance

SVM: Excellent detection capability is indicated by high TP in all classes; for FN, SVM: Greater for classes 1 and 2, lower for class 0; It also has Low FP in every class;

2. Random Forest

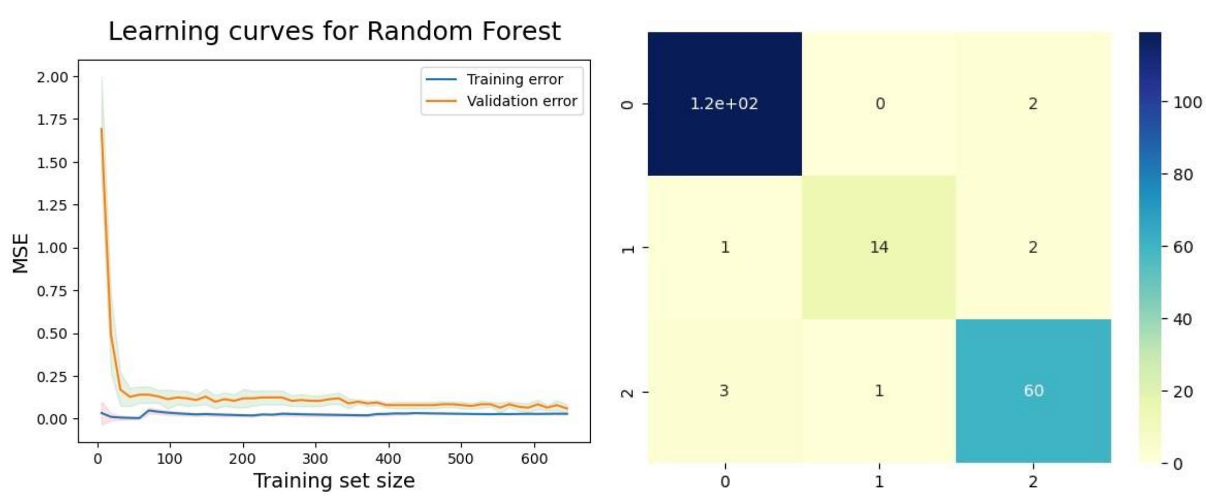


Figure 16: Learning curve for RF

RF models shows that a model that is well-balanced may have low training error and somewhat greater validation error.

- **Random Forest Performance Evaluation**

Class	TP	FN	FP	TN	Precision	Recall	F1-Score	Accuracy
0	119	2	4	77	0.97	0.98	0.98	0.96
1	14	3	1	184	0.93	0.82	0.87	
2	60	4	4	134	0.94	0.94	0.94	

Table 6: Random Forest performance

Random Forest and Decision Tree have similar FP values, slightly higher for class 2, and comparable TP to SVM, Random Forest is somewhat lower for class 0. It also has similar FN values, slightly better than SVM for class 0. Additionally, it includes High TN in every class.

3. Decision Tree

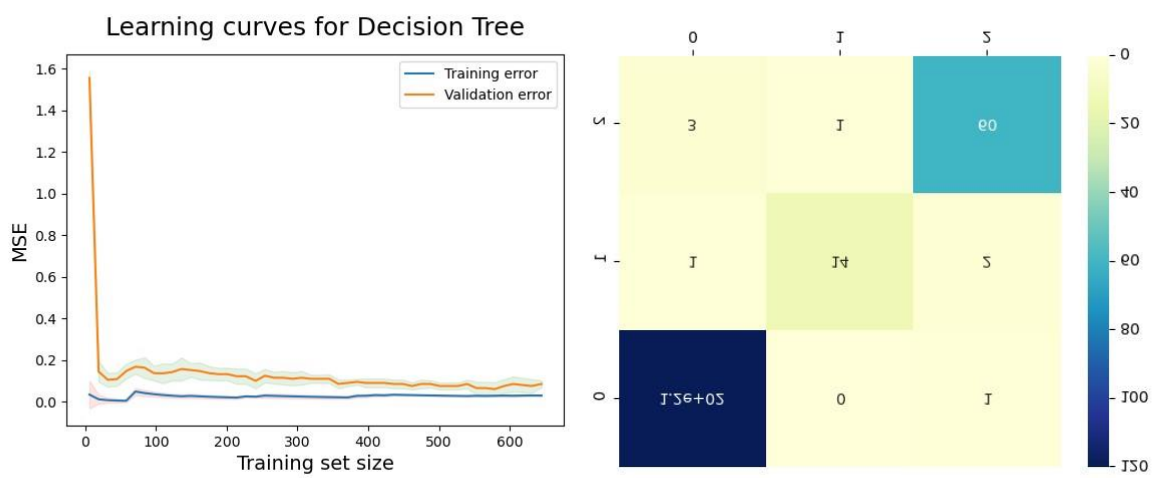


Figure 17: Learning curves for Decision Tree

Overfitting is indicated by low training error with higher validation error. The findings indicate a validation accuracy that raises the possibility of some overfitting control mechanisms.

- **Decision Tree Performance Evaluation**

Class	TP	FN	FP	TN	Precision	Recall	F1-Score	Accuracy

0	120	1	4	77	0.97	0.99	0.98	0.96
1	14	3	1	184	0.93	0.82	0.87	
2	60	4	3	135	0.95	0.94	0.94	

Table 7: Decision tree model performance

With a few minor exceptions, it is comparable to Random Forest in terms of TP; it has high TN in all classes; similar FN values, slightly better than SVM for class 0; and similar FP values, slightly higher for class 2.

4. Logistic Regression

Figure 18: Learning curves for Logistic Regression

Under fitting is indicated if both errors are quite high but near. The accuracy, particularly in complicated classifications, suggests a potential under fitting.

- **Logistic Regression Performance Evaluation**

Class	TP	FN	FP	TN	Precision	Recall	F1-Score	Accuracy
0	120	1	20	61	0.86	0.99	0.92	0.88
1	14	3	1	184	0.93	0.82	0.87	

2	44	20	3	135	0.94	0.69	0.79	

Table 8: Logistic regression performance

Its lower TP for class 2 indicates that it is harder to detect this class; Once more, it shows Low TN for class 0, affecting overall accuracy; High FP for class 0, affecting precision; and High FN for class 2, indicating poor recall.

5. KNN (K-Nearest Neighbors):

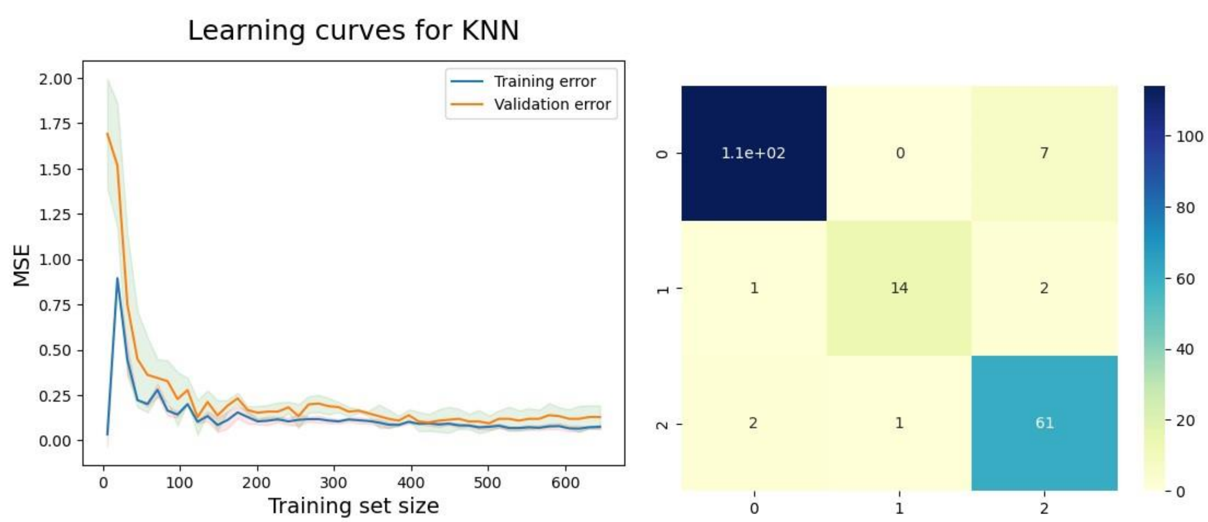


Figure 19: Learning curves for KNN

A good balance is suggested by the validation accuracy; nevertheless, overfitting must be prevented by keeping an eye on the difference between training and validation error.

- **KNN Performance Evaluation**

Class	TP	FN	FP	TN	Precision	Recall	F1-Score	Accuracy
0	114	7	3	78	0.97	0.94	0.96	0.94
1	14	3	1	184	0.93	0.82	0.87	
2	61	3	9	131	0.87	0.95	0.95	

Table 9: KNN model performance

Higher FN for class 0 in comparison to other classes; Higher FP for class 2 in comparison to SVM and Random Forest; Lower TN for class 2. Slightly lower TP for class 0 in comparison to SVM and Random Forest.

Indeed, across all classes, the SVM model performs the best overall, with the highest accuracy (97%), precision, recall, and F1-scores. While they have significantly lesser accuracy, Random Forest and Decision Tree models also work admirably. Class 2 is difficult for logistic regression to handle, while KNN is less precise in this domain. Based on the supplied metrics as well as confusion matrices, the SVM model is therefore the most suitable option for this classification assignment.

5.4.2 Prediction Results

Among many machine learning models, 5 models have been tested such as SVM, Random Forest, Decision tree, Logistic Regression Accuracy and KNN models. But the best one I found out, was SVM for this work as seen in data analysis.

The bellow table shows the prediction button on dash board to predict the faults and provide recommendation for removing the faults.

3-Ph_IM Data

Timestamp	Temperature	Current1	Current2	Current3	Vibration	Speed	Actions
Dec. 27, 2023, 4:27 a.m.	3.0	2.0	2.0	2.0	3.0	3.0	Predictions
Dec. 27, 2023, 4:27 a.m.	3.0	3.0	3.0	3.0	1.0	3.0	Predictions
Dec. 27, 2023, 4:27 a.m.	3.0	3.0	3.0	3.0	3.0	3.0	Predictions
Dec. 27, 2023, 4:28 a.m.	3.0	3.0	3.0	3.0	1.0	3.0	Predictions
Dec. 27, 2023, 4:28 a.m.	3.0	1.0	1.0	1.0	1.0	3.0	Predictions
Jan. 4, 2024, 8:26 a.m.	3.0	1.0	1.0	1.0	3.0	3.0	Predictions
Jan. 4, 2024, 8:29 a.m.	3.0	3.0	3.0	3.0	1.0	3.0	Predictions
Jan. 4, 2024, 8:29 a.m.	3.0	3.0	3.0	3.0	3.0	3.0	Predictions
Jan. 4, 2024, 8:30 a.m.	3.0	1.0	1.0	1.0	3.0	3.0	Predictions
Jan. 4, 2024, 8:30 a.m.	3.0	1.0	1.0	1.0	1.0	3.0	Predictions

Table 10: detailed data with fault prediction button

In the above table we have seen the detailed data with the corresponding action which shows the fault as well as the recommendation on each and every fault. When you click on action the following image appears on dashboard.

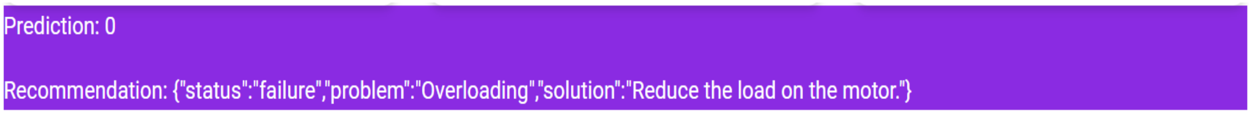


Figure 20: appeared message when clicking on action button

On the data taken on 04th January, the motor showed the status of failure due to overloading where by the action to take is to reduce the load on the motor, this was done in Lab and is applicable in industrial sector while operating the process involving the motor usage.

Many prediction corresponding to the action to remove faults were presenting on the dashboard.

CHAPTER 6: CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

To reliably detect anomalies and defects in three phase induction motors, a novel portable design prototype has been created and demonstrated. The system offers diagnostic information regarding the motor's state. This acquisition gear works well for motor monitoring without needing access to the motor when paired with automated data processing procedures. Sensor data was collected, saved in database and a dashboard were used to graphically monitor the sensor values. Examination of a number of machine learning models, including SVM, Random Forest, Decision Tree, Logistic Regression, KNN, and others, have been done and discovered that SVM is the most accurate model. Tests were conducted on both mechanical and electrical malfunctions, including overloading, poor vibration, overheating, and power supply imbalance.

From this, the time taken by industrial operator or user to troubleshoot and fix an issue will be reduced from the fact that issue and action to perform is displayed on his screen to know what to do. Also production will increase due to reduction of downtime caused by stoppages.

6.2 Recommendation

Monitoring three phase Induction Motor Performance for Predictive Maintenance Using IoT and ML requires integrating technology in to enhance production in industries. Based on that

1. We recommend the industries to use ML technologies to reduce the downtime caused by the classic way of diagnosing the faults and adopt the one of ML
2. We recommend the further researchers to work on internal faults of the three phase motor since some faults covered were based on external one.

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