# ASHESI UNIVERSITY

## FAULT DETECTION AND PREDICTION IN INDUCTION MOTORS

**CAPSTONE PROJECT**

B.Sc. Electrical and Electronic Engineering

**Daniel Afriyie**

**2022**

**ASHESI UNIVERSITY**

# FAULT DETECTION AND PREDICTION IN INDUCTION MOTORS

**CAPSTONE PROJECT**

Capstone Project submitted to the Department of Engineering, Ashesi University in partial fulfilment of the requirements for the award of Bachelor of Science degree in Electrical and Electronic Engineering.

**Daniel Afriyie**

**2022**

# DECLARATION

I hereby declare that this capstone is the result of my own original work and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature: ……………………………………………………

Candidate's Name: Daniel Afriyie

Date: 21st April 2022

I hereby declare that preparation and presentation of this capstone were supervised in accordance with the guidelines on supervision of capstone laid down by Ashesi University College.

Supervisor's Signature:

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Supervisor's Name:

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Date: …………………………………………………………

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# Abstract

Induction motors are expensive and the backbone of every industry. There would be no production when induction motors break down. It is also costly to repair them after a sudden shutdown. Industries are gradually adapting to predictive maintenance to prevent unnecessary shutdowns and reduce the cost of maintenance. The objective of this paper is to even make the predictive maintenance of inter-turn short circuit fault in induction motors more reliable by adding fault detection and deploying the entire system in an alarm and display system. In this project, secondary current data from a three-phase induction motor has been used because of the current's capabilities of detecting a higher percentage of electrical faults. This is achieved using predictive maintenance toolbox in MATLAB.

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# Chapter 1: Introduction

## 1.1 Background

Industries have been the driving force of a good economy. Almost all industries rely on induction motors for their functioning, and it consumes more than half of the total generation capacity of industrialized nations [1]. Therefore, the breakdown of these induction motors would mean there would be no production of goods and services, affecting the economy. This makes it crucial for the recent research interest in monitoring the condition of induction motors to detect any fault and failure in advance. Most industries have started implementing predictive maintenance in their equipment to make them reliable. However, rarely the prediction of faults in their machines would always be accurate. There could be times when the machine will suddenly develop faults without a prior warning. Hence, this project will focus on combining the detection and prediction of faults in induction motors using the Predictive Maintenance toolbox in MATLAB [2].

## 1.2 Problem Definition

Induction motors have high efficiency, performance, and reliability, and their speed can easily be controlled electronically [3], making them the most widely used motors in the industries. These motors are the backbone of many industries. Production comes to a halt if these motors break down [1]. Induction motors are expensive and operating them under faulty conditions can cause deviation in their regular performances, more damage, and reduce the machine's lifespan. They are very expensive to replace or repair when they break down. The cost of repairing a machine after failure is three times the cost of performing predictive maintenance on that same machine [4]. Hence the need to detect and predict any fault to save cost and ensure the reliability of these motors.

## 1.3 Objectives of the Project Work

The objectives of the project are to:

1. design and construct a functional prototype for detecting and predicting faults in induction motors

2. investigate and tests the various methods that will make the system very responsive to inter-turn short circuit faults.

3. be able to analyze the various faults with the suitable fault analysis technique.

## 1.4 Expected Outcomes of the Project Work

After the completion of this fault detection and prediction in induction motors, the following outcomes were achieved:

1. A well-built prototype that would be able to detect and predict inter-turn faults in induction motors.

2. An integrated system that is responsive with a very quick reaction time to detect and predict inter-turn short circuit faults in induction motors.

3. A functional fault detection and prediction system with almost a perfect accuracy and efficiency.

## 1.5 Motivation of Project Topic

Electrical machines like induction motors are the backbone of industries in the world. They consume 50% of all the energy generated in the world [4]. When these machines break down due to faults, the economy comes to a standstill. This has received global attention. Hence, the motivation to integrate emerging technologies to build a prototype that would diagnose, detect, and predict the different faults to ensure the continuous running of the machine.

## 1.6 Research Methodology Used

The research methodology used for this project included:

1. Systematic literature reviews
2. Interviews with predictive maintenance engineers in the industry.
3. Computer modelling, software processing, and simulation

## 1.7 Facilities Used for the Research

These facilities used for the project included:

1. Ashesi Electrical and Electronics Lab
2. Ashesi Mechanical Workshop
3. Online Libraries like IEEE, google scholar, Institute of Physics Journal
4. Software like MATLAB, EasyEDA, SolidWorks, and others

## 1.8 Scope of Work

This project is primarily based on research using scholarly articles and scientific research papers. A model is trained to detect and predict inter-turn short circuit faults efficiently and effectively using secondary data. The model is integrated into an alarm and a display unit to alert the maintenance team whenever the system detects or predicts a fault.

# Chapter 2: Literature Review

## 2.1 Introduction

Many techniques exist for diagnosing, detecting, and predicting faults in electrical machines. These fault detection techniques include but are not limited to Signal Processing, Knowledge-Based techniques, model-based techniques, and the hybrid technique. Also, there has been the use of predictive maintenance approaches in the industries to ensure the reliability of their equipment. In this chapter, the functioning of these techniques will be explored, and their shortcomings identified.

## 2.2 Induction Motor

An induction motor is an electrical machine invented by Nicholas Tesla in 1888 [5] that operates at speed less than its synchronous speed. It consists of the stationary part called the stator and the rotating part called the rotor. The motor's type is derived from the type of rotor used. Hence, an induction motor can be a squirrel-cage or wound type. Figure 2.1 shows the schematic drawing of an induction motor.

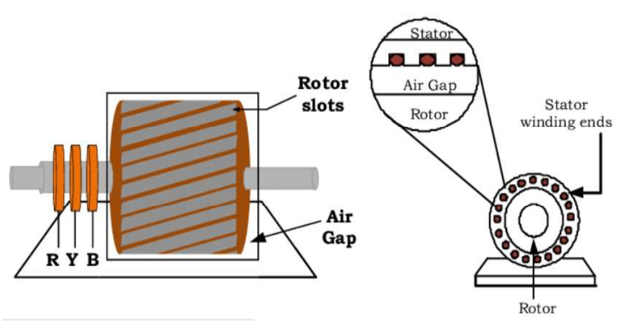



Figure 2. 1: Schematic drawing of an induction motor

## 2.3 Faults in Induction Motors

Induction motors become prone to catastrophic failure if their faults are not detected early. These faults can be electrical, mechanical, or environmental and can be found inside or outside the motor. Examples of induction motor faults include but are not limited to inter-turn short circuits of the stator windings, bearing failure, end ring failure, and broken rotor bars. Inter-turn short circuit fault is the puncturing of the insulation between conductors having different potentials in the same slot [2]. The bearing failure consists of two different types: the single point fault and the generalized roughness fault. The single point fault is caused by the overloading of the motor, which in turn causes a fatigue crack in the bearing surface. The generalized roughness fault is the deformation of the bearing surface caused by the lack of lubricant or misalignment [7]. According to Electric Power Research Institute (EPRI) research, 42% of faulty induction motors are associated with bearing failures. Inter-turn short circuit of the stator windings constitutes 31% of the faults, while end ring and broken rotor bars make up 9% of the faults reported in induction motors [6]. Figure 2.2 shows the various types of faults in an induction motor.

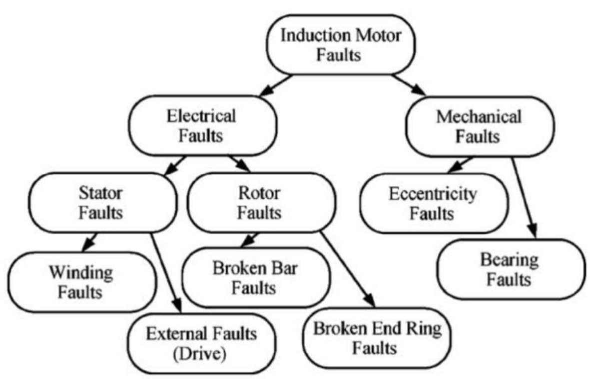



Figure 2. 2: The various types of faults [7]

## 2.4 Importance of Fault Detection and Prediction in Induction Motors

The goal of performing maintenance on an induction motor is to ensure the motor's reliability. That is the ability of the machine to continuously run to increase production quantity and quality while lowering production costs. Therefore, induction motors must be kept in completely functional and efficient operating conditions to get maximum throughput. When overlooked for a very long time, maintenance will result in an increment in the cost of maintenance. It is mostly around 15% - 60% of the cost of production in the industry [9]. Hence, it has become one of the industry's most demanding and vital cultures. The breakdown of induction motors causes an increase in their downtime, which slows down the production of goods and services. Though fault detection and prediction help to ensure the reliability of the equipment, it is costly to put the system in place, especially in cases where there are many machines to be monitored. The criticality of the equipment is, therefore, assessed before choosing, in order, to acquire the essential equipment to monitor.

## 2.5 Equipment Criticality

Equipment criticality is a rating that determines how frequently equipment should be maintained and which equipment should be prioritized in the case of a failure. Any equipment that could cause the process to stop or result in higher production costs if it fails is considered critical. An assessment is done to determine the criticality of equipment in the industry, the likelihood of failure (vulnerability), and the consequences. The assessment is numerically scored, allowing the assignment of a low, medium, or high-risk level to any piece of equipment that applies. The repercussions of an equipment failure determine whether it is worthwhile to do an equipment criticality assessment [10],[11]. Assigning a criticality rating to equipment ensures that the maintenance of all equipment is in the right direction

## 2.6 Milestone in Fault Detection and Prediction of Induction Motors

Engineers and researchers have made sure that there is continuous production in the industry with a cut down in the downtime of their induction motors. This fruitful journey started from breakdown or corrective maintenance to preventive maintenance. Condition monitoring then came into existence, and through this powerful technique, engineers and researchers brought forth predictive maintenance. Predictive maintenance cannot exist on its own since it needs condition monitoring techniques to forecast if there will be a failure [4].

## 2.7 Breakdown or Corrective or Reactive Maintenance

Breakdown or corrective maintenance is typically a series of complicated manual repairs requiring specialized training. The primary purpose of performing breakdown or corrective maintenance is to restore the machine that has broken down [9]. Unless and until there is a failure of equipment or a system, no maintenance operations are performed. In this maintenance method, even if minor problems or faults exist, no maintenance is performed until the entire system fails. As a result, the maintenance costs are the highest. Some precautionary services, such as lubrication and adjustments, are carried out, but no substantial repairs or system rebuilding are carried out until the system or equipment fails to function [9]. This technique is the most expensive because of the high cost of spare parts and the significant labor expenses associated with machine downtime [12]. This raises costs and puts a strain on other systems.

## 2.8 Preventive Maintenance

There are several types of preventive maintenance, but a very close look at each one shows that they are all time-based. Maintenance duties are time-driven, which means they are scheduled according to operation time [12]. The number of hours a given piece of equipment or system will work during its life cycle is used to schedule preventive maintenance activities. Figure. 2.4 describes an example of a machine train's life. The lifetime of every machine is represented by the following mean-time-to-failure (MTTF). The likelihood of failure for every machine is high on the first day of operation, as shown in Figure. 2.3. This is due to adjustments, calibration, and other factors. However, once this phase is completed, the likelihood of failure reduces and becomes stable for a more extended period. As time passes after this normal operation period, the likelihood of failure rises once more [7]. The preventive maintenance task schedule is centred on this life cycle graph. With reference to this graph, it is made with the assumption that the machine will break down. Even if the life expectancy of each type of machine is known, the actual life expectancy is determined by how it is used and maintained during its entire life cycle. The main disadvantage of this preventive maintenance is the increase in the cost of production [9]. This is because production is halted, and a huge amount of money is spent on performing maintenance that may not be required.

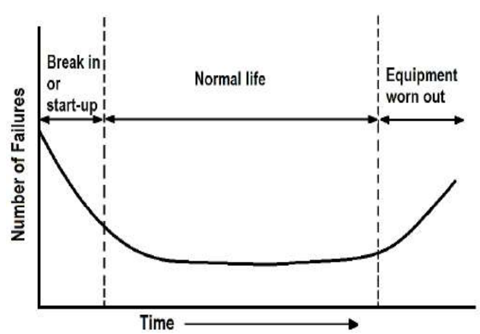



Figure 2. 3: Mean-time-to-failure curve

## 2.9 Condition Monitoring

Condition monitoring is a technique of checking a particular machinery condition while it is in use. These conditions can be pressure, current, voltage, temperature, vibrations, and others. It entails gathering data, analyzing it, comparing it to trends, benchmarks, and sample data from similar healthy machines. Condition monitoring uses a potential failure (P-F) curve in analyzing the data it collects from the machines under monitoring. This P-F curve is a graphical representation of equipment's health or condition before it reaches a state that can be considered a failure [13]. Condition monitoring studies various conditions of machines and analyzes those conditions using different techniques to determine if there is a failure. These condition monitoring techniques include oil analysis, vibration analysis, Motor Current Signature Analysis (MCSA), Infrared thermography, and many more. The data translation from these analyses into information and then using that information for maintenance optimization and reliability improvement is a critical challenge in condition monitoring [14].

### 2.9.1 Oil Analysis

Oil Analysis is one of the effective means of performing condition monitoring in induction motors. Much information about the induction motor's running state can be gathered from its lubricating oil. The induction motor's wearing state developing trend can be monitored to detect a potential problem in time [8]. This makes it possible to maintain the induction motor promptly before the breakdown, hence decreasing the amount of money spent on maintaining the induction motor and enhancing the motor's efficiency and security.

### 2.9.2 Vibration Analysis

Vibration analysis is a condition monitoring technique that monitors vibration levels and patterns from an electrical machine to detect abnormalities in the vibration event and assess the machine's overall state [8]. Vibration levels rise when mechanical problems like bearing faults occur in high-speed rotating equipment. The radial forces caused by the air-gap field are the most significant sources of vibration and noise in electric devices. For example, when there is a crack in a motor's bearings, there would be periodic collisions that can change the vibration pattern. Vibration analysis is a cost-effective and time-saving method of obtaining condition indicators for machine health management. The best way for defect diagnosis is vibration-based diagnostics. However, this requires expensive accelerometers and accompanying wiring. This restricts its use in various applications, particularly in tiny machines where cost is a significant consideration when selecting a condition monitoring approach. Moreover, when the diagnosis is based on numerous motors working in tandem with much noise, this constraint becomes even more complicated [15].

### 2.9.3 Motor Current Signature Analysis

This is a condition monitoring technique developed by the Oak Ridge National Laboratory [16]. It offers a sensitive, efficient, and cost-effective way to monitor a wide range of industrial machines in real-time. This technique can be implemented using either time-domain or frequency domain, and it is best used for bearing failure and inter-turn short circuit detection. However, it involves a lot of mathematical computations making it error prone.

### 2.9.4 Infrared Thermography

Infrared thermography is a non-contact technique for mapping the spatial pattern of heat and temperature measurement. It uses the concept of detecting infrared radiation emitted by a piece of equipment warmer than the Absolute Zero temperature. These radiations are transformed into electrical signals or pulses with the help of an infrared detector, which can subsequently be viewed on a monitor as a colour image, indicating the equipment's entire surface temperature map. This technique is helpful in detecting many electrical faults. However, the technique requires vast sums of money, and it is very slow in processing the thermal images [16].

## 2.10 Methods for Fault Diagnosis

The methods for fault diagnosis are the tools used for tracing faults by studying trends in the data from the induction motor. These tools are used for performing and interpreting the results of condition monitoring techniques. These methods include signal processing, model-based, knowledge-based and hybrid methods.

### 2.10.1 Signal Processing Method

For fault diagnosis, signal-based approaches rely heavily on signal processing technologies. Typically, these methods necessitate pre-determined circumferences [17]. Signals are influenced by their characteristics. They are considered abnormal once the signal or features have passed outside their range. There are numerous approaches when using the Signal analysis method. The signal processing method is used to analyze condition monitoring techniques like vibration analysis and MCSA.

### 2.10.2 Model-Based Technique

The dynamic system model is typically used in model-based fault diagnostic techniques. The actual system and model output benefit the industrial system's model-based techniques. The simulation and the real world can be compared, and actual data outputs, and hence, through visualization, the state of a motor can be determined [17]. Physical modelling can be used to create dynamic models. The most important challenge with model-based techniques is the fact that the correctness of the model describes how the diagnosis system behaves.

### 2.10.3 Knowledge-Based Technique

Knowledge-based model solutions typically use a human brain-like understanding of the process [17]. The human professional expert in real-time fault diagnostic methods could be an engineer who implements and operates with a strong understanding of diagnosing faults in induction motors. Knowledge-based strategies are prone to human errors, though they are effective when the signals are not working.

### 2.10.4 Hybrid Method

Combining numerous approaches may be a viable alternative because each defect diagnosis method has its own limitations. Several writers have proposed combining techniques such as neuro-fuzzy, neural network, and Bayesian interface with the expert system. A hybrid system called generic integrated intelligent system architecture was proposed [17]. Different Artificial Intelligence techniques, such as fuzzy logic and neural networks, were incorporated into the system.

## 2.11 Predictive Maintenance

Predictive maintenance is the application of data-driven condition monitoring techniques approaches to examine and assess equipment conditions and forecast when a machine will fail so that corrective maintenance can be planned before it happens. The goal is to plan maintenance at the most efficient and cost-effective time possible, maximizing the equipment's reliability. The stages involved in performing predictive maintenances are acquiring and storing data, data transformation, performing condition monitoring using the acquired data, asset health evaluation, predicting, developing a decision support system, and creating a human interface to interpret the results. Predictive maintenance is performed with the help of Machine Learning algorithms like the Support Vector Machine and K-Nearest Neighbour.

## 2.12 Remaining Useful Life (RUL) of an Induction Motor

The RUL of an induction motor is the length of time between its current condition and when it will fail. RUL is very useful to the maintenance team for scheduling purposes, optimizing the operating frequency, and reducing unplanned downtime. The methods used to estimate the remaining useful life of a machine are the survival model, similarity model, and the degradation model. The survival model is used to estimate the RUL of a machine when the data have a proportional hazard model and the probability distribution of the machine's failure time. The similarity model estimates the RUL when run-to-failure data of a similar machine is available**.** The RUL can also be estimated with the degradation model when the only information available is the threshold beyond which the machine will fail.

## 2.13 Survey of Related Work and Gaps Identified

Recently, many different approaches like the Motor Current Signature Analysis (MCSA) are being used for electrical machines' predictive maintenance applications. However, they involve a lot of mathematics. This makes them error-prone when applied to complicated systems. Due to their inability to manage non-linearity, these approaches are inefficient for electromechanical systems because of their high mathematical reliance [18]. Machine Learning using the MATLAB predictive maintenance toolbox, which comprises of the Diagnostic Feature Designer App and the Classification Learner App, is a robust methodology for fault detection and prediction. This methodology is robust because it is nonparametric, does not require complex mathematics, and can be implemented using basic tools. Predictive maintenance has taken over the field of maintenance of electrical machines. Most industries are deploying predictive maintenance techniques to ensure the reliability of their equipment. However, predictions can never be entirely accurate. There could be instances where the machine can fail without getting a warning earlier. Hence, there is the need to ensure that even if the machine escapes fault prediction, the fault within the machine must still be identified. This paper looks into the combination of fault detection and prediction and the remaining useful life to ensure the maximum reliability of induction motors.

# Chapter 3: Design Methodology

## 3.1 Introduction

This chapter focuses on the entire design of the system to detect and predict faults in induction motors. It introduces the detailed steps followed to achieve the goal of this project. That is to develop an efficient system to detect, predict faults, and estimate the remaining useful life (RUL) of an induction motor

## 3.2 System Requirements and Architecture

Table 3.1 shows the system requirements and their justifications for the system.

Table 3. 1: System requirements for alarm unit

| No. | System Requirement | Justification |
|---|---|---|
| 1 | An efficient microcontroller must be used to help display the fault details on an LCD and sound and alarm. | The microcontroller is the brain of the alarm system, hence an efficient one must be used for quick response |
| 2 | Alarm unit must have a different power source not more than 9V | This helps to maximize the sounding effect. |
| 3 | System must be enclosed fully in a container | This helps to avoid electric shocks |
| 4 | Must detect and predict inter turn short circuit fault in the motor | This helps to monitor the health status of the induction motor |
| 5 | Must not cost much to build | Less expensive makes most industries use it to prevent unexpected breakdown |
| 6 | There should not be any delay in sounding the alarm unit | No delay helps the maintenance team to quickly react |

### 3.3 Design Decision

Engineering projects are concerned with uniquely developing and defining new alternatives, solutions, and requirements to solve technical problems [13]. Hence, deciding on what the design of a project should look like is one of the most critical aspects of any engineering project. In deciding on the best microcontroller to use to meet the design requirements of this project, a PUGH chart was designed to help make the right choice. The ESP32 microcontroller was selected as the baseline for the comparison. The different microcontrollers are compared based on processing performance, cost, and availability criteria. The comparative analysis using the PUGH chart, as shown in Table 3.2, proved that ESP32, with the highest total score, is the best microcontroller for this project.

Table 3. 2: PUGH chart for microcontroller selection

| Selection Criteria | Weight (Out of 5) | ESP 32 (Baseline) | STM32 | AtMega328p | Arduino Uno |
|---|---|---|---|---|---|
| Processing Performance | 5 | 0 | -2 | -3 | -4 |
| Cost | 4 | 0 | +1 | +3 | 0 |
| Availability | 4 | 0 | -1 | -1 | 0 |
| TOTAL | | 0 | -10 | -7 | -20 |

### 3.4 Hardware Design

Electronic components and devices characterize this project's hardware design and implementation. These components include a microcontroller (ESP 32), an LCD, a relay, a

9V power supply from a battery, and an alarm unit consisting of a speaker and LEDs, as shown in Table 3.3. These components and devices are chosen based on engineering concepts, extensive research, and characteristics. Figure 3.1 shows the block diagram of the hardware design of the project.

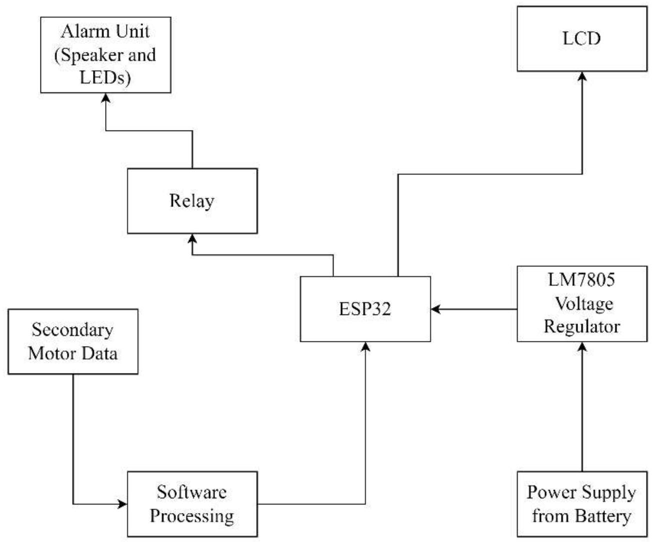
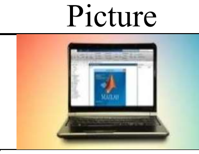
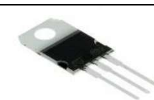



Figure 3. 1: Block Diagram of the System

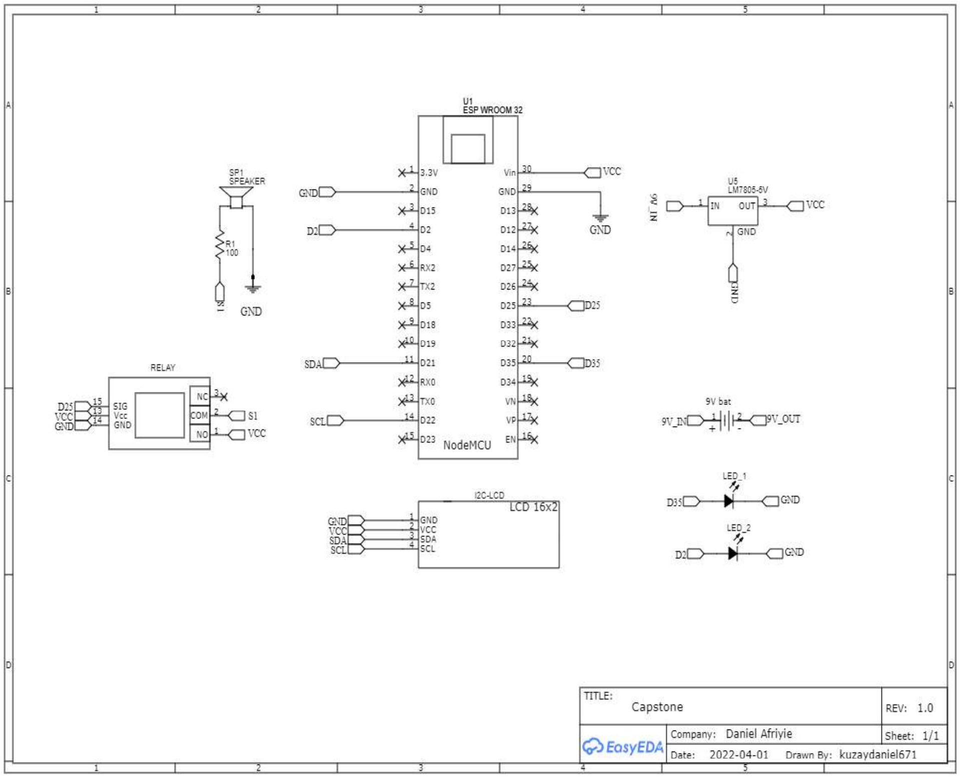
Table 3. 3: Electronic components and description

| Block | Description | Picture |
|---|---|---|
| Software Processing | MATLAB was used to preprocess the .csv file of the motor stator current data for the model |  |
| ESP32 | The ESP32 with a high processing power was the best microcontroller for the project based on the Pugh Chart. |  |
| Relay | The relay used electromagnetic coil to control a high current circuit with a lower one |  |

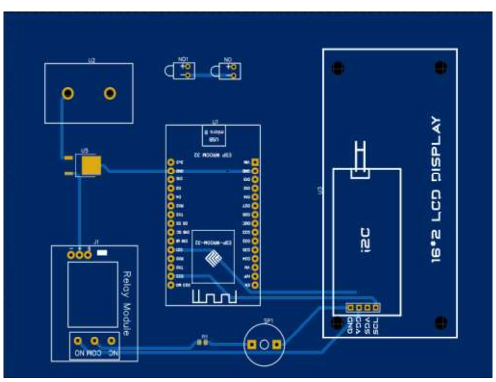
| | | |
|---|---|---|
| Power Supply from Battery | The 9V battery was used as the power supply purposely to give the speaker an independent supply. |  |
| LM7805 | The 9V from the battery is regulated by the lm7805 to provide a constant 5V to the ESP32 |  |
| LCD | This is a 2 by 16-character display for showing if there is a fault |  |
| Alarm Unit (Speaker and LEDs) | The speaker sounds while the LEDs light when fault is detected or predicted |   |

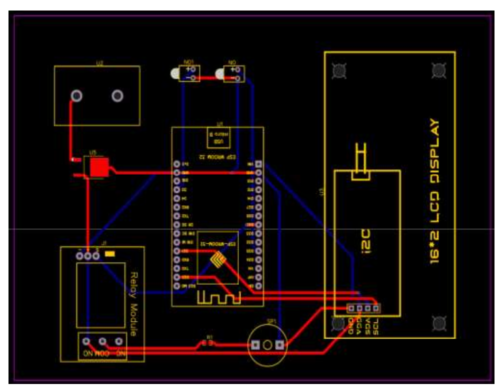
## 3.5 Circuit Design for Alarm and Display System

The alarm unit consists of a speaker and LEDs that are activated anytime a fault is detected or predicted by the algorithm. Figure 3.2 (a) shows the schematic circuit drawing of the alarm system. The circuit was designed using Easy EDA software, and then routed as shown in Figure 3.2 (b). The Printed Circuit Board (PCB) is autogenerated as shown in Figure 3.2 (c)




(a)




(b) (c)

Figure 3. 2: (a) Schematic drawing. (b) Printed circuit board. (c) Routing circuit.

## 3.6 Design Theory

Inductance and resistance are the main parameters of the circuit of an Induction motor. Studying the outcome of these parameters' malfunctioning helps identify the parameters and the conditions that can affect their value. These two main parameters are further divided into self-inductance, mutual inductance, and resistance.

### 3.6.1 Self-Inductance

Magnetizing and leakage inductance make up the self-inductance in stator and rotor windings. Because the windings of a healthy machine are identical, the self-inductance of all stator windings will be similar.

$$L_A = L_B = L_C = L_{ms} + L_{\ell s} \quad (1)$$

Magnetizing inductance of the stator is given by:

$$L_{ms} = \frac{\mu_\circ l r N s^2 \pi}{4g} \quad (2)$$

Where l is the motor's length, r is the radius of the cross section of the motor, g is the radial length of the air gap and $N_s$ represents the effective number of turns of the stator windings.

### 3.6.2 Mutual Inductance

Mutual inductances can exist from stator-to-stator as shown in equation (3).

$$L_{xsys} = \frac{\mu_\circ l r N s \pi}{4g} \text{ Cos } \theta_{xsys} \quad (3)$$

where $\theta_{xsys}$ is the angle between the stator windings x and y, and $L_{xsys}$ is the inductance between any stator winding x and any other stator winding y.

By substituting equation (2) into equation (3),

$$L_{xsys} = L_{ms} \text{Cos } \theta_{xsys} \quad (4)$$

The normal winding distribution in a healthy induction motor has two stator windings that are displaced 120˚ apart in one direction and 240˚ apart in the other direction. Hence Cos $\theta_{xsys}$ in equation (6) can be rewritten as:

$$\cos\theta_{xsys} = \cos(\pm 120^\circ) = \cos(\pm 240^\circ) = -0.5 \tag{5}$$

From equations 5-7, the mutual inductance between two stator windings is:

$$L_{AB} = L_{BA} = L_{AC} = L_{CA} = L_{CB} = -0.5L_{ms} \tag{6}$$

where $\theta_{xsys}$ is the angle that exist between any stator winding x and y [19].

The above equations show that the inductive flux in the motor's windings decreases when there is an inter-turn short circuit fault in the motor. This is because, when there is a short circuit, the current passes through the windings with the least or no resistance. This decreases the Ns from equation (2) and, in turn, decreases the flux. The reduced flux in one phase winding of the stator exposes the motor to unbalanced currents, which causes a negative sequence current.

### 3.6.3 The Resistance

The resistance value is given as:

$$R = \frac{\rho l}{A} \tag{7}$$

where R is the resistance measured in ohms (Ω), l is the cross-sectional area of the cable measured in meters square ($m^2$), and the ρ is the resistivity measured in ohm meter (Ω.m).

## 3.7 Experimental Set-up

Secondary data for this project was obtained from an online data source of an induction motor [22]. The secondary data is obtained from a test bench consisting of a 4-pole and 3-phase induction motor with a rated amperage and voltage of 3A and 220V, respectively. The testbench is a 1H motor that operates at a frequency of 50Hz. The data has time labeled as 'TIME,' and current values from the four poles of the motor labelled as CH1, CH2, CH3, and CH4. The stator circuit was re-wound, allowing access to the winding's ramifications to introduce inter-turn short circuits. Different short-circuit levels were emulated, ranging from less severe to most severe.

## 3.8 Fault Detection and Prediction Approach

This project focuses on using MATLAB Predictive Maintenance Toolbox to detect, predict faults and estimate the remaining useful life of the motor. The Predictive Maintenance Toolbox includes functions and interactive apps like the Diagnostics Feature Designer and Classification Learner App that help extract and rank the four current values (CH1, CH2, CH3, and CH4) by the importance of the data and models, including statistical and time-series analysis. Extracting and sorting the most important current values from data using time-series approaches was crucial in monitoring the condition of induction motors. Figure 3.3 shows the block diagram for the detection and prediction algorithm.

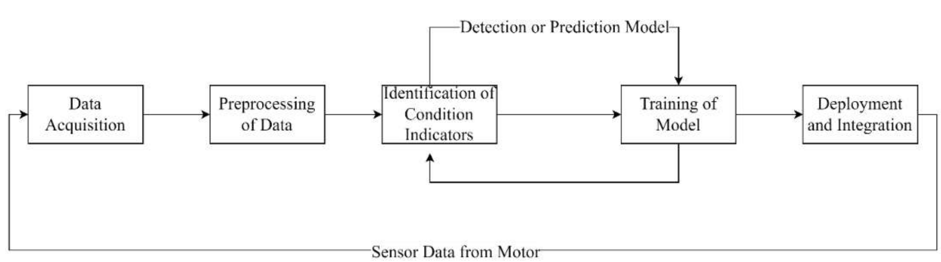



Figure 3. 3: Detection and prediction algorithm

### 3.8.1 Data Acquisition

Secondary data consisting of the current values of the motor was used for this project. The secondary dataset was already grouped into seven (7), from 0 to 6. Data under the 0 group was the data for a healthy motor with no faults. Those under group 1 were slightly faulty, and they were in the initial stages of developing inter-turn short circuit fault. The severity of the fault increased as the group number of the motor increased from 0 to 6 [20]. The secondary data had 100,000 rolls of current values for each group of motor data. The number of rolls was trimmed to 35001 for training purposes on an ordinary computer. An extra column was created in the excel sheet containing the data to include the different motor groups as the fault condition of the motor. Figure 3.4 (a) shows a picture of the sample current data of a healthy under no-load motor data, and hence, belonging to the group 0. Figure 3.4 (b) also shows a sample current data of a faulty motor under no-load condition, and hence belonging to group 6. The full dataset was imported into MATLAB for the model training. The current rating of the motor used for the experiment was 3A. Looking at the current values, namely, CH1, CH2, CH3, and CH4, Figure 3.4 (a) has values far below the 3A current rating of the motor used to get this secondary data.

On the other hand, Figure 3.4 (b) has current values either very close to or beyond the rated current value of 3A. The CH1, CH2, CH3, and CH4 current values follow the same trend for motor groups (1-5). The current values get close to or go beyond the rated current value of 3A, making the current values important features for machine learning model training.

| 1 | TIME | CH1 | CH2 | CH3 | CH4 | CONDITION |
|---|---|---|---|---|---|---|
| 2 | 1:58:25 AM | 1.584 | 1.32 | 2.1 | 0.9 | 0 |
| 3 | 1:58:26 AM | 1.592 | 1.32 | 2.1 | 0.92 | 0 |
| 4 | 1:58:27 AM | 1.624 | 1.36 | 2.12 | 0.92 | 0 |
| 5 | 1:58:28 AM | 1.608 | 1.38 | 2.14 | 0.9 | 0 |
| 6 | 1:58:29 AM | 1.592 | 1.4 | 2.14 | 0.92 | 0 |
| 7 | 1:58:30 AM | 1.592 | 1.44 | 2.16 | 0.92 | 0 |
| 8 | 1:58:31 AM | 1.608 | 1.46 | 2.18 | 0.94 | 0 |
| 9 | 1:58:32 AM | 1.624 | 1.46 | 2.22 | 0.94 | 0 |
| 10 | 1:58:33 AM | 1.664 | 1.5 | 2.22 | 0.94 | 0 |
| 11 | 1:58:34 AM | 1.672 | 1.52 | 2.24 | 0.96 | 0 |
| 12 | 1:58:35 AM | 1.64 | 1.54 | 2.26 | 0.96 | 0 |
| 13 | 1:58:36 AM | 1.624 | 1.56 | 2.28 | 0.94 | 0 |
| 14 | 1:58:37 AM | 1.704 | 1.58 | 2.28 | 0.98 | 0 |
| 15 | 1:58:38 AM | 1.688 | 1.6 | 2.3 | 0.98 | 0 |
| 16 | 1:58:39 AM | 1.624 | 1.64 | 2.3 | 1 | 0 |
| 17 | 1:58:40 AM | 1.656 | 1.64 | 2.34 | 0.98 | 0 |
| 18 | 1:58:41 AM | 1.752 | 1.68 | 2.34 | 1 | 0 |
| 19 | 1:58:42 AM | 1.768 | 1.72 | 2.34 | 1.04 | 0 |
| 20 | 1:58:43 AM | 1.688 | 1.72 | 2.36 | 1.02 | 0 |

(a)

| TIME | CH1 | CH2 | CH3 | CH4 | CONDITION |
|---|---|---|---|---|---|
| 2:05:00 | 2.58 | 2.75 | 2.17 | 3.6 | 6 |
| 2:05:01 | 2.57 | 2.75 | 2.15 | 3.6 | 6 |
| 2:05:02 | 2.58 | 2.75 | 2.15 | 3.47 | 6 |
| 2:05:03 | 2.6 | 2.7 | 2.15 | 3.47 | 6 |
| 2:05:04 | 2.63 | 2.78 | 2.15 | 3.4 | 6 |
| 2:05:05 | 2.65 | 2.78 | 2.15 | 3.4 | 6 |
| 2:05:06 | 2.68 | 2.75 | 2.15 | 3.4 | 6 |
| 2:05:07 | 2.68 | 2.75 | 2.15 | 3.38 | 6 |
| 2:05:08 | 2.67 | 2.7 | 2.18 | 3.35 | 6 |
| 2:05:09 | 2.65 | 2.7 | 2.15 | 3.37 | 6 |
| 2:05:10 | 2.65 | 2.68 | 2.15 | 3.35 | 6 |
| 2:05:11 | 2.65 | 2.67 | 2.17 | 3.3 | 6 |
| 2:05:12 | 2.65 | 2.65 | 2.17 | 3.28 | 6 |
| 2:05:13 | 2.63 | 2.65 | 2.15 | 3.28 | 6 |
| 2:05:14 | 2.65 | 2.63 | 2.15 | 3.23 | 6 |
| 2:05:15 | 2.65 | 2.6 | 2.17 | 3.23 | 6 |
| 2:05:16 | 2.65 | 2.57 | 2.17 | 3.2 | 6 |
| 2:05:17 | 2.63 | 2.57 | 2.17 | 3.18 | 6 |
| 2:05:18 | 2.63 | 2.55 | 2.17 | 3.17 | 6 |
| 2:05:19 | 2.65 | 2.53 | 2.2 | 3.13 | 6 |

(b)

Figure 3. 4: (a) healthy no-load motor data. (b) Faulty no-load motor data

### 3.8.2 Pre-processing of Data

The pre-processing of data involved analyzing the current signals and time series of the online motor data and preparing the signals for the next step. Pre-processing the data was essential for converting the data into the form that the condition indicators can use. It entailed converting unstructured or raw data into a usable format. Data pre-processing required tracing signals into several domains to extract condition indicators from them and generate data ensembles for effective handling of data. The random features discovered using signal processing techniques and feature extraction were the current signals of the motor [21]. Time-domain analysis was the main feature extraction technique used in the data pre-processing stage. In analyzing the signals, operations like filtering, smoothing, and labelling were performed on the signals. Performing these operations on the signals was user-friendly as it helped to get a clear graphical distinction between the healthy and faulty data as well as getting rid of any outlier signal.

### 3.8.3 Identification of Condition Indicators

The Diagnostic Feature Designer App in MATLAB analyzed and extracted the most important current values from the dataset. The current values were sorted and selected based on one-way ANOVA statistical tool for further processing. The identification of condition indicators from the one-way ANOVA helped rank the current values for effective training of the model in the Classification Learner App in MATLAB. The current values were ranked to select the most important ones as condition indicators from the raw data. The current values selected as the most important were the current values from CH1, CH2, CH3, and CH4 of the original dataset. Ranking and selecting the most important set of current values with one-way ANOVA ensured that the model's accuracy improved. One Way ANOVA is a parametric test that assumes that the normally distributed data sample has a homogenous variance and independent cases [23]. One Way ANOVA was used because of its statistical power and the ability to compare independent variables with different group means [23].

Mathematically, equation (8) represents one-way ANOVA for testing a null hypothesis.

$$H0{:}41=42=43 \tag{8}$$

For one-way ANOVA, the results will either accept or reject this null hypothesis. When there is a rejection, it can be interpreted as there is unequal distribution means. Scatter plots are used for identifying the groups that are different, because the one-way ANOVA is unable to classify the groups that are not the same. The scatter plot is used to compare two of the variables to find out the relationship that exists between them.

### 3.8.4 Training of Model

The most important current values selected and ranked in the Diagnostic Feature Designer App were exported into Classification Learner App in MATLAB. For this model, all the current values (CH1, CH2, CH3, and CH4) were selected by the Diagnostic Feature Designer App. The model was classified and trained using Machine Learning algorithms deployed in the Classification Learner App in MATLAB. The Classification Learning App separated the data imported into MATLAB into three sets to increase the accuracy of the Machine Learning Models. The three sets of data were training, validation, and test data. The data was separated to have a higher accuracy of the trained model. Hence, 70% of the data was reserved for the training, 15% was used for validation, and 15% was used for testing. The classification of the different stages of inter-turn short circuit fault depended on the conditions indicator (rated current value of 3A), which distinguished a healthy motor from a faulty one. The Classification Learner app was used to monitor the induction motor's present conditions and detect and diagnose faults. It determined the machine's health, if it was failing and what was failing. The selected condition indicator trained a model using different machine learning algorithms to detect and predict inter-turn short circuit fault in the induction motor. The machine learning algorithm for model training focused on Support Vector Machines (SVM) and the K-Nearest Neighbor (KNN) algorithms. These algorithms were chosen because they are not complicated and have a high-performance ability to accurately predict even with limited data.

Support Vector Machine is a machine learning algorithm in which the data for model training is separated by hyperplanes characterized by the sum of the support vectors. The hyperplanes separate the data into positive and negative classes [24]. This type was used because both separable and non-separable data were available in the data set.

On the other hand, K-Nearest Neighbor is an instance-based supervised learning algorithm that classifies an unfamiliar instance by using an effective distance to compare it to a known instance. A data set is partitioned into a fixed number of clusters (k) in KNN. The KNN classifier is trained using the centroid, which can be real or imaginary, as the center data point in a cluster. The procedure of determining the centroid value is iterative. The emanated classifier is used to build an initial array of random clusters. The centroid value is then adjusted until it becomes stable. The stable centroids are used to classify input data by changing an unknown dataset into a known one [27]. Figure 3.5 shows the validation percentage and the range of current values from the one-way ANOVA performed on the current values using the Diagnostic Feature Designer App. 15% of the data was set aside for validation of the model to protect against overfitting data. The range of current values from Figure 3.5 in the dataset was trained with the SVM and the KNN machine learning models.

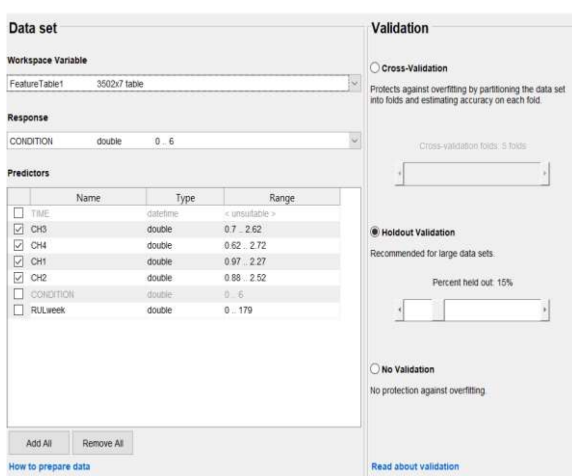



Figure 3. 5: Range of each current set of values exported for model training

### 3.8.5 Deployment and Integration

A MATLAB function was automatically generated from the developed algorithm. The MATLAB function with a .mat extension was converted to a .c extension (C programming) using the Coder App in MATLAB. The C programming code was then uploaded onto the ESP32 microcontroller for building the alarm and display unit. A 9V battery passed through the LM705 voltage regulator that powers the unit. A relay drives the speaker that sounds to alert the maintenance. The LCD also displays the RUL whenever the system detects or predicts an inter-turn short circuit fault. Figure 3.6 shows the CAD model of the alarm and display unit designed using SolidWorks.

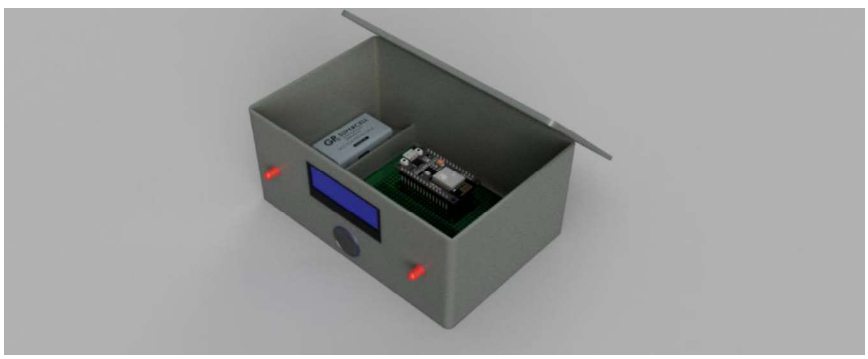


Figure 3. 6: CAD model of the alarm and display unit

## 3.9 Detection of Inter-Turn Short Circuit Fault

In a short-circuit fault for a given phase, the number of turns of the winding will reduce, causing the resistance to increase, as shown in equation (7). As shown in equation (2), the inductive leakage flux also decreases. The inter-turn short circuit was introduced for the testbench used by taking out insulations from sections of the coil of a phase and connecting it to a conductive material. The severity of the inter-turn short (the percentage of short turns) depended on the particular turn of the coil on which the conductive material is connected [22]. Detecting the inter-turn short-circuit fault was done in three ways: threshold comparison, the negative current sequence, and the machine-learning algorithm.

### 3.9.1 Negative Sequence Current

The current sequence of the healthy motor is the positive sequence current. When the inter-turn short circuit fault occurs, two of the windings of the current signals are swapped. Based on that, an inter-turn short circuit can be detected.

### 3.9.2 Threshold Comparison

Comparing the threshold of healthy motor data signals to a faulty one was one of the methods used to detect the inter-turn short circuit fault. The rating of the induction motor whose current values were used for this project was 3A. Hence, when the signals of these current values went beyond this threshold, it indicated that the induction motor was faulty. However, this method was inefficient since it only tells there is a fault and does not specifically determine if the fault is an inter-turn short circuit of the stator windings.

### 3.9.3 Machine Learning Algorithm

The machine learning algorithm detects inter-turn short circuits of the stator windings when the algorithm predicts that the test data is classified under group 6. For group 6 motors, they have no remaining useful life. The motor has completely developed the inter-turn short circuit fault.

## 3.10 Prediction of Inter-turn Short Circuit Fault in Stator Windings

Prediction of the inter-turn short circuit fault in the stator windings of the induction motor was based on the results of the machine learning algorithms deployed. The algorithm forecasts the inter-turn short circuit fault level by returning a number from 0 to 6. Number 0 meant there was no inter-turn short circuit fault in the stator of the induction motor. As the number increased from 0 to 6, the severity of the inter-turn short circuit fault increased, making group 6 the faulty motor with a total inter-turn short circuit fault.

### 3.11 Estimation of the Remaining Useful Life (RUL)

The life expectancy of a three-phase induction motor from run-to-failure experiments shows that the motor can run for about 30,000 hours or 179 weeks before it breaks down [28]. Assuming the motor with a fault code of 0 or group 0 is a new motor with a remaining useful life of 179 weeks, the motor with a fault code of 6 has broken down and has no remaining useful life (0 weeks). Hence interpolation is used to estimate the remaining useful life of the other motors of groups 1, 2, 3, 4, and 5. Interpolation is the estimation of unknown values that fall between known data points. It is used to forecast unknown values for any data points with a geographical correlation. The formula for interpolation is given by:

$$\frac{\text{RUL of motor with fault code 0} - \text{RUL of motor with fault code 6}}{\text{RUL of x fault code} - \text{RUL of fault code 6}} = \frac{0-6}{\text{x fault code} - 6} \qquad (9)$$

for motor with fault code 1:

let $x_1$, $x_2$, $x_3$, $x_4$, $x_5$ be the RUL of the motor data with fault codes 1, 2, 3, 4, 5 respectively

$\frac{179-0}{x1-0} = \frac{0-6}{1-6}$, $x_1$ =145.83 =146 weeks

for motor with fault code 2:

$\frac{179-0}{x2-0} = \frac{0-6}{2-6}$, $x_2$ = 119.33 = 120 weeks

for motor with fault code 3:

$\frac{179-0}{x3-0} = \frac{0-6}{3-6}$, $x_3$ = 89.5 = 90 weeks for motor with fault code 4:

$\frac{179-0}{x4-0} = \frac{0-6}{4-6}$ ,     $x_4 = 59.67 = 60$ weeks

for motor with fault code 5:

$\frac{179-0}{x5-0} = \frac{0-6}{5-6}$ ,     $x_5 = 29.83 = 30$ weeks

# Chapter 4: Results and Discussion

## 4.1 Introduction

This chapter focuses on the results from the implementation of both the detection and predictive algorithm deployed in chapter three. Statistical analysis is performed to select the best algorithm which is deployed in the hardware design of an alarm and display unit.

## 4.2 Fault Detection Results

The inter-turn short circuit fault was detected in three main ways: threshold comparison, negative sequence current and machine learning algorithms. However, the machine learning was able to detect and at the same time predicts the inter-turn short circuit.

### 4.2.1 Threshold Comparison

Inter-turn short circuit fault was detected by comparing the amplitude of any motor current signal to the threshold of the current signals of a healthy motor. The online testbench motor had a rated current of 3.0 A, so the inter-turn short circuit fault was detected whenever the signal went above the threshold of 3.0A, as seen in Figure 4.1. However, this method was inefficient because other faults could make the current signals go beyond the threshold. It was also unable to detect the level of inter-turn short circuit.

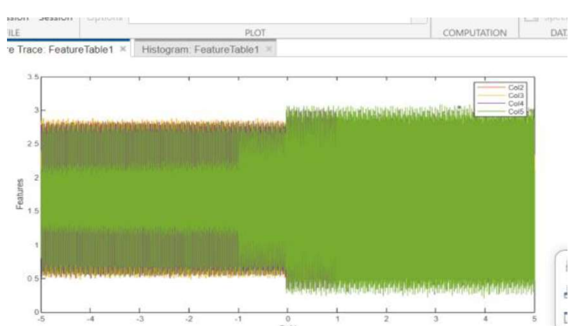
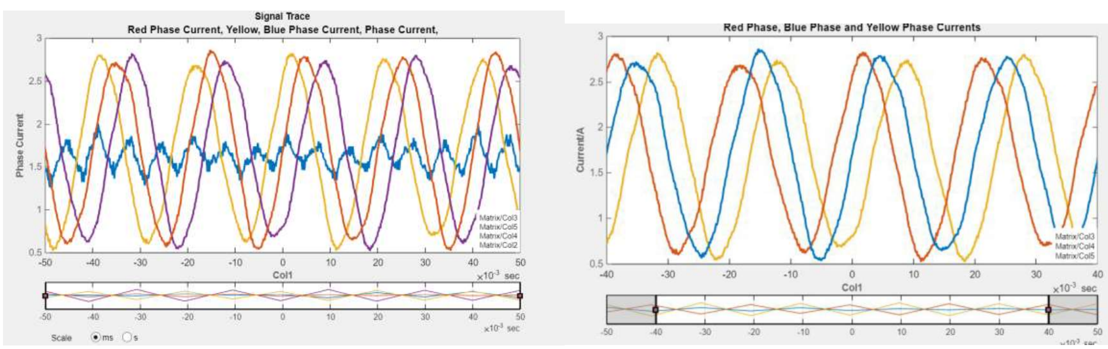



Figure 4. 1: Threshold comparison of current signals

### 4.2.2 Negative Sequence Current

A balanced set of three-phase currents has positive sequence currents only as shown in Figure 4.2(a). Figure 4.2 (a) has unfiltered signals. A negative sequence current is a clear indication of abnormality in the system. During the negative sequence, the direction of two of the current signal switches is seen in Figure 4.2 (b). This fault detection method was, however, not effective. This is because other asymmetry factors could cause the induction of negative sequence current into the system. The negative sequence can also be caused by load fluctuations, unbalanced supply voltage, and instrumentation asymmetries. Hence, it is not a unique method for detecting inter-turn short circuit fault.




(a) (b)

Figure 4. 2: (a) Positive sequence current graph. (b) Negative sequence current

### 4.2.3 Machine Learning Algorithm

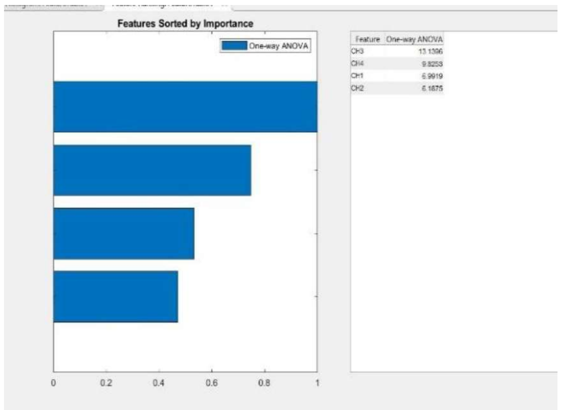
The group six motor data had fully developed inter-turn short circuit fault. So, when the machine learning algorithm predicted a motor under group 6, it meant an inter-turn short circuit was detected. The machine learning algorithm is fully explained in section 4.3.

## 4.3 Fault Detection, Prediction and Remaining Useful Life Estimation

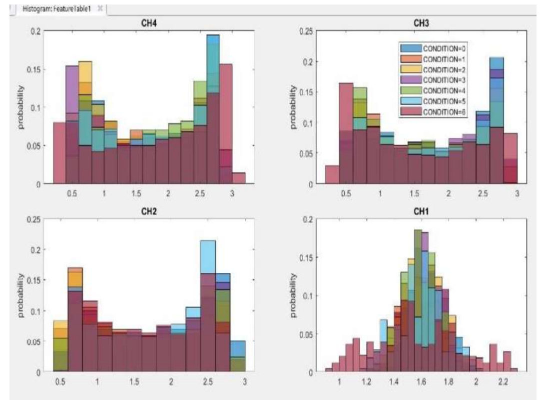
Two machine learning algorithms, Support Vector Machine (SVM) and K-Nearest Neighbour (KNN) were used to detect and predict the inter-turn short circuit fault. The fault was detected when the machine learning algorithm classified the data under group six motor data. It meant the inter-turn short circuit had already occurred, and there are 0 weeks of remaining useful life of the motor as calculated in section 3.11 using equation (9). Under this section is the results from the procedures in training the SVM and KNN models.

### 4.3.1 Feature Extraction and Ranking

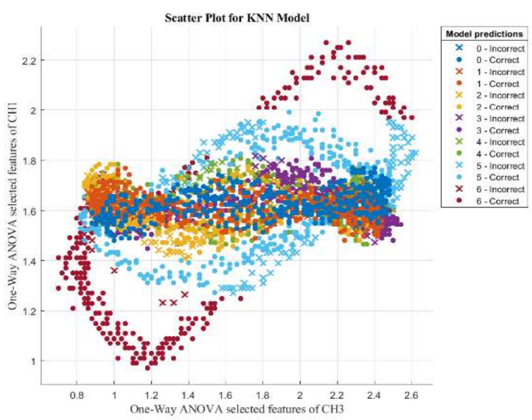
The current values (CH1, CH2, CH3, and CH4) were extracted from the three sets (no-load, half load, and full load) of healthy and faulty data using one-way ANOVA. Figure 4.3 (a) shows the lists of the ranked current values (CH3 first) extracted in the MATLAB Diagnostic Feature Designer App. Histogram plots from Figure 4.3 (b) also help investigate how the important current values in the different classes of motor separated across a bin. The best feature histogram is the one with the motor group appearing in different bins ranges in a particular histogram. Figure 4.3 (a) shows that CH3 was the set of current values ranked as the most important. Figure 4.3 (b) explains it well as there are a lot of different motor groups across the CH3 bin in the histogram. The scatter plot from Figure 4.3 (c) further analyses the extracted features by investigating their relationship**.** For example, from Figure 4.3 (c), there is a high probability that when the current value from CH1 and CH3 are both 1A and belong to group 6, it will predict correctly.




(a)




(b)




(c)

Figure 4. 3: (a) Current signal sorting. (b) Current in histogram. (c) Scatter plot of current

### 4.3.2 Results from Classification Algorithm for No-Load, Half Load and Full Load Induction Motors

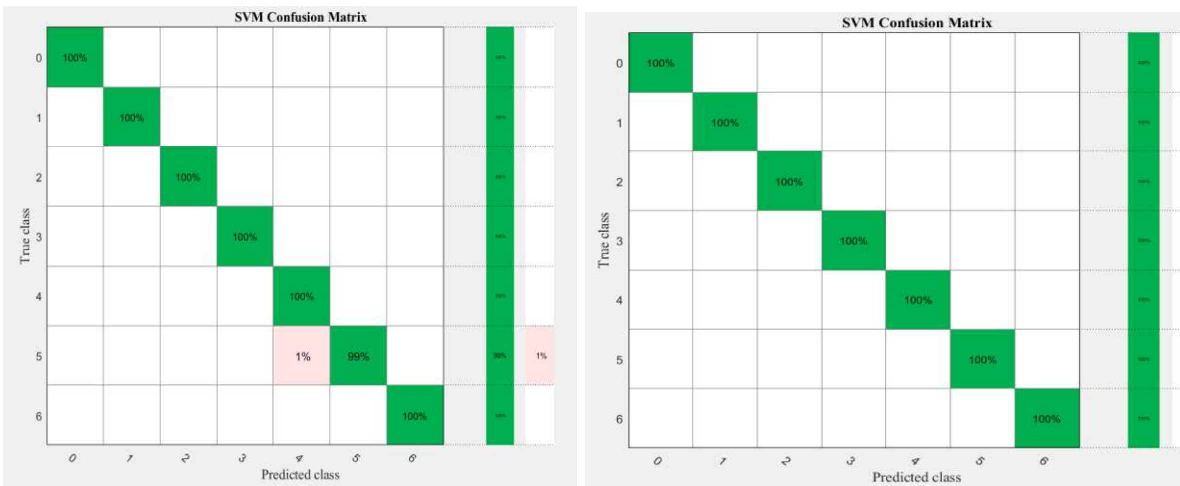
After the feature extraction, the Support Vector Machine (SVM) and K-Nearest Neighbour (KNN) models were used to train the model. All SVM classifiers, namely linear, quadratic, and fine Gaussian SVM, had a classification accuracy of 99.9% for both no-load and half-load motors and 100% accuracy for the full load motor, as shown in Table 4.1. Figure 4.4 (a) shows the confusion matrix, which is the same for the no-load and half-load states of the motor. All classifiers of the SVM model under no load and half load state of the motor had a prediction accuracy of 99.9%. The model correctly predicted all the seven different groups of the motor fault (0-6) of the induction motor, except motors belonging to class 5. The algorithm correctly predicted only 99% of the group 5 motor and classified 1% of the group 5 motor data as group 4 motor data. Similarly, Figure 4.4 (b) shows the confusion matrix for the different SVM classifiers under the motor's full load state. The algorithm correctly predicted the classes the motor data belonged to for the full load state.

The remaining useful life of the motor was then estimated based on the calculations in section 3.11. Each motor group had its remaining useful life. For example, when the algorithm predicted the motor data to belong to group 4, it meant it had 60 weeks remaining useful life.

Table 4. 1: Accuracies for SVM classifiers under different motor loads

| Load State of Motor | SVM Classifier | Accuracy |
|---|---|---|
| No Load | Linear | 99.9% |
| | Quadratic | 99.9% |
| | Fine Gaussian | 99.9% |
| Half load | Linear | 99.9% |
| | Quadratic | 99.9% |
| | Fine Gaussian | 99.9% |

| | | |
|---|---|---|
| Full Load | Linear | 100.0% |
| | Quadratic | 100.0% |
| | Fine Gaussian | 100.0% |




(a) (b)

Figure 4. 4: (a) SVM no and half load confusion matrix. (b) SVM full load confusion matrix

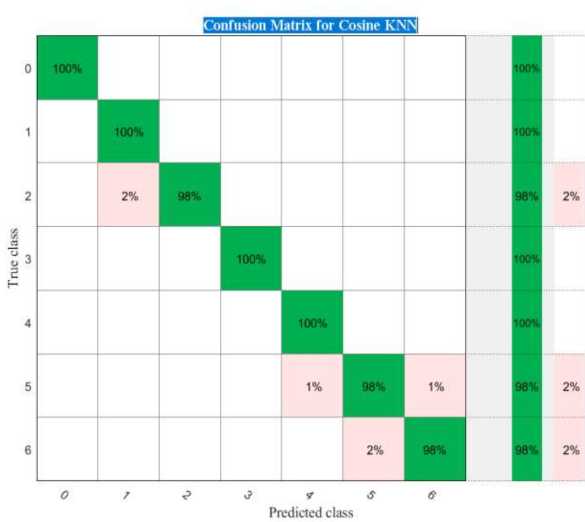
For the KNN classifiers, namely medium, coarse, and cubic KNN, the confusion matrix accuracy of the trained models was 96.1% for all the classifiers under the motor's no-load and half load state, as seen in Figure 4.5 (c). For the motor's full load, the confusion matrix accuracy for the medium, cosine, and cubic were 99.8%, 73.5%, and 99.7%, respectively, as shown in Table 4.2.

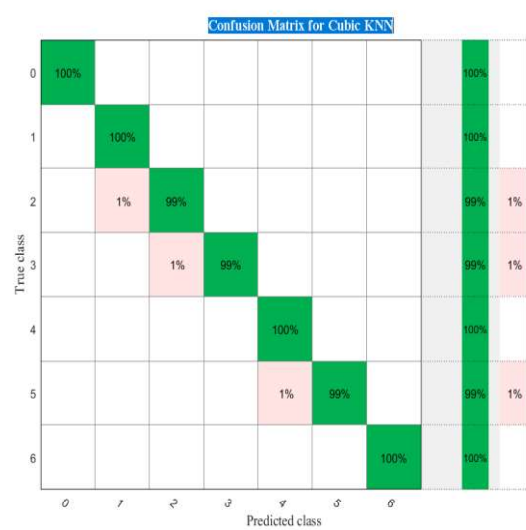
Table 4. 2: Accuracies for KNN classifiers under different motor loads

| Load State of Motor | KNN Classifier | Accuracy |
|---|---|---|
| | Medium | 96.1% |

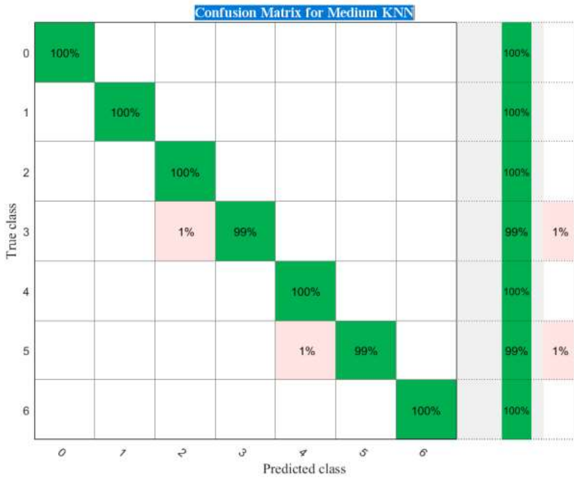
| | | |
|---|---|---|
| No Load | Coarse | 96.1% |
| | Cubic | 96.1% |
| Half load | Medium | 96.1% |
| | Coarse | 96.1% |
| | Cubic | 96.1% |
| Full Load | Medium | 99.8% |
| | Cosine | 73.5% |
| | Cubic | 99.7% |

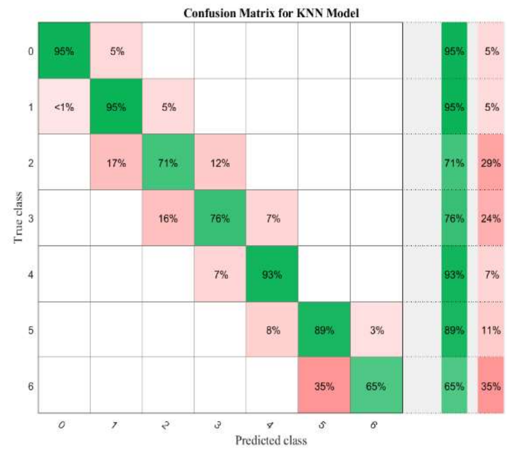
Comparing the accuracies of the classifiers for both the SVM and KNN algorithms showed that the SVM algorithm was the best. The SVM algorithm had 99.9% for no-load and half load and 100% for full load state of the motor. Therefore, the SVM algorithm was chosen for statistical analysis to see if there is a significant difference between the three different types of motor load states (no-load, half-load, and full load).



(a) (b)



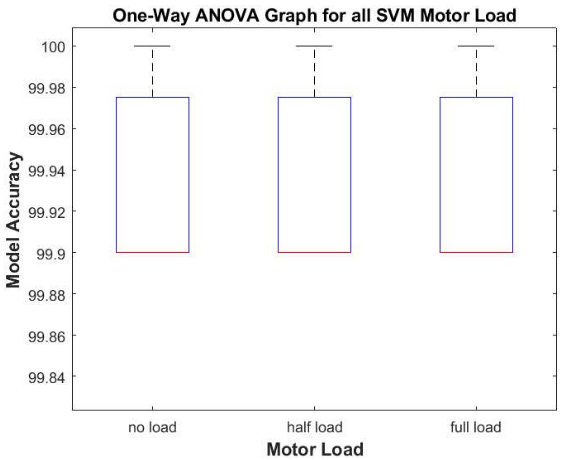




(c) (d)

Figure 4. 5: Confusion Matrices for the KNN models

## 4.4 Results from Statistical Analysis

The accuracy of the different classifiers of the SVM model under the different load states (no-load, half-load, and full load) was investigated to see if there was variation among them. Therefore, a one-way ANOVA test was performed on the SVM no load, half load, and full load accuracy values, as shown in Figure 4.6 (a). From Table 4.1, the accuracy for the different motor loads was almost the same, with no significant differences. The one-way ANOVA was performed to either reject or accept this null hypothesis. After the test, the p-value of 1, as shown in Figure 4.6 (b), was greater than the critical p-value of 0.05. Hence, the hypothesis that the accuracies for the SVM model are statistically insignificantly different was accepted. This showed that the fault prediction accuracy did not significantly depend on the motor load.




| Source | SS | df | MS | F | Prob>F |
|---|---|---|---|---|---|
| Columns | 0 | 2 | 0 | 0 | 1 |
| Error | 0.02 | 6 | 0.00333 | | |
| Total | 0.02 | 8 | | | |

(a) (b)

Figure 4. 6: (a) One-way ANOVA graph. (b) p-value for the ANOVA

## 4.5 Result from Interfacing SVM model with Alarm Unit

The hardware implementation of this project was the alarm unit that was activated whenever a fault was detected or predicted in the induction motor. The remaining useful life (RUL) algorithm was changed from a MATLAB (.mat) file to a C programming (.c ) file with the help of a MATLAB in-built application called Coder. The new code was deployed in an embedded system to sound an alarm and display the RUL of the induction motor. Figure 4.7 (a) shows the internal circuitry of the system, while Figure 4.7 (b) shows the front where the LCD and speakers are attached.


(a)


(b)

Figure 4. 7: (a) internal circuitry. (b) Front view of alarm and display unit

# Chapter 5: Conclusion, Limitations and Future Work

## 5.1 Conclusion

Induction motor predictive maintenance, also known as fault detection and prediction, is useful for monitoring equipment health. Predictive maintenance is a unique technique for diagnosing and prognosing faults in industrial machines. The accuracy of the inter-turn short circuit fault detection, prediction, and remaining useful life estimation depends on getting accurate and enough data from the machine. The data is then pre-processed to identify condition indicators from them. A model is then trained with the condition indicators to get the relationship between the source of mistakes and projected damage [23]. Making an accurate prediction of machine fault is essential to avoid its breakdown, affecting production. Also, detecting and predicting faults in induction motor lowers maintenance costs and improve reliability and productivity. An alarm unit with a display was also integrated into the project for users to be easily alerted when there was a fault. The LCD displayed the exact fault and the number of weeks left for the fault to occur.

## 5.2 Limitations

The level of knowledge needed for the features extraction for the machine learning algorithm increased as the project proceeded. This made it difficult to extract different features to train models depicting the percentage of inter turns of the windings in the inter turn short circuit fault and determine if the direction of the inter turn winding is in vertical or axial position. Time needed to learn new concepts and software to implement in the project was also a constraint. Time constraints restricted the extension of the project to detecting and predicting faults when the motor has a different percentage of load attached as well as when the frequency is varied.

## 5.3 Future Works

Further works can be done to improve this project by incorporating Industrial Internet of Things (IIoT) into the system. Industrial IoT makes use of smart sensors to collect real time data for analysis. The results can be viewed from many places because it is part of a network of systems that can be monitored on devices like the Supervisory Control and Data Acquisition (SCADA) in the industry. This will make fault detection and prediction easier and faster.

Also, a dashboard could be added to the system so that the status of the induction motor could be accessed when logged in on the internet, and not only onsite where the alarm sounds to alert maintenance team if there should be a fault.

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# Appendices

## Appendix A

MATLAB code generated from Diagnostic Feature Designer and Classification Learner apps: https://github.com/kuzaydaniel671/CapstoneProject.git

Code for ANOVA test: https://github.com/kuzaydaniel671/StatisticalAnalysis.git

The secondary data used for training the model can be found in capstoneSecondaryData

## Appendix B: Figures from Predictive Maintenance Toolbox