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Inter-Turn Short Circuit Fault Detection and Prediction in Induction Motors

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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. This paper's objective is to make the predictive maintenance of induction motors more reliable by adding fault detection. This will ensure the reliability of the induction motor, as it will continuously run to increase production quantity and quality while lowering production costs. This project uses secondary stator current data from a three-phase induction motor to detect and predict inter-turn short circuit faults. The stator current data can detect a higher percentage of electrical faults. The predictive maintenance toolbox in MATLAB is used to achieve the fault detection and prediction algorithm. Two classification algorithms, Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) are used to detect and predict the inter-turn short circuit fault. It is found that the selected classifiers of the SVM algorithm gave almost a perfect prediction accuracy as compared to the classifiers of the KNN algorithm. The suggested fault detection and prediction in induction motors work very well, increasing the machine's reliability by decreasing the breakdown time and maintenance cost.

Keywords - *Predictive Maintenance, Inter-turn short circuit, Machine Learning.*

1. Introduction

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 50% of the total generation capacity of industrialized nations [1]. Induction motors have high efficiency, performance, and reliability, and their speed can easily be controlled electronically [2], making them the most widely used motors in the industries. These 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 [3].

When these machines break down, the economy comes to a standstill, as 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, the prediction of faults in their machines would not always be accurate. There could be times when the machine will suddenly develop faults without a warning. Hence, this project will focus on combining the detection and prediction of inter-turn short circuit faults in induction motors using the Predictive Maintenance toolbox in MATLAB [4].

2. Literature Review

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. These condition monitoring techniques include oil analysis, vibration analysis, Motor Current Signature Analysis (MCSA), Infrared thermography, and many more.

In [6], vibration analysis is used to monitor vibration levels and patterns from an electrical machine to detect abnormalities. Vibration levels rise when mechanical problems like bearing faults occur in high-speed rotating equipment. It is a cost-effective and time-saving method of obtaining condition indicators for machine health management. 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.

Oil Analysis is another 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 [3]. However, the analysis intervals are not frequent, which can cause the machine to totally break down.

Motor Current Signature Analysis is also a condition monitoring technique developed by the Oak Ridge National Laboratory [7]. 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.

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 [8]. Physical modelling can be used to create dynamic models. The most important challenge with model-based techniques is its dependent on explicit motor models [9]. The correctness of the model describes how the diagnosis system behaves.

3. Methodology

This section focusses on the detailed steps taken to achieve a detection and prediction model.

3.1 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 resistance, self-inductance, and mutual inductance.

3.1.1 The Resistance

The resistance value is given as:

$$R = \frac{\rho l}{A} \qquad (1)$$

where R is the resistance measured in ohms (Ω), l is the length of the cable in meters (m), A 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).

3.1.2 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.

$$L_A = L_B = L_C = L_{ms} + L_{\ell s} \qquad (2)$$

Magnetizing inductance of the stator is given by:

$$L_{ms} = \frac{\mu_0 l r N s^2 \pi}{4g} \qquad (3)$$

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.

3.1.3 Mutual Inductance

Mutual inductances can exist from stator-to-stator as shown in equation (4).

$$L_{xsys} = \frac{\mu_0 l r N s \pi}{4g} \quad \mathrm{Cos}\theta_{xsys} \qquad (4)$$

where θ_{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 (3) into equation (4),

$$L_{xsys} = L_{ms} \mathrm{Cos}\ \theta_{xsys} \qquad (5)$$

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 θ_{xsys} in equation (5) can be rewritten as:

$$\mathrm{Cos}\ \theta_{xsys} = \mathrm{Cos}(\pm 120^\circ) = \mathrm{Cos}(\pm 240^\circ) = -0.5 \qquad (6)$$

From equations 2-6, the mutual inductance between two stator windings is:

$$L_{AB} = L_{BA} = L_{AC} = L_{CA} = L_{CB} = -0.5L_{ms} \qquad (7)$$

where θ_{xsys} is the angle that exist between any stator winding x and y [10].

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 (3) 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 (an indication of the presence of an inter-turn short circuit fault).

3.2 Experimental Set-up

Secondary data for this project was obtained from an online data source of an induction motor [11]. 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 1hp 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.

3.2.1 Fault Detection and Prediction Approach

This project focuses on using MATLAB Predictive Maintenance Toolbox to detect and predict inter-turn short circuit faults of an induction 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. Figure 3.1 shows the block diagram for the detection and prediction algorithm.

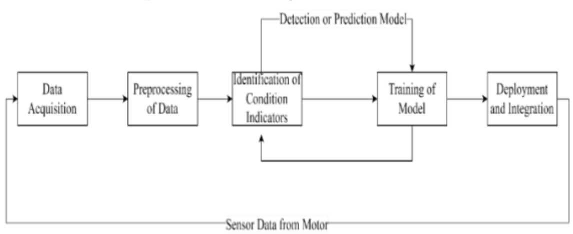


Figure 3.1: Detection and prediction algorithm

3.2.2 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 [11]. Figure 3.2 (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 3.2 (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 3.2 (a) has values far below the 3A current rating of the motor used to get this secondary data.

On the other hand, Figure 3.2 (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 3.1: (a) healthy no load. (b) Faulty no-load motor data.

3.2.3 Pre-processing of Data

The pre-processing of data involved analyzing the current signals and time series of the secondary motor data and preparing the signals for the next step. Pre-processing the data 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 [12]. 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.

3.2.4 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.

3.2.5 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. 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 have a high-performance ability to accurately predict even with limited data.

3.3 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 (1). 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 [11]. Detecting the inter-turn short-circuit fault was done in three ways: threshold comparison, the negative current sequence, and the machine-learning algorithm.

3.3.1 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.

3.3.2 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.

3.3.3 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.

3.3.4 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 complete inter-turn short circuit fault.

4. Results and Discussion

This section 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.

4.1 *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.

4.1.1 *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.

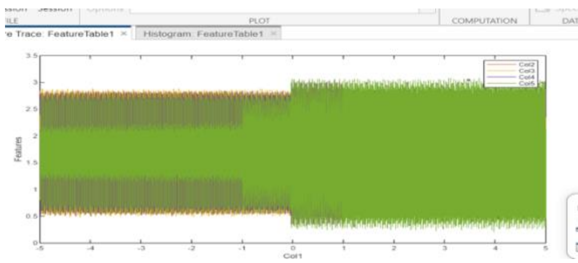
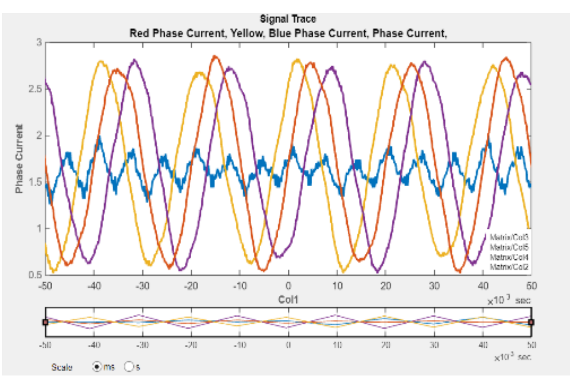


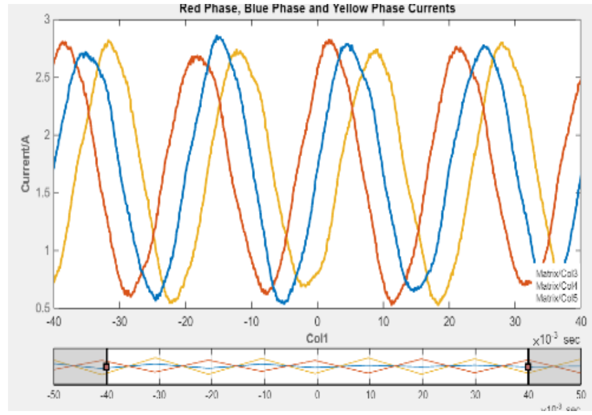
Figure 4.1: Threshold comparison of current signals

4.1.2 *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.



(a)



(b)

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

4.1.3 *Machine Learning Algorithm*

The group six (6) 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 next sections.

4.1.4 *Fault Detection and Prediction Algorithm*

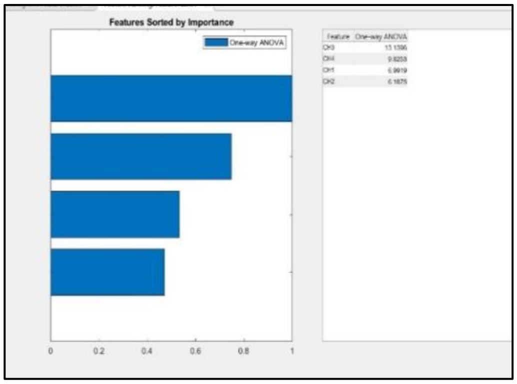
Two machine learning algorithms, Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) were used to detect and predict the inter-turn short circuit fault. The fault was detected when the machine learning algorithm classified the data under group six motor data. It meant the inter-turn short circuit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

4.1.5 *Feature Extraction and Ranking*

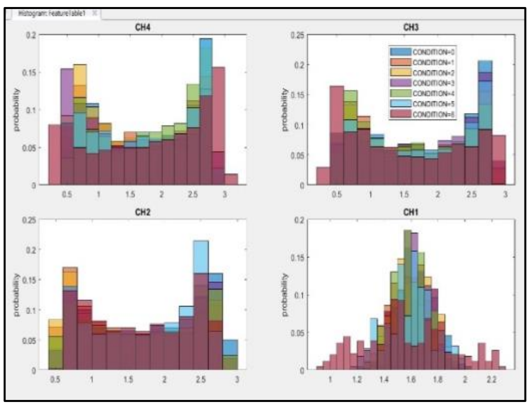
The current values (CH1, CH2, CH3, and CH4) were extracted from the three sets (no-load, half load, and full load) of healthy and faulty data. Figure 4.3 (a) shows the lists of the ranked current values (CH3 first) extracted in the MATLAB Diagnostic

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)



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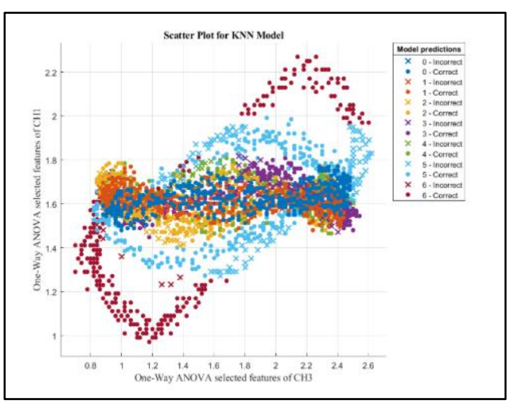


(c)

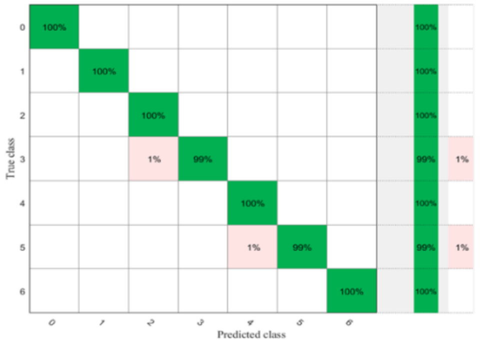
Figure 4.3: (a) Current signal sorting. (b) Current in histogram. (c) Scatter plot of current

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

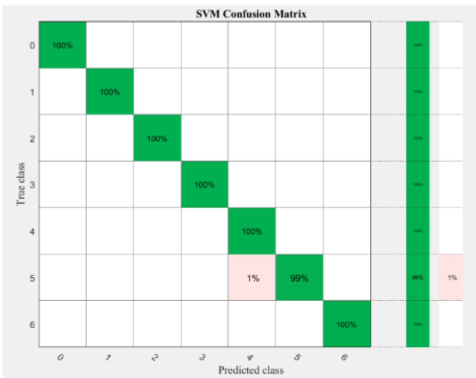
After the feature extraction, the Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) models were used to train the model. All SVM classifiers, namely linear, quadratic, and fine Gaussian SVM, had a classification accuracy of 99.8% for both no-load and half-load motors and 99.9% accuracy for the 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 99.8%. The model correctly predicted all the seven different groups of the motor fault (0-6) of the induction motor, except motors belonging to groups 3 and 5. The algorithm correctly predicted only 99.8% of the groups 3 and 5 motor, and wrongly classified 2% of them as belonging to group 2 and 4 respectively. 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 99.9% of the groups the motor data belonged. Only 1% of the full load motor data was misrepresented as belonging to group 4, when it actually belonged to group 5.

Table 4.1: Accuracies for SVM classifiers under different motor loads

Load State of Motor	SVM Classifier	Accuracy
No Load	Linear	99.8%
	Quadratic	99.8%
	Fine Gaussian	99.8%
Half load	Linear	99.8%
	Quadratic	99.8%
	Fine Gaussian	99.8%
Full Load	Linear	99.9%
	Quadratic	99.9%
	Fine Gaussian	99.9%



(a)



(b)

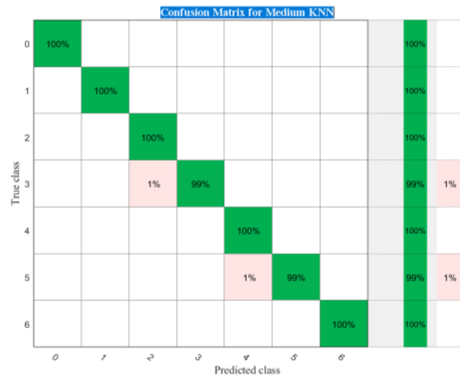
Figure 4.4: (a) SVM no and half load confusion matrix. (b) SVM full load confusion matrix.

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.

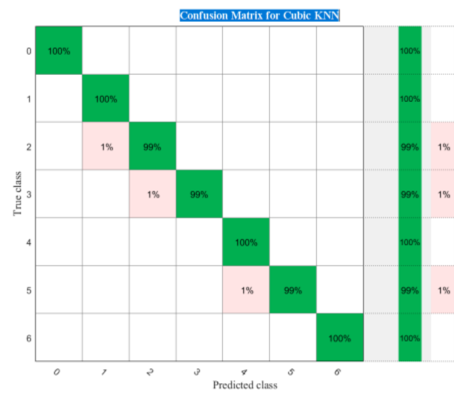
Table 4.2: Accuracies for KNN classifiers under different motor loads

Load State of Motor	KNN Classifier	Accuracy
No Load	Medium	96.1%
	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 99.8% for no-load and half load, and 99.9% 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)



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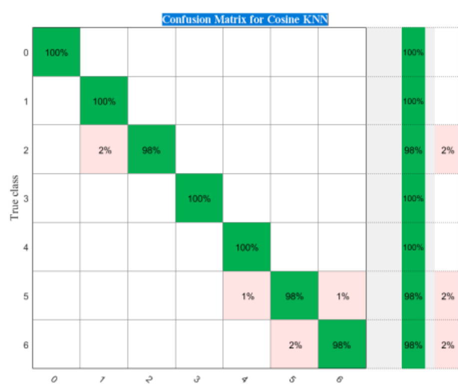
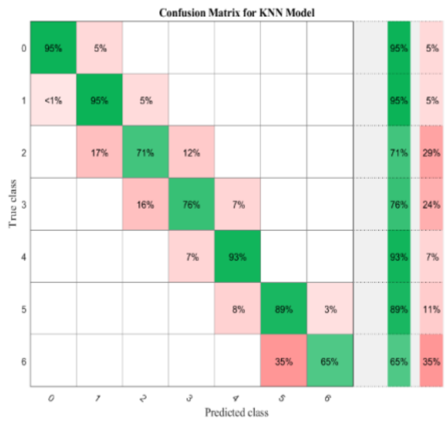


(c)

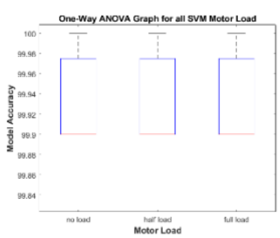


(d)

Figure 4.4: Confusion Matrices for the KNN models

4.2. 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 not rejected.



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 ANOVA

5. 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 and prediction 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 [14]. 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.

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