# Detection of Inter Turn Short Circuit Faults in Induction Motor using Artificial Neural Network

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***Abstract*—This paper proposes a new method using Artificial Neural Network (ANN) for detection of different Inter Turn Short Circuit (ITSC) faults in an induction motor under different loading conditions. The stator current signal was obtained experimentally from a healthy motor and a faulty motor with ITSC faults. The statistical time domain features was extracted from stator current signal, these features are used to train and test an ANN in order to diagnose ITSC faults. A complete study is performed by considering various diagnosis methods from ANN and machine learning algorithms, including Decision Tree (DT), K-Nearest Neighbors (KNN), Naïve Bayes (NB), Random Forest (RF) and Support Vector Machine (SVM) for diagnosis ITSC faults. The performance of the proposed method was compared with machine learning algorithms, the proposed method has a higher accuracy than the other algorithms. Trained neural networks are able to classify different states of the ITSC faults with satisfied accuracy. The efficiency of this approach has been proven using experimental tests to diagnose ITCS faults in a 1.5Hp squirrel cage induction motor.**

## I. INTRODUCTION

Induction Motor (IM) is a very important electrical machine in industrial plant. These machines face various stresses during operating conditions. These stresses might lead to many types of faults. It is therefore useful to investigate machine fault diagnosis techniques. The most common faults are short circuits winding or opening in stator phase, broken rotor bar and bearing failures [1] – [3]. The stator inter-turn fault is happened due to heavy current flow in the short-circuited coils and insulation downgrading [4]. The deterioration of stator winding insulation progresses to an inter turn short circuit fault. Short circuit in the stator winding takes very short time to damage the motor. This will cause industry production break off. Detection of ITSC fault at an early stage improve the reliability and availability of an existing system. This paper presents ANN to diagnose ITSC Fault. ANN has a higher accuracy compared with machine learning algorithms. It is able to diagnose different states of faults with satisfied accuracy. Recently many researchers have been concentrated on IM faults. Many techniques have been illustrated to detect faults. The inductance analysis of the stator windings and the on-line diagnosis method of the ITSC fault under various operating conditions are proposed in [5]. The ITSC fault in an induction motor has been detected by wavelet transform algorithm and advanced digital signal processing technique [2]. The discrete wavelet transform is applied to the Park's vector modulus of current signals [6]. The stator current analysis has been considered as one of the most popular fault diagnostic technique to detect the common faults in electrical rotating machines [7].

In this work the three-phase stator currents are converted to stationary axis using Clarke transformation method to improve the diagnostic possibilities of induction motors ITSC faults. These signals are pre-processed by statistical feature extraction technique. It has an important role for signal feature extraction [8], it reduces the large amount of information contained in the stator current signal to a small number of features that reflects the overall characteristics of the signal. Artificial Intelligence (AI) such as Fuzzy Logic, ANN and Adaptive Neural Fuzzy Inference System (ANFIS) are a high potential data processing tool that creates fault diagnosis techniques [9]. FL provides a simple method to heuristically implement fault detection principles [10]. ANN is a powerful tool has been suggested for IM fault diagnosis [11]. ANFIS is applied for the detection and classification IM faults [12]. IM faults diagnosis depend on Machine Learning (ML) algorithms are mostly investigated [13], [14].

Several experimental tests are discussed which are implemented on a three-phase IM with different faults conditions: 2%, 5%, 7% and 10% ITSC faults at different loading conditions: 10%, 20%, 30, 40, 50, 60, 70, 80, 90 and 100% of load. In this work, ANN based on feature extraction have been used. The proposed method is based on the stator current signature analysis. The unnatural transient signals can be applied to recognize IM faults by statistical feature extraction. Furthermore, ANN is proposed to classify and identify IM fault, ANN plays a main role in correct input-output fault diagnosis relation. The ANN technique and feature extraction can be powerful tools for IM faults diagnosis. The analysis has clearly showed that the effect of the IM faults on the IM stator current profiles. The ANN has high accuracy and give better resolution for IM faults. This robust technique is trained with a dataset generated in order to diagnose IM faults of real IMs. Accordingly, the training and monitoring stages use datasets obtained from experimental setup. The experimental results give evidence to the robustness and scalability of the technique, which yielded relatively good degree of motor fault diagnosis accuracy.

The present work developed a diagnostic tool for diagnosis ITSC fault in an IM at the early stage using the various AI and ML approaches. Among AI, the ANN is selected. In ML: DT, KNN, NB, RF and SVM are utilized. The experiment test is implemented at different load conditions with various faults pattern identification in order to increase accuracy and reduce diagnosis error rate. The extracted features are used to train the ANN and ML algorithms. The performance of the ANN and ML are evaluated and motor fault classification and diagnosis are discussed.

The rest of this paper is planned as follows: Section 1 gives an introduction while Section 2 presents feature extraction. Section 3 delivers Artificial Neural Network. Section 4 illustrates proposed the method. Section 5 discusses the experimental setup. Section 6 explains results and discussion. Section 7 concludes the article.

## II. Feature Extraction

Feature extraction techniques are widespread and can range from statistical to model based techniques. It is always desirable to reduce the large amount of information contained in the current signal to a small number of features that reflects the overall characteristics of the signal. This procedure is known as signal feature extraction [15]. The features are extracted from time-domain current signal through the statistical parameters. The current signal should be pre-processed to fit the intelligent system. The raw current signal needs to be converted to multiple features, which support the intelligent system learn how to distinguish between features representing healthy and faulty machine operation. The statistical parameters are used: Root Mean Square value ($X_{RMS}$), Crest Factor ($X_{CF}$), Peak to Peak Value ($X_{PP}$), Impulse Factor ($X_{IF}$), Energy ($X_E$) and Kurtosis Value ($X_{KV}$) [16].

Root mean square value:

$$X_{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2} \tag{1}$$

where N is number of samples of the signal and x is a signal.

Peak to peak value:

$$X_{PP} = \max(x_i) - \min(x_i) \tag{2}$$

Crest factor:

$$X_{CF} = \frac{\max(x_i)}{X_{RMS}} \tag{3}$$

Impulse factor:

$$X_{IF} = \max(x_i) / \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{4}$$

Energy:

$$X_E = \left(\frac{1}{N}\sum_{i=1}^{N}\sqrt{|x_i|}\right)^2 \tag{5}$$

Kurtosis Value:

$$X_{KV} = \frac{1}{N\sigma^4}\sum_{i=1}^{N}(x_i - x_{mean})^4 \tag{6}$$

where $x_{mean}$ is the mean and $\sigma$ is the standard deviation

$$x_{mean} = \frac{1}{N}\sum_{i=1}^{N}x_i$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - x_{mean})^2}$$

## III. Artificial Neural Network

ANN is a powerful technique to diagnose IM faults more accurately. Neural networks are pattern classifier. So that a neural network can be created to solve many problems by using pattern classification, these problems usually involve the recognition of something, which is variable that cannot be entirely described or predicted such as IM faults [17], [18]. ANN is a mathematical or computational model that simulates the human brains thinking process. It has similar parallel processing, self-organizing, self-learning, classification and non-linear mapping abilities [19]. The most commonly used neural network for classification purposes is the multi-layer feed-forward neural network (MFNN). The feed-forward neural network has the ability to learn various types of complex linear and nonlinear functions [19]. In this proposed method MFNNs trained by back propagation algorithms. The network structure consists of an input layer with units representing the input data, hidden layer, output layer, network connections, initial weight assignments and activation functions as presented in Fig 1.

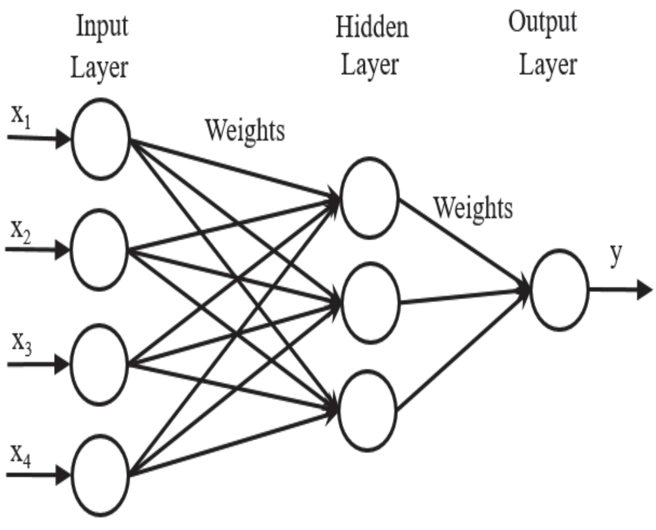


Fig1. A Multi-Layered Feed-Forward Artificial Neural Network

There is no analytical method for finding the neurons number in the hidden layer. Therefore, it only found by trial and error. Big number of neurons and layers may cause over fitting and may cause decrease the generalization ability, whereas, too small neurons number in hidden layer the network may not be trained or not strong [19]. The most significant properties of the neural networks are their ability to learn and to generalize. The neural networks learn to recognize certain patterns and give the correct output response to these patterns. Neural network Learning methods can be divided into two types supervised and unsupervised learning. The procedure most commonly used to train an ANN is a back propagation. This is a supervised method of learning used to train multilayer neural networks. In supervised learning, a set of inputs are applied to the network, then the resultant outputs produced by the network are compared with that of the desired ones. The mean square error is calculated and propagated backwards via the network. Back propagation network uses it to adjust the value of the weights on the neural connection in the multiple layers. This process is repeated until the mean square error is reached to minimum value [17] – [20].

## IV. PROPOSED METHOD

An overall schematic representation of the work is presented in Fig 2. The intelligent diagnosis procedure begins with the act of data collection of the three-phase stator currents of an IM has different faults conditions: 2%, 5%, 7% and 10% ITSC faults at different load conditions: 10%, 20%, 30, 40, 50, 60, 70, 80, 90 and 100% of load conditions. These currents are converted to qd frame. The current signals are pre-prepossessed using statistical feature extraction. These extracted features are fed to classifiers to diagnose ITSC faults.

The accuracy and the Area Under Curve (AUC) of the Receiver Operating Characteristic (ROC) curve can be used as performance metrics to select the optimal classifier. A ROC curve is the resulting true positive rate (Sensitivity) against the false positive rate (Specificity) for different thresholds. If the ROC curve is the more to the upper left corner, the classifier performance is better [21].

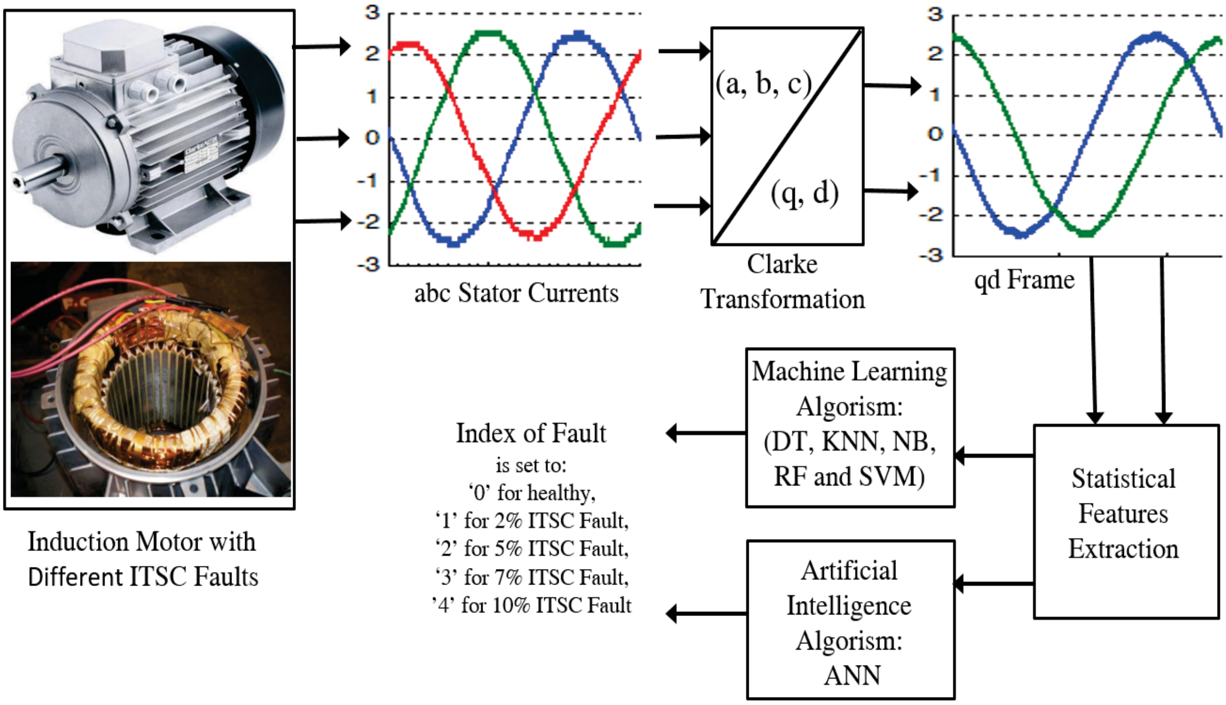


Fig 2. Schematic Diagram of the Proposed Method.

TABLE I. TESTED SQUIRREL CAGE IM SPECIFICATIONS

| IM Specifications | Unit | Value |
|---|---|---|
| Power | HP | 1.5 |
| Voltage | Volt | 380 |
| Rated current | Amp | 2.8 |
| Rated speed | RPM | 1400 |
| Frequency | Hz | 50 |
| Number of rotor bars | -- | 28 |
| Number of turns per phase | -- | 348 |

## V. EXPERIMENTAL SETUP

A laboratory test bench was set up using a 1.5 Hp/380 V three-phase squirrel cage induction motor. The electrical characteristics of the IM are represented in Table I. Fig 3 shows three-phase Squirrel Cage Induction Motor (SC-IM) is coupled to a DC generator (car alternator). The generator is supplied by a DC voltage source. The variation of the motor load is achieved by the variation of the resistance connected to the generator by a selector switch that is designed in a printed circuit board as presented in Fig 3.

The motor is supplied directly by a balanced three-phase sinusoidal voltage source. It is composed of 28 bars in the cage rotor and Y connected stator windings with 348 turns per phase. The motor is equipped with specific access points to diverse turns of stator windings in order to achieve different cases of fault, as explained in Fig 3. They are in the level of (7, 17, 24, and 35) turns in phase "a" represent (2%, 5%, 7%, and 10%) of turns per stator phase. Fig 4 gives ITSC faults schematic diagram. The choice of this number of shorted turns is imposed using switches on the printed circuit board as provided in Fig 3. In order to carry out the different experimental tests, Current/Voltage isolator and Oscilloscope are connected to measure the three-phase stator currents. Several measurements were performed in which the three phase stator currents waveform were acquired for a healthy stator winding and for the same IM with the different number of shortened coils under different cases of load conditions. The three-phase stator currents are converted to qd currents. Example of qd stator currents for healthy and unhealthy work are displayed as given in Fig 5. It was clearly observed that the effect of the IM faults on the IM stator current profiles. The amplitude of the signals are increased as percentage of the ITSC fault increased.

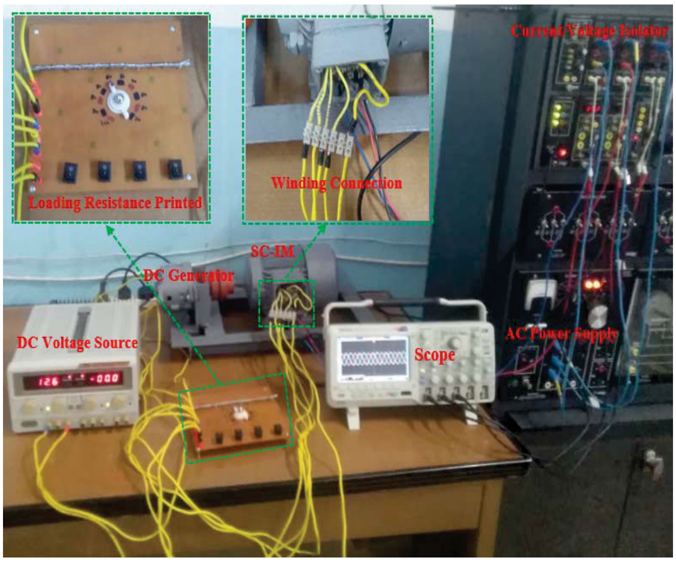


Fig 3. Experimental Setup

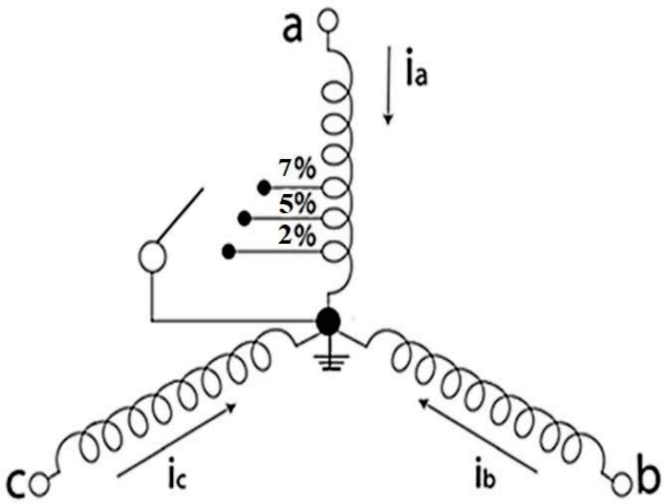


Fig 4. Stator ITSC Faults Schematic

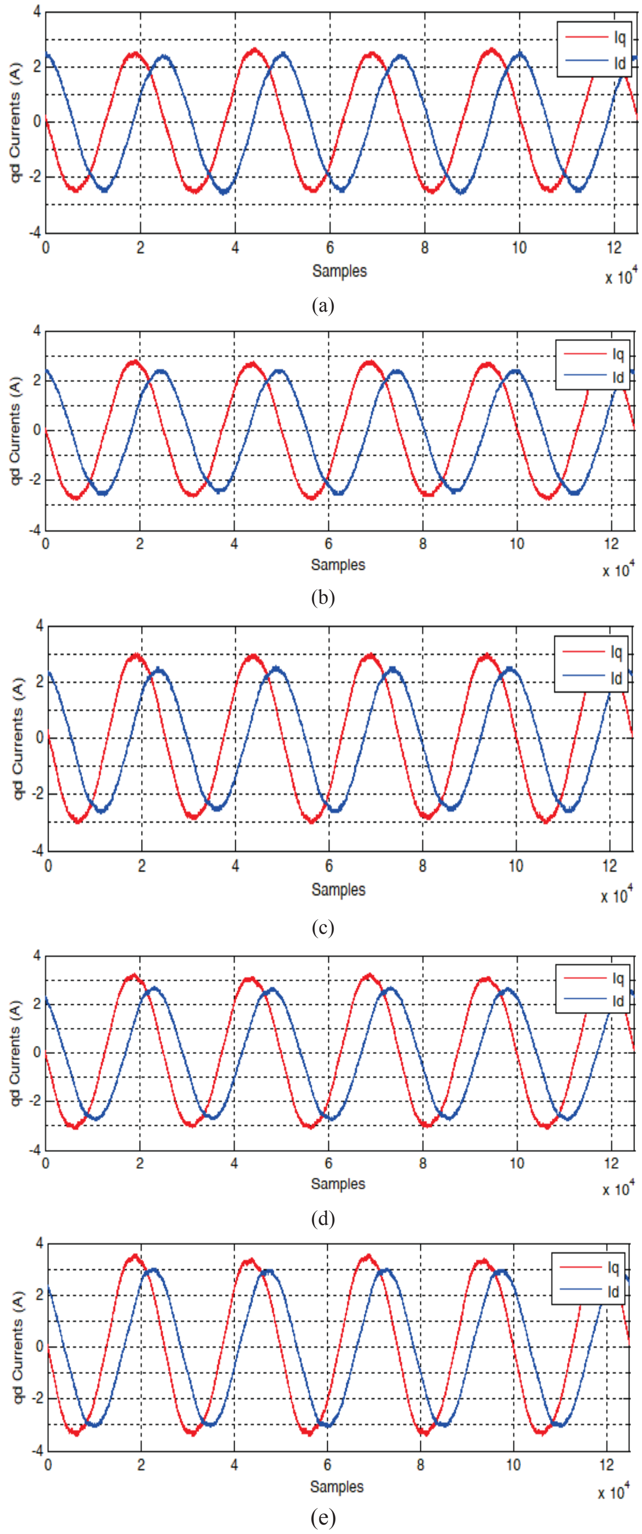


Fig 5. The qd Stator Currents for: (a) Healthy Winding (b) 2% ITSC (c) 5% ITSC (d) 7% ITSC (e) 10% ITSC

## VI. RESULTS AND DISCUSSIONS

In the first case study, the experiment test is performed on IM at No load condition using proposed method. In this experiment, the task was to collect stator current signals in different states of health. There are different conditions of stator winding were tested: healthy, 2% ITSC, 5% ITSC, 7% ITSC and 10% ITSC. The current signals were collected at sampling rate of 1250 KSa/s. The three phase stator current are converted to qd frame using Clarke Transformation. The numbers of samples collected were 125000 for each signal for duration of 0.1 s. Each signal was divided in 40 segments of 3125 samples as described in Table II. Feature extraction is needed for processing the raw current data that can reduce the size of the training set while preserving features that correspond to the condition of the IM faults. Six features were extracted from these segments. There are two signals, Iq and Id so the number of features are 12. The dimension of the dataset is 12 × 200. These features are selected as the input features of the neural network model as displayed in Fig 6.

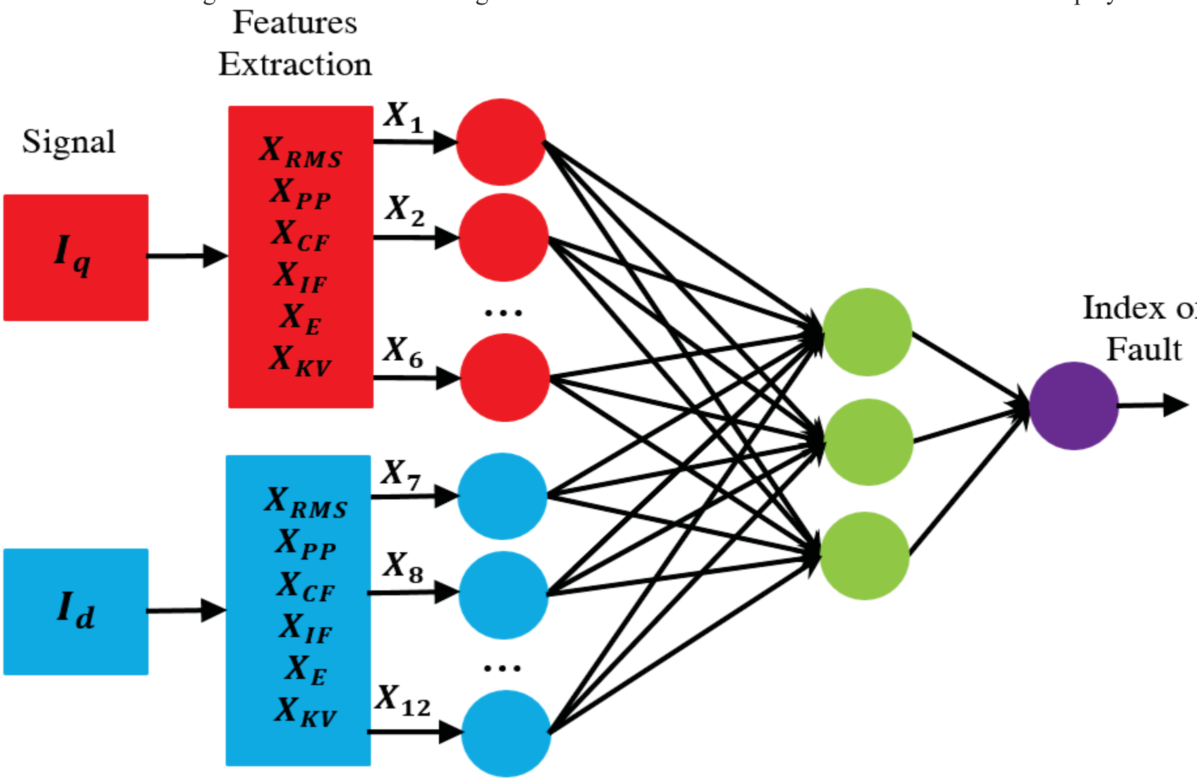


Fig 6. ANN Model Classifier

TABLE II. DESCRIPTION OF THE USED DATASET

| Condition | Class Label | Total Samples | Samples Segments | Feature Extraction Samples | Dataset Samples | Training Samples | Testing Samples |
|---|---|---|---|---|---|---|---|
| Healthy | 0 | 125000 | 40 x 3125 | 40 | 200 | 140 | 60 |
| 2% ITSC Fault | 1 | 125000 | 40 x 3125 | 40 | | | |
| 5% ITSC Fault | 2 | 125000 | 40 x 3125 | 40 | | | |
| 7% ITSC Fault | 3 | 125000 | 40 x 3125 | 40 | | | |
| 10% ITSC Fault | 4 | 125000 | 40 x 3125 | 40 | | | |

The dataset is split randomly into subsets of training and testing. The ratio of each subset is defined as 70 % and 30% which are commonly used. The training dataset is used to train the ANN model. In the experiment, the training is run. The Cross Validation (CV) metric and testing set are employed to evaluate the performance of classifier by means of scores of accuracy and the ROC curve, including its AUC metric. ANN algorithm has been designed with python programing language. This experiment is done with ML algorithms: (DT, KNN, NB, RF and SVM). Fig 7 shows a testing ROC curve for evaluation of AI and ML classifiers for different ITSC faults at No load.

The accuracy and AUC are calculated to evaluate the performance of the classifier. Table III displays the diagnosis results using ML compared with the proposed approach. The proposed method and RF achieved better performance. Proposed method obtained the highest scores of CV accuracy of 99%, testing accuracy of 100%, CV AUC of 1 and testing AUC of 1 while RF achieved CV accuracy of 99%, testing accuracy of 100%, CV AUC of 0.99 and testing AUC of 1. NB performs lower performance and obtains the lowest scores of CV accuracy of 47%, testing accuracy of 45%, training AUC of 0.67 and testing AUC of 0.67. For other classifiers, CV accuracy scores are greater than 84%, testing accuracy scores are greater than 85%, training AUC scores are greater than 0.90

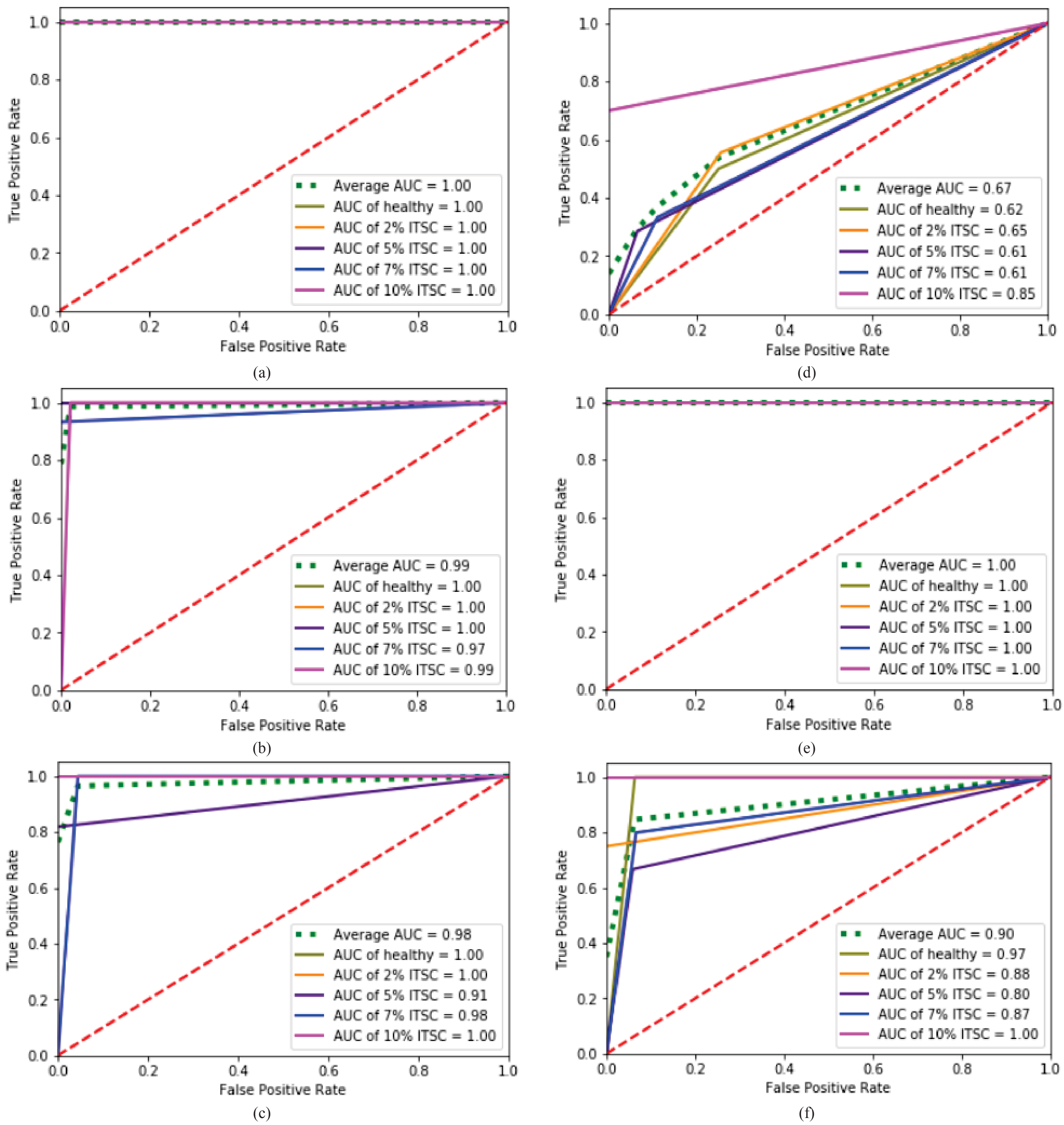

Fig 7. Testing ROC Curve for Different ITSC Faults at No Load (a) ANN (b) DT (c) KNN (d) NB (e) RF (f) SVM

TABLE III. EVALUATION OF ANN AND ML CLASSIFIERS

| Classifier | CV Accuracy | Testing Accuracy | CV AUC | Testing AUC |
|---|---|---|---|---|
| ANN | 99 | 100 | 1 | 1 |
| DT | 92 | 98.33 | 0.95 | 0.99 |
| KNN | 98 | 96.67 | 0.99 | 0.98 |
| NB | 47 | 45 | 0.67 | 0.67 |
| RF | 99 | 100 | 0.99 | 1 |
| SVM | 84 | 85 | 0.90 | 0.90 |

In another case study, the experiment test is implemented on IM at different load condition: 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% and 100%. There are different conditions of stator winding were tested: healthy, 2% ITSC, 5% ITSC, 7% ITSC and 10% ITSC using proposed method and RF. The same statistical features in the time domain are used and dataset preparation is done in this case as in the first case study. In this experiment, the training is run. The testing dataset is then used to test the fault diagnosis. The performance of the classifier is evaluated by scores of CV accuracy and testing accuracy and the ROC curve, including its AUC metric.

The accuracy and AUC are calculated to evaluate the performance of the classifier. Table IV illustrates the diagnosis results using RF compared with the proposed approach. Proposed method achieved the highest overall CV accuracy of 96.30%, overall testing accuracy of 96.50%, overall CV AUC of 0.97 and overall testing AUC of 0.98. RF obtained the lowest overall CV accuracy of 93.30%, overall testing accuracy of 94.17%, overall CV AUC of 0.95 and overall testing AUC of 0.96. Hence we conclude that ANN based statistical feature extraction gives better performance as compared to all other approaches for ITSC fault diagnosis.

TABLE IV. EVALUATION OF ANN AND RF CLASSIFIERS

| Load Condition | ANN | | | | RF | | | |
|---|---|---|---|---|---|---|---|---|
| | CV Accuracy | Testing Accuracy | CV AUC | Testing AUC | CV Accuracy | Testing Accuracy | CV AUC | Testing AUC |
| 10 % | 93 | 90 | 0.94 | 0.94 | 89 | 86.67 | 0.91 | 0.91 |
| 20 % | 96 | 91.67 | 0.97 | 0.95 | 90 | 91.67 | 0.93 | 0.95 |
| 30 % | 98 | 100 | 0.97 | 1 | 97 | 100 | 0.97 | 1 |
| 40 % | 97 | 100 | 0.97 | 1 | 95 | 95 | 0.95 | 0.97 |
| 50 % | 97 | 100 | 0.98 | 1 | 93 | 93.33 | 0.95 | 0.96 |
| 60 % | 97 | 98.33 | 0.97 | 0.99 | 97 | 98.33 | 0.97 | 0.99 |
| 70 % | 93 | 95 | 0.95 | 0.97 | 88 | 90 | 0.94 | 0.94 |
| 80 % | 98 | 96.67 | 0.97 | 0.98 | 93 | 95 | 0.96 | 0.97 |
| 90 % | 97 | 96.67 | 0.98 | 0.98 | 97 | 100 | 0.99 | 1 |
| 100 % | 97 | 96.67 | 0.98 | 0.98 | 94 | 91.67 | 0.96 | 0.95 |
| Overall | 96.30 | 96.50 | 0.97 | 0.98 | 93.30 | 94.17 | 0.95 | 0.96 |

## VII. CONCLUSION

This paper presents a new application of ANN and ML techniques to diagnose the induction motor ITSC faults. The statistical features extraction are computed in time domain from the stator current. The motor is at different load conditions: 10%, 20%, 30, 40, 50, 60, 70, 80, 90 and 100% of load. The faulty conditions of the IM considered are 2%, 5%, 7% and 10% ITSC. The experiments were conducted on IM with different ITSC faults at No load condition using ANN and ML techniques. The analysis of the results establishes that ANN and RF archive higher accuracy and higher AUC scores and NB is the worst classifier. The experiments were performed on IM with different ITSC faults at different load conditions using ANN and RF techniques. The evaluation analysis of the results establishes that ANN obtains the best accuracy and AUC scores and RF is the worst classifier. The effectiveness of using ANN technique to diagnose the ITSC faults in three-phase IM is investigated using experimental tests. The analysis results give evidence to the robustness and scalability of the technique, which yielded relatively good degree of motor fault diagnosis accuracy.

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