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Induction Motor Fault Classification using Pattern Recognition Neural Network

Shaina Grover, Amandeep Sharma, Lini Mathew, Shantanu Chatterji

Abstract*: *The industrial growth has escalated the use of induction motors as prime movers in modern industry. This is due to its low cost, simple construction and ruggedness. Although rugged, these may fail earlier than expected life due to, excessive mechanical, electrical and environmental stresses. Automatic Artificial Intelligence (AI)-based systems are nowadays widely employed in the domain of induction motor fault identification with high success rate. Artificial neural network are utilized extensively for the detection and diagnosis of various induction motor faults. These systems generally use supervised learning, where the models are pre-trained such that these are skilled enough to classify the absence or presence of faults in motor under investigation. In this paper, a highly effective approach for detection of different motor fault conditions, based on pattern recognition technique is presented. In the proposed method the statistical time domain features are computed from three phase motor current and used as inputs of ANN. Seven different classes of motor conditions: healthy, broken rotor bar, broken rotor bar with stator winding short circuit and inner and outer race bearing defects were considered. The results indicates that the proposed methodology is highly effective for diagnosis of various induction motor faults with high success rate.

Index Terms*: *Artificial neural networks (ANN), Condition monitoring, Fault diagnosis, Induction motor. About four key words or phrases in alphabetical order, separated by commas.

I. INTRODUCTION

Induction motors are frequently integrated in different types of industrial equipment such as those used in manufacturing and processes industries. Being a vital part of many industrial equipment viz. blowers, conveyers, drills, elevators, vacuum cleaners, vacuum pumps and other machine tools, it is subjected to research in the field of sophisticated control, reliable operation and timely maintenance. Although being rugged and reliable induction motor are subjected to different types of faults such as those related to stator winding [1-2], broken rotor bars [3-4], bearing faults [5] and eccentricity [6]. These faults start as a minute defects and propagates to larger faults overtime. These defects if not checked in time could results into catastrophically failures.

These days, conventional maintenance strategies such as scheduled maintenance and run-to-failure maintenance is being replaced by Condition Based Maintenance (CBM) [7]. The CBM involves the placement of sensors on motor for regular monitoring of motor operating parameters such as drawn current, frame vibration and winding temperature, etc. to estimate the condition of motor. This helps in appropriate scheduling of maintenance activities beforehand, depending on the motor health. This not only reduces the costly maintenance but also helps in minimizing the unwanted downtime and catastrophic failure [8].Condition Monitoring (CM) and fault diagnosis of induction motor has gained attention of various researcher in the past few decades. A number of fault detection techniques such as vibration, current, acoustic and magnetic flux have been developed [9]. A practical automatic condition monitoring method requires the monitoring of aforementioned parameters along with a computer based intelligent algorithms for detection and diagnosis of motor conditions. Recently, Artificial Intelligence (AI) based approaches like Artificial Neural Network (ANN), Support Vector Machine (SVM), Adaptive Neuro-Fuzzy Inference System (ANFIS), k-Nearest Neighbour (k-NN), Fuzzy Logic and Deep learning etc. have been successfully applied in the domain of CM and fault diagnosis [10-13]. ANN’s has gained considerable attention in the field of CM and fault diagnosis of machines in the last few decades. The artificial neural network (ANN) is a statistical supervised learning approach, where faults can be detected by training the network to classify and detect faults. ANN has been prevalently used for detection of motor faults such as bearings [14], 5roken rotor bar [13] and stator winding short circuit [11, 16]. In [17] authors used motor vibration data for extracting frequency domain features and classified the motor bearing defects with the help of ANN. In [18], the authors used pattern-recognition methodology to study the progression and orientation of outer race bearing scratches.

This paper describes the application of Feed-forward Back Propagation Neural Network (FFBPNN) for detection and diagnosis of different motor fault conditions. The Pattern-recognition Neural network (PatternNet), a special type of FFBPNN, used for pattern recognition and classification problems was used for detection and classification of induction motor faults. The Pattern recognition NN (PatternNet) is a type of ANN that can be used for pattern recognition problems, where the objective is to recognize the input data sets belonging to different classes.

Basically, it is a FFBPNN trained using supervised learning, where the target data comprises of binary values representing 1’s signifying the inherited class and 0’s otherwise.

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Different time domain features were extracted from motor current signal and used as input for the neural network. The ANN was trained using several concealed layer of neurons with two different training functions namely ***'trainlm'*** and ***'trainscg'***.
The results for each case is presented and compared in terms their performance.

II. ARTIFICIAL NEURAL NETWORK (ANN)

ANN is considered as an imitation of human brain, consisting of a group of interconnected nodes called as neurons. The most popular form of ANN comprises of three layers, where each layer consists of a number of processing nodes. Fig. 1 shows the basic diagram of an ANN, consisting of neurons, connection weights and biases. Here the neuron are represented by circular nodes, connection weights are represented by arrows connecting different nodes between input, hidden and output layers.

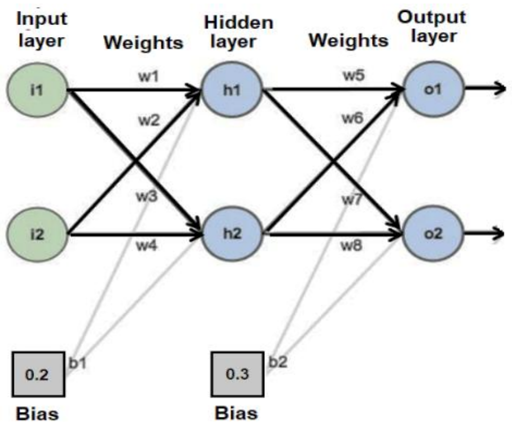

Fig. 1. Artificial Neural Network

FFBPNN is the most popularly used multi-layered feed forward ANN which employ backpropagation algorithm for training. The ANN performs best with backpropagation learning when the number of hidden layer neurons is optimal. Usually, a smaller network is unable to learn, whereas a much larger network will have poor generalization [19]. The performance of ANN improves with larger training dataset; however, this requires more training time. Thus, a number of backpropagation training algorithms are devised to improve the performance and reduce training time [20].

Training backpropagation algorithm adjusts network weights toward the steepest descent (i.e. adverse gradient).Although this is the path where magnitude of performance function degrades most rapidly however, it does not ensure the quickest convergence. In case of conjugate gradient-based training methods, search is carried out along conjugate directions, generally resulting in faster convergence than steepest descent path. For conjugate gradient algorithms, the step-size is altered for every single iteration. Here, search is performed in the conjugate gradient direction to calculate the step size for which the performance function is minimized for particular search path.

The ***trainscg*** is a backpropagation training method that updates network weights and biases according to the Scaled Conjugate Gradient (SCG) algorithm. It was introduced by Moller [21] to prevent the time-inefficient line search, integrating the model-trust region method (used in ***trainlm***) along with scaled conjugate gradient approach.

The ***trainlm*** is the speediest algorithm for training networks with moderate size. Although it requires more memory than other training algorithms, ***trainlm*** is the most widely recommended and used training method for obtaining higher classification accuracies. It is based on Levenberg-Marquardt (LM) backpropagation algorithm, which is considered as one of the fastest backpropagation algorithm for training the neural network.

III. EXPERIMENTAL SETUP AND DATA COLLECTION

The experimental configuration consisted of a three-phase, 4-pole, 0.5-hp induction motor linked to mechanical load using belt pulley system. The motor terminals were connected to a 3-phase power source through a Direct-On-Line (D-O-L) starter. Fig. 2 shows the experimental setup for data acquisition and condition monitoring of three-phase induction motor.

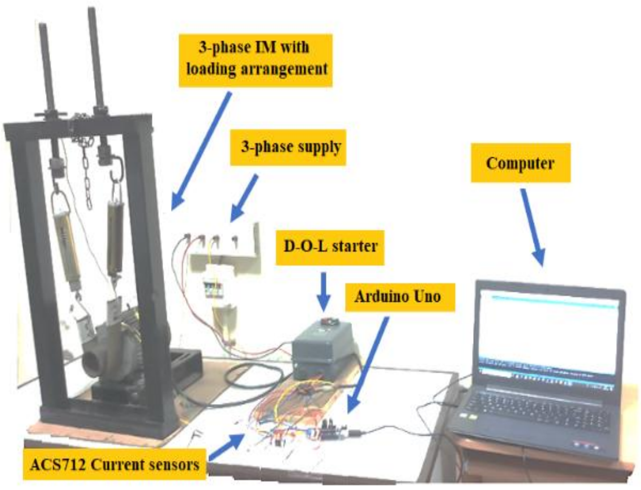

Fig. 2. Experimental setup for fault detection of induction motor

The data acquisition system for current measurement comprised of three current sensors (ACS712) combined with an Arduino Uno board connected to a computer via a USB interface. The personal computer employed serial monitor program of Arduino IDE to acquire the save data from Arduino's flash memory. The technical specifications of induction motor and other hardware components used are given in Table 1 and Table 2.

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Table I. Specifications of induction motor

Parameters	Value
Motor type	3-phase, 4-pole ac induction motor
Power	0.37Kw
Frequency	50Hz±5%
Current	1.1A
Voltage	415V (Y)±10%
Power Factor	0.74
Speed	1400rpm

Data was acquired repetitively for 20 runs with 200 samples acquired for each phase at a sampling rate of 3.33 kHz. Recorded data was transferred to personal computer via USB serial-port at a rate of 9600 baud.

Table II. Specifications of hardware components

Component	Specifications
Current sensor	ACS712 current sensor Range - 20 Amperes AC/ DC Sensitivity – 100mV/A Supply voltage - 5 Volts Output – Voltage (ratio-metric)
Arduino Uno	Microcontroller: ATmega328 Operating voltage: 5V Digital I/Os: 14 (with 6 PWM output) Analog inputs: 6 Input voltage range: 7 to 12V
Personal computer	Processor – i5 Intel processor @ 2.4 GHz RAM - 4 GB Hard drive – 1Tera Byte @5400 RPM. Operating System - Windows 10 Home

A data pre-processing stage was used which included milli-volt conversion, equation (1) and zero-compensation, equation (2) and scaling, equation (3) to convert the measured values read using Arduino command ***analogRead()*** to actual current values in amperes.

$$B(milliVolts) = \frac{A \times 5000}{1023} \quad (1)$$

$$C = B - \left(\frac{V_{CC}}{2 \times 1000}\right) \quad (2)$$

$$D = \frac{C}{S} \quad (3)$$

Where, A = values obtained from ***analogRead()*** command, B is the value in milli-Volts, C is the value obtained after zero compensation, while D is the final sensor reading. Here, S is the sensitivity of different sensors in millivolts/ ampere (i.e. 100mV/A) and V_{cc} is the supply voltage of current sensors.

IV. PROPOSED WORK

The Fig. 3 shows the ANN based fault detection and diagnosis methodology.

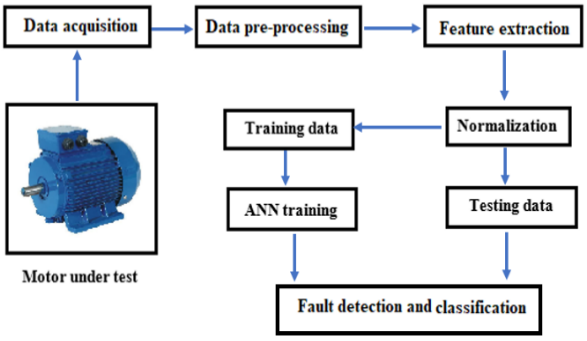

Fig. 3. Proposed methodology for fault detection

The motor under investigation is operated near full load conditions (industrial conditions) and three-phase current is acquired using especially made data acquisition system. Different faults are created in the motor artificially and data is acquired for each fault condition successively. The different motor conditions considered are:

1) Healthy motor (HEALTHY)
2) Bearing with outer race defect (OUR)
3) Bearing with inner race defect (INR)
4) Broken rotor bar with 20 stator turns shorted (BRB20T)
5) Broken rotor bar with 10 stator turns shorted (BRB10T)
6) Broken rotor bar with 3 stator turns shorted (BRB3T)
7) Broken rotor bar fault (BRB)

The data acquisition is followed by pre-processing and feature extraction stages, where the acquired data is converted into meaningful values and time-domain features are extracted respectively. Feature extraction stage comprised of computing the following 9-time domain statistical features from three-phase current data, Table 3.

Table III. Time domain statistical features computed from motor data

Sr. No.	Feature
1.	$Root\ Mean\ Square = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2}$
2.	$Skewness = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^3}{(Standard\ deviation)^3}$
3.	$Kurtosis = \frac{\sum_{i=1}^{N}(x_i-\bar{x})^4}{(RMS\ value)^4}$
4.	$Crest\ Factor = \frac{max\lvert x_i\rvert}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2}}$
5.	$Impulse\ Factor = \frac{\max(\lvert x_i\rvert)}{\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert}$
6.	$Shape\ Factor = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2}}{\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert}$
7.	$Median = \left(\frac{N+1}{2}\right)^{th}$ term in an ordered list
8.	$Range = [max(x_i) - min(x_i)]$
9.	$Margin\ Factor = \frac{\max(\lvert x_i\rvert)}{\left[\frac{1}{N}\sum_{i=1}^{N}\sqrt{\lvert x_i\rvert}\right]^2}$

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Computed features were normalized (scaled) between bounds [0 1], before feeding as input to ANN for training and testing stages. This step ensures that all the features (inputs to ANN) gets equal weightage. It is done to improve the classification results and eliminate the undue bias to any particular feature, as all features are considered equally significant. The feature matrix consisted of 420 rows (feature vectors) and 9 columns (features), corresponding to 20 runs for 7 motor condition, obtained by acquiring 3-phase motor current, i.e. generating a 20 X 3 X 7 = 420 feature vectors in all. The output feature matrix for pattern recognition neural network was selected in the following manner:

Healthy: $[0\ 0\ 0\ 0\ 0\ 0\ 1]^T$

OUR: $[0\ 0\ 0\ 0\ 0\ 1\ 0]^T$

INR: $[0\ 0\ 0\ 0\ 1\ 0\ 0]^T$

BRB20T: $[0\ 0\ 0\ 1\ 0\ 0\ 0]^T$

BRB10T: $[0\ 0\ 1\ 0\ 0\ 0\ 0]^T$

BRB3T: $[0\ 1\ 0\ 0\ 0\ 0\ 0]^T$

BRB: $[1\ 0\ 0\ 0\ 0\ 0\ 0]^T$

The whole feature matrix was split into training (315) and testing (105) dataset i.e. 45 training samples and 15 testing samples for each motor condition. The PatternNet was trained using training data set with two different training algorithms (***trainlm*** and ***trainscg***) for different number of hidden layer neurons to test their performance and suitability for the given classification problem. Each network was trained and tested 10 times using the same dataset and the best result (classification accuracy) is reported. Total number of epochs for obtaining best validation performance, classification accuracy for testing dataset and Mean Square Error (MSE) were selected for comparing the performance for different network configurations.

V. RESULTS AND DISCUSSION

The Table 4 and Table 5 shows the results obtained using scaled conjugate gradient and Levenberg-Marquardt training algorithms for several concealed layer of neurons. It is observed that the number of epochs for training phase of network decreases for moderate network size, i.e. network with 10 to 14 hidden layer neurons. Also, it is observed that the highest testing accuracy, 77.1% and 91.4% is obtained in case of network with 12 hidden layer neurons for ***trainscg*** and ***trainlm*** training algorithms. Thus, it can be clearly perceived that both the training algorithms perform best for moderate number of hidden layer neurons, viz.12 neurons, which is the optimum for given classification problem.

Table IV. Results with *trainscg* training function

No. of hidden layer neurons	Training		Testing	
	Validation performance (MSE)	Epochs	Testing Performance (MSE)	Classification Accuracy (%)
2	0.1096	30	0.0993	40.0
4	0.0731	37	0.0841	59.0
6	0.0501	36	0.0685	67.6
8	0.0570	35	0.0518	73.3
10	0.0505	37	0.0731	66.7
12	**0.0391**	**35**	**0.0558**	**77.1**
14	0.0924	43	0.0564	72.4
16	0.0602	51	0.0506	76.2

Table V. Results with *trainlm* training function

No. of hidden layer neurons	Training		Testing	
	Validation performance (MSE)	Epochs	Testing Performance (MSE)	Classification Accuracy (%)
2	0.0603	29	0.0591	72.4
4	0.0411	19	0.0388	85.7
6	0.0439	18	0.0405	84.8
8	0.0398	14	0.0256	89.5
10	0.0492	10	0.0322	87.6
12	**0.0415**	**11**	**0.0204**	**91.4**
14	0.0433	10	0.0404	84.8
16	0.0299	13	0.0253	88.6

From results, it is evident that for different number of hidden layer neurons the number of epochs required for achieving lowest validation error is smaller (11 and 35 for 12 hidden layer neurons) for ***trainlm*** as compared to ***trainscg*** respectively. This verifies that the ***trainlm*** provides faster training and more accurate results as compared to ***trainscg*** (default training function for PatternNet) for pattern recognition neural network.

Fig. 4(a) and (b), shows the target outputs and classification outputs of PatternNet for 12 hidden layer neurons for different motor conditions using ***trainscg*** and ***trainlm*** respectively. The points overlapping with target outputs are correctly classified testing samples. It can be clearly seen that the ***trainlm*** outperforms in terms of lesser number of miss-classifications.

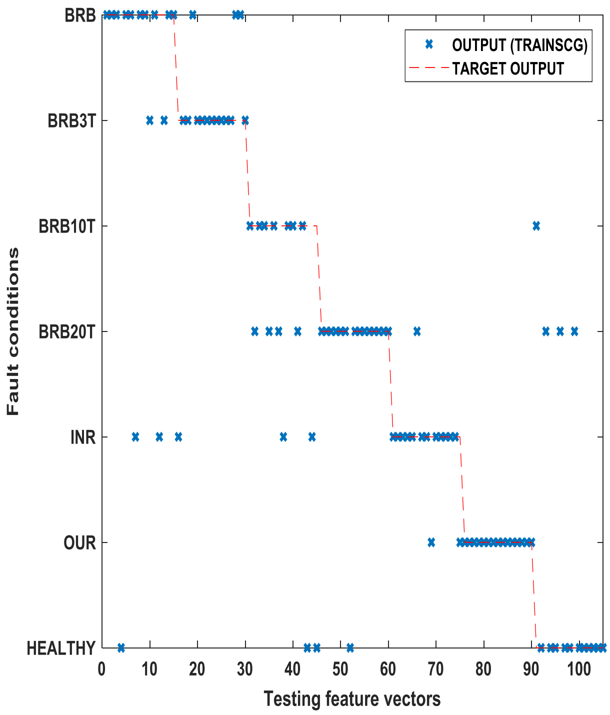

Fig. 4(a) Actual and target outputs for *PatternNet* using *trainscg* backpropagation algorithm

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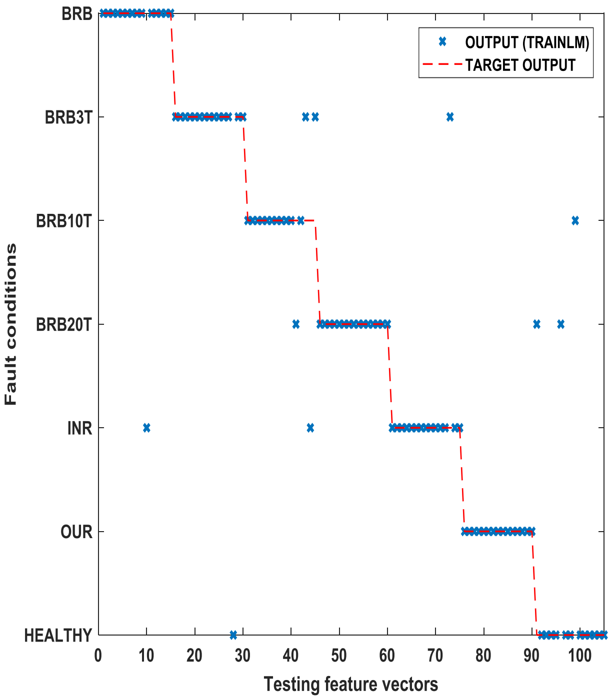

Fig. 4(b) Actual and target outputs for *PatternNet* using *trainlm* backpropagation algorithm

In Fig. 5 (a), it was observed that 5 out of 15 training samples of class BRB20T were mis-classified as BRB3T, (i.e. 33.3% inter-class misclassification). However, no such phenomenon was observed for ***trainlm***. Also, it was observed that BRB3T, BRB20T, OUR and HEALTHY conditions are accurately classified by ***trainlm*** with 100% classification rate, whereas only BRB3T was detected with 100% accuracy in case of ***trainscg*** based network training for 12 neurons in hidden layer. Overall classification accuracy (both inter-class and intra-class) obtained is better for ***trainlm*** as compared to ***trainscg***.

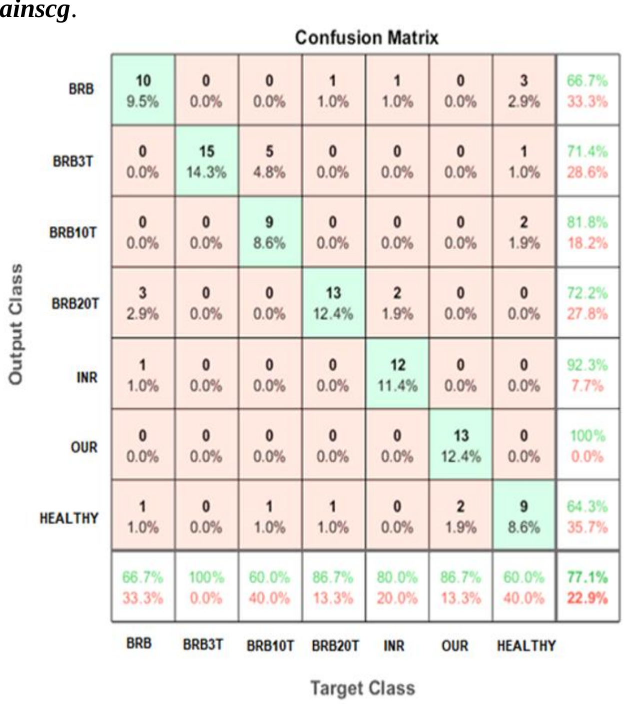

Fig.5 (a) Confusion matrix for classification using *trainscg* with 12 hidden layers

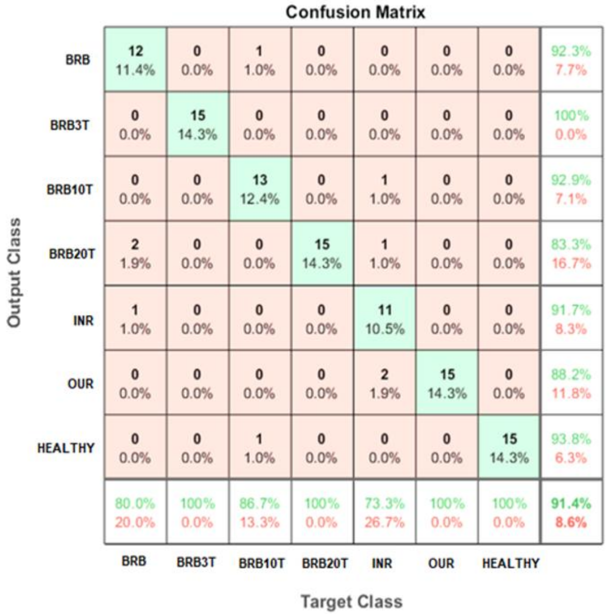

Fig.5 (b) Confusion matrix for classification using *trainlm* with 12 hidden layers

VI. CONCLUSION AND FUTURE SCOPE

In this paper, the experimental work is carried out for classification of different induction motor fault conditions. Using two distinct training algorithms the PatternNet neural network was trained with variable number of hidden layer neurons for classification of motor faults. The overall classification results produced by ***trainlm*** are much better than ***trainscg***. The analysis results for ***trainlm*** method effectively classifies the motor conditions with high accuracy (91.4%). This shows that the proposed method can successfully detect induction motor faults.

This work can be further extended in terms of integrating IoT with the data acquisition stage and sending the data on cloud platform for remote processing and monitoring. Different machine learning classification algorithms as k-NN, SVM, decision trees etc. can be considered for improving the efficiency of classification performance of present work. Also, a greater number of motor faults such as eccentricity, single-phasing, rotor imbalance etc. can be considered for classification purpose.

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