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Fault classification of three phase induction motors using Bi-LSTM networks

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Abstract

The induction motors are back bone of the modern industry and play very important role in manufacturing and transportation sectors. The induction motor faults are mainly classified into internal faults such as inter turn short circuits , broken rotors and external faults such as over load, over voltage faults and asymmetry in supply voltage. The identification of type of fault is very important for safe operation and for preventing risk of machine failures. In this work, a Bidirectional Long Short Term memory networks (Bi-LSTM)-based machine learning methodology is proposed for classification of external faults of Induction Motors. The line voltages of the three phases and the three line currents are considered as the inputs to the Bi-LSTM network for identifying types of fault. Line voltage and line current data sets are considered for six different types of fault conditions. The six different conditions of the three phase induction motor are normal output (NO), overload (OL), over voltage (OV), under voltage (UV), Voltage unbalance (VUB) and single phasing (SP). The BI-LSTM network is trained using Adam optimization algorithm. The classification results are obtained with Bi-LSTM network are compared with LSTM networks to show the advantage of the proposed approach.

Keywords: Three phase induction motor, Machine learning techniques, LSTM, Bilstm, Fault classification

Introduction

Three-phase induction motors are widely used in industrial applications due to their simplicity, robustness, and low maintenance. Though the induction motors are most reliable machines, sometimes during their operation exposed to severe mechanical and electrical faults which are necessary to be identified and rectified for preventing revenue losses and for smooth operation. The induction motor faults are mainly classified as internal faults and external faults. The internal faults are due to damage in mechanical parts of the induction machine like faults in bearings and rotor bars due to aging and excessive use of machine under different operating conditions. The external faults are due to unbalanced power supply and voltage limit violations. The faults of the induction motors can cause severe damage to the motor if not detected and corrected in time. Many authors suggested approaches based on fuzzy logic, neural networks and machine learning based techniques for fault classification. The Zhongming and Bin [1] discussed

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neural networks and fuzzy logic-based induction motor fault detection and classification algorithms. Zidani et al. [2] proposed a fuzzy logic based approach for induction motor faults detection using stator current Concordia patterns. Wu and Chow [3] proposed a radial basis function neural network based approach for induction machine faults classification. Silva et al.[4] developed a method using the wavelet transform for feature extraction and artificial neural network for fault classification in transmission lines. Nandi et al. [5] discussed various techniques used for electric motor fault diagnosis and highlighted the challenges in this area of research. Martins et al. [6] proposed an unsupervised neural-network-based algorithm for detecting and diagnosing stator faults in induction motors using only measured line currents. Bellini et al. [7] presented a detailed report on advanced fault detection techniques for induction machines. Bacha K et al. [8] proposed a method based on neural network-based decision and stray flux EMF measurement for accurate and reliable induction machine fault detection. M. Seera et al. [9] proposed a neuro fuzzy based approach combined with motor current signature analysis for effective fault detection and diagnosis of induction motors. Soualhi et al.[10] proposed an improved artificial ant clustering technique for accurate and efficient fault detection and diagnosis in induction motors. Sun et al.[11] developed a sparse auto encoder based deep leaning approach for fault classification of induction motors. Bessam et al. [12] used a neural network-based approach for detecting broken rotor bar faults in induction motors at low load conditions. Skowron et al. [13] presented an approach based on self-organizing neural networks for classifying rotor and stator faults in induction motors. Sabir et al. [14] proposed long short term memory (LSTM)-based networks identifying faults in bearings using motor current signals. Hadi Salih and Babu Loganathan [15] identified that probabilistic neural network-based approach is efficient for induction motor fault classification compared to support vector machines and artificial neural networks. Belagoune et al. [16] proposed a LSTM network-based method for identifying type of the fault and fault location in large scale multi-machine power systems. Chandran et al.[17] investigated the use of machine learning models such as ensemble bagged trees and SVM classifiers for classifying external faults in induction motors. Muhwezi [18] proposed a method for detecting and diagnosing faults in induction motor using current signature analysis(MCSA) . Ali et al.[19, 20] proposed machine learning algorithms to detect and classify faults in induction motors and variable frequency drive fed induction motors based on measured stator currents and vibration signals. Choudhary et al. [21] proposed a machine learning-based approach for fault diagnosis of induction motor bearings using infrared thermography. Cho et al. [22] suggested a fault detection and isolation method for induction motors using dynamic Bayesian modelling and recurrent neural networks. Zaman et al. [23] proposed a fault diagnosis method for direct online induction motors using a greedy-gradient max cut algorithm that utilizes a max-cut technique and a greedy-gradient method to improve the accuracy of the algorithm. Lee and Lin [24] proposed a fault diagnosis method for induction motors based on a feature selection method using the fast correlation-based filter with particle-swarm optimization method and neural networks. Hossain and Kolla [25] developed long short-term memory based algorithm for of external faults in 3-Phase induction motor.

So far many researchers have developed fault classification methods for three phase induction motor based on the defects in the constructional features like stator bars rotors bars using thermography and based on current and voltage signals. Recently few authors published based on machine learning techniques using LSTM networks for over voltage and over current faults. The LSTM networks takes larger time to converge and hence in the preset work a Bi-LSTM based machine learning approach is proposed for fault classification of Induction motors. In this work in Section "Three phase induction motor faults" the different types of faults are discussed and in Section "Machine learning techniques" the architectures of machine learning techniques are discussed. In Section, "Three phase induction motor fault classification using Bi-LSTM networks" the fault classification of induction motors using Bi-LSTM networks is discussed. Finally in Section "Results and discussions" the simulation results are presented and in Section "Conclusions" the conclusions are discussed.

Three phase induction motor faults

The induction motors even though robust enough when they are exposed to severe harsh conditions for long time during operation results in deterioration of the motor. It is essential to detect and rectify the fault for minimizing the impact on productivity and financial losses in industry. In this section, the different types of external faults are discussed in detail. Some of the common external faults include Normal output (NO), Overload (OL), Overvoltage (OV), Under voltage (UV), Single Phasing (SP), Voltage Unbalance (VUB). These faults can cause temperature rise of the machine, abnormal noise, vibrations and reduced motor performance. Regular maintenance and monitoring of the induction motor operation can detect and prevent these faults can increase the lifespan and reliability of the motor.

The NO fault condition of a three phase induction motor refers to the normal operating condition of the motor running under rated load and voltage conditions. In this condition, the motor is operating efficiently and producing the expected output power. In the case of over load (OL) fault, the induction motor draws higher currents when the load on the motor increases than the rated load and the speed decreases. The heat dissipation rate decreases with increase in currents due to overload conditions of the motor and effects the life of the insulation. Finally, the motor has to run on reduced load than the rated load and hence the overload faults must be identified and corrected.

The overvoltage (OV) fault in a three phase induction motor occurs when the supply voltage exceeds the motor's rated voltage. This can happen due to various reasons such as voltage transients, voltage spikes, or faults in the power distribution system. When the induction motor operates under over voltage conditions the core losses increases and causes the machine to become overheat. The under voltage (UV) fault in a three phase induction motor occurs when the supply voltage falls below the motor's rated voltage. This can happen due to various reasons such as faults in the power distribution system, voltage sags, or low power supply. In order to supply the required power to the load, the induction motor draws more current under low voltage conditions. The excessive currents drawn by the motor causes over heat and can harm the insulation of the motor windings.

Voltage unbalance in a three phase induction motor occurs when the voltage in one or more phases of the power supply to the motor is different from the other phases. The main causes of these voltage unbalance are improper transposition in supply lines, unsymmetrical faults either within induction motor or from supply feeder lines and also due to unequal transformer tap settings. Unbalanced supply voltage causes negative sequence currents to circulate in the motor, which increases the stator and rotor heating. The presence of voltage unbalance causes increase in stator and rotor copper losses, eddy current losses and overheating and the finally effects motor efficiency. The motor may also be subjected to mechanical vibrations and hence it is required to monitor voltage unbalance to protect from mechanical damage and for reliable operation. Single phasing (SP) in a three phase induction motor occurs due to various reasons such as a line to ground fault in a power distribution system, a blown fuse or a broken wire. When one of the connections of three phase power supply to the induction motor is lost, voltage unbalance occurs and negative sequence currents flows in the rotor circuit. The negative sequence current causes the rotor to become over heat and increases the copper losses.

Machine learning techniques

In this section, the architectures of long short term memory (LSTM) networks and Bi-directional long short term memory networks (Bi-LSTM) are discussed [26–28].

Long short term memory networks

Long short term memory (LSTM) networks are the advanced version of recurrent neural networks (RNN) and can overcome the vanishing gradient problem that is associated with RNN architectures. LSTM has a memory cell that can remember the information for long periods, and three gates (input, forget, and output) that control the information flow into and out of the cell. These gates make it possible for the network to selectively keep or discard the information at each time step, allowing it to remember the important information and forget the irrelevant information.

The LSTM block uses the current cell state $\mathbf{c}t{-}1$, hidden state $\mathbf{h}t{-}1$ and input sequence X_t to compute the updated cell state $\mathbf{c}t$ and output state. The following equations describe the four different steps involved in obtaining the output state of the LSTM network.

$$fg_t = \sigma_g(W_{fg}x_t + R_{fg}h_{t-1} + b_{fg} \tag{1}$$

$$\mathrm{cs}_t = \sigma_\mathrm{c}(W_\mathrm{cs}x_t + R_\mathrm{cs}h_{t-1} + b_\mathrm{cs}) \tag{2}$$

$$\mathrm{ig}_t = \sigma_\mathrm{g}(W_\mathrm{ig}x_t + R_\mathrm{ig}h_{t-1} + b_\mathrm{ig} \tag{3}$$

$$og_t = \sigma_\mathrm{g}\left(W_{og}x_t + R_{og}h_{t-1} + b_{og}\right) \tag{4}$$

In the above equations, Eq. (1) represents the forget gate and computes the cell state reset (*fg*) values. The forget layer decides the content that can be removed or forget from the present cell state and it is done by using sigmoid layer. The Eq. (2) tells the new cell state information (*cs*) that is to be used to update current cell state. The Eq. (3) representing the input gate (ig_t) computes the input gate state (*ig*) which is used to control the cell state new information. The Eq. (4) gives the output gate value. The updated cell state and hidden state are calculated by using Eq .(5) and Eq .(6).

$$C_t = \mathrm{fg}_t \odot C_{t-1} + \mathrm{ig}_t \odot \mathrm{cs}_t \tag{5}$$

$$h_t = \mathrm{og}_t \odot \sigma_c(C_t) \tag{6}$$

In the above equations, $\odot$ denotes the Hadamard product which is the symbol for computation of element-wise multiplication of vectors.

Bidirectional long short term memory networks

Bi-LSTM layer is a type of recurrent neural network (RNN) layer used in machine learning. It is a variation of the standard LSTM layer that processes input sequences in both forward and backward directions, allowing the network to capture information from past and future time steps. In a traditional LSTM layer, the output at each time step is determined solely by the input sequence up to that point. However, a Bi-LSTM layer processes the input sequence both forward and backward, allowing the network to capture information from future time steps as well. This is useful in tasks where the context of the entire sequence is important, such as natural language processing (NLP), speech recognition, and audio processing. The Bi-LSTM layer consists of two LSTM sub-layers, one processing the sequence forward and the other processing it backward. The outputs from both sub-layers are then concatenated and passed to the next layer in the network. This allows the network to learn from the context of the entire sequence, rather than just the past or future.

$$h_t^f = \left(W_x^f x_t + R_h^f h_{t-1} + b^f\right) \tag{7}$$

$$h_t^b = \left(W_x^b x_t + R_h^b h_{t+1} + b^b\right) \tag{8}$$

$$y_t = \left(W_y^f h_t^f + W_y^b h_t^b + b^y\right) \tag{9}$$

The output calculation of the Bi-LSTM equations can be represented using the above three equations.

Three phase induction motor fault classification using Bi-LSTM networks

The faults of a 3-phase induction motor are classified as per their current and voltage signatures. In this, the Bi-LSTM model is trained by the current and voltage signatures data which are given like as shown in the following figure (Figs. 1, 2, 3, 4 and 5).

The faults are classified based on three line voltages V_{RY}, V_{YB} and V_{BR} and the three line currents I_R, I_Y and I_B of the Three phase induction Motor. The data set of the voltages

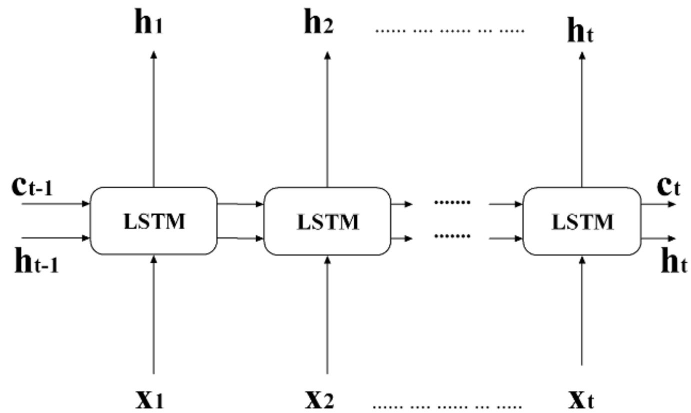

Fig. 1 LSTM Network architecture

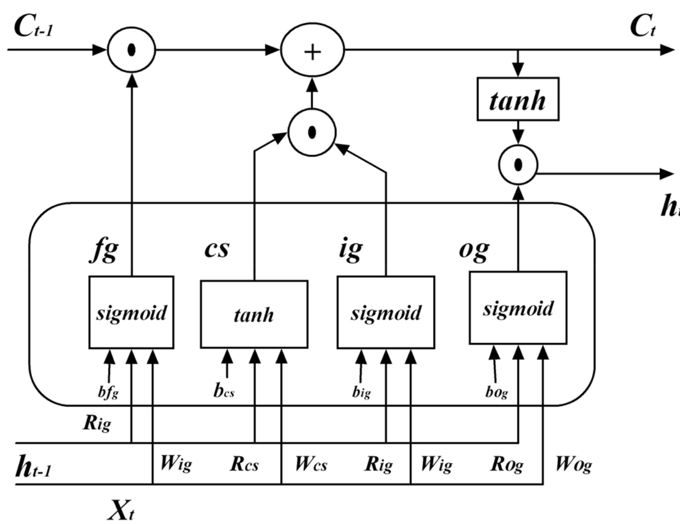

Fig. 2 LSTM layer architecture

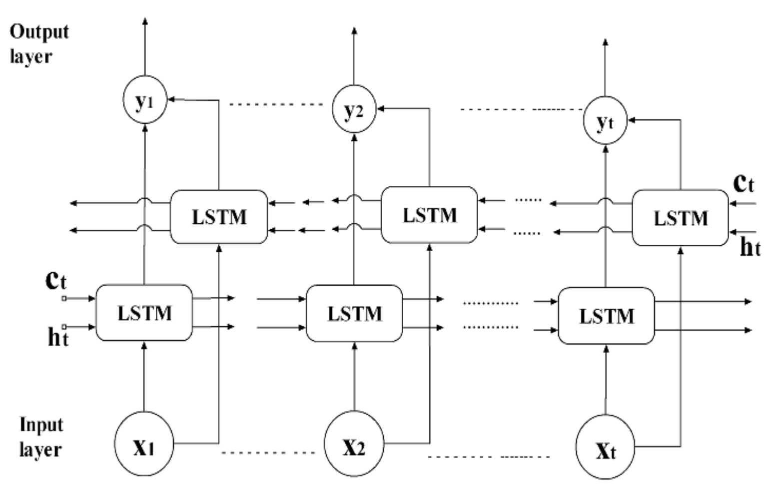

Fig. 3 Bi- LSTM Network architecture

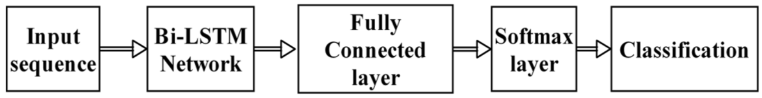

Fig. 4 Bi- LSTM Network architecture

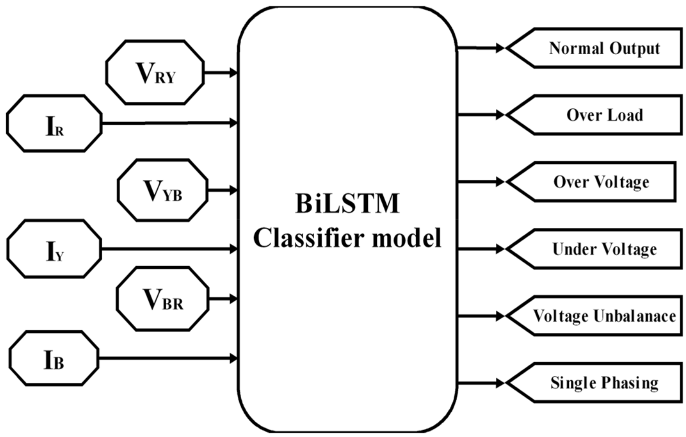

Fig. 5 Bi-LSTM fault classifier for three phase Induction motor

and currents for the previously identified faults are given to the Bi-LSTM network. The Bi-LSTM network is trained with the voltage and currents data set using Adam optimization algorithm.

Adam optimization algorithm

The Bi-LSTM network is trained using Adam optimization algorithm [29] which is derived by combining the advantages of root mean square propagation algorithm and adaptive gradient algorithm. The name of the algorithm Adam is derived from adaptive moments estimation and mainly well suited for problems with large data sets. Adam is a computationally efficient optimization algorithm which is based on adaptive estimation of lower order moments and works efficiently with sparse gradients and online parameter tuning. The Adam method computes adaptive learning rates for different parameters individually from the estimates of first and second moments of the gradients.

$$mv_t = \beta_1 mv_{t-1} + (1-\beta_1)\nabla E(\theta_t) \tag{10}$$

$$vv_t = \beta_2 vv_{t-1} + (1-\beta_2)[\nabla \mathrm{E}(\theta_t)]^2 \tag{11}$$

In the above equations, Eq. (10) and Eq. (11) mv_t and are the moment vectors and β_1 and β_2 are the exponential decay factors. $E(\theta_t)$ is the stochastic objective function and θ_t is the parameter to be updated.

$$\widehat{mv_t} = \frac{mv_t}{(1-\beta_1)} \tag{12}$$

$$\widehat{vv_t} = \frac{vv_t}{(1-\beta_2)} \tag{13}$$

$$\theta_t = \theta_{t-1} - \frac{\propto \widehat{mv_t}}{\sqrt{\widehat{vv_t}} + \int} \tag{14}$$

$\widehat{mv_t}$ and $\widehat{vv_t}$ biased estimates of the moments and $\propto$ is the step size.

The first moment is calculated using gradient and the second moment is calculated based on the square of the gradient of the objective functions considered. These moving averages are then used to update the weight parameters. The parameter update rule uses the biased estimates of the moments.

Performance metrics of the Bi-LSTM networks

Accuracy

The accuracy [30] is an evaluation metric in machine learning algorithms used in classification problems which measures the percentage of the accurate predictions out of the total predictions.

$$\text{Accuracy} = \frac{\text{number of total correct predictions}}{\text{number of total predictions}} \tag{15}$$

In the present work, Bi-LSTM network is trained in such a way if the fault is identified correctly then the output of that particular category will be unity and other categories outputs are zero. The accuracy is calculates as the ratio of number of total correct predictions to number of total predictions. The total number of correct predictions consists of summation of total true positives and total true negatives. The total number of predictions consists of summation of total true positives, true negatives along with false positives and false negatives.

Entropy loss cost function

In machine learning algorithms, the optimum classification model is obtained by minimizing the Cross Entropy loss objective function. The parameters of the Bi-LSTM network are trained using Adam optimization algorithm by minimizing the Cross-Entropy loss objective function. The cross entropy loss objective function is mainly depends on output of the softmax layer. In the machine learning algorithms, a softmax layer [29] is used after the fully connected layer of the LSTM networks and Bi-LSTM networks. The softmax function which is used for the multi class functions can be represented by the following equation.

Table 1 Confusion matrix for fault classification

	NO	OL	OV	UV	VUB	SP
NO	1	0	0	0	0	0
OL	0	1	0	0	0	0
OV	0	0	1	0	0	0
UV	0	0	0	1	0	0
VUB	0	0	0	0	1	0
SP	0	0	0	0	0	1

$$S_j = \frac{\exp(y_j)}{\sum_{j=1}^{K}\exp(y_j)} \tag{16}$$

Where S_j is the output of the softmax function of the jth class and y_j is the output of the fully connected layer of the jth class of the Bi-LSTM network. K is the total number of classes.

The cross entropy loss objective ($\mathrm{Loss}_{\mathrm{CE}}$) can be described by the following objective function [29].

$$\mathrm{Loss}_{\mathrm{CE}} = -\frac{1}{N}\sum_{n=1}^{N}\sum_{j=1}^{K} T_{nj}\ln(S_{nj}) \tag{17}$$

Table 2 Training data for fault classification [31]

Voltages and currents values (Training data)						Type of classification
V_{RY}	V_{YB}	V_{BR}	I_R	I_B	I_Y	
402.7	402.9	403.2	7.75	7.75	7.75	NO
403.0	410.0	407.3	7.15	7.94	8.09	NO
410.2	410.3	410.4	7.68	7.68	7.68	NO
413.8	414	414.1	7.65	7.65	7.65	NO
420	420.1	420.2	7.6	7.6	7.6	NO
399.6	400	400.3	9.0	9	9	OL
399.1	399.2	399.4	9.2	9.2	9.2	OL
399.2	399.3	399.3	9.7	9.7	9.7	OL
398.9	399.3	399.8	9.95	9.95	9.96	OL
399.6	400.3	400	10.46	10.45	10.45	OL
441.8	442.1	442.4	8.02	8.03	8.02	OV
443.1	443.3	443.6	8.01	8.02	8.01	OV
444.8	445.2	445.6	8	8	8	OV
446.8	447	447.2	7.98	7.99	7.98	OV
444.2	444.6	445	7.44	7.444	7.43	OV
361.1	361.3	361.4	8.3	8.3	8.3	UV
357.3	357.6	357.9	8.37	8.35	8.36	UV
352.4	352.7	353	8.48	8.46	8.47	UV
342.6	343	343.2	8.67	8.66	8.67	UV
336.7	336.8	337	8.8	8.8	8.8	UV
409.6	389.5	400	9.46	7.25	6.96	VUB
407.5	400	391.9	8.41	8.65	6.46	VUB
409.6	400	389.5	8.54	8.9	6.14	VUB
411.5	395.9	391.7	9.06	8.46	6.1	VUB
411.4	391.7	396.1	9.41	7.83	6.45	VUB
284.4	400	362.8	0	16.75	16.75	SP
286.8	402.9	365.3	0	16.65	16.65	SP
305.4	416.4	377.8	0	16.13	16.13	SP
273	391.9	355.2	0	17	17	SP
256.6	379.7	343	0	17.45	17.45	SP

Where N is the number of samples, K is the number of classes and T_{nj} is the truth value of jth class of the nth sample. The truth value of the class is either zero or one in a particular sample. In a sample, the output will have a value unity for that particular class to which the sample belongs to and for all other classes the truth value is zero.

In the present case the fault classification model will have six inputs in a sample and six outputs representing each class. If the sample belongs to a particular fault condition, i.e. for example, over voltage then the output of that particular over voltage class will have truth value unity and other outputs will have zero value in the training model.

Since Softmax function is an exponential based function it is continuously differentiable and the derivative of the Softmax function with respect to every parameter can be calculated. Hence using Adam optimization which requires the gradients estimation can be used to adjust model parameters to force the loss function towards minimization.

Table 3 Training results with LSTM network [25]

	NO	OL	OV	UV	VUB	SP
NO	**0.9988**	0.0002	0.0000	0.0004	0.0004	0.0001
NO	**0.9959**	0.0014	0.0022	0.0000	0.0000	0.0004
NO	**0.9989**	0.0001	0.0004	0.0001	0.0004	0.0001
NO	**0.9971**	0.0001	0.0021	0.0001	0.0005	0.0001
NO	**0.9419**	0.0001	0.0563	0.0000	0.0015	0.0002
OL	0.0005	**0.9990**	0.0000	0.0004	0.0000	0.0001
OL	0.0002	**0.9995**	0.0000	0.0002	0.0000	0.0001
OL	0.0000	**0.9998**	0.0000	0.0001	0.0000	0.0000
OL	0.0000	**0.9999**	0.0000	0.0001	0.0000	0.0000
OL	0.0000	**0.9999**	0.0000	0.0000	0.0000	0.0000
OV	0.0001	0.0000	**0.9999**	0.0000	0.0000	0.0000
OV	0.0001	0.0000	**0.9999**	0.0000	0.0000	0.0000
OV	0.0000	0.0000	**1.0000**	0.0000	0.0000	0.0000
OV	0.0000	0.0000	**1.0000**	0.0000	0.0000	0.0000
OV	0.0001	0.0000	**0.9999**	0.0000	0.0000	0.0000
UV	0.0009	0.0015	0.0000	**0.9968**	0.0007	0.0000
UV	0.0006	0.0012	0.0000	**0.9976**	0.0006	0.0000
UV	0.0004	0.0009	0.0000	**0.9982**	0.0004	0.0000
UV	0.0002	0.0005	0.0000	**0.9989**	0.0003	0.0000
UV	0.0002	0.0004	0.0000	**0.9992**	0.0003	0.0000
VUB	0.0002	0.0000	0.0000	0.0001	**0.9997**	0.0000
VUB	0.0007	0.0000	0.0000	0.0005	**0.9988**	0.0000
VUB	0.0001	0.0000	0.0000	0.0002	**0.9997**	0.0000
VUB	0.0000	0.0000	0.0000	0.0001	**0.9999**	0.0000
VUB	0.0001	0.0000	0.0000	0.0001	**0.9999**	0.0000
SP	0.0001	0.0001	0.0001	0.0000	0.0000	**0.9998**
SP	0.0001	0.0001	0.0001	0.0000	0.0000	**0.9998**
SP	0.0001	0.0001	0.0001	0.0000	0.0000	**0.9997**
SP	0.0001	0.0001	0.0000	0.0000	0.0000	**0.9998**
SP	0.0001	0.0001	0.0000	0.0000	0.0000	**0.9998**

The bold values represent classifications identified

Results and discussions

The three phase induction motor conditions of the data set are taken from the literature [31] is trained using Bi-LSTM for fault classification. The network consists of six sequential input layers and two hundred hidden units. The network is in fully connected state and at the output softmax layer is used for fault classification. The confusion matrix for the induction motor fault classification is shown in Table 1.

The training data set is taken from [31] is shown in Table 2. The network trained with the data using Adam optimization algorithm identifying six different conditions of the motor out of which five fault conditions and one no fault condition. The results obtained with proposed BiLSTM network are compared with LSTM network-based approach proposed in [25]. The fault classification results obtained with LSTM network [25] are shown in Table 3 and with Bi-LSTM network are shown in Table 4. From Tables 3 and 4, it can be observed that the fault identification is slightly better with Bi-LSTM network compared to the LSTM network based algorithm.

Table 4 Training results with proposed Bi-LSTM network

	NO	OL	OV	UV	VUB	SP
NO	**0.9990**	0.0001	0.0000	0.0004	0.0005	0.0000
NO	**0.9999**	0.0001	0.0000	0.0000	0.0000	0.0000
NO	**0.9995**	0.0000	0.0000	0.0001	0.0004	0.0000
NO	**0.9996**	0.0001	0.0000	0.0000	0.0003	0.0000
NO	**0.9995**	0.0001	0.0000	0.0000	0.0004	0.0000
OL	0.0012	**0.9933**	0.0000	0.0052	0.0002	0.0000
OL	0.0005	**0.9962**	0.0000	0.0031	0.0001	0.0000
OL	0.0001	**0.9994**	0.0000	0.0005	0.0000	0.0000
OL	0.0000	**0.9998**	0.0000	0.0002	0.0000	0.0000
OL	0.0000	**0.9999**	0.0000	0.0000	0.0000	0.0000
OV	0.0324	0.0005	**0.9668**	0.0000	0.0001	0.0001
OV	0.0164	0.0003	**0.9832**	0.0000	0.0001	0.0001
OV	0.0060	0.0001	**0.9938**	0.0000	0.0000	0.0000
OV	0.0023	0.0001	**0.9976**	0.0000	0.0000	0.0000
OV	0.0167	0.0000	**0.9831**	0.0000	0.0001	0.0000
UV	0.0003	0.0006	0.0000	**0.9988**	0.0003	0.0000
UV	0.0002	0.0004	0.0000	**0.9992**	0.0002	0.0000
UV	0.0001	0.0003	0.0000	**0.9995**	0.0001	0.0000
UV	0.0000	0.0001	0.0000	**0.9997**	0.0001	0.0000
UV	0.0000	0.0001	0.0000	**0.9998**	0.0001	0.0000
VUB	0.0009	0.0000	0.0000	0.0005	**0.9985**	0.0000
VUB	0.0011	0.0000	0.0000	0.0006	**0.9983**	0.0000
VUB	0.0001	0.0000	0.0000	0.0002	**0.9996**	0.0000
VUB	0.0001	0.0000	0.0000	0.0001	**0.9998**	0.0000
VUB	0.0001	0.0000	0.0000	0.0002	**0.9997**	0.0000
SP	0.0001	0.0000	0.0000	0.0000	0.0000	**0.9999**
SP	0.0001	0.0000	0.0000	0.0000	0.0000	**0.9999**
SP	0.0001	0.0001	0.0000	0.0000	0.0000	**0.9998**
SP	0.0001	0.0000	0.0000	0.0000	0.0000	**0.9999**
SP	0.0001	0.0000	0.0000	0.0000	0.0000	**0.9999**

The bold values represent classifications identified

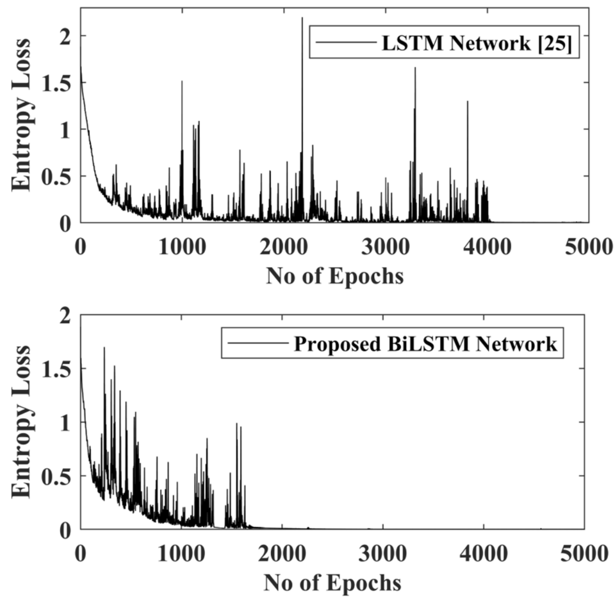

Fig. 6 Entropy loss Comparison with Bi-LSTM and LSTM classifiers

The entropy loss metric to demonstrate the efficiency of the training algorithm and the BiLSTM network is shown in Fig. 6. From Fig 6, it can be observed that the convergence is achieved much earlier with proposed BiLSTM network compared to LSTM network based algorithm. It can also be observed that the Entropy loss converged to the minimum value with less number of epochs in the case of Bi-LSTM network compared to the LSTM network.

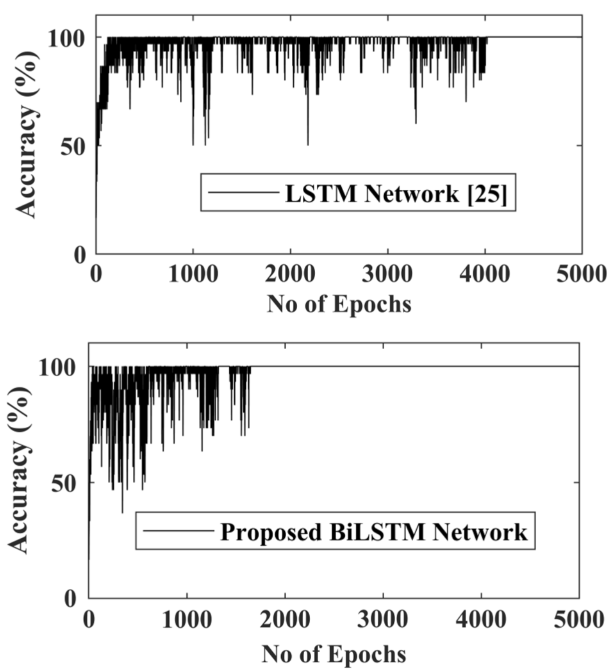

Fig. 7 Accuracy Comparison with Bi-LSTM and LSTM classifiers

Table 5 Data for validation with Bi-LSTM trained network

Voltages and currents values (Validation data)						Type of classification
V_{RY}	V_{YB}	V_{BR}	I_R	I_B	I_Y	
405.1	405.4	405.6	7.74	7.72	7.73	NO
399.7	400	400.2	9.45	9.43	9.44	OL
443.2	443.4	443.5	7.44	7.45	7.44	OV
347.6	347.8	348.0	8.55	8.54	8.54	UV
407.5	395.9	396.2	8.74	7.99	6.75	VUB
292.1	400.6	368.8	0	16.54	16.54	SP

Table 6 Confusion matrix for validation data

	NO	OL	OV	UV	VUB	SP
NO	**0.9993**	0.0001	0.0000	0.0002	0.0004	0.0000
OL	0.0001	**0.9988**	0.0000	0.0010	0.0001	0.0000
OV	0.0320	0.0001	**0.9677**	0.0000	0.0001	0.0001
UV	0.0001	0.0002	0.0000	**0.9996**	0.0001	0.0000
VUB	0.0026	0.0000	0.0000	0.0009	**0.9965**	0.0000
SP	0.0001	0.0001	0.0000	0.0000	0.0000	**0.9998**

The bold values represent classifications identified

From Fig. 7, it can be observed that the accuracy performance is much better with Bi-LSTM networks compared with the LSTM network classifier.

The validation data for the induction motor classification for testing the trained network are shown in Table 5. The fault identification results obtained with Bi-LSTM network with the validation data are shown in Table 6 and it can be observed the proposed Bi-LSTM classifier trained with Adam optimization algorithm successfully able to classify the three phase induction motor external faults.

Conclusions

In this work, a Bi-LSTM-based induction motor fault classifier is proposed for fault detection of induction motor faults. The external faults of the induction motor are classified into six different groups based on three phase line voltages and line currents of the induction motor. The BI-LSTM network consists of a softmax layer at the end of the network which classifies the faults based on an exponential probability function. Simulation results proved that fault classification of a 3-phase induction motor is more efficient with BILSTM classifier method when compared to LSTM classifier method. The results in terms of convergence characteristics of the performance metrics accuracy and entropy loss are much better in the case of Bi-LSTM network compared to LSTM network. In the present work, supervised learning algorithm-based BiLSTM network considering the data samples of a single machine is developed for fault classification. But in industry there is possibility of induction machines with different ratings for various kinds of applications. Hence a combination of unsupervised and supervised learning methods based algorithm development for identifying the type of the induction machine and classification of both internal and external faults is considered as a future work.

Abbreviations

b_{ig}	Bias values of the input gate
b_{fg}	Bias values of the forget gate
b^{f}	Bias values in forward mode of BiLSTM network
b^{b}	Bias values in backward mode of BiLSTM network
b^{y}	Bias values of output of BiLSTM network
b_{cs}	Bias of the cell gate
C_t	Cell state at time *t*
cs_t	Cell gate at time *t*
$E(\theta_t)$	Stochastic objective function
h_t^{f}	Hidden state values in forward mode at time step *t*
h_t^{b}	Hidden state values in backward mode at time t
h_{t-1}	Hidden state values at time step $t-1$
h_{t+1}	Hidden state values at time step $t+1$
ig_t	Input gate at time t
fg_t	Forget gate at time *t*
mv_t	First moment vector at time step *t*
N	No of samples
og_t	Output gate at time t
R_{ig}	Recurrent weights of the hidden state
R_h^{f}	Recurrent weights of the hidden state in forward mode
R_h^{b}	Recurrent weights of the hidden state in backward mode
R_{fg}	Recurrent weights of the forget gate
R_{cs}	Recurrent weights of the cell gate
S_j	Output of the softmax layer
T_{nj}	Truth value of *j*th class of the nth sample
S_j	Output of the softmax layer
T_{nj}	Truth value of *j*th class of the nth sample
vv_t	Second moment vector at time step t
W_x^{f}	Weights of the input in forward state
W_x^{b}	Weights of the input in backward state
W_y^{f}	Weights of the hidden state in forward state
W_y^{b}	Weights of the hidden state in backward state
W_{ig}	Weights of the input sequence
W_{fg}	Weights of the forget gate
W_{og}	Weights of the output gate
W_{cs}	Weights of the cell gate
$\nabla E(\theta_t)$	Gradient of the stochastic objective function
θ_t	Parameter of the objective function
y_j	Output of the fully connected classification layer

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Author contributions
JV conceptualized the idea for Induction Motor fault classification with LSTM networks, performed simulations and prepared the original draft. DPR, SJ and JJ have done the literature survey, performed simulations and prepared the simulation results. BG has developed the methodology for fault classification with LSTM networks and reviewed and edited the manuscript. SRG has developed the methodology for induction motor fault classification with BiLSTM networks and prepared the original draft. AA has conceptualized the idea for Induction Motor fault classification with LSTM networks and reviewed and edited the manuscript. All authors read and approved the final manuscript.

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Declarations

Competing interests
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