A Deep Learning based Non-invasive and Real-Time Fault Detection System for 3-Phase Induction Motors

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Abstract:

Induction motor (IM) plays a major role in industry. Despite of its strong structure, IMs are often prone to faults. There are different types of faults which occur in induction motors such as bearing faults, rotor bar faults, winding faults, etc. Thus, motors in major applications require continuous and effective monitoring. In this paper, a stand-alone and non-invasive condition monitoring system is developed that can monitor the condition of 3-phase IM using motor current signature data with aid of deep learning (DL) approaches. The proposed system acquires the data using non-invasive current sensors then converts the acquired data to digital data using an analog to digital converter (ADC), and saves the acquired data in files. The raw current data acquired from induction motor is used to train the DL models including Multilayer Perceptron (MLP), Long Short-term Memory (LSTM), and One-Dimensional Convolutional Neural Networks (1D-CNN). The comparative analysis demonstrated the LSTM model as the best fault classifier among the comparative DL models with the accuracy up to 100% owing to its deep hierarchical structure. At the end, the real-time testing of the device is performed which confirms that the developed system can effectively monitor the motor using non-invasive current sensors and DL models.

Keywords: *Deep learning; Current Sensors; Non-invasive; Fault Detection; Induction motor*

1. Introduction

Three phase induction motors (IMs) have been widely employed in various industries including railways, aeronautics, petrochemical, gas plants, and automotive industry [1, 2]. According to the research reports the power consumption by induction motor in the industries is about 60% of total power generated by any country [3, 4], which implies that IMs are an essential part of industry [5, 6]. Among various types of motors, the squirrel cage motors have been widely used in industrial applications owing to its reliable operation and cost-effectiveness. The proper function of the motor is of high priority, once it becomes faulty, it costs a fortune. Bearings are the most vulnerable part of IMs that causes serious damages to motors.

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If any fault is left unnoticed it may cause major damages to rotating machinery, which in turn costs huge amount of money for repairing and eventually it causes process to halt [7, 8]. Thus, early fault detection in rotating machines is a goal that ultimately assists in saving system from major damages

Generally, a motor requires electric current for rotor to produce torque, which is obtained by electromagnetic induction from magnetic field of stator winding. In various industries 3-phase IMs are widely used because these motors are efficient, reliable, compact, less expensive, and easy to operate [6, 9]. Three phase motors are also used in electric vehicles and railways owing to its robust structure and high performance [10]. Manufacturers over the years are trying to build reliable motors; yet they pose many types of faults which cause huge losses and downtime. Therefore, condition monitoring of motors is essential in almost every industry. Further, condition monitoring can be done through various methods such as vibration, current, voltage, temperature, and sound analysis of a machine to detect various faults. Among these methods, motor current signature analysis (MCSA) have been widely employed to monitor condition of IMs. As this sensing method provides highly sensitive information relating to behavior of motors. Thus, it is used for condition monitoring of heavy Industrial machinery [11]. The current analysis method is also helpful in effective fault detection of three phase IMs.

Deep learning (DL) as an advance version of artificial intelligence and hierarchically learns representations even from raw data through employing multiple layers in different architectures [12]. It has become hotspot for researchers as an effective solution for health monitoring systems. It has been evolving with the flow of time in terms of capabilities. Various DL architectures have been successfully utilized for effective and reliable condition monitoring of industrial system including multilayer perceptron (MLP), autoencoders, convolutional neural networks (CNN), recurrent neural networks (RNN), and generative adversarial networks (GAN) [13, 14]. However, DL methods can address big-scale data through its multi-level architectures. Long short-term memory (LSTM) is an upgraded version of RNN, capable of learning long term dependencies and the most popular solution to the gradient vanishing problem.

Recent researches have employed current signature data with different analysis methods for motor fault detection and classification task. In this context, C. Morales-Perez, et al. [15] have proposed sparse representations and dictionary learning based technique with the motor current data to detect bearing faults. The 3-phase motor was operated under two load conditions. The sparse representations allowed to limit the reconstruction error of the method which in turn increased the detection accuracy up to 96.94%. In [16] authors have used CNN with current signature data for broken rotor bar (BRB) fault detection. They have used notch filter to get rid of the fundamental frequency and then applied Short Time Fourier transform (STFT) on transient current data. Subsequently, the data was transformed into the images of five different sizes and then fed to the model for representations learning. The method was able to automatically detect different severity levels of broken rotor bar fault with the accuracy up to 100%. However, the method demonstrated slow response during fault detection owing to the pre-processing of the data. Authors of [17] have used LSTM with empirical mode decomposition (EMD) combined with correlation analysis and wavelet threshold de-noising for bearing fault classification. The LSTM model was fed with the signal components obtained from maximum correlation of EMD. The results demonstrated that the method was able to effectively classify the bearing faults with the 97.84% accuracy.

In this paper, a non-invasive and end-to-end fault diagnosis system is proposed. The system is developed using the current signature analysis and DL models. Different form aforementioned researches, we propose a method to effectively detect and identify faults of the motor in real-time through a non-invasive current sensing method. The end-to-end automatic fault diagnosis system is developed using DL methods. Remaining

paper is organized as follows: Section 2 discusses the current signature analysis and its importance, Section 3 explains components used in this research, Section 4 discusses the methods used in this investigation, Section 5 reports and discusses the results, and Section 6 Concludes this paper.

2. Current signature analysis

Induction motors are prone to various electrical and mechanical faults due to various reasons such as harsh environment, overloading, and improper power supply [18, 19]. These faults are diagnosed using different signatures such as vibration, current, temperature, etc. Among these methods, current signature have been employed by researchers as an effective method even for mechanical fault diagnosis. Mechanical faults such as bearing faults in motor generates spurious frequency which are reflected in the stator's current spectrum as given in Eq. (1). Thus, different mechanical faults of the motor can be detected using current signature analysis [15].

$$F_{is} = |F_s \pm kF_v| \qquad (1)$$

where, F_{is} represents spurious frequency, F_s is the frequency of the power supply, F_v characteristic frequency of the fault and $k \in \mathbb{N}$. Moreover, non-invasive current signature analysis have multiple advantages including easy implementation, inexpensiveness, and no interference with other signals of motor [4]. Thus, it is has been point of attention for the researchers in this domain.

3. System Components

This section consists of discussions of all the components used to develop this condition monitoring system, and each component is described as under:

3.1. Sensors

To acquire 3-Phase current data from the IM three SCT-013-005 current sensors are used as shown in Fig. 1. The SCT-013-005 is a non-invasive current sensor that works on the principles of a transformer and manufactured by the Beijing Yaohuadechang Electronic Co., Ltd (YHDC). When the primary coil is fed with an input voltage, magnetic flux is produced and it induced voltage in the secondary coil of transformer, the same phenomenon is followed by the SCT-013-005 current sensor. However, this sensor has only one coil in its internal structure that works as secondary coil and its primary coil is the live phase wire of the IM [20].

Fig. 1. Clamp type current sensor [20]

Since, it is used for a 3-phase induction motor that is why each phase require a current sensor, to fulfill this condition three SCT-013-005 current sensors are installed on the each phase of the IM. The specifications of the sensor are given in Table I.

TABLE I.   SPECIFICATIONS OF THE CURRENT SENSOR [4]

S. No.	Metrics	Description
1.	Opening size	13*13mm
2.	Non-linearity ±3%	±3%
3.	Di-electric strength	1000v AC/1min
4.	Operating temperature	25°C to +70°C.
5.	Input Current	0-5A
6.	Output Voltage	0-1V

An analog to digital converter (ADC) is used for the interfacing between analog current sensor and raspberry pi microcomputer. As the output of current sensors is analog, the Raspberry-pi supports digital data. Thus, to resolve this problem a 16 bit, 4-channel ADC, ADS1015 is employed with three current sensors. The ADC is able to convert only 100 samples per second simultaneously of the three channels.

However, increase in the sampling rate causes data loss.

3.2. Raspberry-pi

Raspberry pi is developed and distributed by the Raspberry Pi Foundation. It is a stand-alone board, which was developed for prototyping and development of embedded systems. It has been widely used by professionals and hobbyists in various application systems like robotics, condition monitoring, object recognition systems, etc. There are several models available for raspberry pi. The model used in this project is the Raspberry Pi 4B. It supports the Linux based operating system. The specifications of the Raspberry Pi 4 B are mentioned in Table II [22]:

TABLE II.   RASPBERRY PI SPECIFICATIONS [22]

S. No.	Metrics	Description
1.	CPU	1.5 GHz quad-core A72 64-bits
2.	RAM	4 GB
3.	Storage	Micro-SD slot (expandable)
4.	Power	5V, 3A (Type-C cable)
5.	Operating System	Linux

The results of the developed system are displayed by interfacing a 7-inch touch screen display with the Raspberry-pi microcomputer. The resolution of the 7-inch LCD display is 1024*600 pixels.

3.3. Three Phase Induction Motor

For development of the proposed system, a 3-phase squirrel cage IM is used. It has the following specifications given in Table III:

4. Methodology

To develop a stand-alone fault detection system different components are used including the induction motor, current sensors, analog to digital convertor, and raspberry-pi board. The non-invasive current sensors are used to acquire the data from the induction motor and provide analog signal output. Since, the current sensor provide analog output that is why ADC is interfaced with it to convert the analog data into digital form to save it to the Raspberry-pi microcomputer. The data acquisition system will store the data in a comma separated value (CSV) file for training the DL models. Then the acquired data is further split into the ratio of 7:2:1 as training, test, and validation set, respectively. Following DL models are employed in this research for fault detection and comparison of performance on the acquired data. Fig. 2 shows the block diagram of the method employed in this research.

TABLE III.   MOTOR SPECIFICATIONS

S. No.	Metrics	Value
1.	Power Rating	0.5 H.P.
2.	RPM	1450
3.	Current Rating	3A
4.	Phase	3

4.1. LSTM

LSTM is an upgraded version of RNN, capable of learning long term dependencies. Remembering information for long period of time is in its default behavior. LSTM network is the most popular solution to the vanishing gradient problem. Table IV shows the structure of the model and the distribution of layers in the model is described below:

- LSTM corresponds to the input and the hidden layers.
- Dropout is a regularization technique that is used to ignore certain set of neurons during the training stage.
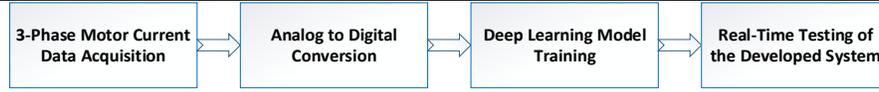- Dense corresponds to the output layer.

3-Phase Motor Current Data Acquisition	Analog to Digital Conversion	Deep Learning Model Training	Real-Time Testing of the Developed System

Fig. 2. System block diagram

TABLE IV. STRUCTURE OF THE LSTM MODEL

Layer type	Units
LSTM	128
LSTM	64
LSTM	32
Dropout	0.2
Sigmoid function	2

4.2. MLP

MLP is a fundamental DL model. It is a type feed forward artificial neural networks that uses a supervised technique called 'back propagation' for training process. It has multiple layers that make it different from the linear perception. The linearly inseparable data can be classified using MLP deep learning model.

In Table V there are 6 layers in which:

- Dense layers corresponds to the hidden layer.

TABLE V. STRUCTURE OF THE MLP MODEL

Layer type	Units
Dense	64
Dense	64
Dense	32
Dense	32
Dense	16
Dropout	0.2
Sigmoid function	2

4.3. 1D-CNN

1D-CNN is used for time series or sequential data which tends to slide the kernel is one dimension only. The 1D-CNN takes 1-dimensional input data and provides 1-dimensional output data against it. Table VI shows the structure of the model.

TABLE VI. STRUCTURE OF THE 1D-CNN MODEL

Layer type	Units
Conv1D	128
Conv1D	128
Max-Pool	128
Conv1D	64
Conv1D	64
Dropout	0.2
Flatten	64
Dense	100
Sigmoid function	2

Primarily, the parameters that are used for the training of each DL model are:

- Batch size = 64
- No. of samples = 2,50,000
- No. of iterations = 1000
- Learning rate = 0.000001
- Data split = 70:20:10 as training data, validation data, and cross validation or testing data.

Generally, to train any DL model, the data is divided into three sections i.e. training set, testing or cross validation set, and the testing set. The training data set is used to train the algorithm. The validation data set is used to tune parameters of the model and the test data set is used for prediction and for obtaining the performance characteristics i.e. accuracy of the model. The work flow of the real-time fault classification system is shown in Fig. 3.

5. Results and Discussions

The performance of the DL models is evaluated on the basis of accuracy, precision, recall, and F1-score. Formulas of these performance indexes are given as under [23]:

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn} \quad (2)$$

$$\text{Precision} = \frac{tp}{tp + fp} \quad (3)$$

$$\text{Recall} = \frac{tp}{tp + fn} \quad (4)$$

$$F1- Score = 2(\frac{Recall * Precision}{Recall + Precision}) \quad (45)$$

Where,

(i). tp = the classifier's predicted value was true, and the real value was also true.

(ii). tn = the classifier's predicted value was false, and the real value was false.
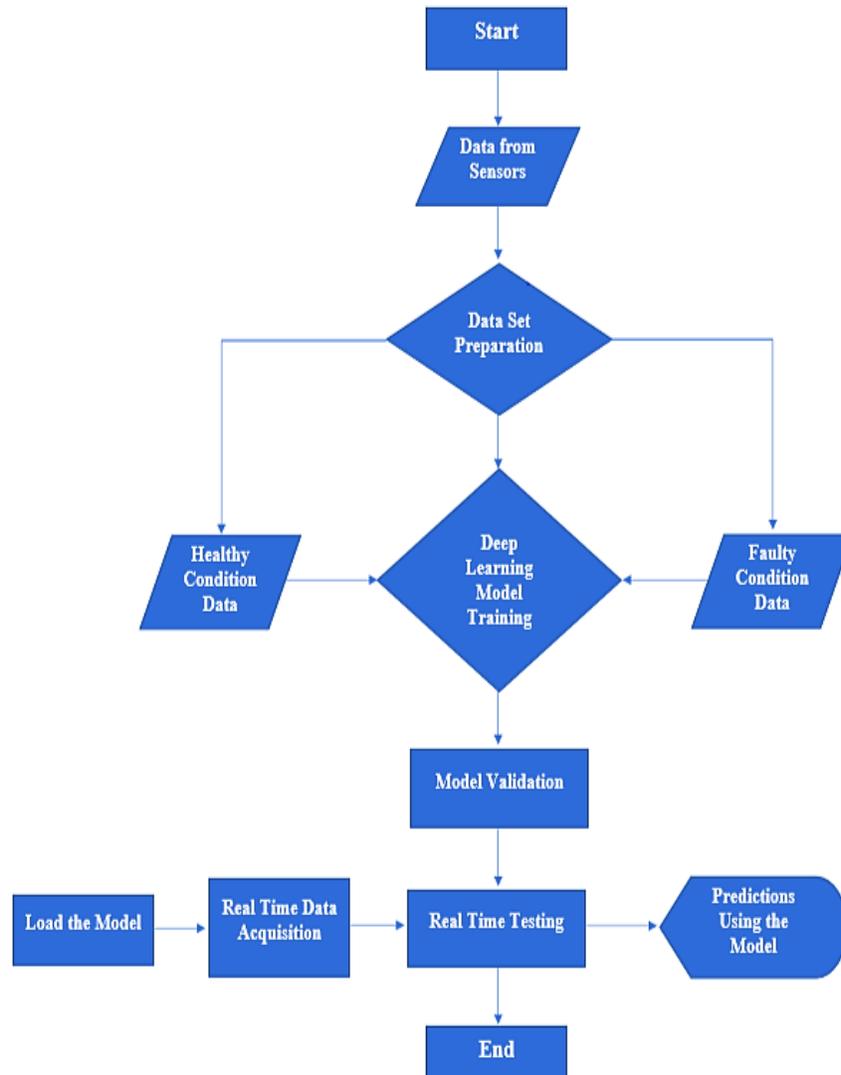

Fig. 1. Workflow diagram of the real-time fault detection system

(iii).   fp = the classifier's predicted value was true, and the real value was false.

(iv).   fn = the classifier's predicted value was false, and the real value was also true.

In this paper, a comparison of three DL models is provided. In comparison with the other two DL models, LSTM model provided 100% accurate results in predicting condition of the IM. The training and testing accuracy obtained from each DL model is presented in Table VII.

It can be observed from the table that the LSTM model has demonstrated best results among all the three DL models on the provided dataset and the set hyperparameters.

TABLE VII. TRAINING & TESTING ACCURACIES OF THREE COMPARED MODELS

Table Head	LSTM	MLP	1D-CNN
Training Accuracy	100%	86%	94.52%
Testing Accuracy	100%	85.8%	93.50%

A confusion matrix is a technique used for summarizing or describing the performance of machine learning or deep learning models. It is kind of a table describing the number of correct and incorrect predictions made by a model. The confusion matrices for each of the DL model used in this research are described in Fig. 4.

It can be observed from Fig. 4(a) that in the confusion matrix of LSTM model none of the prediction is incorrect, while for the other models certain predictions are incorrect. It can be summarized that the LSTM model provides the best accuracy among all other models. The classification report of these models is shown in Table VIII. From the table, it can be concluded that LSTM has higher Precision, Recall and F1-score among all.
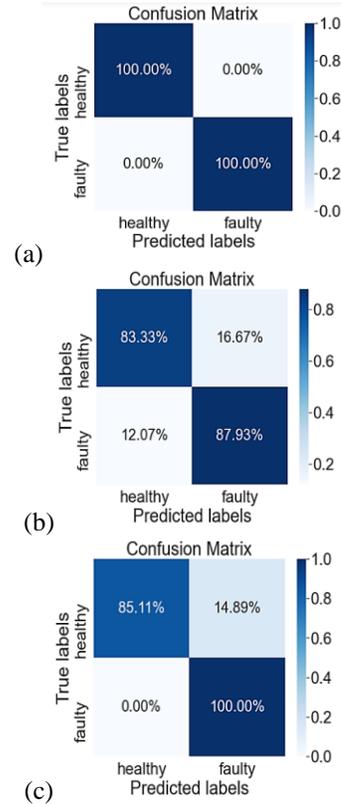

(a)

(b)

(c)

Fig. 3. Confusion Matrices of (a)LSTM, (b)MLP, and (c) 1D-CNN
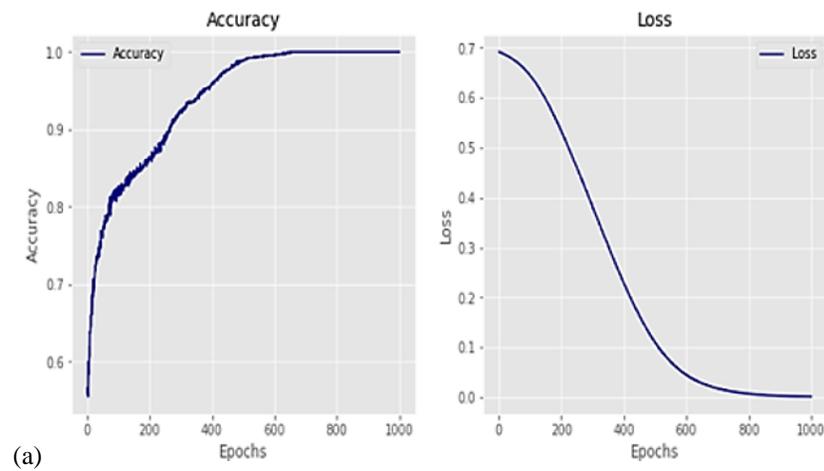
The loss and accuracy graphs of LSTM, MLP and 1D-CNN are given in Fig. 5. These graphs were obtained during training process of the DL models. From the graphs shown under, it can be concluded that in graph (a) when epochs reach at 1000, the accuracy of the LSTM model is 100% and the loss falls to almost 0%. Furthermore, the LSTM model shows most stable response among the employed models. While in graph (b) and graph (c) when epochs reach at 1000 the accuracy is less than 100% and the loss increases. Moreover, response of the MLP and 1D-CNN model keeps fluctuating during the training process. Thus, LSTM model can be

referred to as the best model amongst the employed DL models.

The final prototype of standalone motor condition monitoring system is in shown in the Fig. 6. Overall, the developed demonstrated effective performance. However, the system posed problem in data acquisition owing to low processing power of the Raspberry-pi model 4b.

TABLE VIII. CLASSIFICATION REPORT OF THREE COMPARED MODELS

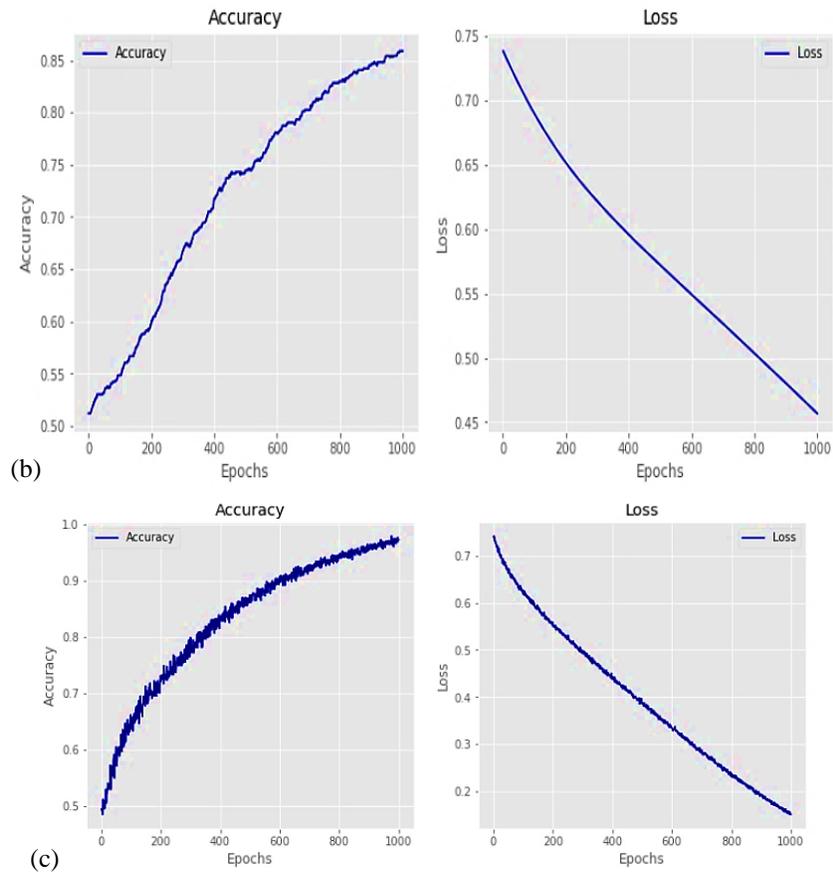| Table Head	Precision	Recall	F1-score
LSTM			
Healthy	1.00	1.00	1.00
Faulty	1.00	1.00	1.00
MLP			
Healthy	0.85	0.83	0.84
Faulty	0.86	0.88	0.87
1D-CNN			
Healthy	1.00	0.85	0.92
Faulty	0.89	1.00	0.94

(a)

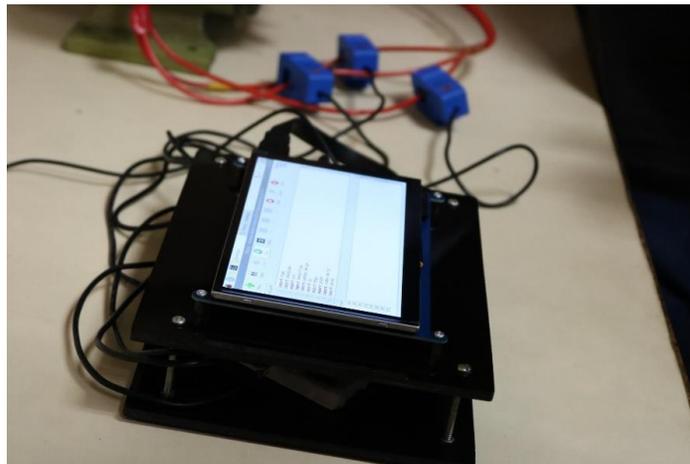**Fig. 4.** Loss and accuracy graphs of (a) LSTM, (b), MLP, and (c) 1D-CNN

Fig. 2. Standalone real-time motor condition monitoring system

6. Conclusion

This paper reported a non-invasive condition monitoring device for 3-phase IM based on current signature data and DL models. The developed device is a real-time fault diagnosis system that detects and classify the status of the motor through the provided input data. The current data is acquired using clamp type non-invasive current sensors, an ADC, and Raspberry-p. The comparative analysis among the three DL models including LSTM, MLP, and 1D-CNN. The results confirmed the LSTM model as the best model. Moreover, the developed system is stand-alone and non-invasive that can be clamped on any 3-phase IM to detect its bearing faults in real-time by using the 3-phase current data and the LSTM classifier. The output results are displayed on a 7-inch touch screen LCD display, the user can interactively monitor the developed system using the touch-screen display. The compact size and portability of the developed system makes it easy for user to deploy it on any motor. The extended version of this system can be deployed on industrial motors for effective condition monitoring. The developed system has a limitation of data acquisition at low sampling rate. The system was only able to acquire simultaneous data from three sensors at the rate of 100 samples per second. In future, the limitation can be addressed by using high performance data acquisition board.

DATA AVAILABILTY STATEMENT

The datasets generated or analyzed during this study are not publically available because these datasets are the sole property of NCRA-HHCMS Lab, Mehran UET Jamshoro, Sindh, Pakistan. But, these datasets are available from the corresponding author on reasonable request and can be shared if permission is granted from the Lab.

CONFLICT OF INTEREST

Authors of this paper declare no conflict of interest.

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