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Towards soft real-time fault diagnosis for edge devices in industrial IoT using deep domain adaptation training strategy

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A B S T R A C T

Artificial intelligence and industrial internet of things (IIoT) have been rejuvenating the fault diagnosis systems in Industry 4.0 for avoiding major financial losses caused by faults in rotating machines. Meanwhile, the diagnostic systems are provided with a number of sensory inputs that introduce variations in input space which causes difficulty for the algorithms in edge devices. This issue is generally dealt with bi-view cross-domain learning approach. We propose a soft real-time fault diagnosis system for edge devices using domain adaptation training strategy. The investigation is carried out using deep learning models that can learn representations irrespective of input dimensions. A comparative analysis is performed on a publicly available dataset to evaluate the efficacy of the proposed approach which achieved accuracy of 88.08%. The experimental results show that our method using long short-term memory network achieves the best results for the bearing fault detection in an IIoT environmental setting.

1. Introduction

Deep learning (DL) and Industrial Internet of Things (IIoT) have been playing a pivotal role in modern industry. Various industrial systems have been effectively monitored through these technologies. IIoT with DL has setup new horizons like edge devices but this development brings up new challenges such as purpose-built hardware systems and secure IoT platforms. Meanwhile, industrial motors in the IIoT setting are also being monitored to avoid halt in operations caused by the degradation of various components. Bearings are the critical components of a motor that allow them to operate smoothly. They start degrading owing to various causes such as oil-contaminations, corrosion, misalignment, temperature, distorted components, poor fitting, fatigue, excessive loads, and manufacturing defects. Continuous degradation leads to major faults and subsequently to permanent failure. Therefore, it is crucial to monitor and detect faults earlier which will assist in avoiding motor failure [5,23,3,34]. The fault detection in industrial scenarios is generally carried out through vibration analysis [35,36,24] which detects the faults in motors at their inception. For effective vibration analysis, it is highly essential to select a proper sensor on the basis of properties such as size, weight, cost, power consumption, range, reliability, and tolerance [13].

Various studies related to condition monitoring of bearing have been carried out since the last half-century, using different tools and techniques. Researchers have performed studies mainly using model-based techniques. These techniques have shown effective results in terms of detection or prediction of faults in industrial motors under various conditions. However, there are certain limitations of these techniques like noise sensitivity and system complexity in a real environment [8]. Moreover, these techniques are difficult to implement owing to complex mathematical equations [9]. To overcome these limitations of model-based approaches, recent developments in AI such as machine learning (ML) and DL have opened new horizons for industrial diagnosis and prognosis. These methods can analyze the raw data directly, therefore, they are also referred to as data-driven methods. These methods are extensively applied in IIoT environments to develop effective methods that can analyze huge amount of data. Data-driven methods can extract hidden representations from historical raw data of a system owing to their multilayer architecture and non-linear mapping [41,44] and these methods are easy to implement. On the other hand, the development of mathematical models requires prior knowledge and a lot of endeavors [29]. Thus, the advantages

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of data-driven methods like better performance and smooth implementation make them a promising tool for the diagnosis and prognosis of different industrial systems.

Various DL and ML based methods have been increasingly used in fault detection of machines and mainly employed methods include support vector machines (SVM) [10,14], random forest (RF) [17], decision trees (DT) [30], and multi-layer perceptron (MLP) [49]. Although, conventional ML models were used for fault classification and prediction they require manually engineered features as input to the models [39,20]. Contrary to these models, DL as a subdomain of AI has been in the limelight and applied in various applications owing to its better generalization capabilities and easy end-to-end implementation. Meanwhile, DL models also have been applied for motor fault detection including MLP, auto-encoders (AE), deep belief networks (DBN), deep Boltzmann machine (DBM), and recurrent neural networks (RNN). Among these models, LSTM as an advanced version of RNN is capable of learning complex representations from raw spatial or temporal data. LSTM network has become hotspot among researchers owing to its advantages such as hierarchical feature learning, higher generalization accuracy, long-term independency, and selective memory mechanism [38,47,48]. Thus, LSTM and its variants have been widely employed for analysis in different domains.

Recently, DL algorithms have been employed in studies to detect various faults in motors. R.G. Vieira et al. [42] have employed MLP to classify the stator winding faults. The model was using frequency features of the current data and reported results to show the effectiveness of the model in terms of fault detection. It was observed that the accuracy of the model increases with the increase in the fault severity. The method achieved maximum accuracy of 92.68% and 76.94% at no-load and full-load conditions, respectively. In [31], authors have used MLP to classify the induction motor faults in which input was current and voltage as time domain signals. The MLP model yielded better results with maximum accuracy of 91.85% compared to the other ML models such SVM and K-Nearest Neighbors (KNN) which achieved 87.5% and 89.4% accuracy with 300 input units, respectively. G.H. Bazan et al. [4] have employed the MLP model to detect bearing faults using current data of a 3-Phase induction motor. The classifier detects the faults using mutual information between two phases. The results demonstrated the MLP as the most suitable model in comparison to the existed models such as SVM and KNN in terms of accuracy and robust performance. Both the MLP and SVM achieved 100% accuracy, while KNN demonstrated 90.7% accuracy. Further, the authors have suggested real-time implementation of the model.

Although, various studies conducted in the area of fault diagnosis using DL models and have demonstrated high accuracies. However, still there is a need for betterment and effectiveness. More specifically, when a DL classifier is trained on one type of data and achieves high accuracy on that dataset while demonstrates poor performance on another data. The possible cause of it may the features extracted from raw data. Thus, researchers have been striving for DL models which can effectively perform on raw input data [50,51]. Another problem is that the model trained on a type of dataset with defined dimensions cannot perform well on the dataset with different dimensions. To resolve the first problem, there have been various studies conducted by introducing cross-domain adaptation (CDA) in different domains [25,33]. Thus, CDA approach is employed which addresses the domain variance problem through feature sharing between source and target domain. To resolve the second problem, we propose a new CDA model which can be trained on a dataset with one dimension and can perform on a dataset with different dimensions.

In this study, an early fault detection device is developed based on the Raspberry-Pi board and a tri-axial accelerometer. Compared to previous studies, this work utilizes the DL algorithms on Raspberry-Pi microcomputer for real-time bearing fault detection using vibration data. We have used LSTM that is one of the most applied DL models in various condition monitoring systems owing to its hierarchical architecture and generalization power. A comparative analysis with the other ML algorithms is performed to confirm the effectiveness of the method. Additionally, the system is remotely monitored on a secure IoT platform. The performance of the methods is also verified using the bearing dataset of the University of Ottawa (U_Ottawa) [18]. This bearing data were acquired under time varying speed conditions of the motor with a sampling of 200 kHz and sampling duration of 10 s. The dataset includes three conditions of bearing such as healthy, inner-race fault, and outer-race fault under varying speed condition. In this research, only two datasets are used including healthy and a faulty condition of bearing to perform binary classification. Moreover, in this investigation only the vibration data is used from the selected datasets. The contribution of this research can be summarized as under:

(i). Real-time motor fault detection using the raw tri-axial vibration data.
(ii). Benchmarking of the established dataset through validation the DL models on an open-access vibration dataset.
(iii). Implementation of the CDA model which can diagnose bearing conditions on the datasets with varying input dimensions.
(iv). The motor can be remotely monitored through a secure IoT platform.

The remainder of this paper is organized as follows: Section 2 reports the material used in this system, Section 3 reports the data acquisition process and the AI models employed in this research, Section 4 presents the implementation of the approach and its application in fault detection of induction motor. Section 5 presents and discusses the results obtained in this research. In the end, Section 6 concludes the study and discusses future work.

2. System components

In the first stage, a vibration data acquisition system is developed using a Raspberry-Pi microcomputer, a tri-axial vibration sensor, and some connecting wires.

2.1. Raspberry Pi microcomputer

Raspberry-Pi Model 3B+ is employed for the development of this system. Raspberry-Pi has been a point of attention for the researchers and hobbyists owing to its advantages like it provides multiple hardware interface capability, built-in Wi-Fi, Bluetooth, and much more. It has got additional features like general purpose inputs and outputs (GPIOs), inter-integrated circuit (I2C), and serial port interface (SPI) communication protocols which makes it suitable for data acquisition. Considering the facts such as affordability, small-size, low-power consumption, reasonable performance, and support availability; researchers are employing it in prototyping and in developing various real-world applications. It has been used for different purposes like data acquisition, data storage, data transmission, and in various IoT applications. It is a fully-functioned microcomputer that runs on a Linux operating system (OS) better known as the Raspbian. It can perform various tasks in real-time just like a computer. The specifications of this microcomputer are given in Table 1 [1,28].

2.2. Accelerometer

Currently, MEMS based vibration sensor are getting popular and widely used in various applications owing to their advantages like

Table 1
Specifications of the Raspberry-Pi 3B+.

Metrics	Specifications
CPU	Cortex-A53 (ARMv8)
Memory	1 GB
Size	82 × 56 × 19.5 mm
Onboard Network	WiFi, LAN, and Bluetooth
Power Ratings	5V/2.5A DC power input

Table 2
Specifications of the accelerometer.

Metrics	Values
Working Voltage	2 to 3.6 V
Size	3×5×1 mm
Weight	20 mg
Output Resolution	10 to 13 bit
Bandwidth	0.1 to 3200 Hz

Table 3
Specification of the induction motor.

Metrics	Specifications
Bearing Type	NU-204
Phase	3
HP	0.5
Operating Frequency	50 Hz
Working Voltage	400

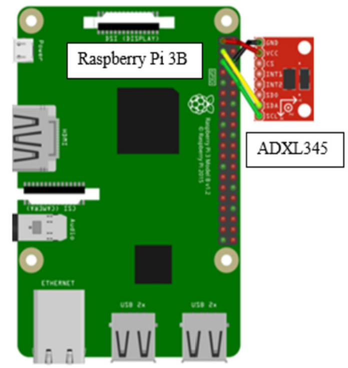

Fig. 1. Raspberry-Pi connections with ADXL345 accelerometer.

Fig. 2. Bearing with the inner race fault of 1 mm.

inexpensiveness, low power requirement, digital interfacing, and light weight. These accelerometers function on principle of a mass on a spring. Their mass tries to remain in original state owing to inertia, in response to acceleration produced by the system on which they are attached. While, the spring continues to stretch and compressed and allows to detect the generated force corresponding to the applied acceleration. Meanwhile, these sensors have been widely used to develop reliable and inexpensive vibration monitoring systems for various applications such as wind plant monitoring, structural monitoring, and engine condition monitoring. The ADXL345 accelerometer is used in this research. It has a resolution of 13 bits and can measure vibration up to ±16 g. It can measure both static and dynamic acceleration of gravity with the support of I2C and SPI serial interfaces [7]. It has been employed in various vibration monitoring applications [15,19]. The specifications of the accelerometer are given in Table 2 [11]. The sensor was attached on top of the 3-Phase induction motor.

2.3. Induction motor

The developed system includes a 3-Phase induction motor of 0.5 HP. Its parameters are given in Table 3.

3. Data collection and classifiers

This section reports the developed data acquisition system and the classifiers used in this investigation. Each of these is discussed as follows.

3.1. Data acquisition

Data is acquired using an accelerometer and a Raspberry-Pi board. Fig. 1 shows the connection diagram of these components. In the beginning, data of the healthy bearing is acquired, then a fault of 1 mm diameter and 1 mm depth is introduced in the roller bearing as shown in Fig. 2. Subsequently, the data of the faulty bearing is acquired using the developed system. Considering, supervised learning approach, healthy data is labeled as '0' and faulty data is labeled as '1'. The data is collected and stored in a comma-separated file (CSV) for model training purposes. The complete dataset comprises 60000 samples of tri-axial vibration. In the next step, it is split into three sets as testing, training, and validation data with the percentages of 70, 20, and 10, respectively. The dimensions of the data are 1×3 as the accelerometer generates as tri-axial vibration data.

To visually, interpret the difference in the acquired vibration data of the healthy and faulty bearing conditions, the data of the classes are plotted against each other, as shown in Fig. 3. It can be observed along the main diagonal of the figure that a comparison of data on similar axes shows the difference in feature magnitude spread of the two bearing data classes. While, the scatter plots of the one axis against another axis show the difference in the data samples. It can also be observed there is variance among vibration data points on the different axes of the two different data classes.

3.2. Long short-term memory model (LSTM)

LSTM is one of the most frequently used DL models with time-series or sequential data. Generally, its architecture includes an input layer, one or more hidden layers, and an output layer as shown in Fig. 4. It can learn representations from raw input data utilizing inherent temporal or spatial data without manual feature designing. It also addresses the long-term dependency problem of recurrent neural networks (RNN) through selective memory mechanisms. It has been applied in various engineering applications [24,43] and trained using back-propagation method which recurrently reduces error on entire training data. To get effective results from this algorithm, it is necessary to select optimal model parameters. Here, parameters correspond to the hidden layers and the number of nodes in each layer, optimizer, learning rate, and batch size. It has been in researchers' attention owing to its robust performance on time-series or sequential data. It has been successfully applied to various subdomains of industry. In this investigation, LSTM is used with 4 hidden layers and each layer consists of 128, 64, 32, and 16 neurons, respectively. The output layer is added with a sigmoid function that predicts the particular classes. The model uses the root means square proportion (RM-

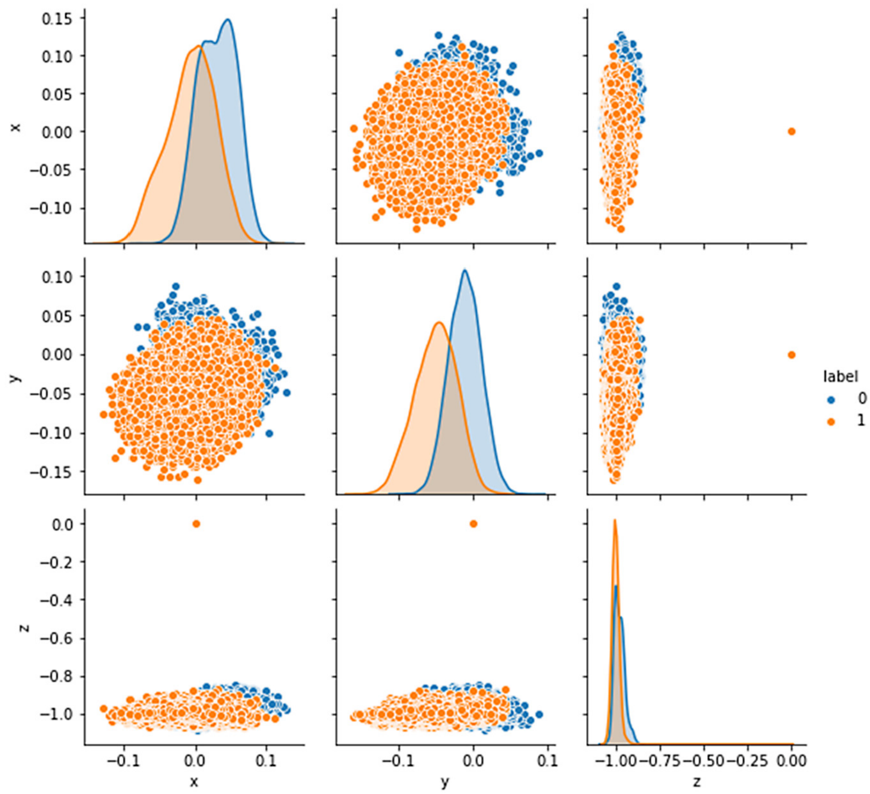

Fig. 3. Comparison of the healthy and faulty conditions with respect to the x, y, z-axis vibration data.

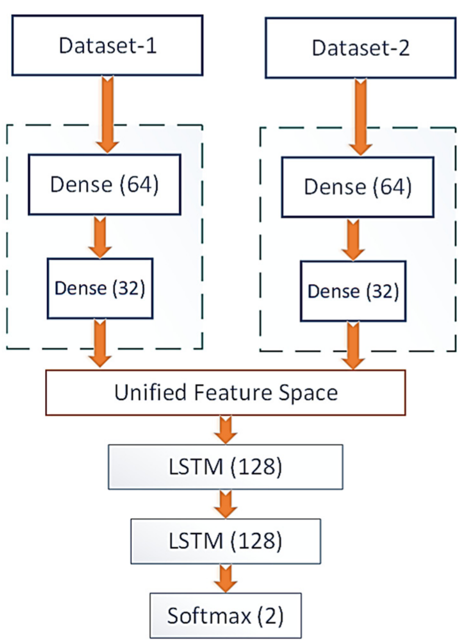

Fig. 4. The hierarchical structure of the LSTM network.

Sprop) optimizer and binary cross-entropy as the loss function. The model is trained with a batch size of 64, dropout rate of 2%, and learning rate is selected as 0.002.

3.3. Random forest (RF)

It is an ensemble of DT model and can be applied to a wide range of problems due to its robust learning power. It can deal with the high variance problem. Compared to DT, it yields better performance with the lesser susceptibility to overfitting. It decreases the correlation between individual classifiers and captures a random subset of features for each class. The class division operation is performed by the bagging function and generates an output based on majority voting [17]. The RF model provides better accuracy by selecting an appropriate number of trees ‘n’ and that’s found through the grid search method. The method yielded optimal results with the value of ‘n’ as 9.

3.4. Support vector machines (SVM)

It is also one of the powerful and popular ML algorithm. It performs well on complex and high-dimensional data and yields competitive performance on a smaller dataset. Hence, it minimizes the computational load. Fundamentally, SVM functions depending on two parameters hyperplane and margin. The classification task is performed by hyperplane and support vectors are identified from the dataset through the margin. The SVM classifies the data by detecting optimum hyperplane and widening the margin between the classes. Its performance depends on the appropriate selection of hyper-parameters [22,45]. The parameters that mainly influence the accuracy of the SVM model are kernel function, threshold function, and cost function.

In this study, one of the most widely used kernel, radial basis function (RBF) or Gaussian Kernel is selected. It is given by Eq. (1).

$$\mathrm{K}\left(x^i, x^j\right) = \exp(-\gamma \left\|x^i - x^j\right\|^2) \tag{1}$$

where, x^i and x^j are the feature vectors and γ is the gamma parameter.

The parameters are obtained through the grid search method which iteratively selects the parameters. Table 4 shows the SVM model specification used in this investigation.

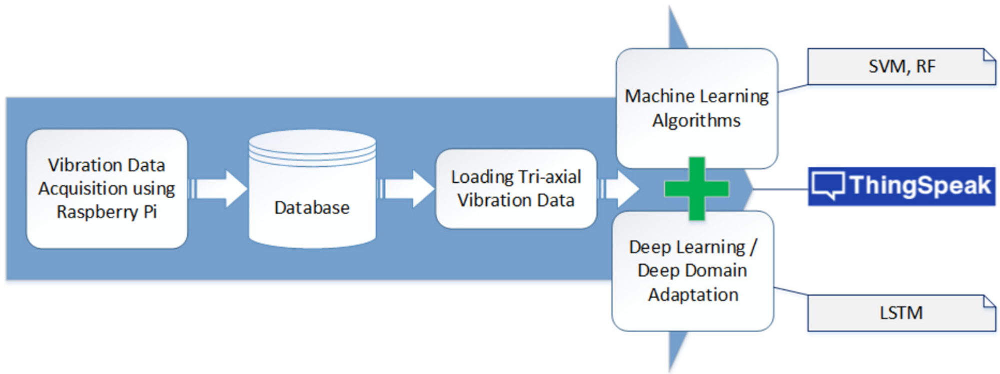

Fig. 5. Overview of the proposed system.

Table 4
SVM Specifications.

SVM parameters	Values
Gamma	16
Cost function	10
Number of classes	2

3.5. Domain adaptation network based on LSTM (DA_LSTM)

The LSTM based domain adaptation model (DA_LSTM) is developed to learn the representations between two different datasets. The model includes two encoding networks which comprise of dense layers within them as shown in Fig. 4. These parallel encoding networks learn representations and produce a unified feature space from the two different datasets including tri-axial vibration data (our dataset) and a single axial vibration dataset (U_Ottawa dataset). The unified feature space is saved as the learned weights in the h5py file. The h5py is a python package interface for the binary data format called HDF5. It allows easy storage and manipulation of huge data using Numpy library.

Furthermore, weights are loaded and two LSTM layers are added on top of the encoding networks the models are retrained and tested. For training purpose, an Adamax optimizer is used that is a generalized form of the Adam optimizer. The reason behind using this optimizer is that it resulted in better performance than other optimizers. The Adamax optimizer corresponds to the recursive formula as given in Eq. (2) [21]:

$$u_t = \max(\beta_2 . u_{t-1}, |g_t|) \tag{2}$$

where, β denotes decay rate and g_t represents gradient distribution.

4. System implementation

The LSTM model is used to classify the healthy and faulty conditions of the bearing using the vibration data. The system is programmed using python and its API namely Keras. In addition, some python libraries such as Numpy, Matplotlib, Sklearn, Seaborn, and Pandas are used for data processing and plotting the results. The input vibration data is obtained from the MEMs accelerometer that is attached to the 3-Phase induction motor. The developed LSTM algorithm is trained on the stored data and then it is tested on the real-time vibration data of the motor. Initially, the LSTM classifier is developed with two layers. Then, hidden layers are increased to improve the performance until the model generates effective results. The model parameters such as neurons, learning rate, optimizer, and batch size, are varied until the model yields optimal results.

Subsequently, two ML models namely SVM and RF are also trained and tested to verify the performance of the LSTM model. At the end of the training process, the model is saved in hp5y format with the best-learned parameters. Later on, the saved model is loaded for real-time fault classification. Fig. 5 depicts the operation flow diagram of this investigation.

The performance of the system is evaluated in terms of the standard performance metrics such as accuracy, precision, recall, and F-1 score. The formulas are given in Eq. (3), (4), (5), and (6) [39].

$$Accuracy = \frac{TP + TN}{m} \times 100 \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F1 - Score = \frac{2(Precision \times Recall)}{Precision + Recall} \tag{6}$$

where, TP is true positives, TN is true negatives, FP is false positives, FN is false negatives, and m is the number of examples.

In addition to the fault classification, the developed system is also monitored using ThingSpeak, which is an open-source IoT platform. The major advantages of this IoT platform are free hosting for data channels, data visualization, and the security feature. It allows secure transmission of the data by assigning the unique application programming interface (API) key for each client. The data can be sent through a 'write API key' and can be retrieved using a 'read API key'. Furthermore, it creates a sense of community through the option of public channels, besides the private channels option [37]. It can easily be connected with the boards such as Raspberry-Pi and Arduino through an internet connection [16]. The platform allows secure monitoring throughout the world using any electronic gadget such as mobile, laptop, or tablet. It also can send the data to an email address or a Twitter account at a scheduled time.

The wireless transmission of the vibration data is achieved by creating an account on ThingSpeak IoT platform and obtaining the API key. In the next step, three fields are created for the each axis of vibration data. Subsequently, the acquired data using Raspberry-Pi and the accelerometer is monitored on ThingSpeak with real-time visualization. Fig. 5 shows the process of the developed system. The system does not require any network extension owing to the built-in Wi-Fi feature in the Raspberry-Pi model 3B+. It allows real-time monitoring of the tri-axial vibration of the induction motor with a latency of 10-15 s over the network.

In this research, the data is acquired in terms of acceleration as g-values. Thus, according to vibration severity charts, if there

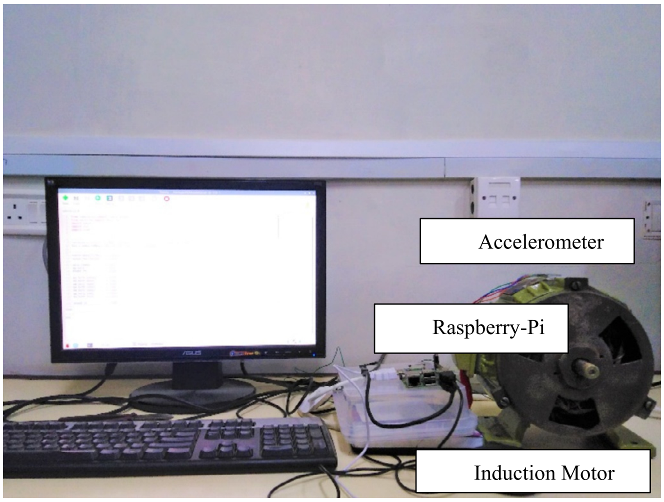

Fig. 6. Experimental setup.

Table 5
Accuracy comparison of the algorithms.

Bearing dataset	Accuracy rate (%)			
	SVM	RF	LSTM	DA_LSTM
U_Ottawa (48000 Samples)	63.94	75.17	77.00	75.33
Our Dataset (48000 Samples)	**87.67**	**88.26**	**89.10**	**88.08**

is a change of 1 g in axial vibration of a rotating machine having a speed of less than 2000 RPM, then the machine is not considered in good condition. Generally, accepted limits of the vibration are found through the vibration severity level charts [12]. Without loss of generality, this wireless monitoring system can allow users to monitor the severity level of the machine vibration, and using vibration severity charts for the comparison. It will surely assist in avoiding major damages to the system. Fig. 6 shows the experimental setup on which this investigation is carried out.

5. Results and discussion

The results obtained in this research are reported in this section. It can be observed from Table 5 that the LSTM model has classified the bearing conditions with a maximum accuracy of 89.10%. Comparatively, SVM and RF models have classified the bearing conditions with the accuracy of 87.67% and 88.26%, respectively. Thus, it can be concluded that LSTM has proved to be the best model among the employed models in this research. It can also accurately detect bearing faults in real-time.

To verify the performance of the employed models 48000 samples of this dataset were fed to the models which are equivalent to the dataset size of this research. The comparative results show that the models perform better on the dataset acquired in this research than the bearing dataset of the University of Ottawa. Thus, it confirms the high quality of the dataset acquired in this research.

Table 6 shows the F1-Score comparison of the models on both the dataset. It can be observed that the models have achieved maximum F1-Score on the dataset obtained in this research. The obtained results confirm the effectiveness of our dataset and LSTM model.

In addition to benchmarking this data, the results obtained in this research are compared with the recent studies performed on U-Ottawa bearing dataset. The accuracy obtained in various researches using the U_Ottawa bearing dataset is summarized in Table 7. The results obtained in this research highlighted in bold

Table 6
F1-Score of the (a) LSTM (b) SVM (c) RF.

Bearing dataset	Fault class	F1-Score			
		SVM	RF	LSTM	DA_LSTM
U_Ottawa (48000 Samples)	Healthy (0)	0.74	0.78	0.78	0.79
	Faulty (1)	0.46	0.72	0.72	0.70
Our_Dataset (48000 Samples)	Healthy (0)	0.88	0.89	0.90	0.88
	Faulty (1)	0.87	0.88	0.89	0.88

letters. The comparative analysis demonstrates that the method and the dataset used in this research have produced effective results without any extensive feature processing.

Fig. 7 shows the confusion matrices of the LSTM, SVM, RF, DA_LSTM on the U_Ottawa dataset, and DA_LSTM on our dataset models.

Fig. 8(a), (b), and (c) show the vibration data of the induction motor on the ThingSpeak IoT platform along the three axes x, y, and z, respectively. The vibration along with the x-axis change between 0.01 g and 0.021 g and along with y-axis vibration data changes between 0.06 g and 0.073 g. While, along with z-axis vibration data changes between 0.905 g and 0.916 g. None of these axes vibrations show a severe level of vibration in the induction motor.

This research allowed the development of an effective fault detection system using affordable components such as Raspberry-Pi and MEMs based accelerometers. The research is carried out through different steps which included data extraction and labeling of healthy and faulty bearing conditions. Considering the supervised learning approach, it is an important task to introduce faults and then labeling them properly. The model tuning is also a challenging and time-consuming process as it requires a continuous change in the parameters until it yields the maximum performance in classifying the conditions. During the experimental evaluation process, the models are also trained and tested on the U_Ottawa bearing dataset in order to confirm the quality of the dataset obtained in this research. The comparative study has demonstrated higher generalization rate using the dataset of this research compared to the analysis performed on the U_Ottawa bearing dataset. It was observed from the results that the ML models demonstrated poorer performance compared to the LSTM. The LSTM which has achieved maximum accuracy of 89.10% and can further be improved with an increase in the amount of data.

In addition to real-time fault detection, the IoT-based monitoring of the system could allow to securely monitor and avoid the major faults through assessing the vibration severity limits of the data. Overall, the system has demonstrated efficacious performance in detecting faults and real-time monitoring of the data.

6. Conclusion

This investigation presented an affordable and effective bearing fault detection system that is developed using Raspberry-Pi, ADXL345 accelerometer, and a 3-Phase induction motor. The system used the LSTM algorithm for real-time bearing fault classification. The model was inputted with tri-axial vibration data and the benchmarking of the dataset done using the U_Ottawa bearing dataset which confirmed the quality of the vibration dataset acquired in this research. The performance of LSTM was compared with the performance of conventional ML algorithms such as SVM and RF. It was confirmed through the results that the LSTM yielded better accuracy compared to the ML models. Besides, the system was wirelessly monitored on the ThingSpeak IoT platform that allowed secure monitoring of the data with the real-time visualizations. The remote monitoring feature of the developed system allowed to monitor vibration severity levels in real-time, which

Table 7
Performance summary of recent studies.

Bearing fault diagnosis method	Results	Remarks
Deep Domain Generalization Network for Fault Diagnosis (DDGFD) [51]	60.13% diagnosis accuracy	The DDGFD method was able to perform cross-domain diagnosis of bearing owing to the prior diagnosis knowledge and deep architecture.
Refined Composite Multivariate Multiscale Symbolic Dynamic Entropy (RCmvMSDE) [46]	99.83% classification accuracy	The RCmvMSDE method effectively classified the faults by diagnosing the complexity level in multivariate time-series data through multivariate multilevel composite analysis. Also, the method attained stability through refined composite analysis.
Frequency Temporal Logic (FTL) [6]	Minimum fault diagnosis error rate 0.020%	The method effectively classified the bearing fault by mapping vibration signals with the formula logic. Moreover, the method is considered interpretable classifiers as it is written in formal language.
Bayesian Augmented Lagrangian (BAL) Algorithm [27]	99.77% diagnosis accuracy	The method improved computational speed by transforming the optimization problems into the various sub-optimization problems under the Bayesian network. It also improved accuracy and eliminated spectrum smearing through denoising and resampling the signals according to the varying speed of the shaft.
Gaussian Mixture Model (GMM) Based Classification [32]	The standard deviation of 1.21%	The GMM based classification methods effectively classified the bearing faults. However, these methods pose the problem of slow convergence.
Feature-based Early Time Series Classification [2]	88.89% diagnosis accuracy and 90.50% earliness	Authors were able to detect data sufficiency for the bearing fault classification with an indication of earliness in fault diagnosis. The limitation of this research is that it can only be used with the classifier designed in this research.
Squeezing Extracting Transform (SSET) [26]	15.43 mean *Renyi* entropy	The method effectively detected the bearing conditions using the vibration data. The SSET as a post-processing method poses problems in practical applications owing to its dependency on the synchro-squeezing transform.
Fractional Frequency Band Entropy (FrFBE) [40]	Recognition error with 1%	The method effectively diagnosed the bearing fault through full multiple fractional frequency filters and full use of entropy sensitivity.
LSTM on U_Ottawa dataset	77% diagnosis accuracy	The model was able to classify the bearing faults owing to the deep hierarchical architecture.
LSTM on our dataset	89.10% diagnosis accuracy	The model effectively detected various conditions of the bearing in real-time owing to the quality of the dataset and the depth of the architecture.
DA_LSTM on U_Ottawa dataset	75.33% diagnosis accuracy	The model demonstrated classification accuracy similar to the LSTM model accuracy on both datasets with domain adaptation capabilities.
DA_LSTM on our dataset	88.08% diagnosis accuracy	

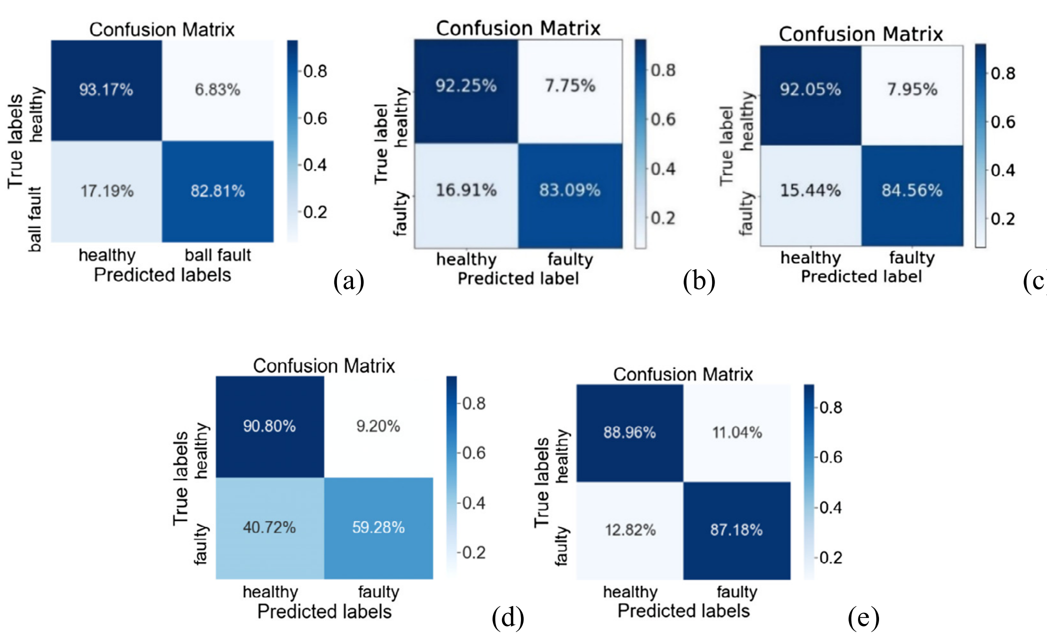

Fig. 7. Confusion matrices of (a) LSTM (b) SVM (c) RF (d) DA_LSTM on the U_Ottawa dataset, and (e) DA_LSTM on our dataset.

could assist in avoiding major damages to rotating machines. The novelty of the developed system consists in the integration of the two topics: DL-based bearing fault detection and IoT-based secure monitoring and a CDA model which can perform on input data with varying dimensions. The proposed approach was able to achieve 88.08% accuracy in bearing condition diagnosis. It can be concluded from the results that the developed system could be used for the effective monitoring of rotating machines in various applications.

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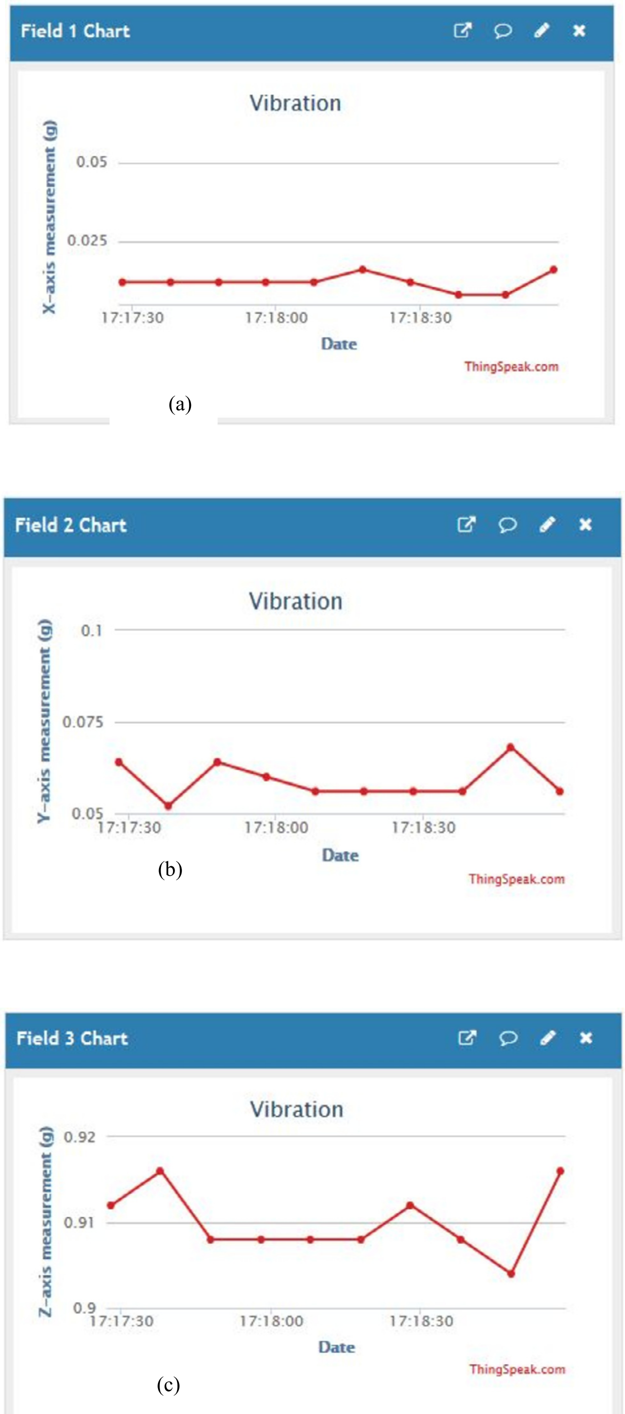

Fig. 8. Tri-axial vibration data of induction motor on the ThingSpeak IoT platform along (a) x-axis, (b) y-axis, and (c) z-axis.

Declaration of competing interest

Authors of this paper declare no conflict of interest.

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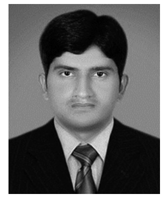

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