Encoder Decoder based Linear Discriminant Analysis Technique for the Condition Monitoring of Induction Motor using Stator Current Signal

Ambuj Kumar[1] Aniket Pathak[2] Maneesh Kumar Singh[3]

[1,2]National Institute of Technology, Delhi, India [3]Findish India Pvt. Ltd.

Abstract— Induction machines are used in every industry due to their robust design, easy construction and high reliability. In-spite of the advantages, these machines are also prone to various faults, which needs to be detected and rectified timely in order to safeguard the concerned industries from system failure. Fault detection plays a crucial part in order to find the most suitable diagnosis method for the machine. In this paper we demonstrate a novel fault classification system for the identification of various health conditions of Induction machine using Autoencoder based Linear Discriminant Analysis (LDA). A total of eleven statistical features are calculated for various health conditions (i.e., healthy, broken rotor bar, inner race bearing fault, outer race bearing fault) by varying the loading conditions. LDA classifier implemented on the reconstructed output feature of autoencoder which is almost similar to normally calculated features having less noise, more learnt information and non-linear transformation. Here, grid search algorithm is used to tune the hyper parameters of autoencoder. Autoencoder assists LDA to project the data in lower dimension with maximized separability that helps LDA to classify more accurately and avoid over fitting. With the advent of this technique fault identification and diagnosis can be done efficiently at real-time in the industries.

Keywords: Autoencoder, linear discriminant analysis, LDA, condition monitoring, induction machine

I. INTRODUCTION

Induction machines (IMs) are critical component of most of the industries such as paper mills, mining, railways, automotive etc. due to their robust, controllable, highly reliable [1], efficient nature [2]. Although induction machines are reliable, sometimes they undergo failures. Continuous condition monitoring of Induction machine is required, that is why extensive research is going on in this field. The study of different type of fault shows that the bearing faults (42% of overall fault) [3] and rotor bar faults (11% of overall fault in squirrel cage IMs) are main faults which occurs in Induction machines [4]. To identify the health state of machines, signals such as vibrations, acoustic emission, and stator current signal are commonly used. Vibrational [5] and acoustic sensors have their own industrial limitation due to high noise and sounds [6]. It is observed that when the fault occurs in the induction machines, linkage flux distribution changes which results in the distortion of stator current waveform. Since the flux distribution varies for different types of fault so current waveform also varies [7]. So, motor current signature analysis is very popular among the researchers for the easy and economical measurement of stator current.

The online condition monitoring system requires an intelligent classifier such as Artificial Neural Network (ANN) [8], Support Vector Machine (SVM) [9], Genetic Algorithms (GA), Fuzzy Logic (FL) [10], Convolutional Neural Network (CNN) [11] etc. Existing literature shows that these classifiers give satisfactory accuracy but the huge numbers of applications of IMs have attracted researchers to find more accurate fault diagnosis techniques. In order to fulfil the rising demand, this paper presents Encoder-decoder based Linear Discriminant Analysis model and for the comparison purpose Normal Linear Discriminant Analysis is also implemented. Data used to train and test these models are the various statistical features of stator current signal at four health state (i.e. Healthy, Inner race bearing fault, Outer race bearing fault and Broken rotor bar fault [12]).

II. THEORETICAL BACKGROUND

A. Autoencoder

An autoencoder neural network is an unsupervised learning algorithms which tries to set the target values equal to the input values with the help of back-propagation algorithms [13]. Autoencoder model consists of two different neural networks with two sets of weights and biases [14]. First neural network is encoder which converts the input data into compressed representation and the second neural network is decoder model which reconstructs the original output from compressed representation. The

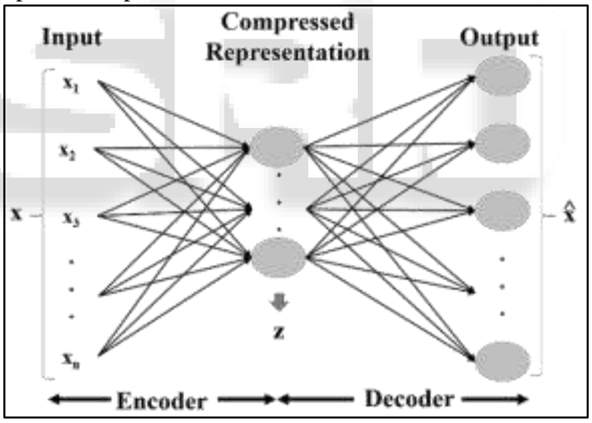

Fig. 1: Visual representation of Autoencoder architectures

structure of Autoencoder model is illustrated in Figure 1. The aim of Autoencoder is to reconstruct the output as similar as possible to input with reduced noise and enhanced information. The ability of autoencoder to learn non-linear transform with the help of non-linear activation functions makes it much more popular than Principal Component Analysis (PCA) [15].

Let X be the input vector and $\hat{X}$ be the output reconstructed vector, then autoencoder tries to minimize the Euclidian distance loss $\|X - \hat{X}\|_2^2$ which is also called re-constructional error in order to make the output very close to input. This error gives the intuition about how close the constructed output vector is to the original input vector. The task here is to find the parameters of autoencoder that give the best possible reconstruction [16].

Mathematically, encoder model can be represented as Eq.1,

$$Z = \sigma(W^{(e)}X + b^{(e)}) \quad (1)$$

and decoder model can be represent as Eq. 2,

$$\hat{X} = \sigma(W^{(d)}Z + b^{(d)}) \quad (2)$$

where, X is input vector, Z is compressed vector, $W^{(e)}$ is the encoder weight, $W^{(d)}$ is the decoder weight, $b^{(e)}$ is the encoder bias, $b^{(d)}$ is the decoder bias and $\hat{X}$ is reconstructed output vector.

In this paper Square Euclidean Loss function is minimized through back propagation, whose mathematical representation is shown in Eq. 3

$$\mathcal{L}(X, \hat{X}) = \|X - \hat{X}\|_2^2 \quad (3)$$

B. Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is one of the most commonly used classification techniques, [17] which not only project dataset onto a lower-dimensional space like PCA but in addition to it, LDA also focusses on the axis which maximizes the separability among known categories [18]. Because of the above two characteristics, LDA avoids over fitting (curse of dimensionality) and also reduces computational cost [19].

Algorithm for the classification using LDA techniques broadly comprises of five steps.

1) Computation of d-dimensional mean vectors for the different classes from the dataset.
2) Computation of the scatter matrices (in-between–class and within-class scatter matrix).
3) Computation of the eigenvectors $(e_1, e_2, \dots, e_d)$ and corresponding eigenvalues $(\lambda_1, \lambda_2, \dots, \lambda_d)$.
4) Sorting the eigenvectors by decreasing eigenvalues and choosing k eigenvectors with the largest eigenvalues to form $d \times k$ dimensional matrix W (where every column represents an eigenvector).
5) Transforming the samples onto new substance using $d \times k$ eigenvector matrix. This is summarized by the matrix multiplication: $Y = X \times W$ (where X is a n×d-dimensional matrix representing the n samples, and y are the transformed n×k-dimensional samples in the new subspace).

The mathematical intuition behind LDA is to find the axis where the value of Ψ (as given in Eq. 4) is maximum.

$$\Psi = \frac{(\mu_1 - \mu_2)^2}{(s_1^2 + s_2^2)} \quad (4)$$

Where, μ_1 is the mean of first class, s_1^2 is the separability (also referred as scatter) of first class, μ_2 is the mean of second class, s_2^2 is the separability of second class.

III. Proposed Detection System

Our proposed fault detection/classification system broadly consists of six stages, which are shown in Fig 2. In first stage current samples of various health conditions are taken at different loading conditions with the help of current transducer and Data Acquisition System (DAQ) system. In the second stage these currents samples are passed through low pass filter to remove the noise and these analog signals are converted into digital signal with the help of analog to digital converter and DAQ system. In the third stage 11 statistical features are extracted from each current sample with the help of MATLAB libraries and mathematical formulas. In the fourth stage these extracted features are fed to autoencoder model which learns the efficient data coding in unsupervised manner and reconstructs them. In reconstruction of data, autoencoder ignores the noise signal and tries to give output as close as possible to input data. Hyper parameters of autoencoder are optimized with the help of grid search technique [20]. In 5th stage reconstructed data are divided into training and test data in 3:1 ratio respectively and LDA classifier is implemented and optimized. In last stage performance evaluation of LDA classifier output are judged with the help of various classification performance evaluating parameters (i.e., accuracy, precision, recall and F1-score).

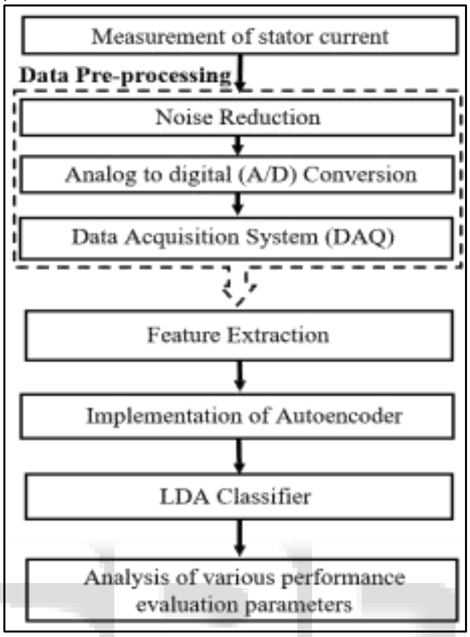

Fig. 2: Flowchart of Proposed detection system

IV. Data Acquisition

A. Experimental setup

To collect the stator current samples at various health state of motor, an experimental setup is specially designed which is shown in Fig. 3. The setup consists of three-phase squirrel cage induction motor having 0.5 hp capacity with 30 rotor bars. Setup also have motor loading arrangement and National Instruments (NI) based Data Acquisition System (DAQ) connected to computers. Three types of faults (i.e. broken rotor bar, inner race bearing fault, outer race bearing fault) are considered in this paper and are manually created to get realistic data. This induction motor consist of total 8 ball bearings with inner race diameter of 20mm and outer race diameter of 47mm with width 8mm. Bearing defect are made by creating holes (2mm diameter) on inner and outer race of Induction motors (shown in Fig 4(a)) [2]. Broken rotor bar is created by drilling holes on

Fig. 3: Motor generator bench arrangement for data acquisition

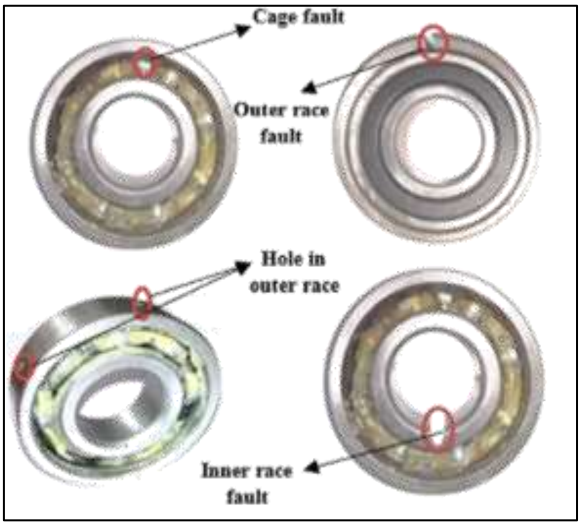

Fig. 4(a): Depiction of Inner race and Outer race ball bearing defects

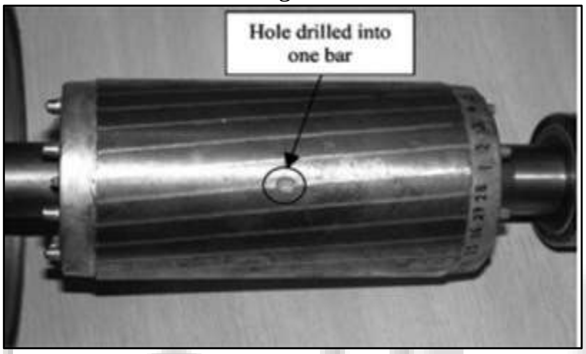

Fig. 4(b): Depiction of Broken Rotor Bar defect

rotor bar or by small cracking (shown in fig 4(b)). Stator current sample are collected at various health conditions by varying the loading [21]. Figure 2 Broken Rotor Bar Fault

B. *Feature Extraction*

This paper considered the four different classes of health conditions of Induction motor (i.e., healthy, inner race fault, outer race fault and broken rotor bar). For each state total 400 stator current samples are collected at the sampling rate of 0.005 seconds with different loading conditions (i.e., different currents and voltages). Out of 400 samples of each class, 300 samples are used to train the model and 100 samples are used to test. Hence, out of total 1600 samples, 1200 current samples act as training data and 400 samples as test data. Before feeding these samples to Autoencoder based LDA classifier, 11 statistical feature are calculated of each samples and these extracted features are used to train and test the classifier. These 11 features are root mean square value, mean value, variance, skew-ness, kurtosis, crest factor, impact factor, shape factor, median, range value of samples and margin factor. These statistical feature are calculated with the help of MATLAB and mathematical representation are shown in Eq. 5 to 14 and normalised by Eq. 15. Normalization helps in taking different features in similar range of values to converge gradient descents more quickly [22].

S. No.	Hyper parameter	Range of Hyper parameter values
1	Encoder hidden layers	[3,4,5,6,7,8,9,10]
2	Decoder Hidden layers	[3,4,5,6,7,8,9,10]
3	No of Neurons	[10,15,20,25,30,35,40,45,50,55,60,65,70,75,80,85,90,95,100]
4	Epochs	[30,50,100,150,200,250,300,350,400,450,500]
5	Bach size	[3,5,10,15,20,25,30]
6	Activation function	Tanh, Sigmoid, Relu

Table 1: Range of Hyper parameter values used in grid search algorithm to find the best Autoencoder model

$$F_1, \mu_{mean} = \frac{1}{N}\sum_{i=1}^{N}|x_i| \quad (5)$$

$$F_2, \sigma^2_{variance} = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2 \quad (6)$$

$$F_2, \gamma_{skewness} = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^3}{\sigma^3} \quad (7)$$

$$F_4, \gamma_{kurtosis} = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^4}{\sigma^4} - 3 \quad (8)$$

$$F_5, X_{crest\ factor} = \frac{\max(|x_i|)}{\left(\frac{1}{N}\sum_{i=1}^{N} {x_i}^2\right)^{1/2}} \quad (9)$$

$$F_6, X_{impulse\ factor} = \frac{\max(|x_i|)}{\frac{1}{N}\sum_{i=1}^{N}|x_i|} \quad (10)$$

$$F_7, X_{margin\ factor} = \frac{\max(|x_i|)}{\left(\frac{1}{N}\sum_{i=1}^{N}\sqrt{x_i}\right)^2} \quad (11)$$

$$F_8, X_{shape\ factor} = \frac{\left(\frac{1}{N}\sum_{i=1}^{N} {x_i}^2\right)^{1/2}}{\frac{1}{N}\sum_{i=1}^{N}|x_i|} \quad (12)$$

$$F_9, X_{range} = \max(|x_i|) - \min(|x_i|) \quad (13)$$

$$F_{10}, X_{rms} = \left(\mathrm{mean}\left(\sqrt{|x_i|}\right)\right)^2 \quad (14)$$

$$X_{norm}(i) = \frac{(x_i - \min(x))}{\max(x) - \min(x)} \quad (15)$$

Normalization helps in taking different features in similar range of values to converge gradient descents more quickly [22].

V. Performance Evaluation

A. *Autoencoder Performance*

All 11 features of stator current signal needs to be pre-processed before feeding to models with different statistical and visualization techniques to get inference about outlier and abnormality of dataset. After data pre-processing, these features are used to implement autoencoder. A number of autoencoder models are implemented with different combinations of hyper parameters such as hidden layers, number of neurons in each layer, activation functions, batch size, number of iterations (epochs), shuffling conditions etc. Along with this Grid Search algorithms are used to find best combination of hyper-parameters. Ranges of hyper-parameters tried by grid search algorithms are shown in Table 1. After optimization it is found that the model having Tanh activation function, batch size 10, epochs 300, encoder hidden layer 5 and decoder hidden layer 6 give the best accuracy with Adam optimizer. Here, mean absolute error is minimised to make output close to input.

Losses of training and validation data of the best obtained autoencoder model from the grid search algorithms are shown Fig. 5. By observing loss plots (Fig. 5) it is found that mean absolute error decreases as the number of iterations increases. After training autoencoder mean absolute error is found to be very less. Hence, it can be concluded that reconstructed output have almost same

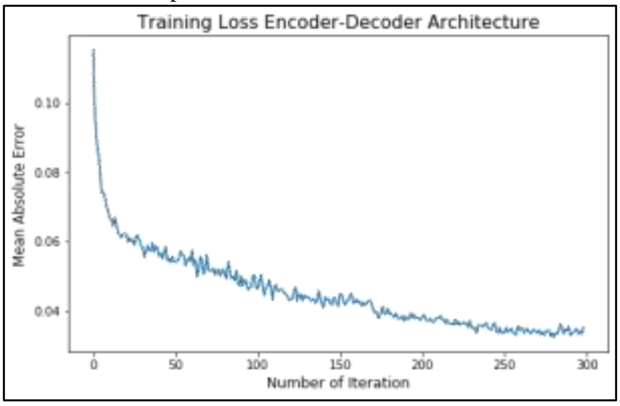

Fig. 5(a): Training Loss of Autoencoder

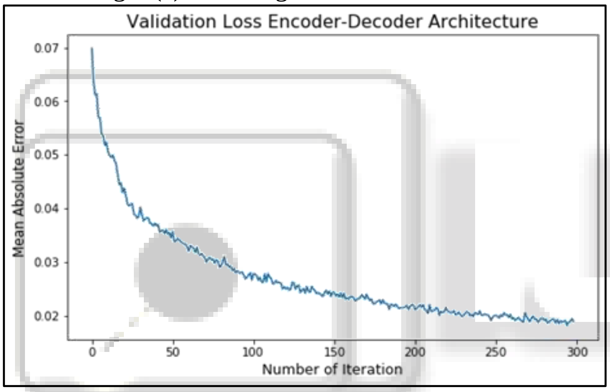

Fig. 5(b): Test Loss of Autoencoder

variance as input data. So, this output of autoencoder can be used to train and test the classifier model instead of original data.

B. LDA Classifier Performance

Reconstructed feature of autoencoder are divided into training and test data in 3:1 ratio. So, total 1200 featured sample are used to train the LDA Classier and 400 featured sample are used to test the model performance. For the comparison purpose LDA Classier are implemented on both dataset (i.e., reconstructed feature data of autoencoder and original feature data) with the help of sklearn python library. It is found that encoder-decoder based LDA classier obtained 97.5% test accuracy and without Autoencoder LDA classifier gives accuracy of 93.75% on test data. Confusion matrix of Autoencoder and without autoencoder based LDA classifier are shown in Fig 6. Analysing the confusion matrix it is observed that without autoencoder based LDA classifier predict the broken bar fault 100% accurately while healthy condition with 95% accurate and inner race and outer race fault with 90% accurate. On the other hand Autoencoder based LDA classifier give 100% accuracy of broken bar and outer race fault while 95% accuracy on healthy and inner race fault. Classification report of both LDA classifier (Autoencoder based and without autoencoder based) is written in Table 2. It is clearly observed that all classification performance evaluating parameters such as Accuracy, precision, recall and f1_score of autoencoder based LDA classifier are better than the normal LDA classifier. This is because of better handling of raw data by autoencoder based LDA classifier.

Parameter	Autoencoder based LDA Classifier	Without Autoencoder based LDA Classifier
Accuracy	97.50 %	93.75 %
Avg. Precision	97.50 %	93.96 %
Avg. Recall	97.50 %	93.75 %
Avg F1_score	97.50 %	93.85 %

Table 2: Classification report of Autoencoder based LDA and without autoencoder based LDA classifier

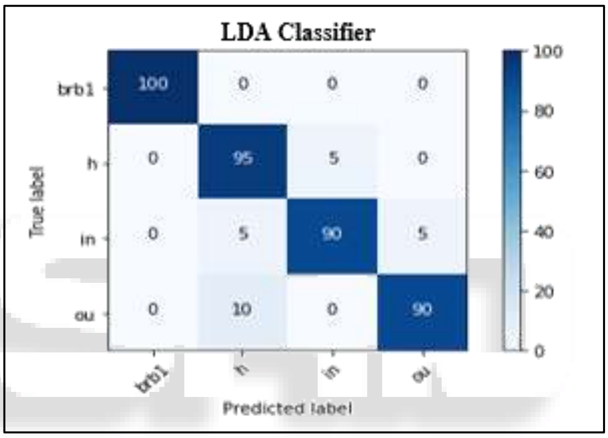

Fig. 6(a): Confusion matrix of LDA Classifier

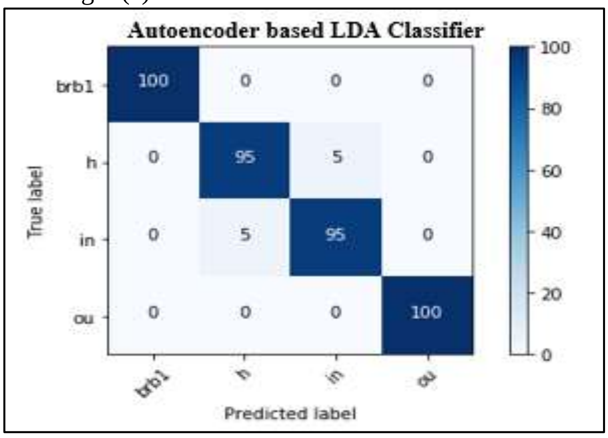

Fig. 6(b): Confusion matrix of Autoencoder based LDA Classifier

VI. CONCLUSION

This paper used simplest method of data collection and feature extraction to make an intelligent classifier. In this method the raw data of stator current signal are used to extract statistical features. Classifying condition of machine and determination of the severity of the faults has always been a complex task and the faults are affected by many factors. The reconstructed output features of autoencoder have less noise and more information as compared to direct extracted raw features. Thus encoder based classifier can learn the insights of dataset more than the simple classifier. LDA classification techniques classify the faults of induction machines with satisfactory performance. Overall as per our expectation, the autoencoder based LDA classifier performs the fault classification much more efficiently in comparison to the autoencoder without LDA classifier.

In future this paper motivates the research to solve the classification problem of Electrical or rotating machine with autoencoder based classifier. Hence, suitable for real-time applications. The present study is focused on fault diagnosis of induction motors using Autoencoder based LDA classification. Preliminary results are encouraging and the same concept can be further extended in other electrical engineering applications like- transmission line fault detection etc.

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