Bearing Fault Diagnosis Using Machine Learning For Real-Time Application

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Abstract- *This paper gives bearing fault diagnosis using machine learning for real-time application in an induction motor of 3-phase. This method is constructed by the support vector machine classifier to identify the bearing fault. In the 3-phase induction motor bearing, a related fault is common causes are a failure. Using advanced diagnosis techniques, it is possible to detect these faults, particularly when the deficiency is at its initial stage, incipient phase, earlier than the catastrophic effect of the failure can occur. All faulty bearing is damaged using electro-discharge machining and placed in the motor drive end side. Vibration information is obtained using an accelerometer (ADXL345) and analyzed the Raspberry pi model using Python software for the time domain analysis which includes the coefficient comparison with time waveform Skewness and kurtosis values for all bearing conditions. The experimental have a look at suggests that the machine mastering based feature extraction can be correctly applied for the bearing fault diagnosis in the 3-phase induction motor*

Keywords- Machine Learning, fault diagnosis, Induction motor, Digital Signal Processing, Support vector machine

I. INTRODUCTION

Three-phase Induction motor is extensively used machine in industrial application these 3-phase motor bearing are connected to the rotor in 3- phase induction machine. When there may be a fault inside the bearing it produces certain vibration is affecting that air gap. If the motor rotated on the faulty bearing its winding is loss and the motor is completely damage. Higher rating three-phase motors are having higher costs and also their regular maintenance is essential to keep repairing costs at the lowest. The bearing faults are the most commonly observed faults that cause motors to get burnt and hence cause more cost and time for the repairing. The early fault diagnosis can be done using a bearing vibration monitoring system which may further prevent winding losses and hence ultimate repairing time and costs. The early fault diagnosis can be used to replace bearings earlier and prevent motor damages.

II. LITERATURE SURVEY

Long wen at al [1] have given a new convolution neural network (CNN) depends on information data-driven fault diagnosis approach

In this paper, the study of developing the image conversion method using signal is primarily based on LeNet-five proposed for fault diagnosis CNN model are applying to the fault diagnosis filed. This method tested on three data set first is including an engine bearing dataset, second is the self-priming centrifugal pump fault detect dataset, and the third is the axial piston hydraulic-pump fault detect dataset. and there are expectation accuracies is 99.79%, 99.481%, and 100% respectively. This effect is good for the CNN system in the data-driven fault analysis field.

Lucia Frosini et al [2] have given an approach dependent on the stray flux measurement in exceptional position around the induction motor is proposed. The simplicity and flexibility filtering stage using custom flux prop is the main benefit of this method. The flux probe should be simply placed at the machine and adapted to a wide range of power levels. This paper addressed the overview of the fault detection technique using stray-flux-based for induction machine, before presenting a novel sensor or analysis theme.

TurkerInce et al [3], have given the One-D convolution neural network is proposed to fast and better machine condition monitoring and early fault diagnosis system that has an inherent adaptive structure to fuse the component extraction and classification period of the motor fault identification into a single learning body. Using this approach is learning to extract optimal features with the right training. This device is carried out to any motor data. Also using this approach is directly suitable to the raw data (signal), and this manner takes out the need for a different characteristic extraction algorithm main to the greater efficient system in terms of each speed and hardware. The experimental result displays its functionality and effectiveness as a real-time machine condition tracking system. It may be easily modifying to include the recognition and category of both mechanical and electrical motor faults with a signature on electric and mechanical quantities

Xuewu Dai et al [4] have reviewed Many of the FDD methods inside the unified data-processing framework to give a full image of FDD and accomplish a substitution level of degree. The author deduces the type of data and the way the different types of data are processed. By the author, the FDD techniques are classified into three categories- model-based on-line data-driven method, signal-based method, and knowledge-based method history data-driven method. An outlook on the possible evolution of FDD in industrial robotization, for example, the hybrid FDD and the emerging network FDD is also presented to expose the longer-term development direction during this filed.

FeiZhong et al [5], have concentrated on the utilization of self-organizing maps (SOM) in induction machine bearing fault identification and present a methodology for induction motor rolling bearing fault detection the use of SOM neural network and time or frequency domain bearing analysis. The SOM is a neural network calculation that is predicted on unsupervised learning and consolidates the task of vector quantization and data projection. A proposed method is given to detect the diagnosis fault to machine adaptively, with stress on fault occurred within the bearing a part of the machine. The test result displays the SOM is an economical instrument for the representation and identity of machine bearing.

Karim Baiche et al [6] have given the wavelet neural network classifier for display work on exploring the performance bearing fault detection. The training and testing of the neural network of a feature vector are required by the implementation and calculation of the wavelet packet. A standard deviation, kurtosis, central moment, wavelet energy these are the statistical feature and another statistical parameter of vibration used as input to the ANN classifier, its signal was utilized using normal condition and abnormal mode. The result shows that this statistical parameter diagnoses the fault classes of rolling part bearing accurately and has a good detection performance.

Shrinathan E. P. et al [7], have given a frequency spectrum determination for diagnosis the fault inside the bearing of a 3-phase induction machine. Their function was isolated by the Fast Fourier transform and also determine as performed by a support vector machine (SVM) classifier. Experimental results had been obtained considering two types of bearing fault at different load for outer raceway and promising results have been obtained.

Zhuyunchen et al [8] have given an enhance fault detection reliability, a new multi-sensor feature fusion method is proposed. The time domain and frequency domain categories are separated from the different sensor signals, after which these features included multiple two-layer sparse auto-encoders(SAE) neural networks for data feature fusion. Finally, fused features vector are frequently considered the device fitness indicators and be used to train a deep belief network (DBN) for additional categories. To check the effectiveness of the proposed SAEDBN schemes, the bearing fault detection technique carried out on an induction motor bearing test platform, and thus different running speed under different vibration data-set were collected for rule validations. For comparison, the multi-sensor fusion carried out to different feature fusion methods. In this experiment result detecting the machine learning condition and compelling outperform different fusion techniques.

III. PROPOSED SYSTEM

As we have reviewed much paper which discussed different technique to detect bearing fault system in the motor. The proposed work may consist of the system as shown in the block diagram in figure1

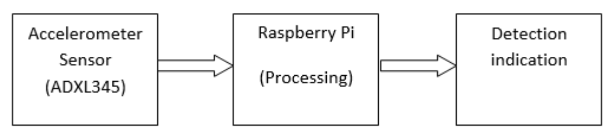


Fig.1.proposed system block diagram

The proposed system consists of an accelerometer sensor to catch the mechanical vibrations in terms of signal. The signal from the accelerometer can be recorded on raspberry pi for analysis. The analysis to be done, consist of a machine learning-based algorithm to detect the fault in the bearing. The respective detected fault will be indicated using a buzzer or indicator as an output from raspberry pi.

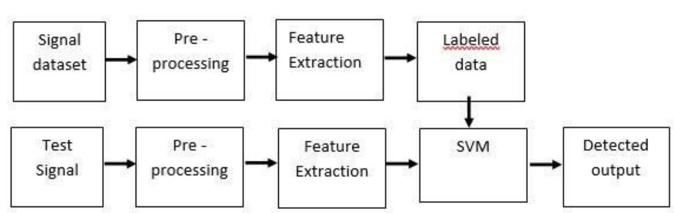


Fig.2. Processing methodology

Figure 2 shows the proposed methodology of processing the vibration signal for fault detection. The fault detection is consisting of a support vector machine-based classifier. The training phase of SVM will require the predefined dataset in faulty and non-faulty (normal) class. The pre-recorded dataset can be used for this purpose. The signal that is recorded may consist of the noise which is required to be removed to get the exact signal for the feature extraction stage. Then we have to feature extraction using skewness and kurtosis. The preprocessing stage in figure 2, shows the noise removal stage.

The fundamental frequency of motor rotation which is in terms of revolutions per minute is required to be considered while pre-processing the signal.

Skewness: The normal distribution skewness is zero and any other dataset should have a skewness up-to zero. If the dataset skewed the left side, then negative value indicates for the skewness we mean that the left tail is long relative to the right tail. If the dataset skewed the right side, then positive value indicates for the skewness we mean that the right tail is long relative to the left tail.

Kurtosis: Along with skewness, kurtosis is a main descriptive statistic of data distribution. However, the two concepts must not be confused with every other. Skewness essentially measured the symmetric of the distribution even as kurtosis determine the heaviness of the distribution tails. In finance, measure the financial risk we are used to kurtosis. A large kurtosis is carried out with a high level of risk of an investment for it suggest that there are excessive probabilities of extremely huge and extremely small return. On the alternative hand a small kurtosis indicator a mild level of risk because the possibilities of excessive return are quite low.

IV. RESULTS AND DISCUSSION

In this work, a system has been developed which helps bearing fault diagnosis for 3-phase induction motor. This system regulates the fault identification without any intervention using machine learning technology.

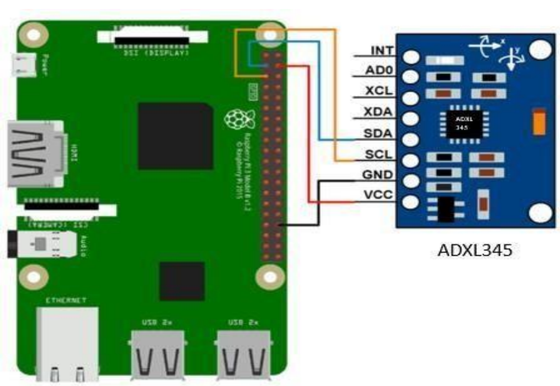


Fig. 3. Connection setup of a fault diagnosis system

Fig.4. Prototype experimental setup

The system predicts accelerometer sensor interfacing with raspberry pi this sensor recoding the vibration in terms of signal and displays the vibration value on the desktop and also displays the excel sheet and signal as shown in Fig. 5 (A), (B) and (C).

Fig.5(A).

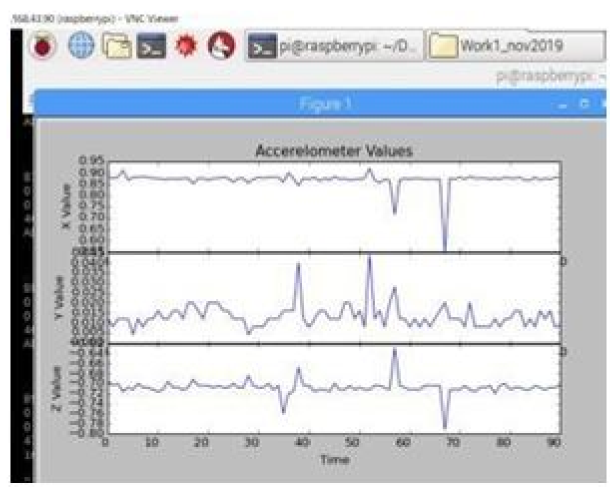
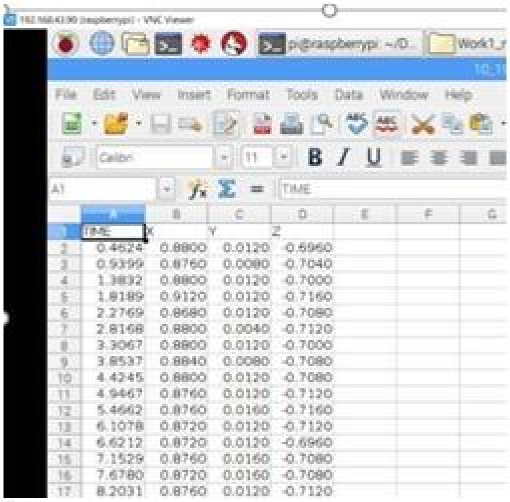


Fig.5(B)



TIME	X	Y	Z
0.4624	0.8800	0.0120	-0.6960
0.9399	0.8760	0.0080	-0.7040
1.3832	0.8800	0.0120	-0.7000
1.8189	0.9120	0.0120	-0.7160
2.2769	0.8680	0.0120	-0.7080
2.8168	0.8800	0.0040	-0.7120
3.3067	0.8800	0.0120	-0.7000
3.8537	0.8840	0.0080	-0.7080
4.4245	0.8800	0.0120	-0.7080
4.9467	0.8760	0.0120	-0.7120
5.4662	0.8760	0.0160	-0.7160
6.1078	0.8720	0.0120	-0.7120
6.6212	0.8720	0.0120	-0.6960
7.1529	0.8760	0.0160	-0.7080
7.6780	0.8720	0.0160	-0.7080
8.2031	0.8760	0.0120	-0.7120

Fig.5(C)

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