Early-stage bearing fault detection using machine learning and deep learning techniques

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***Abstract*—** Rolling bearings are among the most important components in the vast majority of machines. Their health is extremely important, as they are an integral tool in the physical functioning of a wide range of machines used in industrial sites. Thus, detecting bearing faults early on is of paramount importance in the real world, requiring methods to be able to make conclusions on the presence/absence of faults, and the part(s) of the machine affected by these faults. We see that the location of the bearing fault plays an important role in the detection of future faults, as we are then more confident of where (and how) the fault is possibly present.

In this paper, we propose the use of a specific deep learning algorithm to predict the location of different bearing faults in machines. We also intend to compare the performance of different learning algorithms in successfully classifying such faults.

***Keywords*— bearings, deep learning, classification, faults, convolution, location of faults**

I. Introduction

An electric motor converts electrical energy into a mechanical energy which is then supplied to different types of loads. A.C. motors operate on an A.C. supply, and they are classified into synchronous, single phase and 3 phase induction, and special purpose motors.

A 3-phase induction motor is an electromechanical energy conversion device which converts 3-phase input electrical power into output mechanical power. It differs from a 1-phase induction motor, primarily because unlike a 1-phase induction motor, it does not require a starting capacitor. It consists of a stator and a rotor. The stator carries a 3-phase stator winding while the rotor carries a short-circuited winding, also known as rotor winding. The stator winding is supplied from a 3-phase current supply. The rotor winding drives its voltage and power from the stator winding through electromagnetic induction, which is why it is called an induction motor.

Condition monitoring is the process of monitoring a particular condition in machinery (such as vibration, temperature, etc) to identify changes that could indicate a developing fault. Continuously monitoring the condition of equipment and taking note of any irregularities that would normally shorten an asset's lifespan allows maintenance or other preventive actions to be scheduled to address the issue(s) before they develop into more serious failures.

Bearings are parts of the motor that support the rotor and maintain a gap between the rotor and the stator , and transfer the loads from the shaft to the motor frame. They are extremely sensitive, and important parts of the motor, and timely detection of bearing faults can prevent costly and consequential motor failure and greatly reduce losses for a manufacturing firm. Bearings are present on both the drive-end and the fan end of the rotor.

This project will focus on finding and classifying bearing faults, whether they are an inner raceway fault, outer raceway fault, or a ball fault. The Case Western Reserve University Bearing Dataset will be used to obtain a trained model for fault prediction in drive end bearings, which will also be able to predict if failure will occur.

II. MATERIALS AND METHODS

A. Motor selection

To collect the data in the dataset (as expanded on below), a 2 HP, Class - 1 horizontally-mounted Reliance electric motor was used. Under the conditions of the experiment, the motor will be rotating at 1750 rpm with a load of 2 horsepower. The readings will be recorded using accelerometers with a sampling frequency of 48kHz. The bearing model will focus on is 6205-2RS JEM SKF, deep groove ball bearing.

The specifications of the drive-end bearings are as follows:

- Inner Diameter: 0.9843 inches
- Outer Diameter: 2.0472 inches
- Thickness: 0.5906 inches
- Ball Diameter: 0.3126 inches
- Pitch Diameter: 1.537 inches

The specifications of the fan-end bearings are as follows:

- Inner Diameter: 0.6693 inches
- Outer Diameter: 1.5748 inches
- Thickness: 0.4724 inches
- Ball Diameter: 0.2656 inches
- Pitch Diameter: 1.122 inches

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B. Dataset

The dataset used in this project is the Case Western Reserve University (CWRU) bearing dataset, which is the most commonly used dataset by researchers in this field. Single point faults are introduced to the bearings under test using electro-discharge machining with fault diameters of 7 mils, 14 mils, 21 mils, 28 mils, and 40 mils, at the inner raceway, the rolling element and the outer raceway. Vibration data are collected for motor loads from 0 to 3 hp and motor speeds from 1,720 to 1,797 rpm using two accelerometers installed at both the drive end and fan end of the motor housing, and two sampling frequencies of 12 kHz and 48 kHz were used. The generated dataset is recorded and is publicly available on the CWRU bearing data centre website.

The CWRU dataset serves as a fundamental dataset to validate the performance of different ML and DL algorithms, which we will ultimately be doing in this project. The data was taken from the official website of the Bearing Data Center, and was then pre-processed using the open-source Python package, the Multivariate CWRU Bearing Package.

C. Implementation

The project implementation will be done by implementing a convolutional neural network using LabVIEW, integrating it with Python for execution purposes.

Convolutional neural networks are fundamentally inspired by the human visual cortex. Their functioning relies on the convolution operation. The convolution operation, was first introduced to detect image patterns in a hierarchical way from simple features such as edge and corner to complex features. Specifically, lower layers in the network detect fundamental lower level visual features; and layers afterward detect higher level features, which are built upon these simple lower level features.

Using neural networks is predicted to give us greater returns for classification, since we do not need to bother with the tasks of feature extraction, or indeed, of excessive optimization- which is why CNN's are the algorithm being used to train the model.

Tentatively, the data, which is in MATLAB format from the source, will be split in a 2:1 ratio, with two-thirds of it being used to train the model, and the remaining to test the model, which will allow us to calculate key metrics such as recall and accuracy, and compare it with other models.

III. DISCUSSIONS AND FUTURE WORK

A. Future work

The major work remaining is the implementation of the project, and the integration of LabVIEW with the model so as to get the final result.

It might also be possible to compare the algorithm chosen (CNNs) with other machine learning algorithms and to compare the accuracies of both (for example, comparing with baseline logistic regression, or PCA, or naive Bayes methods)

ACKNOWLEDGMENT

I would like to express my gratitude to Professor Ashwin KP, our faculty mentor from the mechanical engineering department of BITS Goa, and Mr. Arun Kumar, Research Director at Electrono Solutions Pvt Ltd for their contributions to this project.

I would also extend my thanks to to Mr. Khadar, of BITS Pilani Hyderabad Campus, for providing LabVIEW software access and to Ms. Nikitha for demonstrating dataset integration into LabVIEW.

Without the help and support of the abovementioned individuals, this project would not have been possible.

Practice school station: Electrono Solutions Bengaluru
Industry Mentor: Arun Kumar S
Faculty co-ordinator: Ashwin K.P.

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