Anomaly Detection of Rolling Element Bearing (REB) using LSTM

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Abstract—The long short-term memory (LSTM) technique is proposed in this research as a deep learning-based bearing defect detection algorithm. Event detection systems in industrial sensors are one example of a wide range of applications for autonomous anomaly detection in data mining. The most serious issue with such a scenario is that the cause of the abnormality is unknown. As a result, typical machine learning approaches are ineffective in solving this type of problem. To differentiate vibration abnormalities from sensor values, this article employs an LSTM model. This simulation seeks to identify whether or not the bearings need to be changed as soon as possible.

Index Terms—Deep learning, rolling bearing, long-short-term memory.

I. INTRODUCTION

Recent days, wireless connectivity advances have enabled a variety of control and monitoring applications in a variety of situations, including Internet of Things (IoT) systems. Some IoT applications, such as smart manufacturing and smart homes, even use fifth-generation (5G) networks, which have been shown to provide higher mobility and reduced latency [1]. The Industrial Internet of Things (IIoT) is a new type of IoT-enabled industrial production system that, when properly implemented, may significantly improve system installation, maintainability, efficiency, scalability, and interoperability while also saving money [2].

Machinery equipment has grown and improved dramatically in modern industries, and it is now used in virtually every aspect of daily life, which, at times, forces those machines to perform tasks under adverse conditions. Numerous components, including as bearings, rotors, shafts, and stators, are required to make these spinning devices [3]. Bearings, also known as rolling element bearings, are the most delicate and crucial components of equipment, and their health, defined as faults or cracks in various positions while functioning under varying loads, is critical and has a significant impact on the machines’ durability, power, stability, and lifetime [4]. The four main components of a rolling element bearing are the outer-race, cage, ball, inner-race, and outer-race (REB) [5].

Deep learning techniques for bearing defect detection have been used in this study, and the best appropriate methods based on accuracy and loss have been examined. The following is a list of the significant contributions made by the paper:

1) Investigation and implementation of the widely used dataset that acquired from the University of Cincinnati’s Center for Intelligent Maintenance Systems (IMS) [20]

2) Proposed deep learning algorithms to detect rolling bearing fault in smart factory environment

3) Considering the best deep learning algorithms based on the accuracy, loss and also their confusion matrix

The outline of the paper is as follows. Brief explanation regarding bearing fault detection and deep learning algorithm implementation to detect anomaly vibration Section II. In Section III, presents the details of the LSTM model. Performance evaluation explained in details in Section IV. Finally, conclusions of this paper and gives directions for future research are given in Section V.

II. IMS BEARING DATASET

The dataset that used for this work is gathered from NASA's Prognostic Data Repository and provided by the University of Cincinnati’s Center for Intelligent Maintenance Systems (IMS) [6]. The sensor readings were put along the same shaft as four bearings that were about to fail. With a constant velocity of 2,000 revolutions per minute provided by an AC motor attached to the shaft via a rubber belt. Two accelerometers were put in radial directions, orthogonal to one another, for each bearing. The data was acquired after the equipment was left working continuously on the NASA site for several days. The collection is made up of files comprising 1-second vibration pulse snapshots captured every 10-minute. At a 20 kHz sampling rate, each file contains 20,480 sensor data points in each bearing, which the bearing sensors may gather. Failures were only found after the bearings had exceeded their intended lifespan. Each bearing’s outer race was fitted with a thermocouple to record the temperature and monitor the lubrication circuit. A magnetic stopper was installed in the oil feedback line to collect debris.

III. PROPOSED SYSTEMS

To begin, a range between 0 and 1 must be normalized in order to complete data pre-processing. If the data has already been reshaped, the LSTM network can utilize it. In a 3-dimensional format, LSTM cells expect data samples, time measurements, and characteristics. Every sample must be inserted into the LSTM networks as a phase with four features. The LSTM is a variation of the standard RNN that retains the temporal component of sequential data by linking neurons to form a network that follows the input data in a direct cycle [7]. It will take the input data, produce a succinct description
of the data’s main driving qualities, and then learn to duplicate it.

Fig. 1: Accuracy of LSTM model

Fig. 2: Loss of LSTM model

Fig. 3: Confusion Matrix of LSTM model

IV. PERFORMANCE EVALUATION

TensorFlow was used for this paper as a form of Google Colab. Fig. 1 showed the training and validation accuracy which can achieved 98.23% while Fig. 2 showed the training and validation loss of LSTM with 0.00037. The performance of confusion matrix can be seen in Fig. 3. In order to validate it, comparison with other machine learning, K-NN was also done in this paper. Table I showed the summarization of all compared algorithms. With all these parameters can be proven that LSTM can perform better than the common machine learning algorithm, K-NN.

V. CONCLUSION

Deep learning algorithms have gotten a lot of recognition in the age of Industry 4.0 for a variety of science applications. DL models have been widely used in machinery fault identification and diagnostic applications in recent years. In this paper, LSTM model has been proposed along with well-known machine learning algorithm, K-Nearest Neighbour (K-NN). The performance evaluation has been done by using IMS Bearing Dataset from the NASA acoustics. From the simulation we can conclude that LSTM has proven to be more accurate to detect anomalies. In the practical way if it possible to gather the dataset by replacing more sensors in one shaft with more duration to prove the effectiveness of DL to process big data in real time. For the future work, it will be possible to add model parameter optimization and use more variance of dataset.

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REFERENCES


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<th>Algorithms</th>
<th>Proposed LSTM</th>
<th>K-NN</th>
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<td>Accuracy(%)</td>
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<td>MAE</td>
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<td>Computing Time (s)</td>
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