70(10A): 289-293; 2022. DOI: 10.18311/jmmf/2022/31239

Print ISSN : 0022-2755

Journal of Mines, Metals and Fuels

Contents available at: www.informaticsjournals.com/index.php/jmmf

Fault Prediction of Ball Bearings using Machine Learning: A Review

Mohammed Shahid Kolhar* **and Niranjan Hiremath**

*School of Mechanical Engineering, REVA University, Bengaluru 560064, Karnataka, India. *Email: mdshahid.kolhar@outlook.com*

Abstract

Machine learning and deep learning algorithms have shown positive outcomes in a variety of industries. The number of defects in machinery equipment is predicted to rise as the usage of smart machinery grows. The use of diverse algorithms to detect and diagnose machine faults is becoming more common. Using both open-source and closed-source data sets and machine learning methods, a variety of studies have been conducted and published. This paper reviews current work that uses the bearing data set to detect and diagnose equipment faults using machine learning and deep learning methods. In this paper, the working algorithm, result, and other relevant details are described, as well as the recently published studies.

Keywords: *Machine Learning, Deep Learning, Condition Monitoring, Bearing fault Prediction, Supervised Learning, etc.*

1.0 Introduction to Machinery Condition Monitoring

When a machine is in operation, noise, vibration, temperature, lubricating oil condition, quality and quantity of motor current drawn, and other indicators are used to determine its present functioning state. These signals are acquired from the machine by transducers in the data collection system, which are used to measure the machine's mechanical characteristics. Machine signals are transferred into the digital realm using analog-to-digital converters, allowing significant information to be recovered. The discrete digital data that correlates to the analog signal is examined using computers. These data might be used in machine failure detection systems[1]. There are three key types of maintenance management.

1. Reactive/breakdown maintenance
2. Preventive or periodic maintenance
3. Predictive or condition-based maintenance

Corresponding Author

1.1 Fault Prognosis

Machine defects may be diagnosed using signals obtained from transducers placed around the machine. The signal qualities are used to diagnose faults, and successful algorithms can also detect incipient flaws. After the problems have been detected and diagnosed, the next question is how long the machine will continue to function in its current form, or how long it will be useable. A range of deterministic and stochastic algorithms are available for forecasting a machine's remaining useful life (RUL).

1.2 Bathtub Curve

Figure 1 shows the usual machine failure rate vs the time graph. There are three zones on the plot: infant mortality, useable duration, and wear-out. In the early phases of the machine, the newborn mortality zone develops, which has a high failure rate. The usable duration (also known as uptime) of a computer is defined after this is resolved. To maximize a machine's availability, maintenance engineers try to minimize downtime.

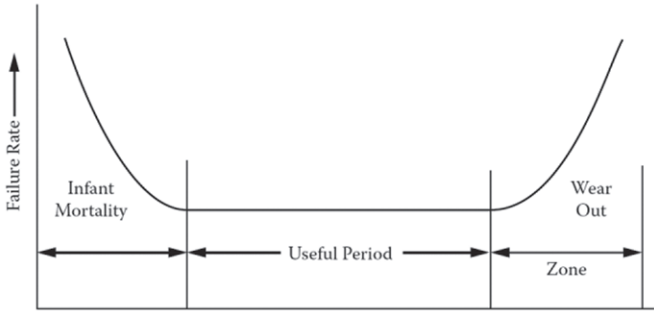

Figure 1: Bathtub Curve [1]

1.3 Condition-Monitoring Techniques

To get the operational condition data of a rotating machine, condition-monitoring (CM) procedures are required. The software can employ vibration signals, noise in the machine, electric current, oil levels and grease used for lubrication, temperature, or a combination of these factors. Time-domain techniques, frequency-domain approaches, and time-frequency approaches can all be used to examine CM data. It is possible to extract data properties such as linearity or nonlinearity, stationary or nonstationary. The most relevant or important characteristics for bearing diagnostics can subsequently be extracted using signal analysis techniques.

1.3.1 Time-Domain Techniques

The vibration signal in the temporal domain is investigated using the quick discerning and identification approach. Statistical characteristics can be used to derive time-domain information from raw vibration data. Several statistical methods are used to assess the state of bearings[2].

1.3.2 Frequency-Domain Techniques

All real-world signals can be broken down into a jumble of unique sine waves. In this domain, each sine wave separated from signals appears as a vertical line. The amplitude is shown by its length, while the frequency is indicated by its placement. The term "spectrum of signals" refers to this type of signal representation. In the case of temporal signal analysis, the signal owing to a minor bearing fault will be lost in the general bearing noise[3].

1.3.3 Time-Frequency Domain Techniques

The time-frequency technique may be used to differentiate the vibration signal frequency segments and their time variation features. Time-frequency domain algorithms can handle both non-stationary and stationary vibration signals. This is the key advantage of time-domain methods over frequency-domain methods.

1.3.4 Other Techniques

Singular Spectrum Analysis (SSA), Fuzzy Logic Systems (FLS), Artificial Neural Networks (ANNs), and other technologies are used to automate the discovery and diagnosis of faults in rolling element bearings.

1.4 Machine Learning

In data science, machine learning is described as the use of statistical learning and optimization methodologies to allow computers to analyze data and find trends. Machine learning approaches employ data mining to uncover previous trends that may be utilized to shape future models. A common supervised machine learning method has three stages[4], a decision process, an error function to estimate accuracy, and an updating or optimization procedure. Many machine learning models are defined by the presence or absence of human effect on raw data, whether in the form of a reward, particular feedback, or labels. The classification of machine learning is shown in Figure 2.

2.0 Literature Review

Various research papers have been published by different researchers for the identification and diagnosis of various faults in rolling element bearings using machine learning. The major goal of this part is to evaluate the literature on bearing health monitoring in the areas of time-domain analysis, frequency domain analysis, and time-frequency domain analysis utilizing various machine learning models and algorithms.

Seryasat et al [6] used two different methods, MSVM and PCA. These methods classify the characteristics of the vibration data set of the bearings. The collected characteristics were correctly categorized using the MSVM classifier, and next subjected to the PCA method. PCA allows duplicate characteristics to be successfully deleted. Most of the characteristics were eliminated, but the average diagnosis accuracy was not compromised.

Sadoughi et al [7] proposed a novel approach to the diagnosis of the bearing fault. It is the Special Kurtosis-based multichannel CNN (SCNN). It combines the signal preprocessing techniques with the modified 1D CNN. SCNN. It was able to detect and locate defects with accuracy better than most of the traditional machine learning and the latest CNN-based techniques. A machinery defect simulator was employed to validate SCNN's performance. It was done to validate the presence of failures other than bearings. Those failures include such as shaft misalignment, and rotor imbalance.

Pan et al [8] offer an improved bearing defect detection technique based on CNN and a long-short-term memory

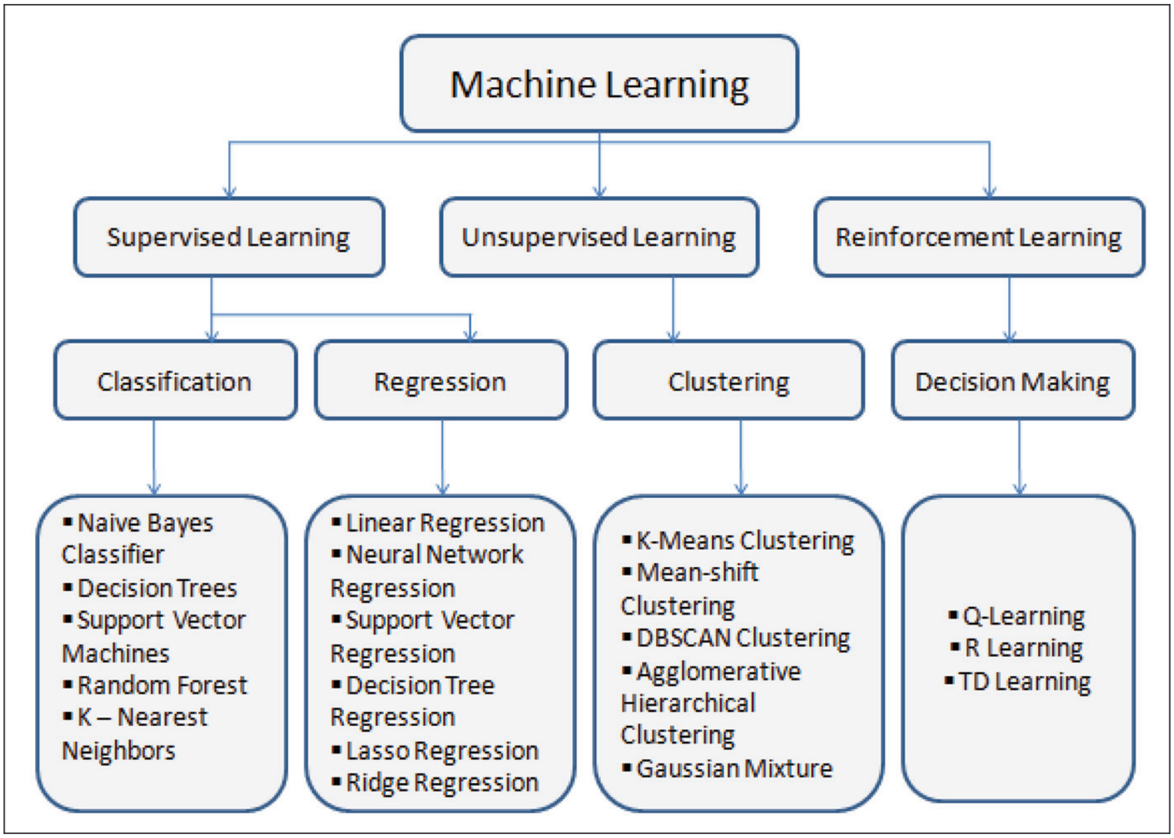

Figure 2: Classification of Machine Learning and their algorithms [5]

recurrent neural network. The output of CNN was used as input to the LSTM to detect the bearing failure types in this research. The findings demonstrate the suggested method's average accuracy rate in the testing data set is greater than 99 per cent, outperforming previous bearing failure diagnostic techniques.

Barcet et al [9] provided the entire technique for diagnosing and monitoring the health of rotating equipment, from condition indicators through classification. A first supervised classification phase uses ensemble learning with three integrated ML algorithms to determine whether an examined observation is healthy or faulty. The principal component analysis' dimensionality reduction allows both healthy and flawed situations to be represented in a two-dimensional space.

He et al [10] used deep learning and wavelet transform technologies to create a defect diagnostic system for rotating equipment. The software interface is user-friendly, and the algorithm generalization ability is strong. System test results have a diagnostic accuracy of above 95%. The system is developed in Python and relies heavily on the PyQt GUI framework and the Tensor Flow machine learning framework.

Hochmann et al [11] showed that the envelope detection approach takes advantage of the spectral domain fact that time-domain periodic signals influence the spectrum in the frequency domain. The envelope detection method uses frequency-domain modulation to discern between different modulation rates. This allows the envelope detection approach to detect not only defects on separate bearings but also the potential source, whether it is an inner race, outer race, or ball fault, from the same time-domain data.

Thakker et al [12] demonstrated the HHT as a signal analysis approach for machine condition monitoring. HHT is a time-domain method for extracting instantaneous frequency data from a signal by applying the EMD to decompose the signal into Intrinsic Mode Functions. The LASSO is a feature ranking approach that aids in selecting only a sub set of the feature vector rather than using all the features to enhance prediction accuracy.

Habbouche et al [13] suggested a method for detecting and diagnosing bearing faults based on VMD, which is employed as notch filter for the more powerful mode cancellation, and a machine learning approach namely the one-dimensional convolution neural network (1D-CNN). The suggested method starts with VMD-based feature extraction for fault detection, then switches to CNN convolution and pooling layers for multi-scale feature extraction for classification and diagnosis. Using the public access Case Western Reserve University experimental dataset, the suggested bearing failure detection and diagnosis approach was assessed in terms of resilience and performance.

Peng et al [14] proposed a new diagnosis to address limitations such as the need for domain knowledge and large training data samples, namely, multi-view feature construction based on genetic programming with the idea of ensemble learning (MFCGPE), which automatically constructs high-level features from multiple views and builds an effective ensemble for identifying different fault types using a small number of training samples. To improve generalization performance even further, an ensemble of classifiers based on k-nearest neighbor is created utilizing the collected characteristics from each view. The results indicate that MFCGPE beats all other techniques in terms of diagnostic accuracy on the three datasets with a minimal number of training data samples.

To discover various flaws in deep-groove ball bearings, Saha et al [15] developed an intelligent fault diagnostic approach. Another important feature of this work is the use of a machine learning (ML) approach to identify bearing faults. The support vector machine was the main algorithm (SVM). The classification accuracy of SVM using a normal grid search cross-validation (CV) optimizer was 92 per cent, but with the PSO-based SVM, it was raised to 93.9 per cent. The created model was compared to other traditional ML approaches such as k-nearest neighbour (KNN), decision tree (DT), and linear discriminant analysis (LDA). In every situation, the new model beat the present methods.

Dineva et al [16] suggest a novel way of diagnosing numerous problems and determining fault severity under noisy settings using a multi-label classification method. Under normal and fault situations, current and vibration signals are collected. The suggested method's applicability is proven under a variety of fault circumstances, including unbalance and misalignment. The parallel severity classification tree's prediction performance was 99 per cent accurate, and most of the vibration data were rated as "good".

Darji et al [17] performed a fault classification using Wavelet Reverse biorthogonal 5.5. Wavelet packet transform (WPT) was used to extract features at the fifth level of decomposition, where energy and kurtosis were retrieved for both horizontal and vertical responses at all WPT nodes. To reduce the experimental error, 400 samples of defective bearings were taken and compared to healthy bearings. The results reveal that for ball-bearing fault identification, ANN with Multilayer Perceptron and CFS criteria performed better than SVM.

Utilizing an Ensemble Empirical Mode Decomposition (EEMD) and Jensen Rényi divergence (JRD) based technique, Singh et al [18] proposed using vibration data to determine the degeneration of rolling element bearings. After then, the proposed approach is put to the test with real-world data (seeded defect data and accelerated bearing life test data). The initial validation on two separate vibration datasets (inner/outer) acquired from seeded defect investigations confirmed the JRD parameter's utility in recognizing a change in the state of health when the severity of a fault changes. The results indicate that the suggested approach might be utilized to evaluate bearing performance decrease.

Based on the over full rational dilation wavelet transform, Singh et al [19] suggested a shift-invariant technique (ORDWT). By maximizing a recommended impulse detection metric termed "Temporal energy operated auto correlated kurtosis," the optimal filter for exactly overlapping the bearing failure caused resonance zone is selected. For better fault classification, autocorrelation of the signal's energy time series filtered through the best subband is shown. The research reveals that the recommended technique's performance is stronger and more consistent than the original fast kurtogram, and wavelet kurtogram.

Chan et al [20] proposed a deep transfer convolutional neural network (DTCNN) overcome the challenges of a huge sample size and long training time. ResNet-50 is chosen as a pre-trained deep convolutional neural network model and applied to bearing fault classification using the transfer learning concept. The suggested approach is assessed on two datasets, one from a motor bearing and the other from a self-priming centrifugal pump. Individual sub-datasets from the motor bearing dataset have prediction accuracy near 100% and enhanced accuracy from 99.48% to 99.98%.

3.0 Conclusion

In the age of Industry 4.0, machine learning algorithms have garnered a lot of attention, and they are being employed in a lot of research. Machine learning models have lately gained popularity in fault identification and diagnostic systems. As computer technology improves at a dizzying speed, ML models will remain strong and appealing devices in machinery fault detection and diagnosis systems. The goal of this research is to summarize and discuss prior attempts and research involving deep learning and the bearing dataset. We made every attempt to cover current studies that combine bearing data sets with machine learning approaches in depth. The authors' recommendations, as well as the problems in dealing with vibration data and the application of machine learning-based models, are also underlined. The authors' recommendations, as well as the problems in dealing with vibration data and the application of machine learning-based models, are all noted, and will surely be valuable in future research.

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