Grease Contamination Detection in the Rolling Element Bearing Using Deep Learning Technique

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***Abstract*—Vibration Analysis is one of the most effective methods used for the condition monitoring of rolling element bearings. The early failure of bearing is mainly due to the presence of solid particles in the grease lubricants. The condition of lubrication in the bearing is an essential parameter to meet the various demanding conditions of the system. This paper aims to analyze the effect of lubricant contamination by solid particles on the dynamic behavior of rolling bearing and to classify them using a support vector machine (SVM) and deep learning algorithm. Experimental tests have been performed with 50 and 100 mg of sand dust particles added to the ball bearings to contaminate the grease lubricant at full load conditions. Vibration signals were analyzed in terms of RMS, kurtosis, skewness, and peak to peak for fault type classification using SVM. In deep learning, the raw vibration signals are converted into a spectrogram image and fed to convolution neural networks (CNN) for fault classification. The results indicate that both SVM and deep learning techniques are effective for fault classification under the influence of lubricant contamination.**

***Index Terms*—bearing contamination, SVM, RMS, Kurtosis, peak to peak, deep learning, CNN-VGG16**

I. Introduction

Rolling bearing is a vital component of rotating machinery subjected to dynamic loading circumstances. Lubrication is an essential factor that defines a bearing performance to meet the system's various demanding conditions. The most common cause of failure in the bearing is generally initiated at the surfaces. This type of defect is mainly due to the presence of contamination and wear debris in the lubricants [1]. When the temperature in the contaminant's medium increases, abrasive wear on the rotating machine surface becomes very severe [2].

Vibration measurement is an effective way of monitoring rotating machinery performance during operation. In rolling bearings, the occurrence of failure can be indicated by the rapid increase in the vibration spectrum. Various other monitoring techniques provide advance warning for fault in the rotating machinery, such as oil analysis, thermography, temperature analysis, motor current signature analysis, etc. [3]. However, vibration monitoring techniques provide a better and wider range of faults in the rotating machines [4]. The vibration signals excite both low and high frequencies due to the presence of flaws in the bearing. The presence of solid contamination and wear debris in the rolling bearing lubricants excites the high-frequency band of vibration spectrum ranging from 600 to 10000 Hz [5]. K. A. Ibrahim Sheriff et al. [6] studied ball bearing performance under the effect of solid contaminants using vibration analysis. They performed the experiment on the ball bearing at different speeds and green sand particle size. Their work shows that the RMS is an effective feature and reflects high energy levels due to wear defects on the bearing surface by contaminants. The vibration features such as RMS and Peak to Peak value are useful features for distributed fault identification [7]. Moreover, kurtosis is an effective time domain feature that reflects the bearing healthy and faulty state [8].

Recently, intelligent diagnosis techniques gained huge attention for automatic fault diagnosis with high accuracy and flexibility. Surojit Poddar and Naresh Tandon [9] developed a fault prediction model for journal bearing using a machine learning approach based on acoustic emission signals. The experiment is conducted on journal bearing under the following conditions such as normal, cavitation, particle contamination, and oil starvation. Finally, an app is built for fault classification using weighted K-nearest neighbour (K-NN). S.Tyagi and S.K. Panigrahi [10] performed a comparative analysis between artificial neural networks and SVM for bearing fault classification. They performed discrete wavelet transform (DWT) for signal preprocessing and feature extraction for the classifier. Their work indicates that SVM is an effective technique as compared to ANN for bearing fault classification. The conventional machine learning technique requires signal preprocessing, denoising, feature extraction, and identification of health indicators for effective fault classification. However, deep learning techniques can easily determine the most important features from the raw data itself [11].

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Further, deep Learning algorithms have grasped the attention of researchers for fault classification. The development in the convolution neural network (CNN) significantly improves the accuracy of fault classification by overcoming the weak feature extraction that affects the diagnosis process [12]. Minh Tuan Pham et al. [13] proposed CNN-VGG16 architecture for the classification of bearing structural fault. They utilized vibration spectrogram images, i.e., vibration signal visual representation of frequencies varying with time and extracted useful information from the non-stationary signal. Their work shows an accuracy of 100% for combined and single-bearing structural fault classification.

In this paper, both machine learning (SVM) and deep learning algorithm (CNN-VGG16) are applied for fault identification of bearing under the influence of solid contamination using vibration analysis. The experiments are carried on the ball bearing under the healthy and contaminated conditions with 50mg and 100 mg of sand particle added to the grease lubricant. First, the Kurtosis value is calculated to identify the state of the bearing. Then, the vibration signal features are extracted, such as RMS, Peak to Peak, Kurtosis, and Skewness, and provided as inputs to SVM for fault classification. In the case of deep learning, spectrogram images are used as the inputs obtained from raw vibration signals using a short-time Fourier transform (STFT). The effectiveness of both methods is measured based on the classification accuracy.

II. Experimental Set-Up

The experiments have been conducted on a simple rotating system as shown in Fig. 1. The set-up consists of a 1HP motor driving a system consisting of a single rotating mass of 0.745kg. The driven and non – drive side bearings are of SKF make YET – 012F. Vibration signals have been captured at a sampling rate of 20000 samples/s. The system is made to run at a speed of 3000rpm. Three test cases are considered. Firstly, the vibration samples are collected for healthy bearing and the same has been repeated for contaminated bearings of varying amounts of 50mg, and 100mg with added silica dust into the bearing through grease filling hole. The dust particles are collected by passing the silica dust through 400 sieve mesh number that passes dust particles of the maximum size of 37 microns.

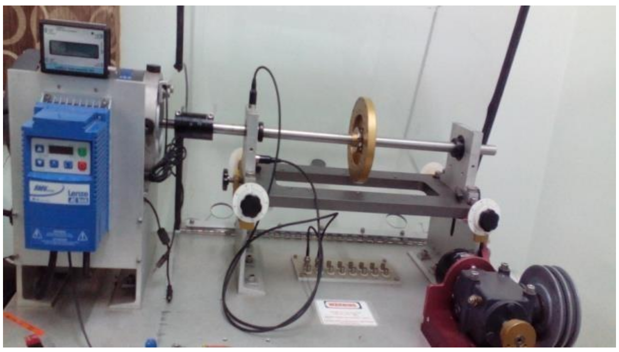

Figure 1. Bearing test rig.

III. Methodology

The flow chart of proposed method for bearing fault diagnosis due to particle contamination is shown in Fig. 2. Firstly, one-minute vibration signals are captured for healthy and contaminated bearing. The signals contain 1200000 data points. Then, signals are split into 1000 signals and each signal contains 1200 data points. The time domain vibration features such as RMS, peak to peak, kurtosis and skewness features are extracted and given as input to SVM for bearing fault classification due to particle contamination.

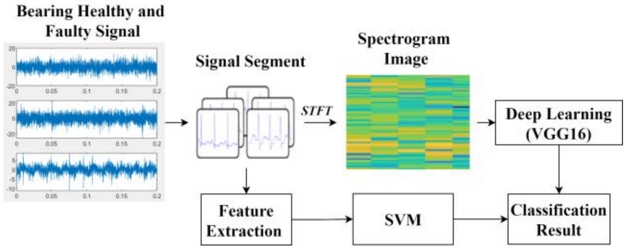

Figure 2. Proposed method for bearing fault classification due to particle contamination.

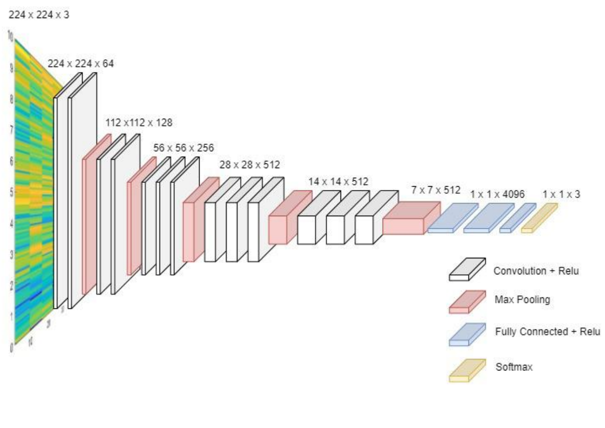

Figure 3. VGG16 architecture using spectrogram image

In deep learning approach, each segmented signal is converted into spectrogram image by performing STFT. The window length of 256 with a hop size of 32 is selected for STFT. The CNN-VGG16 architecture as shown in figure 3, is used for automatic fault classification. The VGG16 has a fixed input size of 224 $\times$ 224 RGB. So, the Spectrogram images are resized to the input size to utilize the VGG16 architecture for classification. The working of SVM and VGG16 for classification are described [14][13].

IV. Results and Discussion

This section represents the results and discussions of fault diagnosis and classification of bearing under the influence of particle contamination.

The FFT spectrum and Spectrogram analysis of bearing signals for healthy, 50 mg and 100mg concentration of particle contamination are shown in Figs. 4 and 5, respectively. The kurtosis values are found to be 2.91, 3.1 and 3.25 for healthy and bearing with contamination of 50mg and 100mg, respectively.

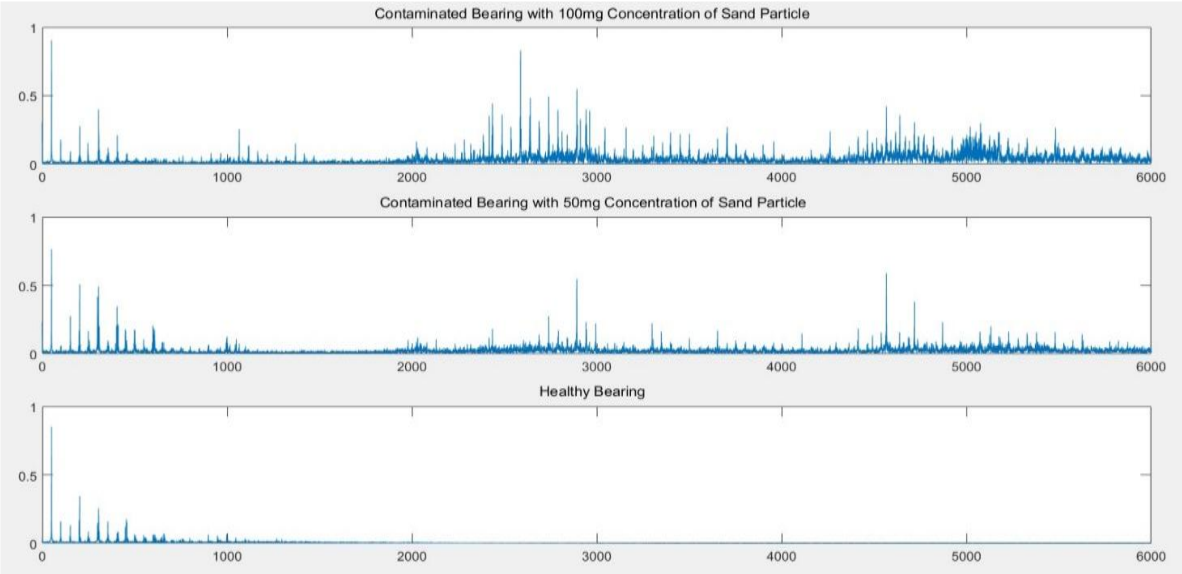

Figure 4. FFT spectrum of healthy and contaminated bearing.

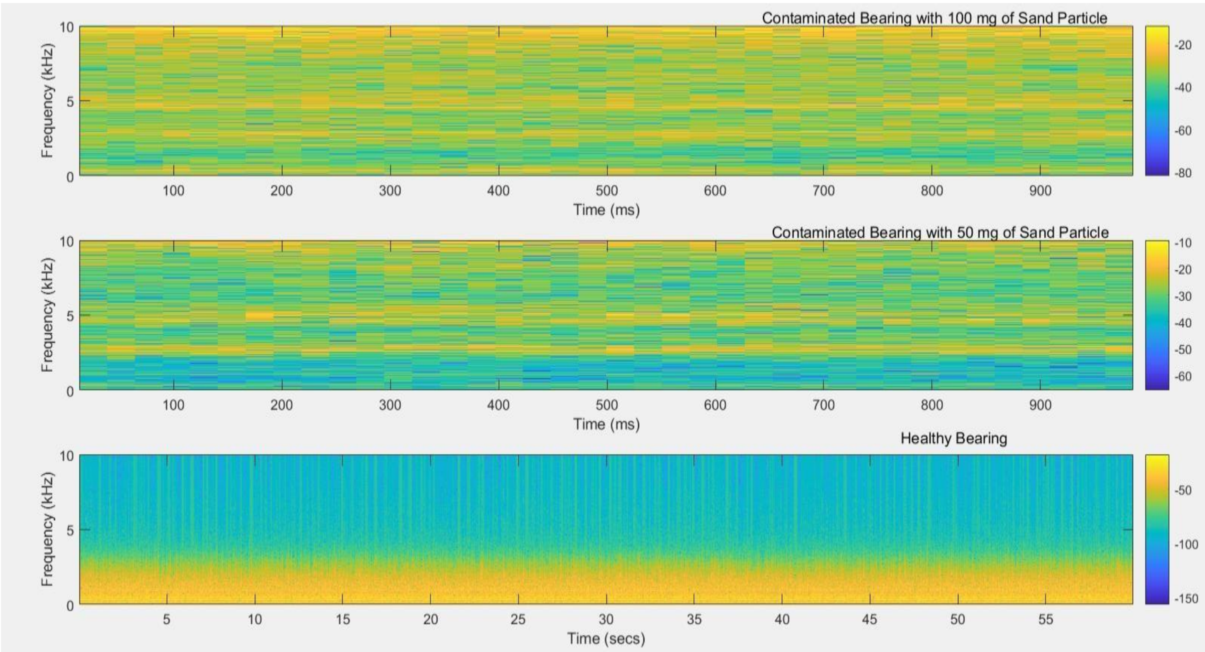

Figure 5. Spectrogram image of the healthy and contaminated bearing.

The kurtosis value above three indicates the presence of a fault in the bearing. The results obtained from the FFT spectrum and spectrogram images indicate that the vibration spectrum changes in the high frequency band range from 1000 to 10,000 Hz because of the presence of solid contamination and wear debris in the bearing surfaces. However, for healthy bearing, no vibration peak is observed in the high-frequency zone. When the contamination level increases, it has been observed that the mound of vibration increases in the spectrum. This is because of more number sand and wear particles rubbing with the bearing surfaces.

The bearing state is divided into three classes such as class 0: healthy bearing, class 1: 50 mg amount of sand particle added to bearing lubricants, and class 2: 100 mg amount of sand particle added to bearing lubricants.

The vibration signal is segmented into 1000 parts after the data augmentation. The RMS, kurtosis, peak to peak, and skewness value are calculated for each segmented sample. These features are used to train the kernel SVM

using the radial basis function. The classification results and confusion matrix are plotted for each feature, as shown in Figs. 6 and 7, respectively. The confusion matrix shows the accuracy for each class of the bearing.

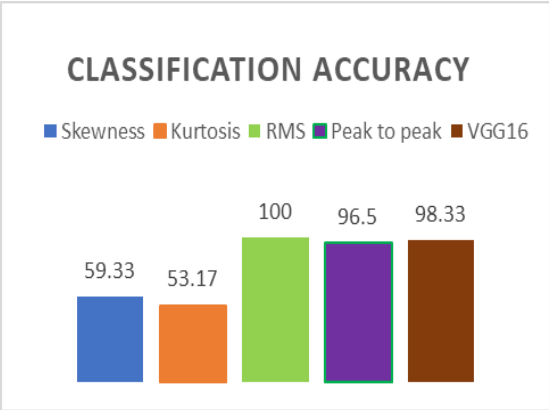

Figure 6. Fault classification result

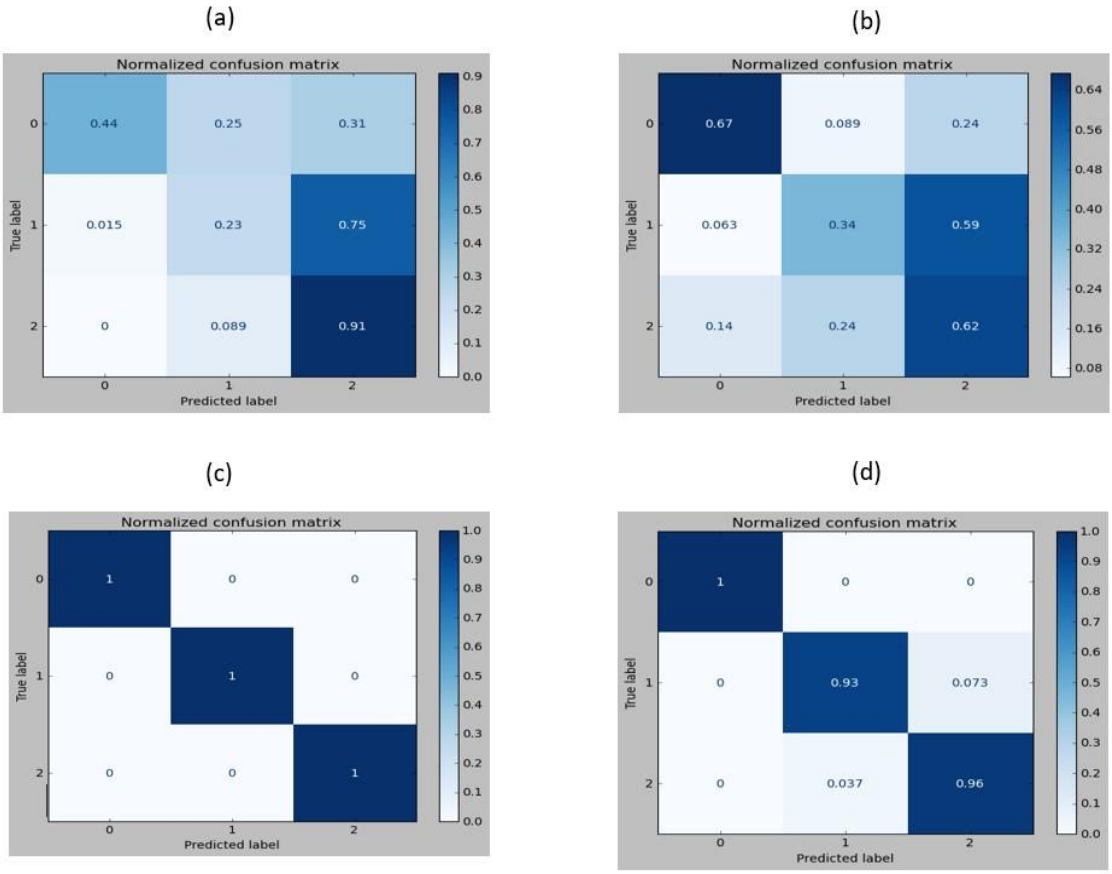

Figure 7. Normalized confusion matrix using SVM from (a) Skewness (b) Kurtosis (c) RMS and (d) Peak to Peak.

The RMS and peak-to-peak values are found to be effective health indicators for bearing, which shows a classification 100 % and 96.5 %. In the presence of contamination, the RMS feature reflects high energy levels on the bearing signal. In skewness and kurtosis, misclassification between the bearing class is remarkably high, with an overall accuracy of 59.33 and 53.17, respectively.

The vibration segmented signals are converted into spectrogram images. These images are used to train the CNN-VGG16 architecture. The classification results and confusion matrix are plotted using a spectrogram image as shown in Figs. 6 and 8.

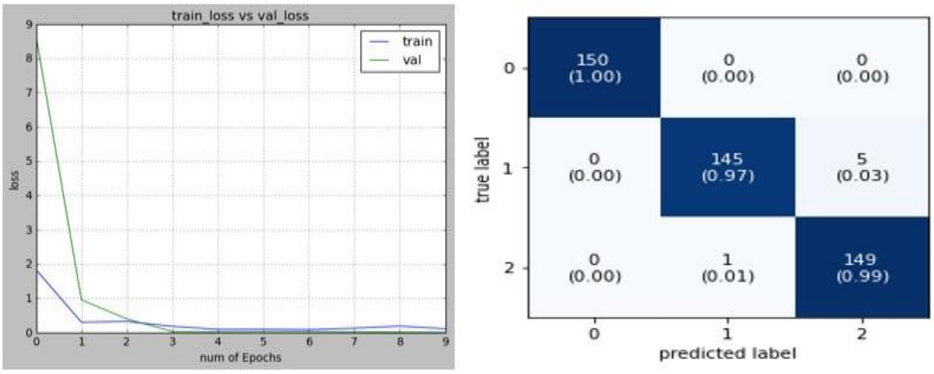

Figure 8. Deep learning analysis result (a) Training loss vs validation loss curve (b) Confusion matrix plot.

The proposed deep learning method shows a fast convergence rate, i.e., 3 to 4 epochs, as shown in figure 8. The confusion matrix result shows that it classifies a healthy and faulty state of bearing with an accuracy of 100%. However, some misclassification occurs between contaminated bearings. The overall accuracy for bearing state classification using the CNN-VGG16 model is 98.33%.

V. Conclusion

The present paper proposes a fault diagnosis method for rotary machine bearings using vibration signals that can identify and recognize faults under the influence of particle contamination. The proposed method is applied when the kurtosis value for the bearing is found to be above three for identification and severity estimation of grease contamination. The vibration FFT and spectrogram image indicate the spectrum changes in the high-frequency band ranging from 1000 to 10,000 Hz because of the presence of solid contamination and wear debris in the bearing surfaces. The time-domain feature such as skewness, kurtosis, peak to peak, and RMS was extracted from vibration signals and given input to SVM for bearing classification. The RMS feature is an effective health indicator for bearing with particle contamination and shows an accuracy of 100%. However, under heavy noise and structural fault, signal preprocessing, denoising, and identifying health indicators are required for fault classification using SVM.

Moreover, the proposed deep learning CNN-VGG16 architecture extracts important information from the raw vibration signal without any preprocessing for the detection of solid contamination in the bearing. The vibration signals were divided into segments and converted into spectrogram images using STFT and given as input to the CNN-VGG16 model for fault classification and shown an overall accuracy of 98.33%. However, it classifies the healthy bearing with an accuracy of 100%. The deep learning method shows the prominent result from the raw signal. Thus, the overall development of an intelligent model for bearing structural and lubricants-related faults, the deep learning methods can be employed. In the case of particle contamination, both methods are effective techniques for fault identification and classification.

The present work can be extended to estimate the wear rate of rolling element bearing under variable operating conditions and mixed fault scenarios like unbalanced, misalignment, and structural fault which are commonly observable faults in rotating machinery. The present work can also extend to tapered bearing, self-aligning bearing, cylindrical bearings for the above-stated operating condition.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Prashant Kumar Sahu conducted the research and was responsible for conceptualization, methodology, formal analysis, validation, writing, review, and editing; T. CH. Anil Kumar was competent for the experiment execution, data acquisition, and drafting; Dr. Rajiv Nandan Rai was responsible for the supervision, review, and editing; all authors had approved the final version.

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