Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 06 Issue 02
2024

Research Article
https://doi.org/10.56979/602/2024

Diagnosis the Bearings Faults through Exercising Deep Learning Algorithms

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Received: December 28, 2023 **Accepted:** January 30, 2024 **Published:** March 01, 2024

Abstract: Rolling bearings are vital components in process industries, and their faults can disrupt industrial processes. This paper presents a novel approach to diagnose the health state of rolling bearings, combining time-frequency domain signal analysis with deep learning models, namely ResNet-50 and DenseNet-121. Utilizing a dataset from the CWRU bearing datacenter containing various bearing health conditions, including normal and faulty states, this research addresses the limitations of conventional statistical feature-based fault detection methods. These scalograms are converted into grayscale images to optimize the learning process. The final grayscale CWT images are fed into the deep learning models for fault classification. Results indicate that the proposed framework, particularly the combination of CWTSV and DenseNet-121, yields promising outcomes of 95.25% and 99.77% respectively, surpassing existing methods for rolling bearing fault diagnosis. This approach holds potential for significantly enhancing industrial maintenance practices and ensuring process reliability.

Keywords: Rolling Bearings; Continuous-wavelet-transformations; Gray-scale images; CNN; Scalogram.

1. Introduction

Rotating machinery like rolling mills, machine tool spindles, turbines, and compressors, are the most valuable elements of process industries. During the manufacturing and processing operations the monitoring of the rotatory element can save the cost of maintenance to these machineries. Monitoring of condition or diagnosis of fault can be interpreted as the field of engineering activity in which the chosen physical parameters, related to the behavior of the machinery operations, are perceived with the intention of identifying system robustness [1]. Minimized costs of instrumentation, enhanced capacity of instrumentation, advanced data management, and efficient data analytics have made the fault diagnosis or monitoring systems more cost-effective [2]. Vibration analysis stands as a robust diagnostic instrument within the realm of condition monitoring. The maintenance of significant rotating machinery remains considerably challenging in the absence of proficient employment of vibration analysis techniques [3]. The collection of signals acquired from the vibration of virtually all dynamic systems i.e. rotating machinery, by means of sensors or data collectors is termed vibration monitoring. Each rotating part of the machinery generates a unique pattern of vibrations or sounds, from which the condition of the rotating machinery can be easily identified. These vibrating patterns can effectively detect the condition of bearings early. This early diagnostic of faulty equipment can lead to effective maintenance of machinery in the process industry. The bearing fault diagnostics method comprises of three main phases: data capturing, processing of data and classification or decision making [4]. The first phase i.e. data capturing is the prime step of vibration-based monitoring techniques. There are several types of transducers that can be used for the collection of vibratory signals from rotating machinery. But Piezoelectric accelerometers are the most efficient electromechanical transducers and can be used for the measurement of displacement, velocity, or acceleration. Usually, a one dimension and three-dimensional accelerometers are used for the collection of vibratory signals from rotating machinery i.e. rotating bearings. The electromechanical transducer or data collection board is used to capture and then transform this data into time-frequency domain for the purpose of monitoring faults in rotating equipment. The prime use of the processing of data is to retrieve the substantial or significant vibratory patterns form the vibrations of faulty bearings. Then, in the third and final phase of diagnosis technique these captured signals are passed through different fault diagnosis techniques for the identification of faults and early maintenance decisions of the faulty machineries. Practically the process conditions of the machinery are not same most of the time. But, in some faulty diagnosis methods these process conditions are neglected. The load on rotating machinery and the conditions are not always in stationery. The operating conditions of the machinery vary due to several reasons i.e. less efficiency of machines, limited feed, operating procedures, results in the different rotations per minute (RPM) and different load. Consequently, the vibratory signals vary due to this non-stationary condition of the operating machinery. Whilst there are different loads on the machinery at different times. So, it is unrealistic to apply the algorithms of fault diagnosis that are developed for these types of non-stationary systems. These kinds of algorithms may result in the misunderstanding of the captured data and can even raise a false alarm or sometimes no alarm when needed. Dealing with these non-stationary conditions of machineries vibration analysis and then relating the non-stationary variables effectively with the vibratory condition monitoring technique is not only the matter of safety but also cost-effective in condition-based maintenance by taking decisions in complex situations. Derived from this critical observation of the dynamic states of machinery, the objective of this research endeavor is formulated. The primary goal of this study is to establish a proficient framework for fault diagnosis, capable of establishing a correlation between the fluctuating process conditions and the recorded vibration signals.

2. Literature Review

Numerous scholarly studies have focused on detecting fault attributes in rolling bearings through the analysis of vibration signals. Unsworth et al. utilized Fast Fourier Transformation (FFT) for defect detection. Sakthivel et al. [5] merged statistical feature analysis with Machine Learning (ML) methods such as k-Nearest Neighbor (k-NN), Decision Tree (DT), and Naive Bayes (NB) approaches. Farokhzad et al. [6] proposed a Decision Tree (DT)-based method for health feature identification and utilized linear classification for diagnosis. Muralidharan and Sugumaran [7] employed Discrete Wavelet Transformation (DWT) with a Decision Tree (DT)-based approach but encountered computational challenges. Sun et al. conducted cyclic spectral analysis, while Zheng and Xin [8] used geometric mode decomposition and power spectral entropy. Yang et al. [11] introduced a framework based on symbolic dynamic entropy, and Qiu et al. [9] utilized Fisher discriminant ratio with Support Vector Machine (SVM). Farokhzad et al. [10] combined FFT with a backpropagation neural network, while Wang and Chen [11] used Wavelet Packet Transform with Partially Linear Neural Network (PLNN). Altobi et al. [12] employed a hybrid approach involving genetic algorithms, Backpropagation (BP). It integrated multisensory data fusion with Convolutional Neural Network (CNN), and used deep learning with SoftMax regression analysis.

However, these studies often directly used sensor data, leading to noise issues and limiting deep learning algorithm applicability, especially with complex datasets. Another study [13] addressed sensor fault diagnosis by generating faulty sensor data with computer software and transforming the problem into an image recognition challenge using Continuous Wavelet Transform (CWT) and CNN, achieving 99.6% accuracy. Additionally, sensor signals can maintain abnormal levels for extended periods, exhibiting either stationary or non-stationary characteristics [14].

Table 1. Comprehensive summary of previous studies analysis on fault diagnosis.

Reference	Author	Model	Accuracy (%)
[5]	Sakthivel et al.	PCA + DT	99.45%
		PCA + KNN	99.43%
		PCA + naïve Bayes	99.3%
		PCA + Bayes Net	99.18%
[6]	Farokhzad et al.	FFT	94.16%
[7]	Muralidharan and Sugumaran	DT + DWT (High Computational Cost)	99%
[8]	Yang et al.	Refined Composite Multivariate Multiscale Symbolic Dynamic Entropy	99%
[9]	Qiu et al.	SVM	83.1%
		BPNN	95.5%
		KNN	94.7%
[11]	Wang and Chen	Wavelet Packet Transform based analysis with a Partially-Linear Neural Network (PNN)	72.05%
[12]	Altobi et al.	MLP-BP	99.5%
		MLP-BP + SVM	98.8%
[15]	Zahoor, et al.	CWT + ANN	99.6%

Additionally, the amplitude of these impulses is often obscured by background macrostructural vibrations present in rolling bearings [15]. To tackle the non-stationary nature of the vibration signal and mitigate the impact of extraneous macrostructural vibrations, time-frequency domain methods like continuous wavelet transformation can be utilized to extract unique features for fault diagnosis in rolling bearings. However, research on fault diagnosis of rolling bearings using deep learning methods is still limited, and its full potential in this field has yet to be thoroughly investigated.

3. Data Collection

The dataset utilized within this research endeavor originates from the renowned bearing data repository housed at Case Western Reserve University (CWRU). The bearing data repository at CWRU has orchestrated a test rig that incorporates a 2 hp motor, a transducer or encoder, and a dynamometer, as illustrated in Figure 1. Artificial faults were induced in the bearings via the utilization of electro-discharge machining techniques.

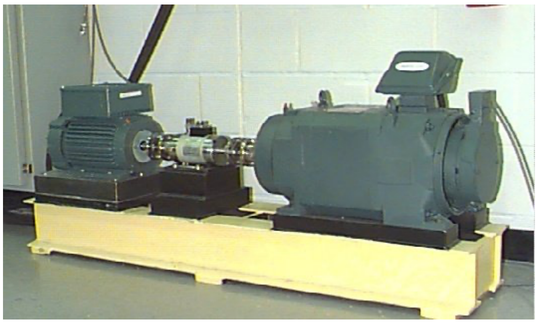

Figure 1. This figure shows the experimental setup for the collection of data from rolling bearings at CWRU Bearing Data center.

Vibratory signals were recorded using the accelerometers that were attached to both the fan end and drive end of the motor housing at 12 o'clock position. A 16-channels DAT recorder was used for the collection of the vibration signals which were later translated and processed to the MATLAB datafile with (.mat) extension. The sampling frequency recorded during the data collection was recorded as 12,000 samples/sec and 48,000 samples/sec.

4. CWT Based Scalogram Visualizations

The main preprocessing step of the research study is to obtain the scalogram visualizations or images based on the continuous wavelet transformation which can be termed as Continuous Wavelet Transformation based Scalogram Visualizations (CWTSV). In this step the recorded MATLAB datafiles were split into equal parts by keeping the sampling frequency to 12,000 samples/sec and 48,000 samples/sec. The CWTSV approach is applied for the generation of images which took place in two steps. The first step involves the decomposition of time-series signal and then visualized using the CWT function. The CWT images contain the information about the energy distribution for different health conditions across the time-frequency plan as shown in Fig 3.2. In the second step on CWTSV preprocessing the generated CWT images are converted to gray-scale images based on the intensity of the RGB (i.e. red, green, and blue) pixels.

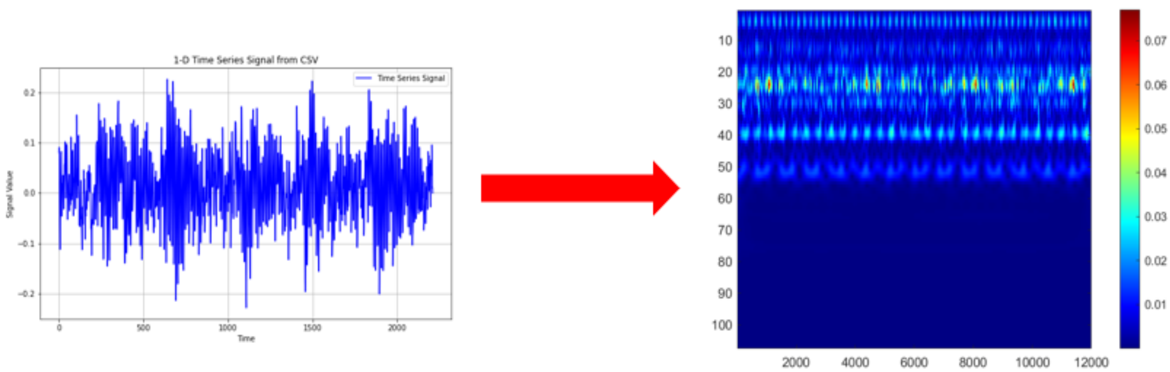

Figure 2. The conversion of time series data into CWT based time frequency scalogram.

4.1 Image Augmentation

The deep neural networks need the data of all the classes to be balanced for the better performance of the trained model and to avoid overfitting or underfitting [16]. The generated CWTSV are passed through image augmentation preprocessing technique for the balancing of both the faulty and normal bearing classes. The dataset consists of 4130 total images in which faulty class has a total of 3680 images whereas the normal class has 450 images. Accordingly for balancing the dataset the normal class images are passed through augmentation techniques to create the remaining 3230 images. The images after augmentation can be seen in Figure 3.

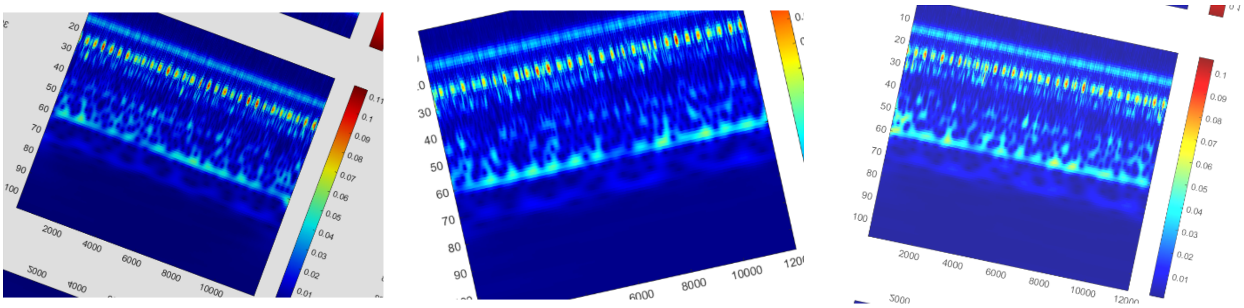

Figure 3. Augmentation results of the scalograms for class balancing.

5. Model Implementation

The model is implemented in three phases. The first phase of the model involves the collection of the data from the CWRU Bearing data center in which different types of faults are introduced in the rolling bearings. The data available on the CWRU bearing data center is a time-series data and available in the MATLAB datafile (.mat). The time-series data is first sliced and then passed to the preprocessing phase which is the second phase of the model. The sliced signals are converted to the continuous wavelet transformation using the MATLAB function for visualizing the magnitude of CWT. Two image classes of the dataset are created by the CWT function, the Normal class, and the Faulty class. The dataset is then checked for the class imbalance and if the dataset is found to be imbalanced then the class with less count of images is passed through the augmentation technique [17]. In our case the Normal class having lesser number of images is passed through the augmentation process so that both the classes are balanced and prevents the model from overfitting. Furthermore, these images are converted to greyscale using the intensity of red, green, and blue which helps in decreasing the number of computations. These grayscale images are resized to (224 x 224 x 1), which is the default size for image compression for ResNet50 and DenseNet121. The resultant images sets are then passed to the 3rd or final phase of the model.

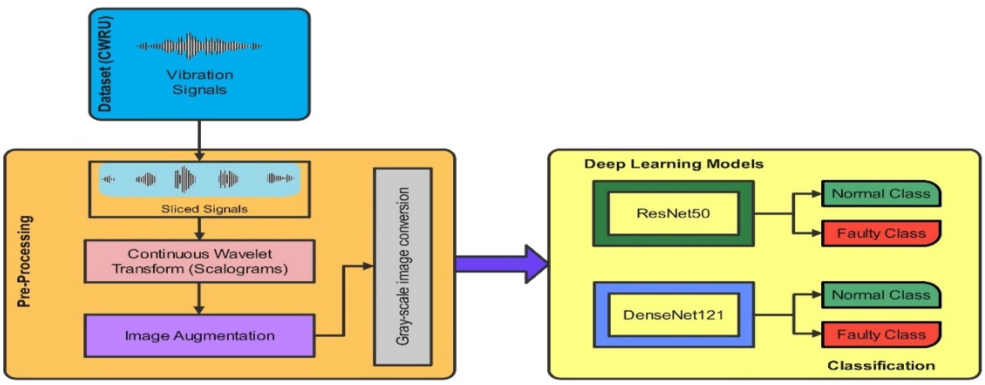

Figure 4. The complete model architecture depicting each phase of the model implemented.

In the third phase of the model, the image data is passed through both the ResNet50 model and the DenseNet121 model. The final classification layers of both the model i.e. ResNet50 and DenseNet121 are removed, and a new layer called globalaveragepooling2d is added to the model. Finally for classification the fully connected layers of 2 units are used followed by the activation function called Sigmoid. The Sigmoid activation function then classifies the image as either normal class or faulty class.

6. Results

This section explains the test/train split of the dataset. Furthermore, this section provides detailed results and comparisons of the framework applied for the diagnosis of faulty bearings. The dataset used in our research study of the acoustic signals is taken from the bearing datacenter of the CWRU. The proposed framework is the combination of the CWTSV and Deep Learning Models (ResNet15 and DenseNet121).

6.1 Performance Metrics

Diving deep into the performance metrics of the models. It can be observed that both the models i.e. ResNet-50 and DenseNet-121 showcased an impressive performance at different critical prospectives. ResNet-50 exhibits the True Positive Rate (TPR) of 95.05 percent and False positive rate of 4.29%. Which clearly indicates that ResNet-50 has the ability of effectively identifying the positive instances, which is Normal Bearings in this case. Similarly, the lower False Positive rate (FPR) of the ResNet-50 model highlights the low rate of incorrectly classifying negative instances as positive. The FPR is significant in case of avoiding false alarm in the rotatory machinery.

On the other hand, the DenseNet-121 model revealed exceptional performance metrics, highlighting its robustness in classifying Faulty and Normal Bearings. The model maintained a remarkable True Positive Rate (TPR) of 99.45%, which showcases its ability to effectively analyze the correct positive instances. On the contrary, the vanishingly low False Positive Rate (FPR) of 0.134% shows its ability in reducing the number of negative instances that are erroneously classified as positive. Which is indeed a crucial factor in preventing false alarms in real word industry. Table 2 shows all the performance metrics of both models.

Table 2. Performance Evaluation Metrics table of ResNet-50 and DenseNet-121

Model	TPR (%)	FPR (%)	Precision (%)	F1-Score (%)	Accuracy (%)
ResNet-50	95.04%	4.29%	95.57%	95.31%	95.4%
DenseNet-121	99.44%	0.13%	99.86%	99.65%	99.77%

Furthermore, the Precision rate of the model indicates the measure of the ratio of true positives to the total predicted true positives. Which depicts the model's ability of making precise positive predictions. The precision rate for the ResNet-50 model is 95.57%, whereas for the DenseNet-121 it exhibits the precision rate of 99.86%. These precision rates of both the models show that DenseNet is more efficient in terms of predicting positive results. On the other hand, the F1-Score for both the models is impressive. The F1-Score balances precision and recall, which means the indication of overall accuracy. The ResNet-50 shows maintained the F1-Score of 95.31%. In contrast, the DenseNet-121 showcased the impressive F1-Score of 99.66%. The results of the Performance metrics for both the models are summarized in the given Figure 9.

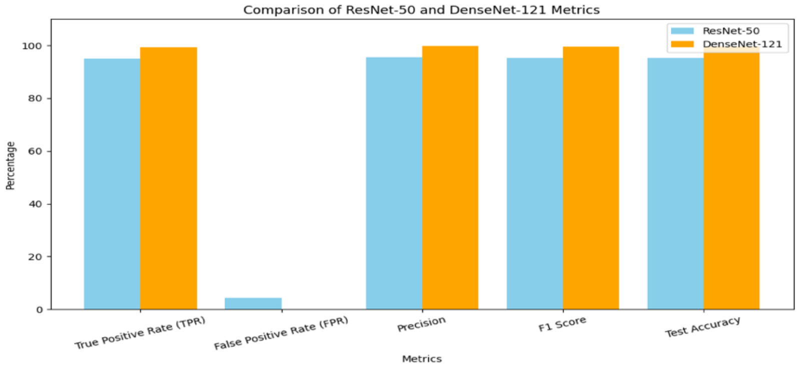

Figure 5. Comparison Chart of Performance Metrics

6.2 Confusion Matrix

The ResNet-50 model's confusion matrix offers a thorough evaluation of its performance in distinguishing between faulty and normal bearings. It accurately detected 713 true faulty instances and correctly predicted 691 true normal instances. However, it also produced 36 false positives, wrongly flagging normal bearings as faulty, and missed 32 true faulty instances, incorrectly labeling them as normal. This analysis reveals both the model's strengths and weaknesses in bearing classification.

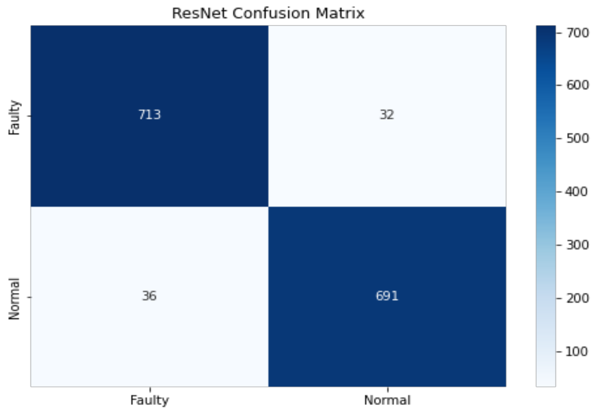

Figure 6. Confusion Matrix of ResNet-50

The confusion matrix of the DenseNet-121 model reveals its strong performance in correctly identifying faulty bearings (744 true positives) and recognizing normal bearings (723 true negatives). Despite its overall good performance, there were a few misclassifications, including 4 false positives (normal bearings incorrectly labeled as faulty) and 1 false negative (a missed actual fault). While these occurrences were infrequent, they indicate opportunities for the model to enhance its sensitivity to faults. In summary, the confusion matrix provides a detailed overview of DenseNet-121's classification effectiveness, showcasing true positives, true negatives, false positives, and false negatives.

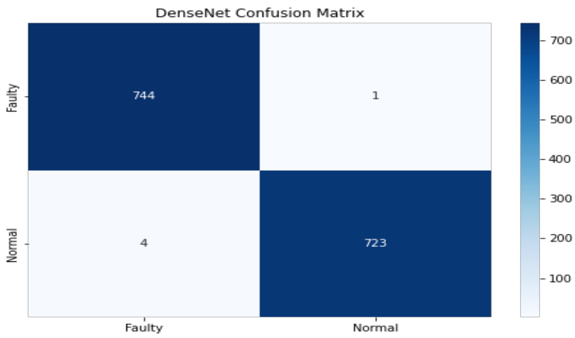

Figure 7. Confusion Matrix of DenseNet-121.

Table 3. Comparison with existing techniques

Ref.	Author	Method	Accuracy
[9]	Qiu et al.	SVM	83.1%
		BPNN	95.5%
		KNN	94.7%
[11]	Wang and Chen	Wavelet Packet Transform based analysis with a Partially-Linear Neural Network (PNN)	72.05%
[12]	Altobi et al.	MLP-BP	99.5%
		MLP-BP + SVM	98.8%
[15]	Zahoor, et al.	CWT + ANN	99.6%
Proposed Model	Ifyakhar et al.	DenseNet-121	99.77%

7. Conclusion

This paper introduces a novel approach for monitoring the condition of rolling bearings. The method combines continuous wavelet transformed (CWT) scalogram-based visualization with ResNet-50 and DenseNet-121 deep learning architectures. By employing CWT to process non-stationary and non-linear vibration signals and integrating them seamlessly with ResNet-50 and DenseNet-121, manual feature analysis is eliminated. The introduced CWT scalogram-based gray-imaging (SGI) facilitates end-to-end diagnosis and provides a comprehensive solution for assessing rolling bearing operation. The benchmark dataset utilized originates from the bearing data center of Case Western Reserve University to validate the framework's performance for fault diagnostics in rolling bearings. Empirical findings demonstrate that the proposed methodology enhances the classification performance of rolling bearing faults. Notably, the frameworks (CWTSV + ResNet-50) and (CWTSV + DenseNet-121) exhibit exceptional performance compared to existing fault diagnosis frameworks. Evaluation metrices assess the proposed methodology's performance, with the DenseNet-121 architecture achieving the highest accuracy of 99.77%. This research yields significant insights and paves the way for further exploration. Future studies may test these models for other fault diagnosis problems to evaluate their generalization. Additionally, leveraging components from both models to create an ensemble technique could enhance robustness and reliability in outcomes.

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