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Performance analysis of pre-trained transfer learning models for the classification of the rolling bearing faults

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Performance analysis of pre-trained transfer learning models for the classification of the rolling bearing faults

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Abstract. Nowadays, artificial intelligence techniques are getting popular in modern industry to diagnose the rolling bearing faults (RBFs). The RBFs occur in rotating machinery and these are common in every manufacturing industry. The diagnosis of the RBFs is highly needed to reduce the financial and production losses. Therefore, various artificial intelligence techniques such as machine and deep learning have been developed to diagnose the RBFs in the rotating machines. But, the performance of these techniques has suffered due the size of the dataset. Because, Machine learning and deep learning methods based methods are suitable for the small and large datasets respectively. Deep learning methods have also been limited to large training time. In this paper, performance of the different pre-trained models for the RBFs classification has been analysed. CWRU Dataset has been used for the performance comparison.

1. Introduction

The fault monitoring of the machine is also called health monitoring of the machines. And it has been found that most rotating machine failures have occurred in the industry due to rolling bearing faults (RBFs) [1]. Because, rolling bearings are an important part of the rotating machine, which needs continuous monitoring of the RBFs [2]. In the industry, different rotating machines operate continuously. And the machine's failure occurs due to the RBFs. Due to the failure of the machine the normal operation of the manufacturing industry gets affected. It may lead to economic loss, accidents, and production loss. [3]. Therefore, the detection of the RBFs type and its location is highly needed to reduce the economic losses, reduce the production losses, and avoid accidents. . For the detection of the RBFs, traditional, and artificial intelligence (AI) techniques have been reported in the literature, and in the era of AI, traditional methods are becoming obsolete. And AI technique based methods are being popular for the diagnosis of RBFs [4]. The AI based methods are mainly classified as machine learning (ML) based [5], deep learning (DL) based [6], and transfer learning (TL) based methods [7]. The ML based needs two important steps and these are: feature extraction and fault classification. First, Feature extraction is an important step in ML, which is used to extract the information related to the faults from non-stationary or nonlinear vibration signals [9]. The most commonly used techniques for the feature extraction are: fast Fourier transform (FFT) [10], empirical mode decomposition (EMD) [11], ensemble empirical mode decomposition (EEMD) [12], and discrete wavelet transform (DWT) [13]. Second, for classification, artificial neural networks (ANN) [10], support vector machine (SVM) [14], and extreme learning machine (ELM) [15] techniques have been used. ML-based fault diagnosis methods need experiences and prior knowledge to extract features from non-stationary vibration signals, also limited to the small data sets. ML based methods has been learn only one or two layers of data, and its overall performance is poor. Therefore, deep learning methods have been developed to solve the problems of machine learning-based methods. DL extracts the features to train the deep network from the raw data and it does not require expertise [16]. DL has also been used efficiently in the areas of image processing for the image classification [17] and these are useful for the identification of the bearing fault with the help of time-frequency (TF) analysis methods. TF analysis method has been used to create the image from a one dimensional vibration signal of RBFs and it has successfully been applied for the RBFs diagnosis [7]. In this work, we have studied and analysed the performance of the continuous wavelet transform and different pre-trained models at different batch sizes for 10 types of fault classification.

The remaining part of the manuscript has been organized as: In Section2, the pre-trained model, transfer learning, has been explained. The dataset, and evaluation parameters have been presented in Section3, Experimental results and performance analysis have been done in Section4, The conclusion of the work has been presented in Section5.

2. Material and methods

2.1 Pre-trained models

In a present scenario there are many pre-trained models available, in this analysis we include alexnet, googlenet, shufflenet, resnet18, resnet50. All pre-trained convolutional neural network models that have been trained with millions of images of the Image Net dataset [17]. The pre-trained network has been used to classify the thousands of images related to the object like pencil, mouse, keyboard, and several animals. The alexnet has one input, one softmax, one output, two norm layer, two dropout, three FC, five convolution, and seven Relu layers and three pooling layers. The googlenet has total 144 layers which includes 57 convolution layers, 57 ReLU layers, 9 Depth concatenation layers, 13 max pooling layers, 2 cross channel normalization, one average pooling, one dropout layer, one fully connected layer, one softmax layer, one input and one output layer. The resnet18 has total 72 layers which includes 20 convolutional layers, 17 ReLU layers, 8 addition layers, 20 batch normalization layers, one input, one output layer, one preprocessing layer, one max pooling layer, one average pooling layer, one fully connected layer and one softmax. the shufflenet has total 173 layers which includes 48 grouped convolutional layers, 48 batch normalization layers, 33 ReLU layers, 16 channel shuffling layers, 3 depth concatenation layers, 13 addition layers, one input, one processing, one convolution, one max pooling layer, one average pooling, one fully connected layer, one, softmax layer, one output layer. The resnet50 has a total 177 layers which include 53 convolutional layers, 53 batch normalization layers, 49 ReLU layers, 16 addition layers, one input, one max pooling, one average pooling, one fully connected layer, one softmax layer and one output layer.

2.2. Transfer learning

Deep learning requires a large number of samples to train a model for better accuracy, for small dataset deep learning is a good choice. TL is commonly used to address the limitations of a small dataset of DL. A small dataset is not sufficient to train your deep learning model from scratch. For TL, pre-trained models have been used and fine tune the last three layers of the model to classify 10 types of faults. Transfer learning is an easy process to train a network as compared to the training of the deep learning model from scratch. In the fine-tuning process, we modified the last layer to match the classes according to our dataset, we also retained the layers of the network that we wanted.

The stepwise explanation of the proposed algorithm has been given below:

Step1: Vibration Signal
The vibration signal of a length 102400 sample point has been considered for the experiments for each fault type.

Step2: Divide and pre-process the vibration signal
Now, the vibration signal for each fault type has been divided into the 100 segments and each segment has 1024 sample points.

Step3: Apply the analytic morlet wavelet based CWT filter bank to plot the scalogram image
CWT filter bank (CWTFB) has been applied to convert each segment of the vibration signal into a time-scale plot scalogram. An amor wavelet is used to compute the CWT because it has good time- frequency analysis ability.

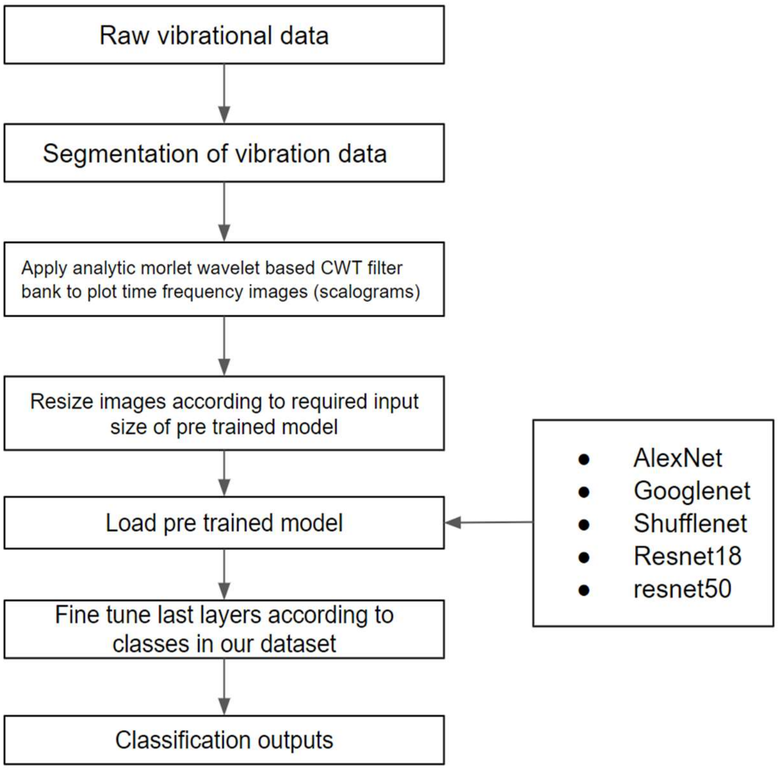

Fig. 1 process flow diagram

Step4: Resize the scalogram images

The scalogram images have been resized according to the input image size of each pre-trained model, each model accepting a different image size. Alexnet accepts images of 227*277*3 where width is 227 pixels, height is 227 pixels, and 3 represent Red Green Blue channels. googlenet, shufflenet, resnet18 and resnet50 accepts images of 224*224*3 where width is 224 pixels, height is 224 pixels, and 3 represents Red Green Blue channels.

Step5: Load the pre-trained model
The images created from vibration signals for all faults at respective load conditions have been applied as an input to the pre-trained model. Model chooses the training and testing samples in the ratio of 7:3 randomly.

Step6: Fine tuning
The fine tuning of the last three layers has been done as per the labelled vibration signal data set for the ten faults.

Step7: Classification of rolling bearing faults
Finally the RBFs type B07, IF07, OF07, BF14, IF14, OF14, B21, IF21, OF21, and normal have been classified successfully.

3. Dataset and evaluation parameters

3.1. Dataset
Data set of RBFs has been downloaded from Case Western Reserve University (CWRU) [18] which is freely available online. This data contains the vibration signals, which have been recorded from motors using an acceleration sensor connected at the fan and drive end. The 12 kHz sampling frequency and 48 kHz sampling frequency have been taken at drive and fan end respectively. At the time of measurement of the vibration signal, different load conditions of 0hp, 1hp, 2hp, 3hp have been considered. Based on the position of the faults, RBFs have been classified into inner race fault (IR), ball fault (B), normal condition (NO) and outer race fault (OF). Each fault occurs at a different position of the diameter except in normal conditions. In this dataset a total of 10 health conditions have been considered which include 9 fault conditions (B07, B14, B21, IF07, IF14, IF21, OF07, OF14, and OF21) and one normal condition (NO). The Vibration signal has a length of 102400 sample points for four load conditions and these sample points have been divided into 100 segments of the length of 1024 sample points for each load condition. So, a total of 400 segments of sample point 1024 for each health condition have been taken. And total numbers of samples for 10 faults are 4000.

***Accuracy* -** Accuracy is the ratio of the sum of TPs and TNs to the sum of the TPs, TNs, false positives (FPs), and false negatives (FNs). It has been calculated using equation (3).

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{3}$$

4. Results and discussion
All these pre-trained models are again trained on small dataset with the system configuration:

Operating system: window 10
GPU: NVIDIA GeForce MX230
Software: MATLAB R2019a

In this section, experiments have been conducted to analyse the performance of cwt and pre-trained transfer learning models for the classification of the 10 types of rolling bearing faults. In this experiment we have selected a total 4000 images for all load conditions that have been created using CWT. These images have been divided into the ratio of 70% and 30% for training and testing samples respectively. Here, the batch size 8, 20, 32 have been selected and trained for 8 epochs and learning rate selected as 0.0001. From table 1 we can observe that alexnet model with 25 layers performing well with prediction accuracy of 99.2% for batch size of 20, googlenet performing well with prediction accuracy of 98% for batch size 8 and 20, shufflenet have highest prediction accuracy 98.8% for batch size of 8, resnet18 has prediction accuracy of 99.8% for batch size of 8, and resnet50 has prediction accuracy 99.9% for batch size 8.

From table 1 we can observe that the resnet50 model which has a large number of layers, that’s why it processes our data with only at batch size of 8, at batch size 20 and 32 resnet50 model requires more computational power. Prediction accuracy of all other models including googlenet, shufflenet, resnet18 decreases with increased batch size and required computational power also increases.

Table 1. Result table

Accuracy with different batch sizes	**Alexnet (25 Layers)**	**Googlenet (144 Layers)**	**Shufflenet (173 Layers)**	**resnet18 (72 Layers)**	**resnet50 (177 Layers)**
Batch size 8	98.1%	98%	98.8%	99.8%	99.9%
Batch size 20	99.2%	98%	97.9%	99.1%	GPU out of memory
Batch size 32	98.7%	96.8%	97.4%	97.9%	GPU out of memory

5. Conclusion

In this study, we have analysed the performance of the CWT and various pretrained networks which includes alexnet, googlenet, shufflenet, resnet18, resnet50. Based on the experimental results it has been concluded that resnet50 model with large number of layers performing well only with the small batch size, at greater batch sizes it requires huge computational power. Results also show that alexnet model which has less number of layers performing well with batch size of 20 and 32 as compared to other transfer learning models. Requirement of computational power is very high for the pre-trained models which contain more number of layers at large batch size. Performance of the transfer learning models can be improved by increasing GPU power.

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