Design a Hybrid Model of Mel-Spectrogram and VGG16 Based Convolutional Neural Network for Diagnosing Motor Bearing Faults

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Owing to rolling bearings' significance as one of the most frequently utilized components of industrial machinery. Therefore, it is crucial to establish a system to check the bearing's condition. In this research, a hybrid method of spectral feature extraction combined with Convolutional Neural Network (CNN) designed to classify faults. Firstly, Mel-spectrogram applied as a method for pre-processing by transforming the raw vibration data. Secondly, a Mel-VGG16 employed as a classifier to detect the bearing faults. The proposed technique tested on the CWRU benchmark dataset to bearings in different rotating speeds. The case study results demonstrated that the proposed model could obtain a higher testing accuracy.

***Keywords**:* *Rolling bearing, Mel-spectrogram, VGG16, Deep Learning, Predictive maintenance.*

1. Introduction

A machine's components encounter variable levels of stress during the period of its operational life. Bearings employed as a means of support and energy conversion in the rotor and shaft of machinery. Vibration measurements have used for a while to diagnose and track the gradual degradation of bearings in rotating machinery, and they have recently improved in cost and consistency [1]. Effective defect identification and diagnosis depend on an understanding of the vibration signals. Hence, three approaches fundamentally used about the vibration signal analysis in time, frequency and time frequency domains over the years. Conventional methods based on the statistical features extraction vastly researched over the time of past twenty years. Methods such as time synchronous averaging, autoregressive modeling, and blind source separation investigated in study with some accuracies and related challenges [2].

The developments in machine learning (ML) and deep learning (DL) with automatic features extraction have forwarded research in their use-cases in machinery health diagnosis. The expertise of ML and DL in analyzing and detecting the state of equipment's health has been the subject of many investigations. This study proposes a condition-monitoring model that empowers vibration monitoring that can happen in machinery motors to predict mechanical faults. Traditional ML methods use handcrafted and feature-based methods [3] have some limitations that can boost performance considerably, but CNNs utilized for increasing performance to reach high accuracies. The proposed model in this paper divided into two main blocks. The first block was to transform vibration data into 2-D spectrograms data. The spectrograms represent the Time, Freq. (Hz), and Amplitude, which are commonly used in speech recognition area [4]. The second block was to perform the transformed data as pre-processing step to VGG16 based CNN and compare the outcomes with those achieved by the current ML models. This study aimed to detect bearing faults using proposed VGG16 classifier combined with spectral feature analysis.

2. Proposed Method

The proposed model in this paper for condition monitoring of the bearing consists of a diagnosis and predictive section. This research adopts VGG16 based CNN architecture to obtain a high-performance accuracy by extracting distinguishable features from different input data transformations. The total model relied on the basis from invariant transference features from sources to target domains. The VGG16 model is better than other famous pre-trained CNNs such as ResNet50 and VGG19 [5].

A. VGG16 Architecture:

In this study, we leverage the VGG16 CNN in developing the proposed hybrid model for classifying the fault states. The input of the model is a RGB image illustrated in the Fig. 1. The model blocks (Conv1 to Conv5) contain convolutional layers and pooling operations, next are fully connected layers (FC6, FC7) and final step is a SoftMax classifier. The architecture represented in Fig. 1 the model truncated after Conv5 pooling operations and Weights frozen before the FC layer, next flattened fed to a new FC classifier. In this paper, the FC6 and FC7 sizes fixed at 4096x1 after some experimentations, where followed by the dense layer at final step with size of 10.

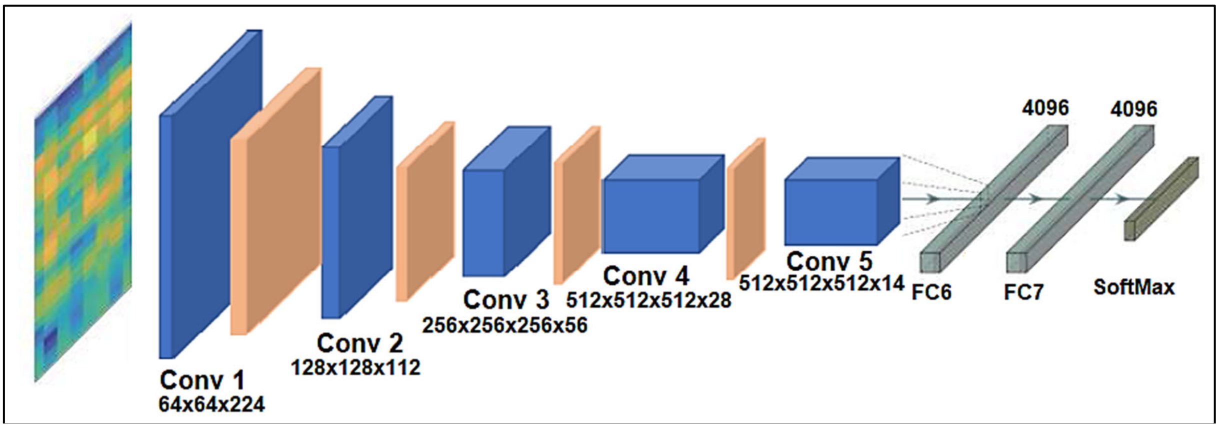

***Figure 1**. VGG16 architecture.*

B. Mel-Spectrogram:

To provide that the CNN designed for processing images can performed to voice signal, pre-processing needed in the 1D data form, can be transformed to a suitable input. In the pre-processing step, the voice feature data in the time-freq. domain extracted by a Mel-spectrogram. Then, the VGG16 trained to regard these 2-D data as an image. This technique can efficiently implemented to voice signal, and the Mel-spectrogram data in the time-freq. domain can used in the anomalies detection [6].

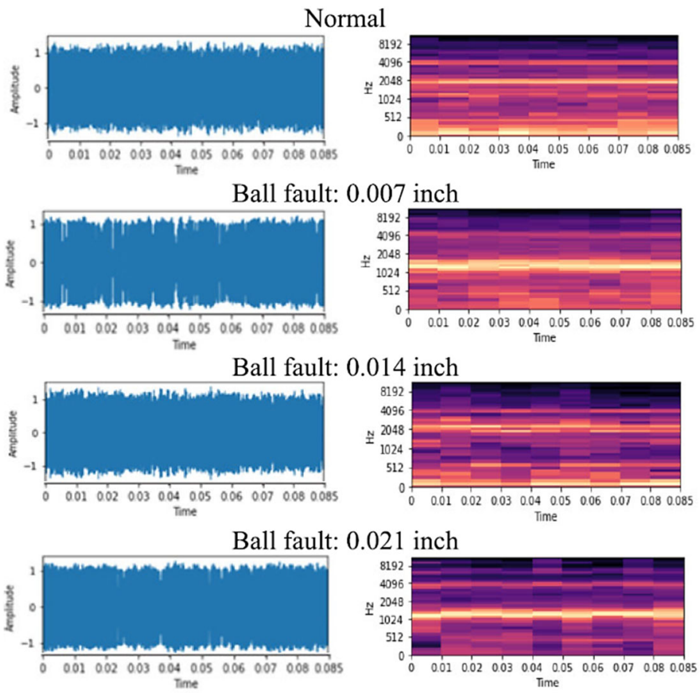

***Figure 2**. Raw signals and Mel-spectrogram images of bearing dataset.*

3. CWRU Bearing Dataset

The CWRU dataset used as benchmark for classifying bearing faults in academic community, the dataset contains vibration data of signals about normal and bearings failures. Vibration data of four classes on bearings measured in the laboratory tests. In brief, CWRU data specify internal and external faults of raceway with noise in this dataset to unknown the real condition of faults that can interfere with the classification performance of the anomaly detection. Nevertheless, in an environment with noises the Mel-VGG16 performed well and had best performance comparison with the other models in the high power ratio of the noises [7].

Table 1. *Example of faults in the CWRU bearing dataset.*

Label	Fault Cause	Severity (inch)
1	Normal	-
2	Ball Fault	0.007
3	Ball Fault	0.014
4	Ball Fault	0.021
5	Inner Fault	0.007
6	Inner Fault	0.014
7	Inner Fault	0.021
8	Outer Fault	0.007
9	Outer Fault	0.014
10	Outer Fault	0.021

4. Experimental Results

In the set of experimental results, the range fitting performance of the Mel-VGG16 was tested. The experiment operated to test the value of data that generalized under different loads. A three loads about dataset used in this paper referred to Table 2.

Table 2. *The dataset information.*

Label	Motor Load	Shaft Speed
A	1hp	1772 rpm
B	2hp	1750 rpm
C	3hp	1730 rpm

Table 3 shows the accuracy of the model on the CWRU dataset in the scenario. When the dataset configured for each load, the train and test sets combined and trained. In the same way, the confirmation load dataset for testing the model validation obtained by combining the training and test sets. The Table 3 compares the accuracies among the proposed Mel-VGG16 and others containing CNN-LSTM on 2D CNN layer with LSTM layers. ResNet-SVM, ResNET-SVM models, an ensemble model about SVM and 2D CNN-based ResNET-18, Snapshot CNN on LeNET-5 with cyclical scheduler of learning rate (LR), WDCNN relied on 1DCNN and parallel architecture of the LSTM, SRDCNN on residual 1D dilated CNN employing the LSTM input gate architecture [8]. As the listing in the following Table, there were just few differences in the fitting about the each load. The proposed model that included the Mel-Spectrum, which can reflect the spectral feature characteristics, demonstrated best performance.

Table 3. *Accuracy (percentage %) of the models*

	Mel-VGG16	CNN-LSTM	ResNet-SVM	Snap-CNN	WD-CNN	SRD-CNN
A to B	98.8	99.54	90.22	94.44	93.60	88.66
A to C	97.33	95.05	92.34	91.80	92.88	93.99
B to A	96.88	92.11	87.34	92.88	93.38	90.67
B to C	96.77	96.22	88.56	93.66	91.40	84.60
C to A	99.33	94.78	91.45	92.23	90.39	92.45
C to B	97.55	92.88	83.35	86.69	89.36	96.21

The models that used the CNN architecture without spectral feature steps generally performed lower performance than the model that integrated with the Mel-Spectrum block, which notices that the model encounters difficulty in fitting to other load ranges. The model demonstrated the best performance on the one hp load training, since its performance usually decreased when on the three hp load training. In addition, it demonstrates the best performance based on the one hp to two hp and the lowest accuracy based on the two hp to three hp. It can noticed that the fitting experiments with respect to each load not regarding to the distance about each load. The proposed method generally obtained good accuracy in Transfer Learning (TR) about each load in comparison with the other models. Moreover, the Mel-VGG16 generally demonstrated best results unconcerned about the performance with load conditions. Accuracy is a metric [9] for evaluating the models can calculated in terms of positives and negatives as follows equation:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

TP: A positive sample correct classification process.
TN: A negative sample correct classification process.
FP: A negative sample misclassification procedure.
FN: A positive sample false classification procedure.

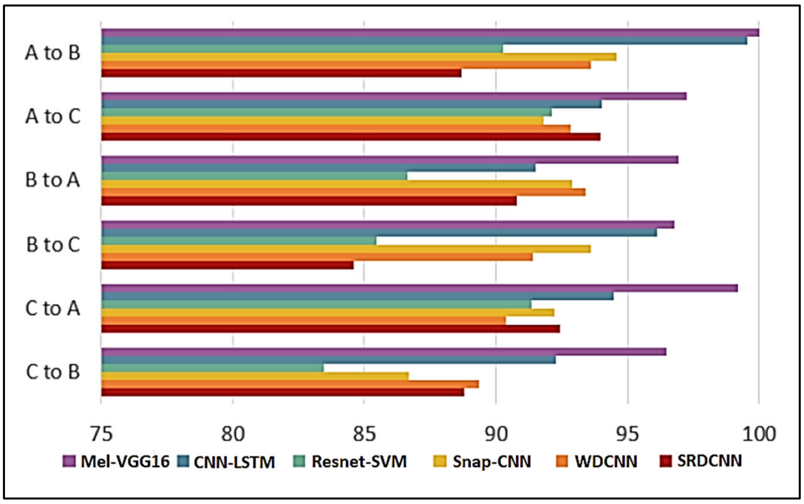

***Figure 3**. Performance Accuracy.*

5. Conclusion

The major research contribution is that it handles the problem of imbalance data in the time-series format about industrial machines and bearings in the steps of data augmentation. In addition, faults can detected early by considering various types of noise in actual industrial environments. Also, it contributes itself to the build of a data based, system of intelligent failures diagnosis for making better productivity of the mentioned machinery equipment with employing Mel-spectrogram that include variety of features extracted from the data of raw signals. The proposed Mel-VGG16 model, which combines the Mel and VGG16, not only allows updated classification performance but also overcomes many problems faced in current intelligent techniques of the databased fault diagnosis, such as variations in the data format of time series, robustness to noise and load. The Mel-VGG16 validated using datasets of valves, pumps, fans, and slide rails for bearings about industrial machines. The model performed better than current fault diagnosis based on the supervised learning methods in different real environments. The proposed method able to extract the Mel-spectrogram spatial features that represent the characteristics of apparent noise in the 2D and 1D CNN models. In addition, it can effectively detect healthy and unhealthy data by extracting the datasets of time-series vibration features in VGG16 layers. To confirm the performance of the Mel-VGG16 model, as future work, we planned to adding noises under different conditions to the datasets about other equipment types such as gearboxes and motors.

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