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Article Title: Intelligent Machine Fault Diagnosis Using Accurate CNN and Transfer Learning

Intelligent Machine Fault Diagnosis Using Accurate CNN and Transfer Learning

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ABSTRACT

The efficient fault diagnostic techniques are needed to assure stability and dependability of mechanically operated equipment in the evolution integrated large scale industrial applications. The Deep Learning (DL) based approaches have a broader range of potential applications because of their end-end encrypted qualities, which are in contrast to the time commitment and poorly maintained performance of standard Machine Learning (ML) based approaches. Nevertheless, the DL methods has some issues including more number of activation functions, challenging control parameter tuning and restrict the system performance etc. Therefore, this paper suggests using accurate Convolutional Neural Network (CNN) and Transfer Learning (TL) to determine problems in intelligent machines. With help of TL algorithm, the high accuracy is attained. Furthermore, Continuous Wavelet Transformation (CWT) is used in data processing to transform vibration signals into 2-D images, and CNNs is used in place of fully connected layers to improve classification. The obtained results of the confusion matrices and convergence curve is evaluated in Python Jupiter platform. These findings shows that the proposed technique is accomplished the highest accuracy under a wide range of conditions.

Keywords: CNN, TL, DL, CWT, Fault diagnosis

1 Introduction

Recent years, the electrical and mechanical machines improvements are currently highly concentrated on integration and automation. The probability of failure increases slightly when the difficulty and polytrophic properties of the operating parameters and working conditions in the mechanical and electrical fields are combined, so there is an urgent need for accurate and effective fault identification for complex equipment to improve the system's dependability and security. [1, 2]. Mechanical fault diagnosis, which is fundamentally pattern recognition and classification problems, is a comprehensive technique that spans several disciplines to monitor, diagnose, and anticipate the running status of machine equipment and assure its safe operation. Data gathering, feature extraction, and health state recognition are the three main steps in defect diagnosis traditionally [3]. In order to gather information including instantaneous speed, vibration and current m any sensors are typically put on machines. This process is known as

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data acquisition. By transforming the data into a low level vector representation, feature extraction entails removing some sensitive features from the collected data. This typically involves Time-Domain Analysis (TDA), Frequency-Domain Analysis (FDA) and Time-Frequency Analysis (TFA) [4-5]. ML based detection methods are utilized to mapping associations between retrieved corresponding health statuses and features for health state recognition.

The authors have been constantly exploring the fields of feature extraction, signal processing, intelligent fault diagnosis, and many diagnostic methods for specific problems have been presented. In [6] Support Vector Machines (SVMs) are utilized to detect defect fault types after the Filtering method, Hilbert-Huang Transform (HHT), and energy entropy are used to extract the fault characteristic of the rotor bearing system.. Experiments are used to validate the effectiveness of this signal processing method. TL is additionally effective in fault detection research [7], in which researchers have been capable of attaining excellent accuracy on three major mechanical datasets by using TFA images as inputs and TL to accelerate CNN training. DL, a key component of ML, has advanced the study of artificial intelligence and been successfully applied in numerous different academic domains, such as image segmentation. [8], object detection [8, 9], smart manufacturing [10] and natural language processing [11, 12]. A three-stage novel fault diagnosis approach based on CNN and Extreme Learning Machines (ELM) is proposed in [13]. To begin, the CWT is used to generate pre-processed representations of raw vibration signals. Second, to extract high-level features, a CNN with a square pooling architecture is built. Due to the models complete absence of additional training or fine-tuning requirements, computational costs are greatly decreased. Finally, the diagnosis framework's classification performance is enhanced by using ELM as a powerful classifier. The findings demonstrate that the suggested method can identify different fault kinds and performs better in terms of classification accuracy than other methods. In [14] generated a novel diagnosis framework by combining TL algorithm and CNN performance is verified using wind turbine and bearing data sets. An ensemble transfer CNN method is used in [15] to analyze multichannel signals of rotating machinery under cross-working conditions, demonstrating superior performance. By combining the best features of TL, DL and ensemble learning, this method achieve the best results.

A unique intelligent fault detection technique based on CNN, CWT, and TL strategies is proposed in this paper for the identification of the health of rotating machines. The CWT is deployed to process and convert input signals into images. The TL strategy is used to speed up the CNN training process. At last, the proposed method is obtained high accuracy is compared to other fault diagnosis approaches, including compound failure detection and single point diagnosis,

2 Proposed System Description

Figure 1 illustrate block diagram for proposed machine fault detection system.

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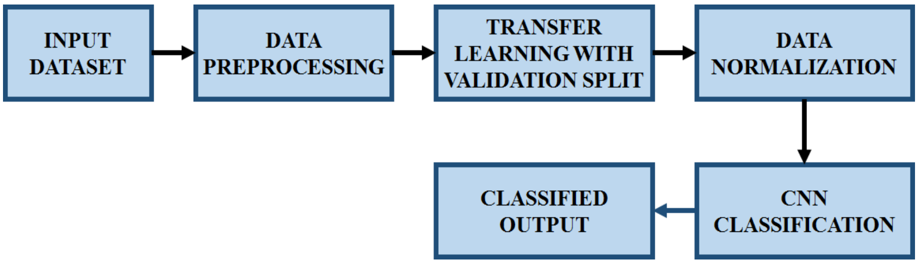

Figure 1: *Block diagram of suggested system*

The suggested system employs accurate CNN and transfer learning to identify intelligent machine faults. TL is combined with split validation and convolutional neural networks in this system (CNN). The validation split aids in model performance improvement by fine-tuning the model after each epoch. The input dataset was used in the early stages of the data preprocessing process. The dataset is then accepted for the next transfer learning process. A split strategy is used in transfer learning with validation to help enhance model performance and decrease time consumption. The data is processed after the normalization stage. The data normalization process is used in subsequent queries and analyses. The information is then passed to the CNN classifier. Finally, the output is predicted.

3 Proposed System Modelling

3.1 Data Preprocessing

Data preprocessing, a subset of data preparation is any kind of processing performed on raw data in order to prepare it for further processing. To begin, the data preprocessing system is used to obtain enough raw vibration signals from rolling bearings in various fault states. By segmenting each original vibration signal by length, equal-length samples are generated for each fault state. Lastly, a sample set is created using samples from various fault states, divided into two parts: a training sample set and a test sample set.

3.2 Transfer Learning

TL is a Machine Learning (ML) research issue that concentrates on storing gained knowledge while tackling machine related problems. ML technicians are attempting to make ML as human-like as conceivable by developing algorithms that facilitate TL processes. Typically, ML algorithms are designed to address separate tasks. Methods for transferring knowledge from one or more of these source tasks in order to enhance learning in a related target task are evolved through TL. The goal of this transfer of learning strategies is to aid in the development of ML so that it is as efficient as human learning.

3.3 Validation Split

Split Validation is a method for predicting a model's fit to a hypothetical testing set when an explicit testing set is unavailable. Split Validation also allows for training on one data set and

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testing on a different explicit testing data set. The validation split contributes to the model's performance.

3.4 Data Normalization

The process of reorganizing data within a database so that users use it for further queries and analysis is known as data normalization. Simply put, it is the procedure for producing clean data. This includes removing redundant and unstructured data and ensuring that the data appears consistent across all records and fields.

3.5 Convolutional Neural Networks

CNN is a popular deep learning model with powerful image processing capabilities. To avoid manual feature extraction operations, it can perform automatic abstracts of hierarchical features. A CNN typically contains fewer parameters than a fully connected network due to its characteristics of local receptive fields, weight sharing, and sparse connections, which means it can more efficiently utilize data, dramatically reduce training difficulty, and is not easily over.

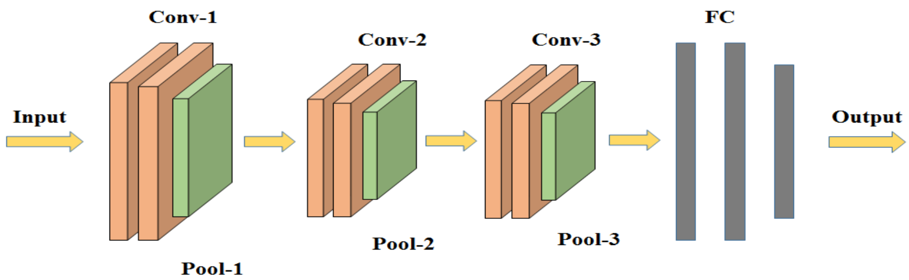

Figure 2: *CNN model*

As shown in Figure. 2, the architecture of a standard CNN commonly includes convolutional layers, pooling layers, and fully connected layers.

3.5.1 Convolutional Layer

The extracting features process is carried out through convolutional layers, in which an exactly equal square convolutional kernel that can be assumed of as a scanner with a specified window size is used to slide on the input feature graph and scan every pixel according to a specified stride. The convolutional kernel will coincide with the several pixels for each step, and the respective elements in the overlap area will be multiplied, summed, and offset to obtain a new pixel value of the output feature image.

3.5.2 Pooling Layer

Pooling layers are frequently placed behind convolutional layers and combined to generate convolution blocks. To construct the deep convolution, multiple convolution blocks are stacked

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architecture. The pooling layer subsamples image data to remove redundant information, reduce the amount of feature data, and improve the algorithm's robustness and calculation efficiency. The most frequent pooling procedures are average pooling and maximum pooling, which signify that the average value or the maximum value inside a pooling zone is picked to be propagated to the next layer, respectively.

3.5.3 Fully Connected Layer

The fully connected layers apply classification or regression using the one-dimensional retrieved features from earlier convolution blocks. In order to produce a probability distribution that may represent the overall outcomes of each category, softmax regression is frequently utilized at the output layer. With the softmax classifier, each element in the output vector adds up to 1, which coordinates the cross-entropy loss to update the network parameters. The output features in this study are extracted by a linearly separable CNN. To develop an appropriate multiclass classifier, the linear kernel is used.

4 Results and Discussion

Machine Fault Prevention Technology (MFPT) bearing fault datasets are also commonly used to diagnose rolling bearing faults. This dataset is one of the crucial references to confirm the effectiveness of the suggested method. Three sets of experimental bearing vibration data and three real fault data make up the MFPT dataset. The baseline bearing data, outer race fault data with varied loads, and inner race fault data with varying loads are some of the items in the three sets of experimental bearing vibration data. The input dataset is shown in Figure 3.

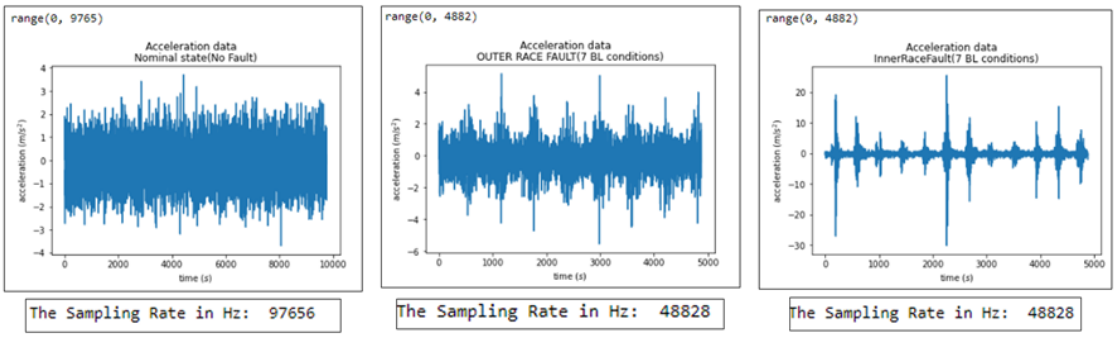

Figure 3: *Data sets of MPFT fault*

Split Validation is a technique for predicting the fit of a model to a hypothetical testing set in the absence of an explicit testing set. Examples of the validation split are shown in Figure 4. Moreover, the Split Validation operator enables testing on an explicit test data set while training on a different data set. Similarly, Figure 5 represents the waveform for Time frequency Image Outer Race fault.

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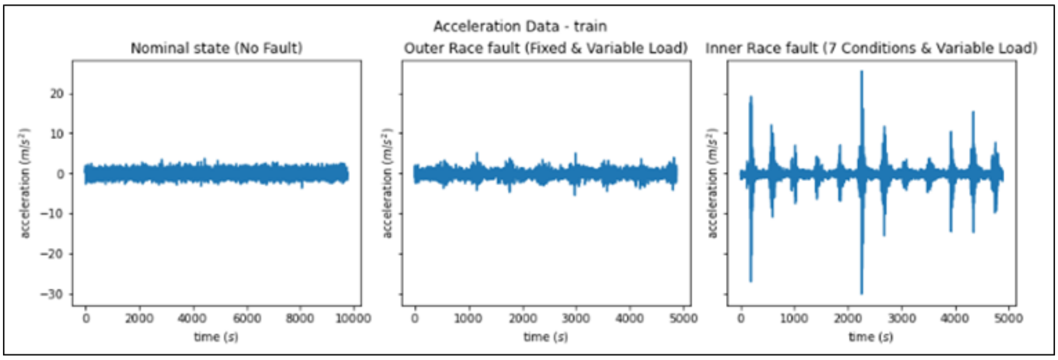


Figure 4: *Validation Split*

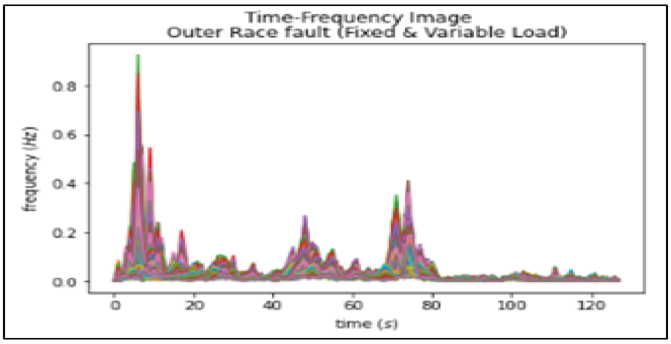
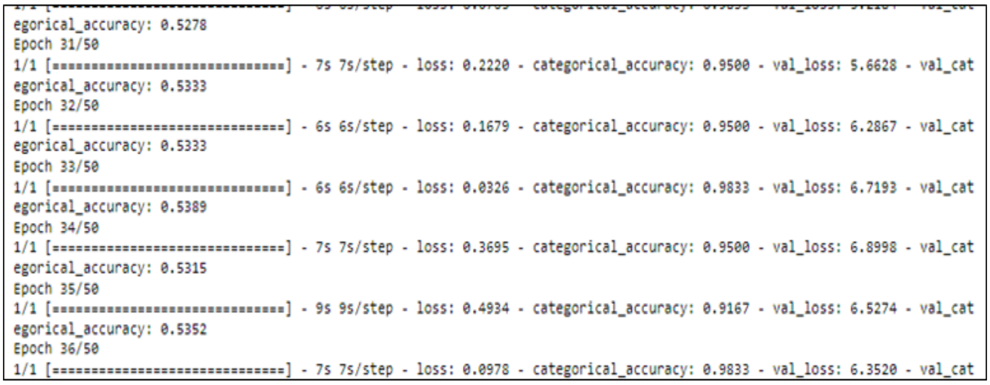


Figure 5: *Time – Frequency waveform*



```
egorical_accuracy: 0.5278
Epoch 31/50
1/1 [==============================] - 7s 7s/step - loss: 0.2220 - categorical_accuracy: 0.9500 - val_loss: 5.6628 - val_cat
egorical_accuracy: 0.5333
Epoch 32/50
1/1 [==============================] - 6s 6s/step - loss: 0.1679 - categorical_accuracy: 0.9500 - val_loss: 6.2867 - val_cat
egorical_accuracy: 0.5333
Epoch 33/50
1/1 [==============================] - 6s 6s/step - loss: 0.0326 - categorical_accuracy: 0.9833 - val_loss: 6.7193 - val_cat
egorical_accuracy: 0.5389
Epoch 34/50
1/1 [==============================] - 7s 7s/step - loss: 0.3695 - categorical_accuracy: 0.9500 - val_loss: 6.8998 - val_cat
egorical_accuracy: 0.5315
Epoch 35/50
1/1 [==============================] - 9s 9s/step - loss: 0.4934 - categorical_accuracy: 0.9167 - val_loss: 6.5274 - val_cat
egorical_accuracy: 0.5352
Epoch 36/50
1/1 [==============================] - 7s 7s/step - loss: 0.0978 - categorical_accuracy: 0.9833 - val_loss: 6.3520 - val_cat
```

Figure 6: *CNN Classification*

Demonstrations of the CNN Classification are shown in Figures 6. A multilayer Perceptron makes up CNN, a sort of deep learning that is mostly utilised in voice and image recognition. A drawback of the Fully Connected Layer is that CNN can apply filters to input data to preserve the appearance of input data. Typically, CNN is divided into three classes based on the input data and filters, multiplied by one another and then added. To match input data and weights, the affine layer, which consists of a Fully-connected layer.

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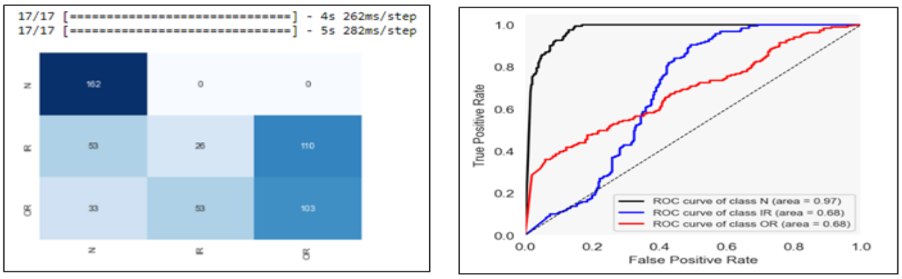

Figure 7: *Output of CNN Classification*

The feature vectors of each bearing condition that were retrieved in the preceding section were assembled into a feature sample set for the defect identification portion. Following that, the training set and testing set were divided at random in a 2:3 ratio. To obtain the average identification accuracy, the CNN classifier is run ten times for the bearing states categorization. Figure 7 provides illustrations of the CNN classification Output.

5 Conclusion

Machine fault diagnosis has become more crucial as the industrial sector has grown quickly in order to maintain safe equipment operation and production. As a result, numerous strategies have been investigated and developed in recent years, with intelligent algorithms developing at a particularly rapid speed. This paper proposes a new advanced fault detection method, in which raw signals are processed by CWT, a diagnosis model is constructed, and TL is used as the best method to detect faults. Employing efficient CNN and transfer learning to find errors in intelligent machines. By transferring low-level features and adjusting high-level layers, the approach increases precision while using less processing power. The suggested strategy is effective, feasible, and has a promising future as a tool for identifying bearing faults. The present method is ideal for diagnosing a variety of bearing faults and has a significant potential for use in practical applications, as shown by all the results.

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