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A DEEP CONVOLUTIONAL TRANSFER LEARNING APPROACH FOR SMART BEARING FAULT DETECTION AND DIAGNOSIS

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Abstract- With the rise of intelligent manufacturing and Industry 4.0, a great deal of focus has been placed on intelligent computing techniques such as deep learning for detection and classification of bearing problems. The deployment of deep learning models may, in certain circumstances, dramatically reduce the influence of human while also increasing fault diagnosis accuracy. Without huge, meticulously organized datasets, such as ImageNet, it is difficult to train deep learning models like a Convolutional Neural Network (CNN) model. The work uses Case Western Reserve University (CWRU) dataset for rolling bearing in the training and validation processes. A new deep transfer learning approach based on Visual Geometry Group (VGG-19) model is proposed for smart bearing fault diagnosis. First, a method is adopted to convert vibration signals in time domain to RGB images. Next, the VGG-19 pretrained model is deployed for extracting features by converting images and obtaining their features. Finally, the extracted features are utilized in training process for a SoftMax classifier. The proposed method is successfully implemented, and the results show the strength of fault diagnosis with a testing accuracy of 99.57%.

Keywords: CNN, Transfer Learning, VGG-19, Fault Detection and Diagnosis.

1. INTRODUCTION

Since 2014, the Fourth Industrial Revolution (Industry 4.0) has been of great interest to the corporate, industrial, and academic research groups [1-3]. Industry is being made intelligent, autonomous, and sustainable through the development of new technology [4].

Due to the ubiquity of sensing and actuation afforded by distributed IoT platforms, fault detection is a popular research area that focuses on the identification and identification of system and process problems. Rolling bearings serve as an important component of rotating machines, and their quality is linked to the mechanical system safety. Due to its complex operating environment, this component is also one of the most susceptible to damage. As a result, fault diagnosis and monitoring of rolling bearing operating conditions are required [5]. Deep learning (DL) techniques have been used to extract and adaptively classify characteristics of raw vibration signals in recent years. Jia et al. [6] proposed a fault diagnostic technique using one dimensional CNN, which has been tested on motor bearing data. Recurrent neural network with wide deep CNN network connections had been proposed by Alex and Martin [7] to identify bearing defects using data obtained from electromechanical systems using a dual-path recurrent neural network. Ahmed and Nandi [8] A two-stage RGBVI-CNN diagnosis strategy for roller bearing faults is proposed and assessed. Zhang et al. [9] developed a bearing fault detection model using principal component analysis and the fuzzy C-means clustering approach to minimize feature dimensionality and classify faults, respectively. Guo et al. [10] developed a transfer learning CNN network for failure diagnostics of bearings on various machines.

In this work, an approach based on VGG-19 network for faults detection and diagnosis is developed with the pre-trained VGG-19 network that serves as features extractor. VGG-19 is a well-known CNN model that has been used to classify images, recognize patterns, and recognize speech [11]. Because the VGG-19 input data format is an RGB image, time-domain vibration signals of the rolling bearings need to be converted first to RGB images. Therefore, a signal to image pre-processing technique is introduced and presented in this paper. The VGG-19 network is then used for extracting the features. Finally, collected features are used to develop a SoftMax classifier that is represented by fully connected layers. The remainder of the paper's structure is as follows: The dataset is described in Section 2. Section 3 illustrates the VGG19 architecture, and the proposed methodology is explained in Section 4. Section 5 presents the findings and discussions, and Section 6 concludes the entire work.

2. DATASET DESCRIPTION

The bearing dataset is one of the most well-known datasets for machine problem diagnostics. A platform was tested and data was collected in the Bearing Data Center at CWRU University [12]. CWRU test stand was used in the data collection process, as depicted in Figure 1. Data collecting methods include microphones, transducers, and vibration sensors. The data is collected in a stable state environment with free of external influences such as noise.

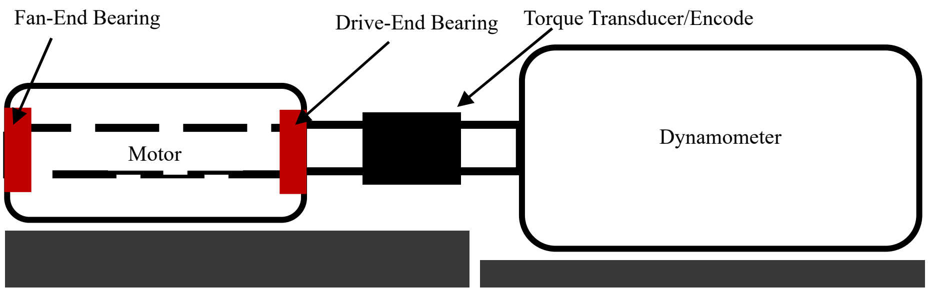


Figure 1. Schematic diagram of experimental setup to extract CWRU dataset [12]

The platform was deployed to test single bearing failure that is generated using electro-discharge machining, as shown in Figure 2. Bearings in different faulty conditions include ball, inner race, and outer race. There are three faults for outer raceway, 3 o'clock located immediately in the load zone, 6 o'clock located orthogonal, and 12 o'clock. There are many sizes present in each fault, including 7, 14, 21, 28, and 40 inches. The motor housing drive end and fan end mounted accelerometers that were used to record vibration data at sampling rates of 12 kHz and 48 kHz, respectively. Additionally, this dataset was produced at four different running speeds: 0 horsepower / 1797 rpm, 1 horsepower / 1772 rpm, 2 horsepower / 1750 rpm, and 3 horsepower / 1730 rpm. Figure 3 shows various vibration signals from rolling-element bearing with different faults.

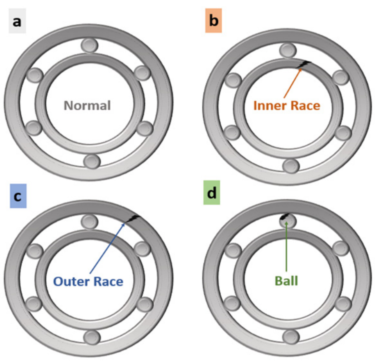
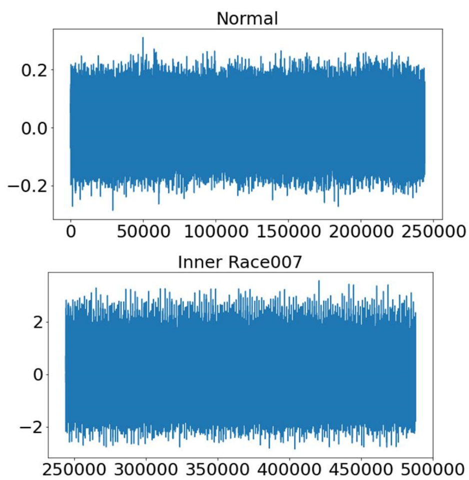
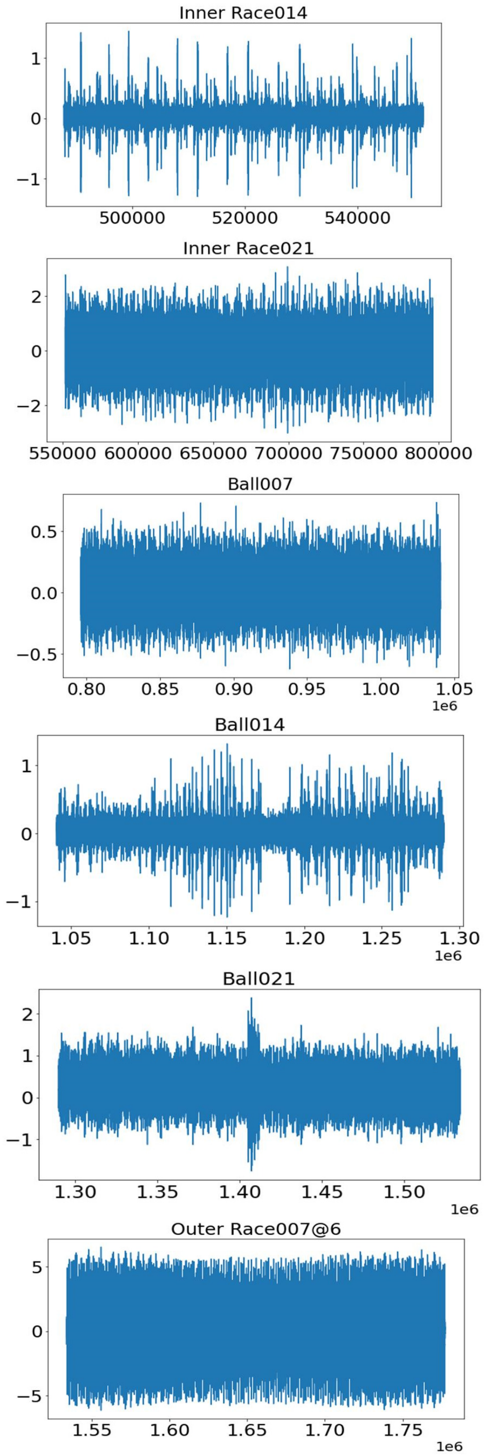


Figure 2. Bearings in different faulty and normal conditions, (a) normal and fault motor, (b) for inner_race, (c) for outer_race, (d) for ball





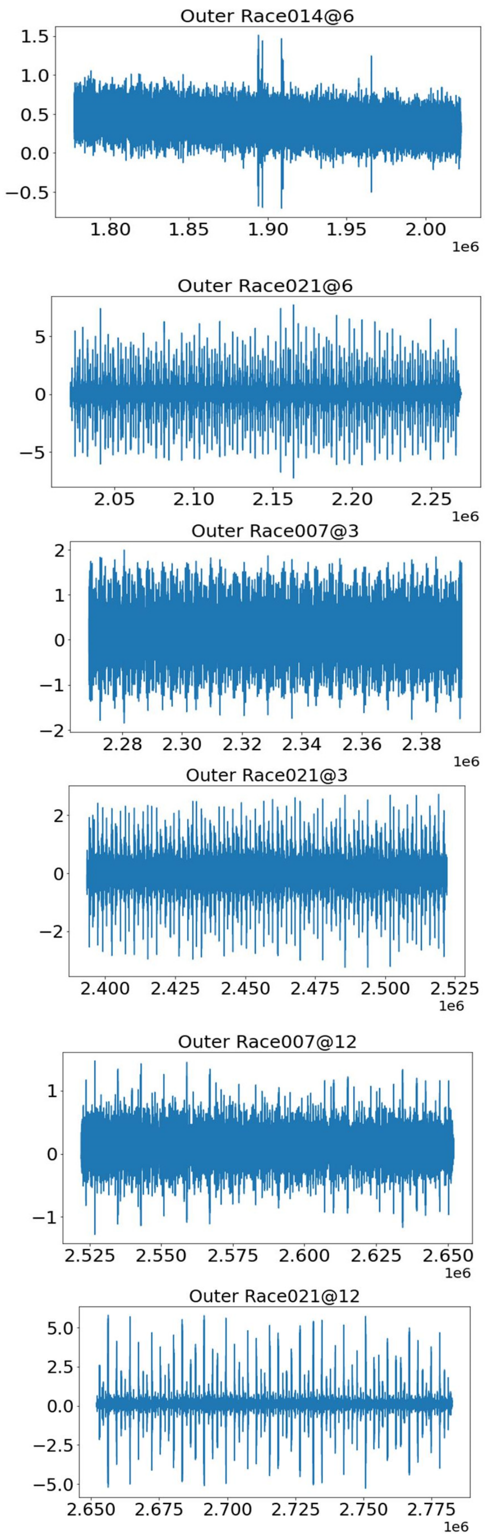


Figure 3. Rolling-element bearing vibration signals with different fault

3. VGG-19 ARCHITECTURE

Recently, deep learning techniques have been effectively applied to a wide variety of disciplines. CNN networks are a standard form of deep learning technique [13]. The CNN architecture is composed of the following layers: convolution, pooling, and fully-connected. The primary goal of convolution layers is to extract features of an input image.

At the output layer, each neuron receives inputs from some neurons in the previous layer [14]. The network is composed of many convolution kernels that learn different feature representations by convolving with the image or the previous layer. Pooling is used to eliminate redundancy, and make features more resilient following convolution process [15].

Max and average pooling are the common pooling operations [16]. A flattening layer transforms 2D pooled features into a 1D input data [17]. Similar to the completely connected layer of a multilayer perceptron, the fully connected layer determines the global compositions of the final convolutional output [18]. As CNN model computations require enormous parameters for feature extraction, the proposed method combines characteristics extracted from VGG-19 pre-trained deep learning network. VGG-19 is derived from VGG architecture, which consists of various layers, including convolution of sixteen layers, MaxPool of five layers, fully connected of three layers, and SoftMax of one layer. The first two fully connected layers include 4096 neurons, whereas the final layer consists of 1000 neurons. The network has a top five accuracy of 90.0% with size 549 MB. The number of parameters 143,667,240 [19]. The important benefit of this method is that we can easily implement transfer learning and make the network compatible with other architectures in addition to this network are its sequential blocks, whose sequential convolutional layers allow for a decrease in the quantity of spatial information required. This architecture is used to classify bearing faults because of its ability to comprehend complicated features. Figure 4 depicts the entire VGG-19 architecture.

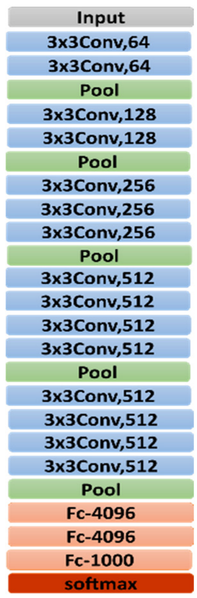


Figure 4. VGG19 architecture [20]

4. METHODOLOGY

Using pre-trained VGG-19 learning model weights, a transfer learning method is adopted and proposed to classify bearing faults in this study. Figure 5 shows the proposed methodology followed in this work.

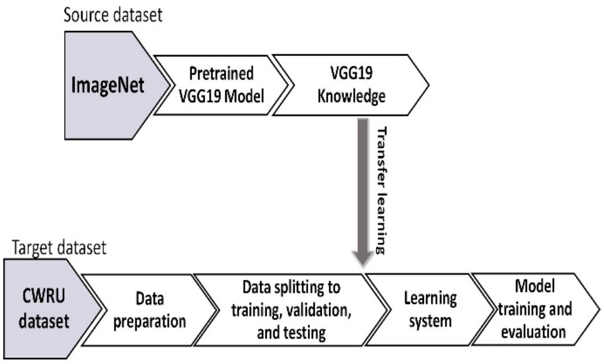


Figure 5. Work methodology carried by the proposed approach

4.1. Data Preparation

This research uses vibration-signals data from an electrical motor's rolling bearings [21], [22]. Signals were sampled at 48,000 sample/sec. Faults were categorized by considering various types and diameter sizes of faults and bearing. So, types of faults and also their severity are determined using this method. As a result, 14 classifications are obtained. Table 1 lists the used characteristic variables in the classification process.

Table 1. Characteristic variables in the bearing [12]

Fault Type	Normal, and Faulty: Inner Race, Ball, and Outer Race
Motor Speed (rpm)	1730, 1750, 1772, and 1797
Load (HP)	3, 2, 1, and 0
Fault Diameter	0.007, 0.014, and 0.021
Outer Race Position	Centered, Orthogonal, and Opposite

RGB images with a specified size are required to train the transferred model [22]. A direct method is adopted to transform vibration data of one-dimensional time-domain signals to two-dimensional grayscale images [23]. Here, the time-domain data is divided to equal segments of 10000 elements, and each element is aligned as a two-dimensional matrix of a 100×100 image. This transformation is mathematically expressed Equation (1) [24]:

$$I = \begin{bmatrix} x_t & \dots & x(t+n-1) \\ & \vdots & \\ x(t+(m-1)n) & \dots & x(t+mn-1) \end{bmatrix} \quad (1)$$

Grayscale images only have one channel, therefore replicating them into three channels and giving each channel a basis will produce two-dimensional images with three channels. Figure 6 shows the process of converting vibration one-dimensional signals to two-dimensional images.

As depicted in Figure 7, the processed images are then separated into three categories: training 70%, validation 15%, and testing 15%. The VGG-19 transferred model is trained using the training dataset and validated using the validation dataset. Testing set is simply deployed to evaluate the performance of the proposed approach and therefore, it is not deployed throughout the training process.

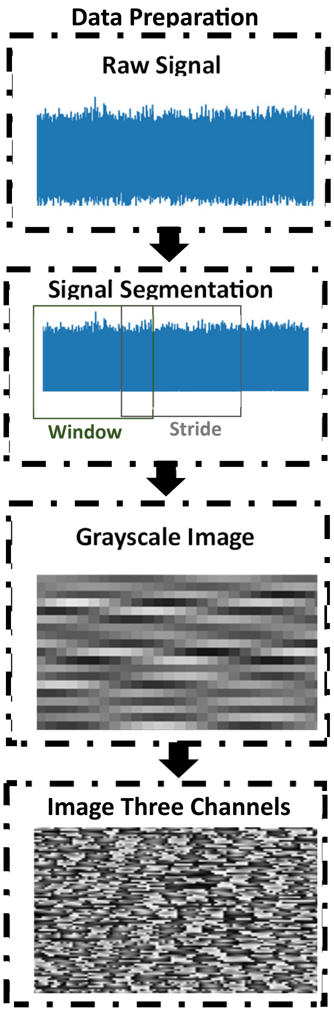


Figure 6. Conversion process of vibration signals to two-dimensional images

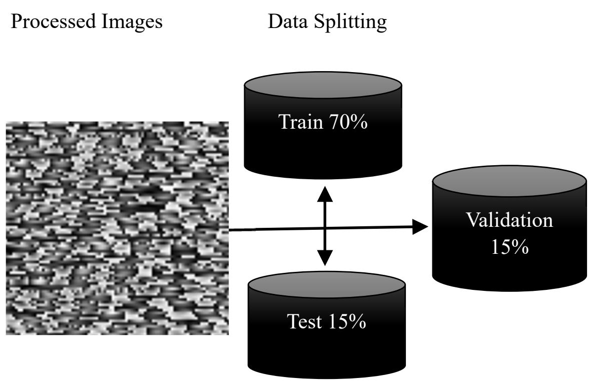


Figure 7. Data partition for learning and evaluation

4.2. Model Transfer

In this study, Transfer Learning (TL) technique is adopted and deployed to transfer pre-trained weights of the VGG19 model, and the TLVGG-19 is presented for fault detection and diagnosis. This is implemented by redeploying the feature extractor of the VGG-19 model with its pre-trained weights that were trained on the Image Net dataset.

Since the size of the input images to the model is 224×224 [25], a function is used to transform the input size to 224×224 to the preprocessed data During the fault diagnosis training procedure, as shown in Figure 8, the VGG-19 is transferred using transfer learning. In order to categorize the image, a flattening layer is provided as input to a new two FC layers, and the SoftMax classifier [14] is used. Hidden neural layers are set to 1024 and 512. In addition, dropout [26] is used to increase the TLVGG-19 performance. These layers were further improved by adjusting training parameters such as batch size, epochs number, folds per epoch, and optimizer. Adam optimization technique is used in this research to speed convergence and avoid local optimality [27], [28]. Figure 8 shows the proposed deep transfer learning architecture.

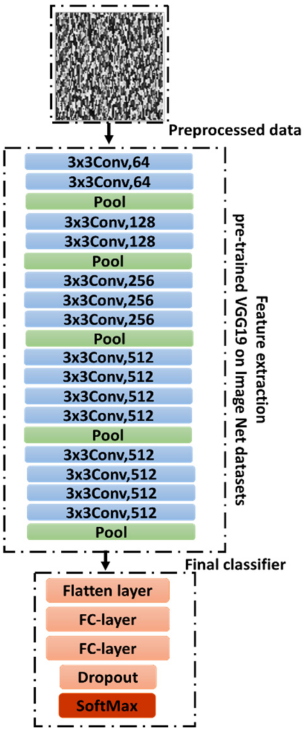


Figure 8. Proposed deep transfer learning architecture

5. RESULTS AND DISCUSSION

Accuracy and Loss percentage, confusion matrix, and t-distribution Stochastic Neighbor Embedding (t-SNE) metrics are used here to evaluate the proposed model performance. the performance of the model is measured using accuracy and loss. the performance of the model is measured using accuracy and loss, which are obtained by Equations (2) [29]:

$$Accuracy = \frac{N_c}{N_t} \tag{2}$$

The difference between the original data and the model's predictions is what is meant by loss. Since there are multiple classes, the total number of mistakes the model produced during the training or validation process can be defined as Equations (3) [29]:

$$Loss_{cross_{entropy}} = \sum_{i=1}^{n} \sum_{j=1}^{m} y_{ij} \log\left(P_{ij}\right) \tag{3}$$

The network is trained for 50 epochs using 14 classes and the VGG-19 architecture. The training accuracy and validation accuracy attained for VGG-19 are 100 % and 99.57%. Figure 9 depicts the accuracy attained for each epoch plotted on a graph. Figure 10 shows a graph of the loss. The second evaluation method, the confusion matrix [28] is used as a teaching tool. In this graph, the model's predictions are shown in the form of rows representing actual data and columns representing what is expected.

This method can be used to evaluate which categories the model forecasted more accurately and which categories had a higher propensity for inaccurate projections, allowing for a more comprehensive model study, as depicted in Figure 11. The last evaluation metric is the t-SNE, which is used for presenting multidimensional data with clear and complete separation [30]. Figure 12 shows results of t-SNE after 2000 iterations. The proposed deep learning model was trained and evaluated using TensorFlow and Keras libraries in conjunction with Google Colab GPU. Using the vibration signals generated by the induction motors in Figure 1, the performance of the proposed fault diagnosis approach can be evaluated. The vibration signals were separated into 10,000 data point sequences without overlap. The more the segmentation, the greater the precision. Adam optimizer approach is a potent strategy that iteratively updates weights and reduces gradient error between ground truth labels and prediction outputs. As see in Figure 10 that as the epoch increases, the loss skew tends to converge.

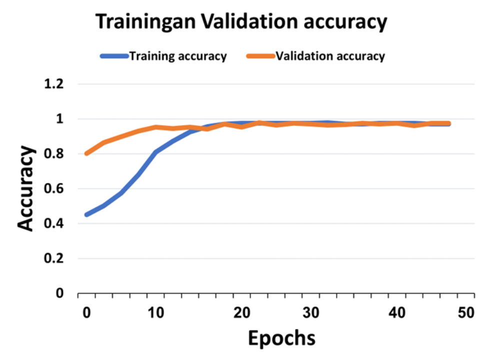


Figure 9. Accuracy graph of VGG19 with 14 classes

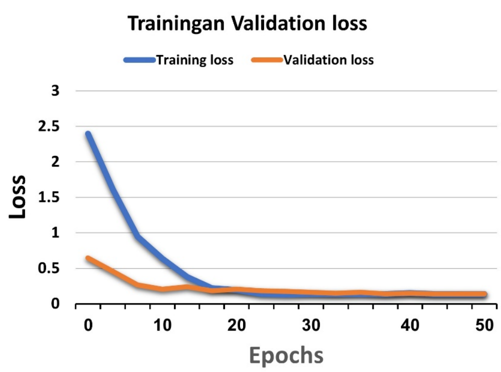


Figure 10. Graph of the loss with 14 classes

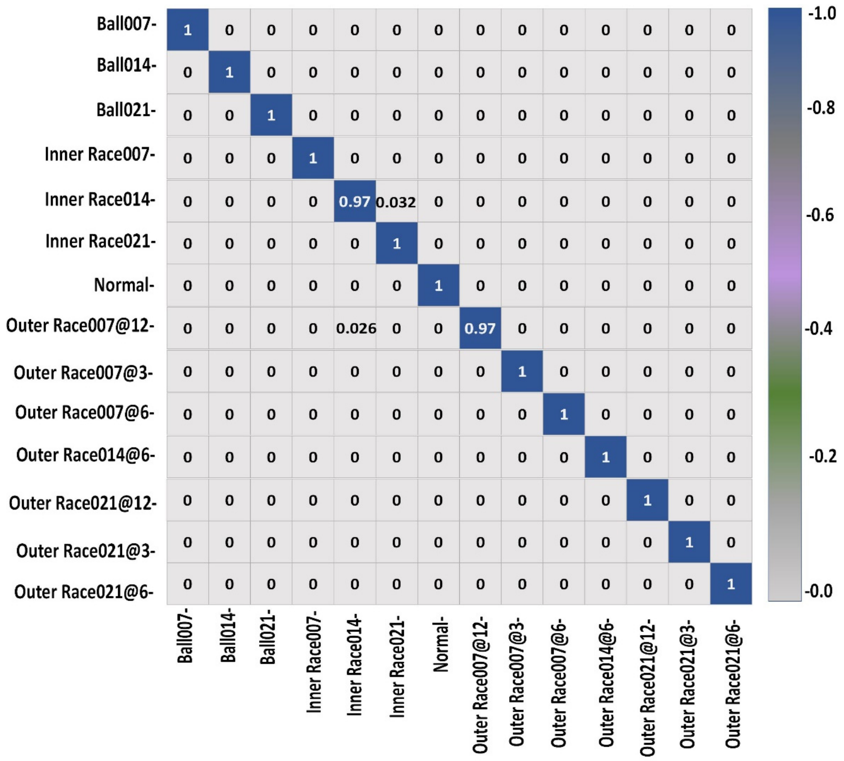


Figure 11. Confusion matrix of 14 classes

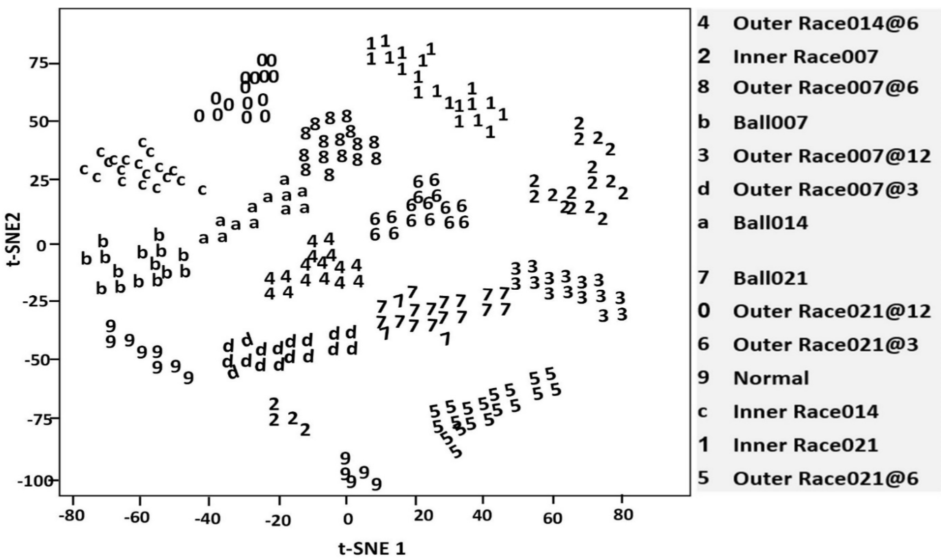


Figure 12. The t-SNE evaluation

In the last several years, a number of studies have been done on fault diagnosis. This is an issue that researchers are working to resolve. Table 2 shows the results of our model compared with other similar research in this section. The proposed model has a classification accuracy of 99.57 % for the fourteen classes. It shows a good performance for fault detection and diagnoses and it outperforms other models proposed in recent up-to-date literature.

Table 2. Models' comparison for bearing fault diagnosis

Methods	Accuracy	Ref
Proposed Model	99.57 %	
1D-CNN	98.83 %	[31]
2D-CNN	99.41 %	[32]
CNN-SVM	99.44 %	[33]

6. CONCLUSIONS

Industry 4.0 concepts have sparked a surge in research into ways for identifying and categorizing machine defects using intelligent approaches. This work provides an approach based on pre-trained VGG-19 deep transfer learning for fault diagnostics. The proposed TL VGG-19 approach relies on motor-bearing data created by CWRU. It achieved an accuracy of 99.57 % that outperforms current available models in up-to-date publications. The pre-trained VGG-19 network was reused to help the VGG-19 network to perform admirably in terms of final prediction accuracy and training time, demonstrating a significant amount of potential in the field of fault diagnosis.

NOMENCLATURES

1. Acronyms

CWRU	Case Western Reserve University
CNN	Convolution Neural Network
VGG	Visual Geometry Group
TL	Transfer Learning
FC	Fully Connected
RGB	Red Green Blue
2D	Two Dimension
1D	One Dimension

2. Symbols / Parameters

I: denotes image of the signal
$x(t)$: vibration function with respect to t
n: total number of samples.
N_c: correct number of predictions made
N_t: true data total number.
$y_{i,j}$: true data
$p_{i,j}$: predicted probability for a model

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