An efficient model for induction motor fault detection using a deep transfer learning network

Alasmer Ibrahim
Wolfson Centre for Magnetics
Cardiff University
Cardiff CF24 3AA, UK
Ibrahima21@cardiff.ac.uk

Fatih Anayi
Wolfson Centre for Magnetics
Cardiff University
Cardiff CF24 3AA, UK
Anayi@cardiff.ac.uk

Michael Packianather
High-Value Manufacturing Group
Cardiff University
Cardiff CF24 3AA, UK
packianatherms@cardiff.ac.uk

Abstract

The reliability and availability of induction motors is significant which can be achieved by monitoring the performance of the motor regularly in the industry. Knowledge-based approaches can be able efficiently to deal with the sensor data for ensuring the reliability with high motor performance. Recently, deep learning networks based on machine learning structures have provided an accurate and faster framework for fault diagnosis by ignoring feature extraction process. However, training a deep convolutional neural network (CNN) is complex and time-consuming procedure. For this reason, this paper proposes a novel deep learning procedure for fault diagnosis using thermal images data of the induction motor applying residual neural network with 50 convolutional layers as feature extraction. The pre-trained deep convolutional (ResNet-50) of the transfer learning is trained on ImageNet based weight. This work includes the effect of data augmentation for enhancing the performance of the proposed model and ensuring its robustness for fault diagnosis. Firstly, the collected images are pre-processed resized as input datatype of Resnet-50 network. Next, transfer leaning model based on convolutional neural network (ResNet-50) structure is built to process the prepared images. Lastly, classifying the prepared images based on the related conditions of the induction motor. The experimental result shows that the proposed model has achieved an accuracy of 99.98%. The presented model has further compared with recent deep learning applications, and it has proved its robustness in fault diagnosis.

Keywords: Thermal mages, ResNet-50 model, pre-trained model, fault diagnosis.

I. INTRODUCTION

It is possible for several problems to arise unexpectedly in the induction motors and causing a failure during even the normal operation which can lead to production loss. However, by applying condition monitoring to check the behavior of the motor. So, the motor lifetime can be extended, and maintenance cost can be minimized [1]. Many types of defects may occur in an induction motor, which can be categorized under electrical and mechanical defects which are caused by abrasion, unbalanced loads, electrical stress. Mechanical failure such as the bearing fault is the most frequent fault in the induction motor which represents around 53% of the motor faults [2]. Electrical fault such as the rotor fault appears with 10% of the motor failure [3]. In addition, stator fault stator failure occurs typically at a rate of 38% of motor failure [4]. In recent years, many researchers have focused their attention on fault diagnostics in different science fields. As a common type of fault diagnosis, data-driven fault diagnostic technique which has attracted the researcher’s attention may construct failure modes using the historical data of the application without the need of signal symptoms [5]. This can make it particularly adapted for complex systems with a large amount of data [6]. With the faster growth of smart manufacturing, the amount of data produced by machines and devices is further increased and easier to be collected. The ability to learn about huge amount of historical data is the most important aspect of the data-driven fault diagnostic technique [7]. A number of methods have applied in this field such as K-Nearest Neighbor (KNN), support vector machine (SVM), Random Forest algorithm (RF), Invasive Weed Optimization algorithm (IWO), and artificial neural networks (ANN). In [3] KNN was suggested to build a diagnostic system to detect the degradation of the bearing and the result was satisfactory based on the diagnostic performance. SVM is proposed in [8] to build a reliable fault diagnosis scheme for incipient low speed rolling elements bearing failure. The Experimental results reported that the proposed model has achieved a highest classification accuracy of 98.4%. In [9] RF was intended to achieve a novel hybrid approach for fault diagnosis of rolling bearings. The obtained results showed that the proposed method reached a classification accuracy rate of 88.23%. In [10] a new diagnostic model is proposed applying the current and the vibration signals. The model combines the invasive weed optimizer with three different machine learning algorithms. The results have confirmed that the performance of the proposed model is satisfactory. A novel model was proposed in [11] for diagnosing bearing faults. The experimental results showed that the proposed scheme is a successful framework. As the aforementioned machine learning methods are comprised of feature extraction and feature selection processes [12]. It is however difficult to extract discriminative features to build a robust classification model [13]. Therefore, Deep learning (DL) has developed as a new area of research in the machine-learning science in order to address the issues mentioned above which it is capable of autonomously learning the representation attributes from raw data [14]. The use of DL

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approaches in the field of fault diagnosis has become increasingly popular such as deep belief network (DBN) and convolutional neural network (CNN) [15]. The use of such DL network show great potential for fault diagnosis can achieve the reduction of the handcrafted features impact created by feature extraction algorithms. However, fault identification requires a minimal number of labelled samples which limit the final prediction accuracies. In addition, DL models can include up to 5 hidden layers [16]. So, it is difficult to train deep CNN models without a huge amount of training datasets to train deep CNN models. Several studies have built deep CNN models by combining transfer learning techniques (TL) on ImageNet [17], then applied these CNN models as feature extractors on a small dataset in another domain [18]. Hence, deep TL can offer promising approaches to the problem of fault diagnosis. TL model uses deep learning network (DL) to transfer high-level properties from source data to target data [19]. One of the advantages of deep transfer learning is to use a layer-by-layer learning pattern to extract attribute from the input data, which allows its deep architecture to produce high data representations with a potential enhancement of the diagnosis performance.

As a result of this, this work proposes an efficient fault diagnosis model using transfer convolutional neural network based on residual neural network as a feature extractor considering 50 layers. ResNet-50 can extract high-quality features from images on ImageNet. It is anticipated that the suggested (ResNet-50) would increase the final prediction accuracy on fault diagnosis. The proposed model is investigated using thermal images of the induction motor.

The rest of this paper is structured as follows: Section II defines the related work; Section III presents the proposed model; materials and methods are illustrated in section IV; Section V reports results; and the conclusion is drawn in section VI.

II.RELATED WORK

This study includes data-driven fault diagnosis utilizing deep CNN networks and feature transfer. Due to the rapid development of smart manufacturing, data-driven fault detection has emerged as a popular research topic in recent years[12]. In [20] a new fault diagnosis based on the use the transfer learning of sparse autoencoder method and the experimental result has achieved a high accuracy of 99.82 %. In [21] The use of recurrent neural networks and dynamic Bayesian modelling to detect faults in induction motors was investigated. The model has carried out the real-time experiments with three motors, estimating the probability distributions for the motor's conditions and the model achieved an efficient result. A new model based on a performance comparison of sparse autoencoder with SoftMax regression was proposed in [22], and the result was satisfactory. In [23] a new model was proposed for intelligent fault diagnosis applying normalized sparse autoencoder of air compressors. In [24] a fault diagnosis method was suggested using stacked sparse autoencoder with ensemble empirical mode decomposition and the result has proved the robustness of the extracted features. In [25] deep learning model based hierarchical diagnosis method to diagnose the rolling element bearing fault, the obtained result has investigated the reliability of the model. A new deep transfer learning model was suggested in [26] to diagnosis the industry application faults, and the achieved result has investigated several state-of-art transfer learning result considering the operating condition and fault severities. Recently, an adaptive deep CNN model was suggested in [27], and the result was effective and robust. In [28] a hierarchical adaptive CNN was investigated for weight updating by adding an adaptive learning rate and a momentum component. In [29] an intelligent fault diagnosis model using hierarchical CNN was proposed for diagnosing rolling bearing faults. The result has proved the effectiveness of the CNN model. A new fault diagnosis based on the use of CNN with empirical mode decomposition was proposed in [30] and its results have indicated that more accurate and reliable than previous approaches. In [31] a CNN model-based approach for fault diagnosis was suggested for rotating machinery. The model compared to traditional techniques that rely on manual feature extraction, the results have demonstrated that the suggested method provides superior diagnostic performance. As reported by the aforementioned methods, there are not any published studies using to ResNet-50 model-based CNN tested on thermal images data of the induction motor. Therefore, a novel intelligent model for fault diagnosis is proposed in this work applying the pre-trained ResNet-50 model with an adjusted densely connected classifier. The robustness of the proposed model was investigated using thermal images of different conditions of the induction motor.

III.PROPOSED TECHNIQUE

The presented work builds a novel application that uses a pre-trained (ResNet-50) model based on CNN as a feature extractor. The whole dataset is divided into train, validation, and test subsamples which each subsample continuously plays the role of validating dataset to achieve the reliable performance for fault diagnosis. This model is trained by applying the weight of the ImageNet dataset. The block diagram of proposed model is shown in figure 1. Images are pre-processed with class imbalance technique and data augmentation technique. This can affect the achieved results by controlling the image zoom, horizontal flip, rotation, translation, and image orientation. Then, the structure of resnet-50 network was initialized restoring the pre-trained weight in ResNet-50. Next, the images are taken as input to obtain the features and training the model for the classification purpose. SoftMax classifier layers were added with 128 hidden neurons and determined with seven label classes. Adam optimizer, ReLU activation function, L2 regulation, categorical cross-entropy (CE), and dropout layers.

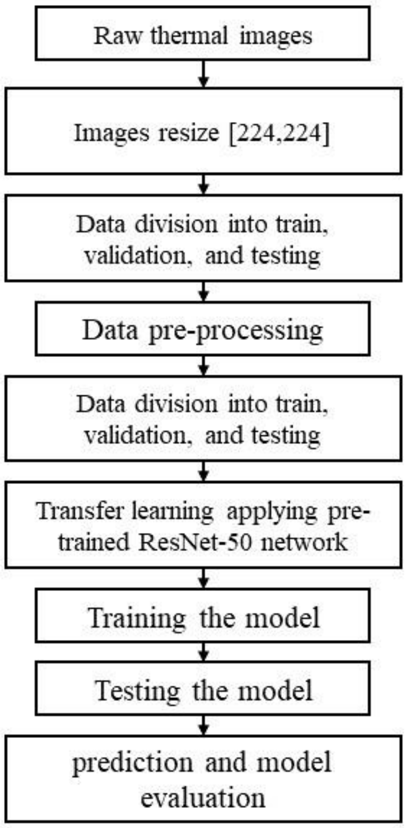

Figure1. Block diagram of the proposed network

The categorical cross-entropy

$$(CE) = -\sum_{i}^{C} t_i \log(f(s)_i) \quad (1)$$

Where t_i is the ground truth, and $f(s)i$ is the standard SoftMax.

$$f(s)_i = \frac{e^{s_i}}{\sum_i^C e^{s_j}} \quad (2)$$

Where s_i presents the given the class, s_j is the scores derived from the net for each class.

IV.MATERIALS AND METHODS

A. Deep ResNet-50 network architecture

CNN models' ability to accurately diagnose faults is constrained with the help of transfer learning that trained on ImageNet [17]. This work uses ResNet-50 that trained on ImageNet to classify different thermal images conditions of the induction motor. Resent-50 model has achieved an efficient performance in the field of images classification which extracts good quality features of images for building a strong fault diagnosis model.

The proposed ResNet-50 is consisted of 50-layers deep CNN[32] which includes one max- pooling layer, one average pool, and 48 convolutional layers. The basic structure of ResNet-50 is illustrated in figure 2 that used as feature extractor. The ResNet-50 is composed of five convolutional blocks of layers. The final convolutional block of a 50-layer deep residual network produces deep residual features that pre-trained on ImageNet. The convolutional blocks of a ResNet-50 are different from those of the traditional CNNs because of the introduction of a shortcut the connection between the input and output of each block. Using identity mappings as ResNet-50 shortcut connections can optimize the training process and minimise complexity[33]. That can lead to achieve a deeper model with fast training and less computational model if compared to i.e. VGG model [34].

The proposed work extracts the features from thermal images using last convolutional block of ResNet-50 (pre-trained model), and the output of the 5th Conv block is trained for fault classification. As a result, the output size of ReseNet-50 then is 2480.

B. Data Collection

The induction motor thermal images were captured in the Wolfson Magnetics Laboratory, School of Engineering Cardiff University, UK. The test rig is displayed in figure 3 which composes of the following components: induction motor, thermal camera (FLIR C2), and dynamometer, which serves as the load. The thermal camera was located approximately 60 cm from the motor housing center.

The thermal images have been captured with seven motor conditions considering the healthy and the faulty motor cases when the motor running at two speeds as described in Table1.

C. Data pre-processing

Due to the input size of the prosed ResNet-50 are 224 × 224 and the size of the collected images are 320×240, these images were resized to 224 × 224. Dataset was built which includes seven classes based on different motor conditions and each class has 350 images. The images are proposed with class imbalance technique and data augmentation technique to improve the model performance. This layer affects the achieved results by controlling the image zoom, horizontal flip, rotation, translation, and image orientation.

Table 1. Motor conditions

Fault mode	**Motor load (rpm)**	**Images No.**	**Class label**
Normal motor	1480/1450	350	0
IBF	1480/1450	350	1
OBF	1480/1450	350	2
8BRBF	1480/1450	350	3
IBF+1BRBF	1480/1450	350	4
OBF+5BRBF	1480/1450	350	5
BBF+8BRBF	1480/1450	350	6

D. Model evaluation

Some evaluation matrices have utilized to assess the performance of the proposed application such as the training accuracy and loss curves and the parameters given in the following equations:

$$\text{Overall accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (4)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (5)$$

$$\text{F1\_score} = 2\times \frac{\text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \quad (6)$$

Where TP is the true positive prediction, FP is false positive predictions, TN presents the true negative predictions, and the false negative predictions is stated by FN.

V. RESULT

The result of the pretrained model is presented for fault diagnosis in this section. Induction motor thermal images with different cases were employed as an input of the pre-trained ResNet model based on 50 layers network to extract the model features on ImageNet dataset. These features were trained on FC layer to predict the correct class. The classification result is presented in Table 2. The model has achieved classification accuracy of 99.98% with training error of 0.0015. In addition, the precision and F1-score have achieved great scores of 98.59, and 94.89; respectively. The overall trained accuracy and loss considering same epochs number are displayed in figure 4 and 5; respectively.

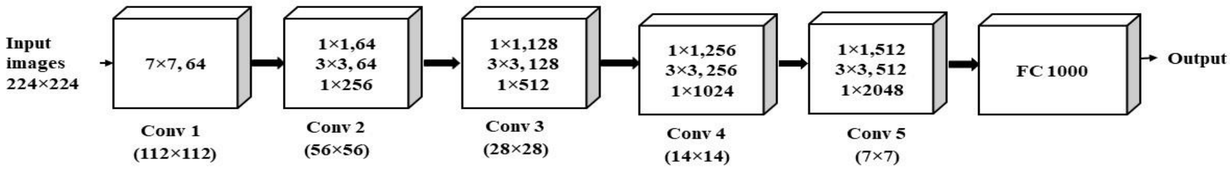

Figure 2. The architecture of the proposed ResNet-50 network

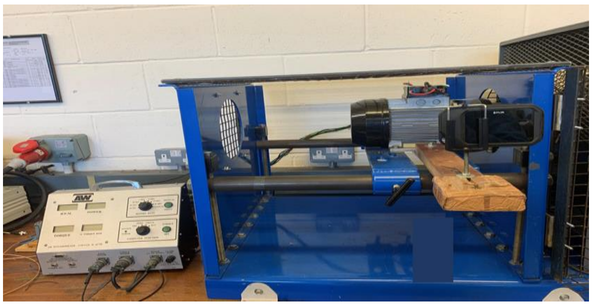

Figure 3. Test rig of the experiments

The classification accuracy of this model is further compared with recent published deep learning methos based (CNN). Normalized SAE was proposed by Jia in [23], stacked sparse autoencoder model was presented by Oi in [24], sparse filter (SF) proposed by Lei in [35], and deep belief network (DBN) presented by Gan [25].

Table 2. model classification result

Train ResNet-50 network with thermal images			
	score	Batch size	epochs
Accuracy (%)	99.98	64	100
Precision (%)	98.59	64	100
Sensitivity (%)	95.99	64	100
F1-score (%)	94.89	64	100

Table 3. accuracy comparison with other methods

Model	Accuracy
Proposed model	**99.98**
NSAE-LCN	99.92
SSAE	99.85
Sparse filter	99.66
DBN	99.03

It has been observed that the proposed ResNet-50 network achieves the best results and the accuracy compassion results are presented in Table 3. It can be concluded that the suggested pre-trained network ResNet-50 trained on ImageNet has successfully achieved a satisfactory application for diagnosing induction motor faults using motor thermal images.

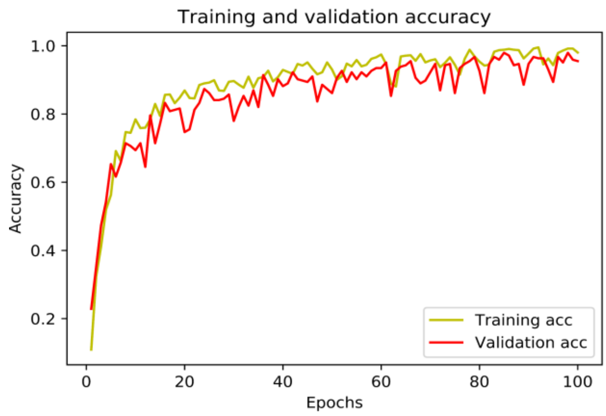

Figure 4. Training accuracy curve applying ReseNet-50

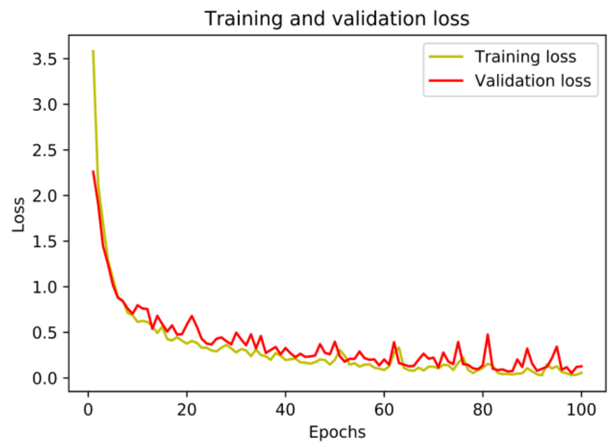

Figure 5. Training loss curve applying ReseNet-50

IV. CONCLUSION

This study develops a new fault diagnosis model applying a ResNet-50 CNN based transfer learning network. Thermal images were applied and pre-processed using data augmentation techniques for improving the final prediction accuracy, then provided as inputs to deeper feature extraction network based pretrained model of ReseNet-50. The combination of the proposed pre-trained network with densely connected classifier has given a highest classification accuracy of 99.98%. in addition, the model has been compared with other deep learning model, and the results show that the proposed resent-50 is the best.

Concisely, the overall accuracy of the classification method is satisfactory, suggesting that this model has potential applicability in the identification of induction motor faults utilizing the thermal imaging data. In future work, detection time is also considered for implementing the model. Moreover, the proposed model is trained using cross-validation technique for further accuracy improvement. Furthermore, this model is implemented for online application that based on fault detection.

VII. ACKNOWLEDGMENTS

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