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New Transfer Learning Approach Based on CNN Network for Fault Diagnosis †

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Abstract: Induction motors operate in difficult environments in the industry. Monitoring the performance of motors in such circumstances is significant which can provide a reliable operation system. This paper intends to develop a new model for fault diagnosis based on the knowledge of transfer learning using the ImageNet dataset. The development of this framework provides a novel technique for the diagnosis of single and multiple induction motor faults. A transfer learning model based on a VGG-19 convolutional neural network (CNN) is implemented, which provides a quick and fast training process with a higher accuracy. Thermal images with different induction motor conditions are captured with the help of flir camera and applied as inputs to investigate the proposed model. The implementation of this task is to use VGG19 (CNN) based pre-trained network which gives autonomous features learning based on minimum human intervention. Then applying a dense-connected classifier to predict the true class. The experimental results confirm that the robustness and reliability of the developed technique which is successfully able to classify the induction motor faults and achieving a classification accuracy of 99.8%. The use of a VGG19network has allowed the attributes to be automatically extracted and associated with the decision-making part. Furthermore, this model is further compared with other applications based on related topics, it has successfully proved the its superiority and robustness.

Keywords: VGG19; Induction motor thermal images; fault diagnosis; pretrained model; deep learning networks

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1. Introduction with Achieving the Performance

Induction motors are backbone in the industry applications because of the production depended on them. Hence, the early maintenance is required to avoid the motor breakdown. Monitoring the condition of the motor regularly can achieve improvement of the availability and production system [1]. Since an initial defect is not identified, damage could be caused in other motor elements and system collapse which leading in massive losses in the production. Standard maintenance is required for the machines to achieve high level of production. This maintenance includes condition monitoring approaches and artificial intelligence techniques based on fault diagnosis.

Induction motor fault diagnosis is a topic that may be researched based on three different categories of attractive research: fault diagnosis based on knowledge, and fault diagnosis based on models, fault diagnosis based on the signal. A hybrid model could be created via the combining of these different approaches [2]. Some approaches based on modelling and identification are utilized in the diagnosis phase, during the determination processor in the industry based individual component. So, the examination of the consistency across anticipated systems can be establish the cause of the presented failure.

Briefly, some domain techniques have been applied by considering the system pattern in fault diagnosis approaches based on signal rather than dealing with system-based models [3]. The knowledge-based fault diagnosis approach, in contrast to the model-based and signal-based fault detection methods, does not require an accurate model or signal pattern in order to do the diagnosis. On the other hand, for establishing a link between raw data and the outcome, a historical process is required in knowledge-based fault diagnosis approach. The methodology of excitation fault diagnosis is achieved by installation multiple sensors precisely for data acquisition. Next, this data is processed to verify the type of the fault. Generally, the methodology of fault diagnosis is performed by following three steps: data collection, extraction, and selection the optimum features, and fault classification. In data collection step, data is captured when the machine is running using a specific sensor such as current transformer to collect the current data and cameras to capture thermal image data. Traditionally, feature extraction is implemented through an accurate domain such as time domain, frequency domain, and time-frequency domain then these features are further processed using feature selection algorithms. In fault classification step, the obtained features are employed to train the traditional machine learning classifiers to predict the correct class. With the continuing growth of intelligent fault diagnosis, several fault diagnosis systems such as expert system has emerged [4]. Artificial neural network was developed in [5], in [6] an efficient application using KNN was proposed, in [7] another fault diagnosis model applying SVM classifier is presented, a robust model in [8] based on the use of random forest classifier is anticipated to diagnose multiple faults, and recent model combines the current and vibration signals with invasive weed optimization algorithm is suggested in [9,10]. These traditional machine learning algorithms on the other hand, have a restricted ability to analyze all data that has been acquired by the sensors [11]. In addition, these approaches use feature extraction and feature selection to generate insufficient classifiers which are based on handcrafted features and human feature selection that is inadequate. What is more, it has been reported in many research studies that the use of handcrafted features with different categorization tasks is a specific task-based approach, which means that features that are utilized to accurately predict the model outcomes under specific conditions are unsuitable for the use in other scenarios [12]. Moreover, it is hard to come up with a collection of attributes that are capable to produce accurate predictions under all scenarios. As a result of its formidable capabilities, deep learning (DL) is an effective way to tackle these challenges [13]. DL application is performed without the assistance of human engineers which investigates the first attributes for classification stage by exploring them directly from the data that has been collected by the sensors [14]. In addition, in the training process, the architecture of the deep network can select automatically optimum attributes that make an accurate prediction in the classification part. In recent years, DL has become increasingly prominent in the field of computer science due to its increased processing power [15]. Various DL algorithms have been proposed in many science areas such as computer vision [16], natural language processing [17], and games [18]. In addition to this, DL has shown itself to be a promising candidate in the area of defect detection [19] for example the use of Convolutional Neural Network (CNN) in [20], in [21] another kind of DL network so-called Recurrent Neural Network (RNN) is proposed, in [22] Deep Boltzmann Machine technique (BDM) is presented, and Deep Belief Network (DBN) is considered for creating an efficient model in [22]. Despite the reality that DL models have proven the effective applications in machine fault diagnosis interests, however there are still issues with this approach. For example, most deep models that have been utilized in most of the publications cited in above papers have small number of hidden layers. Additionally, when the number and size of hidden layers increase, the number of the network parameters will be affected and resulting in involving a large amount of data for an efficient training process. However, deep networks with more than ten hidden layers have not been developed yet, and hyperparameter tuning influences the performance of the model. Hence, transfer learning methodology (TL) is applied to overcome this problem. This technique can be made using deep neural network for extracting high-level features from the original data (raw data) [23]. Moreover, the challenge of fault diagnosis presents opportunities for deep transfer learning to deliver potentially useful solutions. Many engineering field and scientific challenges such as text classification and spam filtering have shown the transfer learning method's excellence and robustness [24]. Another factor to be considered is deep transfer learning's layer-by-layer learning structure can allow it to build large data representations which makes it possible for the performance of the fault diagnosis to be greatly improved with reduction in the extraction and training error [25]. According to the knowledge that have been studied and reported, the VGG19 model-based-networks that are paired with the thermal imaging data have not been the subject of any published research for the purpose of fault diagnosis in induction motor. Hence, this research work proposes a new approach for induction motor fault detection which is built based on combination of the induction motor thermal images with pre-trained model as feature extractor based on Visual Geometry Group (VGG). The contribution of this research is to present an efficient fault diagnosis application to identify different induction motor conditions. The presented model uses thermal images that further pre-processed by applying data augmentation technique, deep transfer learning model based the pre-trained (VGG19) network, and the adjusted densely connected layer for the training and classifying the model. This model uses many deep hidden layers to learn hierarchical representations for achieving accurate model. The performance of the proposed application applying pre-rained model is validated using thermal images of the induction motor.

The remainder of this paper is presented as follow: Related work is in section 2. Proposed Model is presented in section 3. Materials and methods are in section 4. Section 5 reports the results in detail. Discussion is provided in section 6. Lastly, the conclusion is given in section 7.

2. Related Work

Thermal images of induction motors have been used in several studies and research projects to successfully identify flaws in the motors. [26]. However, a few research applications combining thermal images and deep transfer learning approaches (DTL) have been attained for induction motor fault diagnosis task. Model-based transfer learning is a method for transferring previously learnt model parameters to new datasets in order to improve training efficiency. This technique takes into consideration the correlation between two datasets for further increasing the overall training accuracy by using this technique. A new fault detection model was proposed by Yang [27], which uses transfer learning network and the trained parameters for new training model for decreasing both the training time and training data. A high accurate model using transfer learning was suggested in [28] using sensor data that converted to images. The obtained results achieved classification accuracy near 100%. In [29] deep learning model was proposed to solve cross domain data learning using vibration data of 48 bearing. The experimental result has achieved classification accuracy of 93%. In [30] another deep learning model is suggested using 1-D signal for machine fault diagnosis and classification. VGG19 has achieved excellent result in the experiments of the gearbox. In addition, a novel model-based CNN for multiple faults of induction was proposed in [31] using the current signal. The results demonstrated this model outperforms the other methods based on the state of the art. In this work, a motor fault diagnosis framework based on deep transfer learning model is proposed using thermal images.

3. Proposed Model

Deep CNNs are used to build the proposed frame for detecting the operational conditions of the induction motor with great precision and accuracy applying thermal images as input. As mentioned earlier, transfer learning network based on pre-trained model can help for performance improvement. This paper proposes a pipeline that diagnoses the failure of the induction motor automatically from the thermal images. The procedure of this application is presented in Figure 1, which includes capturing the thermal images, preparing the data, building the pretrained model by applying VGG19, and model classification. Deep CNN that generated by Oxford visual geometry group VGG in [23] is implemented in this work as pretrained model. This network has 19 layers, and it is trained on ImageNet based weight. More convolutional layers have been added for fine tuning the thermal images data. First, the pretrained model is tuned after removing some layers of the pretrained and replacing them with output layer that has the same size as the number motor faults (conditions). The output layer that just added is weighted randomly. The earlier layers of this network are frozen in the training process and the weights are set to ImageNet for reducing the error between the true and the predicted labels. The testing dataset is utilized in classification stage to validate the robustness of the proposed model based on the induction motor conditions.

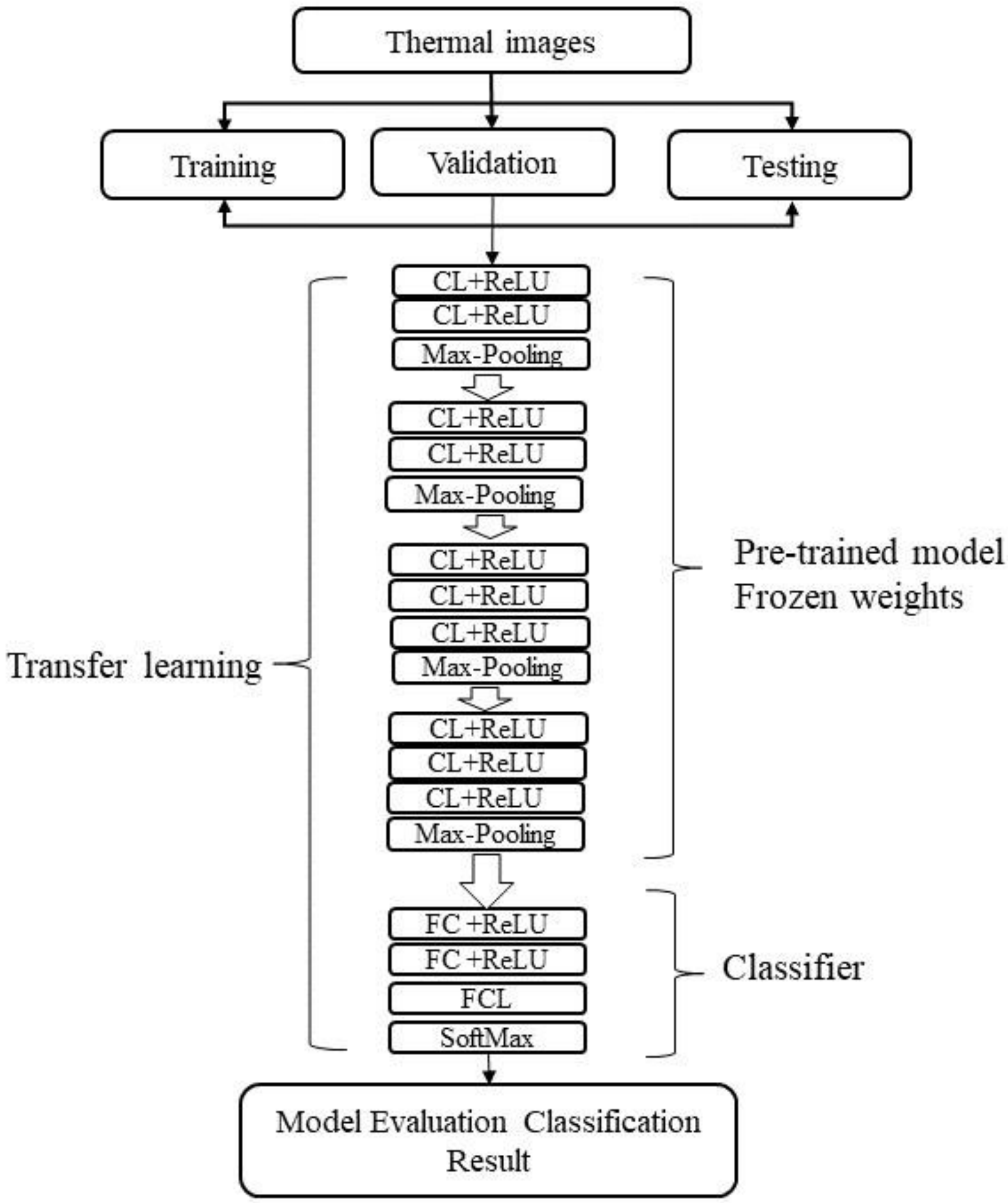

Figure 2. the proposed framework for fault detection applying VGG-19**.**

4. Materials and Methods

4.1. Data Collection

During the course of this investigation, thermal images of the induction motor were carefully acquired with the consideration of both the healthy and its faulty states, as detailed in Table 1. The motor was tested in the laboratory based on two different speeds, namely 1480 and 1380 revolutions per minute. The examinations were performed in the lab of Cardiff University, which is located in the United Kingdom. Figure 2 depicts the testing apparatus. On the bearing inner and outer races, an artificial pit measuring 0.25 centi-meters was created to simulate the inner bearing fault (IBF) and outer bearing faults (OBF) as seen in Figures 3a and Figure 3b; respectively. The ball bearing fault (BBF) as displayed in Figure 3c a single ball was removed from its cage in the bearing to make it. A broken rotor bar fault (1BRBF) as seen in Figure 4, was accomplished by drilling a cavity into one bar of the motor rotor. This cavity which has a certain (cm) in depth and a certain (cm) in diameter. For the fifth and eighth instances of broken rotor bar failures, the same technique was used. That means five bars were drilled in order to generate five broken rotor bar faults (5BRBF) as shown in Figure 4b, and eight bars were bored as shown in Figure 4c to produce eight broken rotor bar's fault (8BRBF). Multi-induction motor faults are also studied in this research. These faults are specifically produced so that they could be shown as a new state of the motor. As an example, labels 8 and 9 include the inner bearing fault with a broken rotor bar into one label (IBF+1BRBF), and the outer bearing fault with five broken rotor bars in one label (OBF+5BRBF); respectively. In Both of these labels the rotor has a broken rotor bar fault.

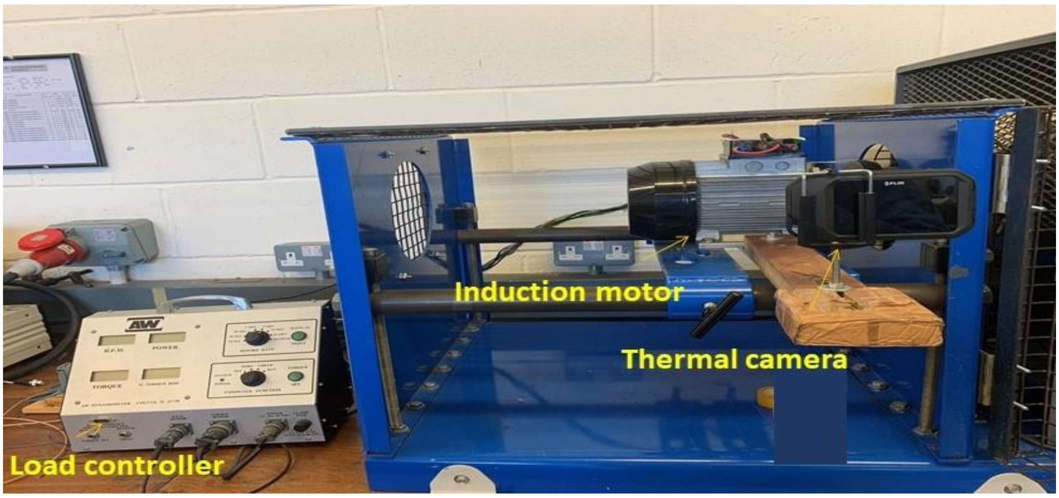

Figure 2. Experimental test rig.

A FLIR thermal camera was used to capture the thermal images, and it was positioned appropriately on the test rig at a certain distance away from the induction motor center as shown on the test rig. Several camera locations were tried before the final one was selected, with the quality of each one factored considered. The thermal images were captured at two speeds after the engine had run for fifteen minutes and then the images stored in JPEG format with size pixel of 320 × 240 as displayed in Figure 5.

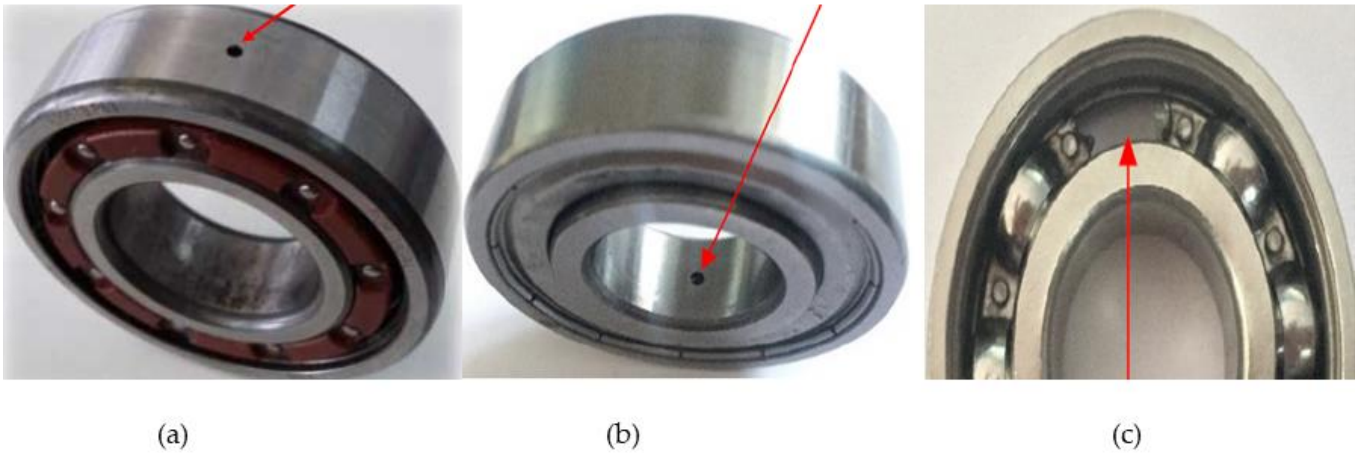

Figure 3. Arificial bearing faults (**a**) Outer bearing fault, (**b**) Inner bearing fault, (**c**) Ball bearing fault.

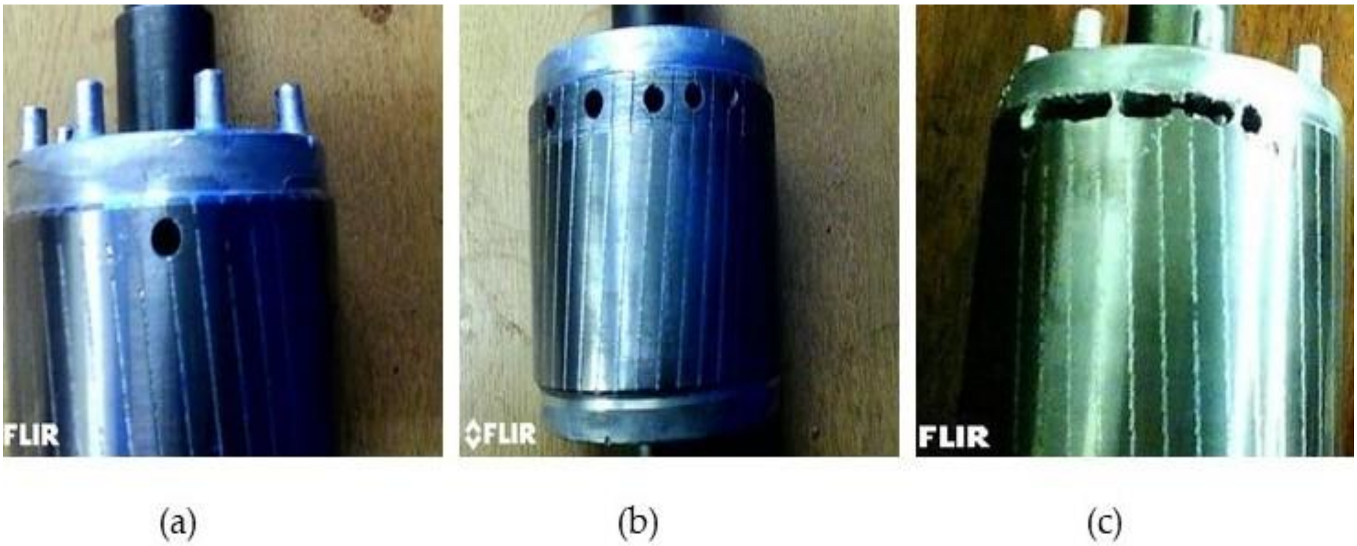

Figure 4. Arificial rotor faults (**a**) One broken rotor bar fault, (**b**) Five broken rotor bars fault, (**c**) Eight broken rotor bars fault.

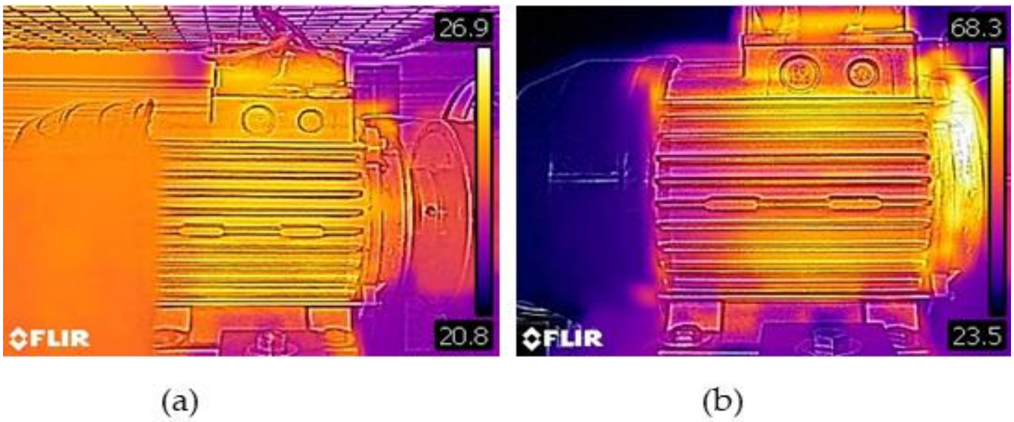

Figure 5. Thermal images. (**a**) Healthy motor run at speed 1480rpm, (**b**) Motor has inner bearing fault and run at speed 1380 rpm.

Table 1. Motor Conditions.

Fault mode	Motor load (rpm)	Images No.	Class label
Normal motor	1480/1380	250	1
IBF	1480/1380	250	2
OBF	1480/1380	250	3
BBF	1480/1380	250	4
1BRBF	1480/1380	250	5
5BRBF	1480/1380	250	6
8BRBF	1480/1380	250	7
IBF+1BRBF	1480/1380	250	8
OBF+5BRBF	1480/1380	250	9
BBF+8BRBF	1480/1380	250	10

4.2. Deep Convolutional Neural Network Architecture based on VGG-19.

When the convolutional neural network is built from scratch, there will be some pros and cons considering large amount of data. However, the use of pre-trained models can achieve promising results due to the limitation of the dataset.

Transfer learning models can help to use the existing machine learning algorithms. Many techniques can be used to perform transfer learning for example by reprocessing the model for feature extraction which means that only the fully connected classifier is trained.

According to recent reports, the VGG-19 CNN architecture achieves great accuracy when it is processed on the wight of ImageNet. To train the VGG-19 model, it uses the ImageNet dataset of 1.2 million general object images from 1,000 different object categories [32]. Moreover, this network contains 19 layers consisting of: the fully connected layer, max-pooling, and the convolutional layer. The trained convolution base is employed with a densely connected classifier. The standard version of the VGG-19 is displayed in Figure 6. Using convolutional layers can apply a convolution operation across an image (feature map) and perform the operation at each location, transferring the result to the next layer in the process [33]. Convolutional filters are trainable feature extractors with a 3 ×3 size and each convolutional layer is followed by a ReLU (rectified linear unit) activation function and a max-pooling procedure. ReLU is now the most widely used nonlinear activation function and it can be defined as given in next equation:

$$f(x) = \max(0, x) \quad (1)$$

Where x is the neuron input.

After down sampling, the max-pooling layer is applied to the model with a filter size of 2 × 2. Each neuron in the densely connected layer gets input from all the neurons in the previous layer. The activation function of this densely-connected layer must be specified depending on the class type [34].

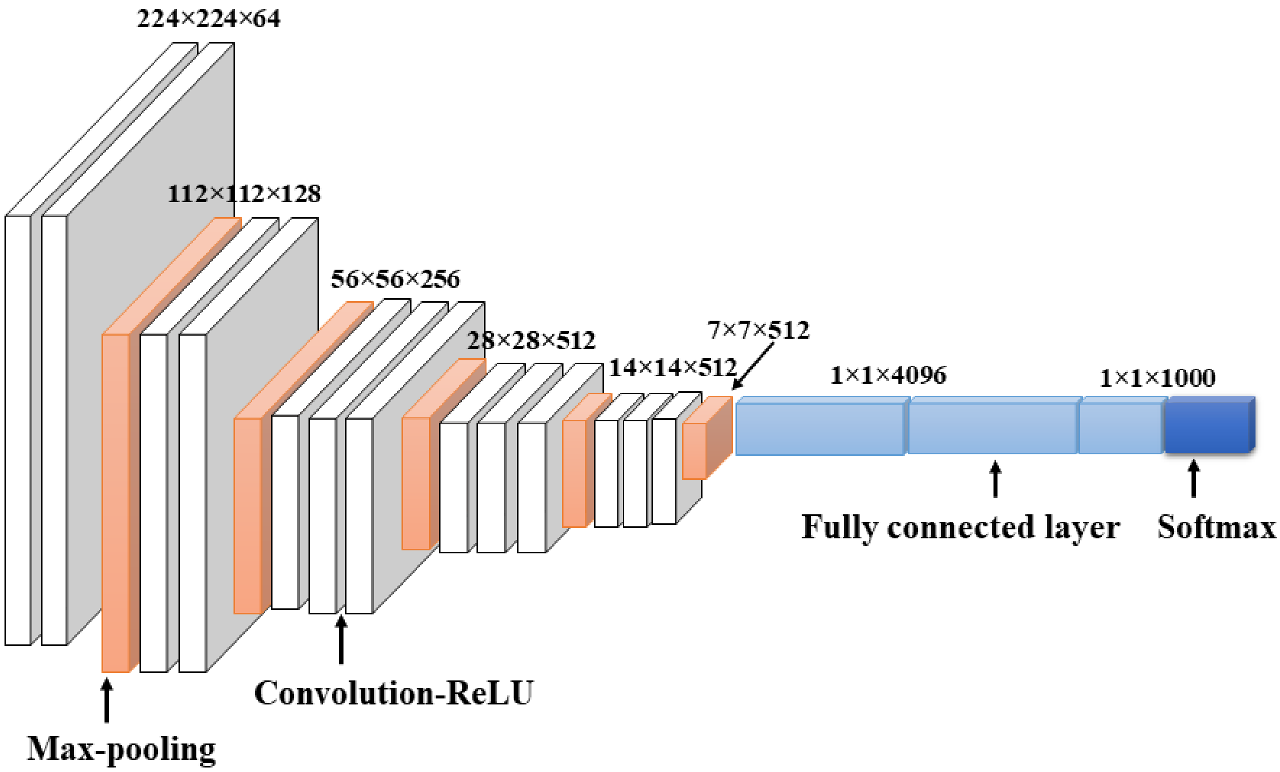

Figure 6. The pre-trained VGG-19 structure.

4.3. Data Pre-Processing and Augmentation

A dataset of 10 classes which each with 500 images was created based on various motor conditions. The original image is cropped to fit within the bounding box, and the resulting images are resized to 224 by 224 which is the same input size required by the classification network. Then, the images are pre-processed on other layer with class imbalance technique and data augmentation technique. By controlling the image magnification, horizontal flip, rotation, translation, and orientation, the overall outcome is influenced with further model improvement.

4.4. Model Evaluation

This work is presented to create a unique application which utilizes thermal images and a pre-trained CNN network-based model as a feature extractor that was done in Python software installed on a 2GHz GPU PC. The ImageNet dataset's weight is used to train this model. Then, transferring the energy of this data to the classification part for model prediction. VGG-19 algorithm is trained using ReLU activation and dropout. Categorical cross-entropy (CE) and SoftMax function (s) were applied as it is a multi-class classification task. The error rate between the original and predicted values is simply achieved [35]. This.

The categorical cross-entropy (CE) and SoftMax (s) are calculated using the following formulas:

$$\mathrm{CE} = -\sum_{i}^{C} t_i \log(f(s)_i) \tag{2}$$

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

$$f(s)_i = \frac{e^{s_i}}{\sum_{i}^{C} e^{s_j}} \tag{3}$$

Where $\boldsymbol{s_i}$ presents the given the class, $\boldsymbol{s_j}$ is the scores derived from the net for each class

Adam optimizer which is extension of the stochastic gradient descent is chosen to implement the presented work. This optimizer can update the weights of the neurons by using backpropagation techniques where the derivative of the error is calculated with respect to each weight. The main key of using this optimizer is to achieve an optimum weight with maximum accuracy and minimum loss. Some evaluation matrices have utilized to assess the proposed application as given in the following equations:

$$\text{Specificity} = \frac{\text{TN}}{\text{FP+TN}} \quad (4)$$

$$\text{Overall accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \quad (5)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (6)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \quad (7)$$

$$\text{F1\_score} = 2\times \frac{\text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \quad (8)$$

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.

5. Results

The proposed model of fault diagnosis has been investigated using induction motor thermal images. Thermal images with different motor conditions were inputted into the VGG-12 pre-trained model to process the energy of the extracted features for predicting the correct class. The classification result based on the use of this model is provided in Table 2 when the model is trained with categorical cross entropy function, adam optimizer on SoftMax classifier. From the achieved results, it can conclude that the proposed pre-trained network VGG-19 with trained ImageNet has accomplished a satisfactory application to diagnose induction motor faults. The experimental result has been attained average accuracy of 99.8% with training loss equal to 0.0144. The other evaluation metrics have been presented the same outcome manner. The validation accuracy and loss based on the same epochs number are displayed in Figure 7, and 8; respectively.

Table 2. Model Classification Result.

Train the model with VGG-19			
	score	**Batch size**	**epochs**
Specificity (%)	99.9	64	40
Accuracy (%)	**99.8**	**64**	**40**
Precision (%)	98	64	40
Sensitivity (%)	97.0	64	40
F1-score (%)	94.2	64	40

According to the comparison with current methods, the suggested method is more accurate than the published deep learning methos based (CNN). A new pre-trained model has been proposed in [36] which uses different 48 bearings fault. This model has given average accuracy 93%. In [37] a fault diagnosis model based on transfer learning-based knowledge is proposed by Kumar and has achieved an accuracy of 99.40%. this model was further trained by k nearest neighbor classier, support vector machine, and random forest and have achieved accuracy of 78.60%, 90%, and 89.40; respectively. A novel and accurate deep learning framework for fault diagnosis was presented by Shao in [38]. This model has been investigated on three different mechanical datasets including the gearbox and bearing datasets. The model has archived accuracies from 94.8% to 99.64%. In [39] a pre-trained-VGG19 model was proposed by Wen for fault diagnosis. The model has converted famous time domain signals from CWRU to images and processing them by

VGG19 and SoftMax classifier. A 99.175% prediction accuracy has achieved from the presented model. another fault diagnosis model was suggested by Grover for rolling element bearing in [40]. The model uses four pretrained models namely Alexnet, VGG-19, Google Net, and ResNet-50. VGG-19 has achieved a validation accuracy of 99.7% by applying Adam optimizer and 94.1% by applying SGD optimizer with few epochs' numbers. In [41] a novel transfer learning model for fault detection was proposed. The model has tested on current signals and has achieved an accuracy of 99.4%. in this work, the proposed model has achieved a higher classification performance when it is compared to the aforementioned models which it has achieved an accuracy of 99.8%.

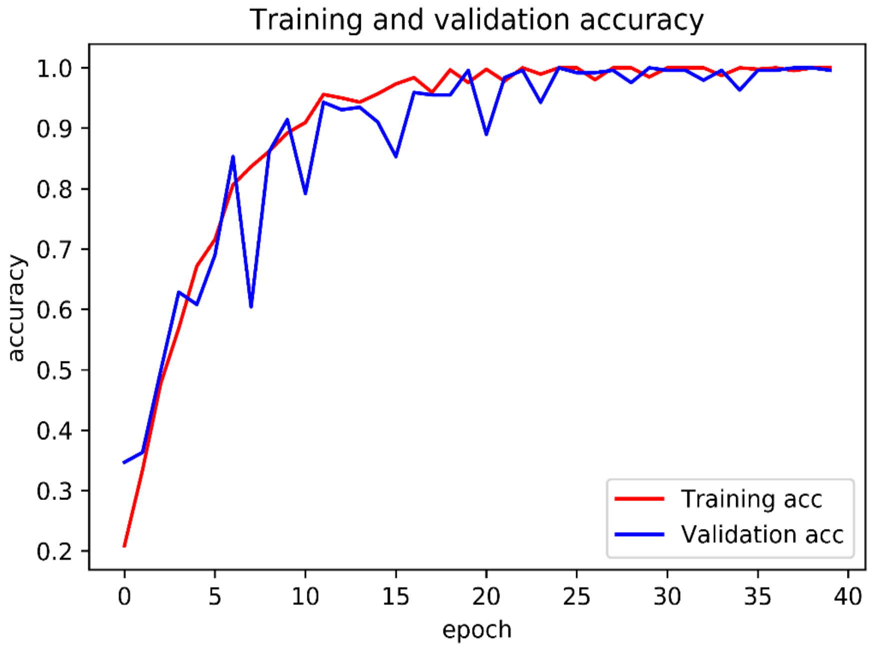

Figure 7. VGG-19 based model accuracy curve.

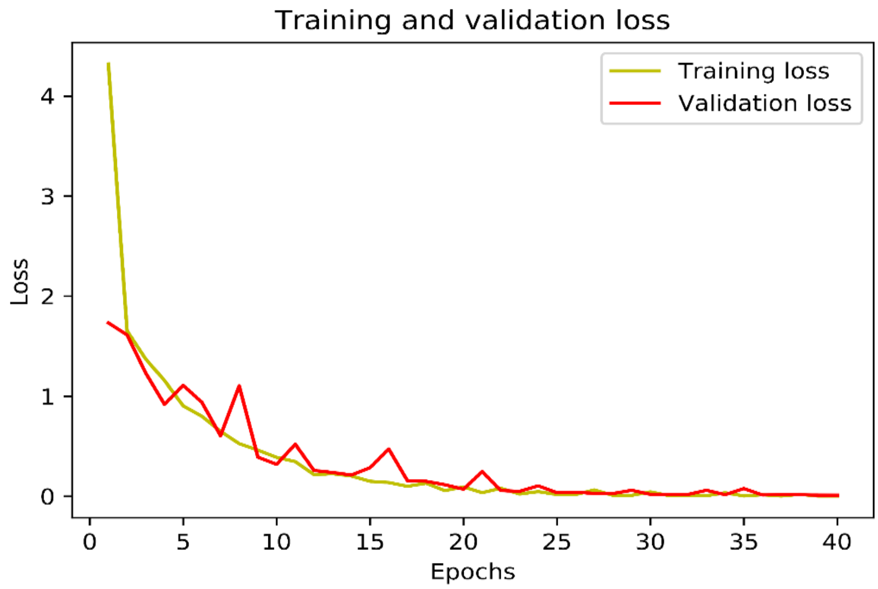

Figure 8. VGG-19 based model loss curve.

6. Discussion

Although many automated machine learning techniques have been introduced for diagnosing the induction motor faults, there is still a lack of solutions to predict the motor conditions. Compared to other methods, it is successfully employed in the content of this work which it is superior since it requires less human involvement while yet producing accurate predictions. Moreover, training a model via transfer learning yields better results. Transfer learning has also compensated the limitation of the traditional techniques and deep CNN networks.

7. Conclusions

In this work, a new application for fault diagnosis based deep learning network is proposed. This application which combines thermal images, deep transfer learning network, and densely connected classifier. This application has applied VGG-19 to construct the first model features from the images directly to achieve a fast and robust classification model. The highest classification accuracy of 99.80% was achieved by combining the suggested pre-trained network with the densely connected classifier.

Concisely, the classification method's accuracy is reasonable, suggesting this model could be employed to identify induction motor defects using thermal imaging data. The VGG-19 network's resilience will be evaluated in future studies using more comprehensive data, not just with transfer learning model, but also by fine-tuning the network's properties. Other deeper networks based on detection time is built considering the prediction challenge.

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Conflicts of Interest: The authors declare no conflict of interest.

References

1. S. Ayas and M. S. Ayas, "A novel bearing fault diagnosis method using deep residual learning network," Multimed. Tools Appl., no. 0123456789, 2022, doi: 10.1007/s11042-021-11617-1.
2. L. Guo, N. Li, F. Jia, Y. Lei, and J. Lin, "A recurrent neural network based health indicator for remaining useful life prediction of bearings," Neurocomputing, vol. 240, pp. 98–109, 2017, doi: 10.1016/j.neucom.2017.02.045.
3. J. Pons-llinares et al., "Advanced Induction Motor Rotor Fault Diagnosis Via Continuous and Discrete Time–Frequency Tools," IEEE Trans. Ind. Electron., vol. 62, no. 3, pp. 1791–1802, 2015.
4. Y. M. Park, G. W. Kim, and J. M. Sohn, "A logic based expert system (LBES) for fault diagnosis of power system," IEEE Power Eng. Rev., vol. 17, no. 2, p. 66, 1997.
5. B. Li, M. Y. Chow, Y. Tipsuwan, and J. C. Hung, "Neural-network-based motor rolling bearing fault diagnosis," IEEE Trans. Ind. Electron., vol. 47, no. 5, pp. 1060–1069, 2000, doi: 10.1109/41.873214.
6. P. Baraldi, F. Cannarile, F. Di Maio, and E. Zio, "Hierarchical k-nearest neighbours classification and binary differential evolution for fault diagnostics of automotive bearings operating under variable conditions," Eng. Appl. Artif. Intell., vol. 56, pp. 1–13, 2016, doi: 10.1016/j.engappai.2016.08.011.
7. M. Kang, J. Kim, and J. M. Kim, "Reliable fault diagnosis for incipient low-speed bearings using fault feature analysis based on a binary bat algorithm," Inf. Sci. (Ny)., vol. 294, pp. 423–438, 2015, doi: 10.1016/j.ins.2014.10.014.
8. Z. Wang, Q. Zhang, J. Xiong, M. Xiao, G. Sun, and J. He, "Fault Diagnosis of a Rolling Bearing Using Wavelet Packet Denoising and Random Forests," IEEE Sens. J., vol. 17, no. 17, pp. 5581–5588, 2017, doi: 10.1109/JSEN.2017.2726011.
9. A. Ibrahim, F. Anayi, M. Packianather, and O. Al-Omari, "New Hybrid Invasive Weed Optimization and Machine Learning Approach for Fault Detection," 2021 56th Int. Univ. Power Eng. Conf. Powering Net Zero Emiss. UPEC 2021 - Proc., no. Cm, 2021, doi: 10.1109/UPEC50034.2021.9548171.
10. A. Ibrahim, F. Anayi, M. Packianather, and O. Al-Omari, "Novel hybrid invasive weed optimization and machine learning approach for fault detection," 2021 56th Int. Univ. Power Eng. Conf. Powering Net Zero Emiss. UPEC 2021 - Proc., pp. 663–668, 2021, doi: 10.1109/UPEC50034.2021.9548171.
11. C. Qian, J. Zhu, Y. Shen, Q. Jiang, and Q. Zhang, "Deep Transfer Learning in Mechanical Intelligent Fault Diagnosis: Application and Challenge," Neural Process. Lett., 2022, doi: 10.1007/s11063-021-10719-z.
12. T. Han, D. Jiang, and N. Wang, "The Fault Feature Extraction of Rolling Bearing Based on EMD and Difference Spectrum of Singular Value," Shock Vib., vol. 2016, 2016, doi: 10.1155/2016/5957179.
13. P. Tamilselvan and P. Wang, "Failure diagnosis using deep belief learning based health state classification," Reliab. Eng. Syst. Saf., vol. 115, pp. 124–135, 2013, doi: 10.1016/j.ress.2013.02.022.
14. Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015, doi: 10.1038/nature14539.
15. I. Chaturvedi, Y. S. Ong, and R. V. Arumugam, "Deep transfer learning for classification of time-delayed Gaussian networks," Signal Processing, vol. 110, pp. 250–262, 2015, doi: 10.1016/j.sigpro.2014.09.009.

16. T. F. Gonzalez, "ImageNet Classification with Deep Convolutional Neural Networks," Handb. Approx. Algorithms Metaheuristics, pp. 1–1432, 2007, doi: 10.1201/9781420010749.
17. R. Socher and C. Manning, "Deep Learning for NLP (without Magic)," NAACL-HLT 2013 - 2013 Conf. North Am. Chapter Assoc. Comput. Linguist. Hum. Lang. Technol. Tutorials, no. July, pp. 1–3, 2013.
18. L. Wu and P. Baldi, "Learning to play Go using recursive neural networks," Neural Networks, vol. 21, no. 9, pp. 1392–1400, 2008, doi: 10.1016/j.neunet.2008.02.002.
19. M. Gan, C. Wang, and C. Zhu, "Construction of hierarchical diagnosis network based on deep learning and its application in the fault pattern recognition of rolling element bearings," Mech. Syst. Signal Process., vol. 72–73, pp. 92–104, 2016, doi: 10.1016/j.ymssp.2015.11.014.
20. L. Wen, X. Li, L. Gao, and Y. Zhang, "A New Convolutional Neural Network-Based Data-Driven Fault Diagnosis Method," IEEE Trans. Ind. Electron., vol. 65, no. 7, pp. 5990–5998, 2018, doi: 10.1109/TIE.2017.2774777.
21. H. C. Cho, J. Knowles, M. S. Fadali, and K. S. Lee, "Fault detection and isolation of induction motors using recurrent neural networks and dynamic bayesian modeling," IEEE Trans. Control Syst. Technol., vol. 18, no. 2, pp. 430–437, 2010, doi: 10.1109/TCST.2009.2020863.
22. H. Shao, H. Jiang, X. Zhang, and M. Niu, "Rolling bearing fault diagnosis using an optimization deep belief network," Meas. Sci. Technol., vol. 26, no. 11, 2015, doi: 10.1088/0957-0233/26/11/115002.
23. K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," 3rd Int. Conf. Learn. Represent. ICLR 2015 - Conf. Track Proc., pp. 1–14, 2015.
24. S. Panigrahi, A. Nanda, and T. Swarnkar, "A Survey on Transfer Learning," Smart Innov. Syst. Technol., vol. 194, no. 10, pp. 781–789, 2021, doi: 10.1007/978-981-15-5971-6_83.
25. L. Zuo, M. Jing, J. Li, L. Zhu, K. Lu, and Y. Yang, "Challenging tough samples in unsupervised domain adaptation," Pattern Recognit., vol. 110, 2021, doi: 10.1016/j.patcog.2020.107540.
26. W. Chen, Y. Qiu, Y. Feng, Y. Li, and A. Kusiak, "Diagnosis of wind turbine faults with transfer learning algorithms," Renew. Energy, vol. 163, pp. 2053–2067, 2021, doi: 10.1016/j.renene.2020.10.121.
27. K. Weiss, T. M. Khoshgoftaar, and D. D. Wang, A survey of transfer learning, vol. 3, no. 1. Springer International Publishing, 2016.
28. Q. Yang, "Highly Accurate Machine Fault Diagnosis Using Deep Transfer Learning," vol. 15, no. 4, pp. 2446–2455, 2019.
29. P. Wang and R. X. Gao, "Transfer learning for enhanced machine fault diagnosis in manufacturing," CIRP Ann., vol. 69, no. 1, pp. 413–416, 2020, doi: 10.1016/j.cirp.2020.04.074.
30. J. Zhou, X. Yang, L. Zhang, S. Shao, and G. Bian, "Multisignal VGG19 Network with Transposed Convolution for Rotating Machinery Fault Diagnosis Based on Deep Transfer Learning," Shock Vib., vol. 2020, 2020, doi: 10.1155/2020/8863388.
31. P. Kumar and A. S. Hati, "Transfer learning-based deep CNN model for multiple faults detection in SCIM," Neural Comput. Appl., vol. 33, no. 22, pp. 15851–15862, 2021, doi: 10.1007/s00521-021-06205-1.
32. X. Zhang, J. Zou, K. He, and J. Sun, "Accelerating Very Deep Convolutional Networks for Classification and Detection," IEEE Trans. Pattern Anal. Mach. Intell., vol. 38, no. 10, pp. 1943–1955, 2016, doi: 10.1109/TPAMI.2015.2502579.
33. A. Handa, P. Garg, and V. Khare, "Masked Neural Style Transfer using Convolutional Neural Networks," 2018 Int. Conf. Recent Innov. Electr. Electron. Commun. Eng. ICRIEECE 2018, pp. 2099–2104, 2018, doi: 10.1109/ICRIEECE44171.2018.9008937.
34. E. Mocsari and S. S. Stone, "Densely Connected Convolutional Networks," Am. J. Vet. Res., vol. 39, no. 9, pp. 1442–1446, 1978.
35. A. Jamin and A. Humeau-Heurtier, "(Multiscale) cross-entropy methods: A review," Entropy, vol. 22, no. 1, p. 45, 2020, doi: 10.3390/e22010045.
36. P. Wang and R. X. Gao, "Transfer learning for enhanced machine fault diagnosis in manufacturing," *CIRP Ann.*, vol. 69, no. 1, pp. 413–416, 2020, doi: 10.1016/j.cirp.2020.04.074.
37. P. Kumar and A. S. Hati, "Transfer learning-based deep CNN model for multiple faults detection in SCIM," Neural Comput. Appl., vol. 33, no. 22, pp. 15851–15862, 2021, doi: 10.1007/s00521-021-06205-1.
38. Q. Yang, "Highly Accurate Machine Fault Diagnosis Using Deep Transfer Learning," vol. 15, no. 4, pp. 2446–2455, 2019.
39. L. Wen, X. Li, X. Li, and L. Gao, "A new transfer learning based on VGG-19 network for fault diagnosis," Proc. 2019 IEEE 23rd Int. Conf. Comput. Support. Coop. Work Des. CSCWD 2019, pp. 205–209, 2019, doi: 10.1109/CSCWD.2019.8791884.
40. C. Grover and N. Turk, "A novel fault diagnostic system for rolling element bearings using deep transfer learning on bispectrum contour maps," Eng. Sci. Technol. an Int. J., vol. 31, p. 101049, 2022, doi: 10.1016/j.jestch.2021.08.006.
41. P. Kumar, A. S. Hati, S. Padmanaban, Z. Leonowicz, and P. Chakrabarti, "Amalgamation of Transfer Learning and Deep Convolutional Neural Network for Multiple Fault Detection in SCIM," Proc. - 2020 IEEE Int. Conf. Environ. Electr. Eng. 2020 IEEE Ind. Commer. Power Syst. Eur. EEEIC / I CPS Eur. 2020, 2020, doi: 10.1109/EEEIC/ICPSEurope49358.2020.9160712.