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INDUCTION MOTOR FAULT DETECTION AND CLASSIFICATION USING THERMAL IMAGES AND DEEP LEARNING

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Abstract

Electro-mechanical systems such as induction motors (IMs) are widely used in industry as driving forces for multiple small and large-scale systems. The advantages of IMs like high reliability, high efficiency, and robust operation have resulted in their widespread applications. The operation of the motors under various electrical and mechanical variations degrades their performance and reduces their life span. For the safe and sustained operation of IMs, existing condition monitoring methods use different sensors for diagnosis. Still, these methods pose some difficulties, such as they require proper sensor installation and are prone to noise. Therefore, more effective diagnosis methods are needed for effective condition monitoring of machines. Infrared thermography (IRT) as a non-invasive technique can efficiently be used to address sensor-related problems. Recently, IRT as a noncontact technique has been widely adopted for condition monitoring of rotating machines. In this work, IRT-based three-phase motor fault detection and identification is proposed. The thermal images acquired under different motor operating conditions are fed to the deep learning (DL) models for fault identification. The supervised DL methods effectively classified the motor conditions owing to their high generalization capabilities. The obtained results demonstrate that the RESNET-50 model achieved the best classification results with an accuracy of 97% without any manual feature extraction method.

Keywords: *Induction motor; Thermal imaging; Deep learning; Condition monitoring; Fault diagnosis*

1. Introduction

Induction motors (IMs) are complex electro-mechanical systems that have been employed in various industries, transportation, and household applications. IMs are most common in various domains because of their advantages, such as robust performance, speed control, ease of installation, and being rugged to harsh environments. Numerous industrial applications are operated using pumps, fans, mixers, air compressors, conveyor belts, and other machine tools [1, 2]. With the continuous operation and variable operating conditions, motors start to degrade, which eventually may lead to permanent failure and a halt in industrial processes. Condition monitoring of IMs is essential to maintain their safe condition and operation before it goes to the critical condition [3, 4]. Generally, progressive faults are the reason for severe damage in rotating machines which may be avoided through effective monitoring [5, 6]. IMs in transportation applications like aerospace, trains, and electric cars may lead to major failure and destroy the whole system [7, 8]. Thus, it necessitates the deployment of robust condition monitoring systems.

The faults in IMs may be electrical faults (i.e., single-phase faults, unbalanced supply voltage faults, under or over-voltage faults, and overload faults), mechanical faults (i.e., rotor faults and bearing faults), and environmental faults (i.e., faults due to temperature and moisture). In IM, frequently happening faults are electrical and mechanical defects classified based on the rotor, stator, bearing, and some other major faults. According to the survey of Electric Power Research Institute (EPRI) and Institute of Electrical and Electronic Engineering of Industry Applications Society (IEEE IAS), the ratio of occurrence of these faults is given in Fig. 1 [9].

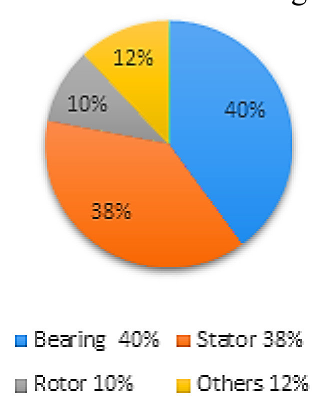

Figure 1: Faults Ratio of Induction Motors

Considering the crucial role of IMs in industry, a halt in its operation due to various faults is unexpected for sustaining the industrial operations. To diagnose various faults, several faults detection approaches based on vibration, current, voltage, and acoustic emissions have been developed and tested. Most of these approaches use invasive sensors require precise mounting and calibration. Moreover, these sensors also face the problem of noise which affects the performance of the algorithms [10-13]. Recent advancement in this technology has allowed us to effectively monitor IMs in different processes in a non-invasive manner. So, infrared thermography (IRT) has emerged as a non-invasive fault diagnosis technique that allows contactless monitoring of rotating machines [14, 15]. Keeping in view the advantages of the IRT technique, this work presents a diagnosis of the different types of faults in the three-phase IM (i.e. healthy IM, rotor fault. low single-phasing fault, moderate single-phasing fault, and cooling fan fault), and these faults are classified using deep learning (DL) techniques. The DL-based methods have been widely explored in different domains owing to their advantages such as high generalization, can deal with noisy data, and do not require manual feature extraction [16, 17]. Two DL models are proposed in this work and their performance is evaluated using accuracy and loss metrics. Fig. 2 shows the generalized block diagram of the proposed approach.

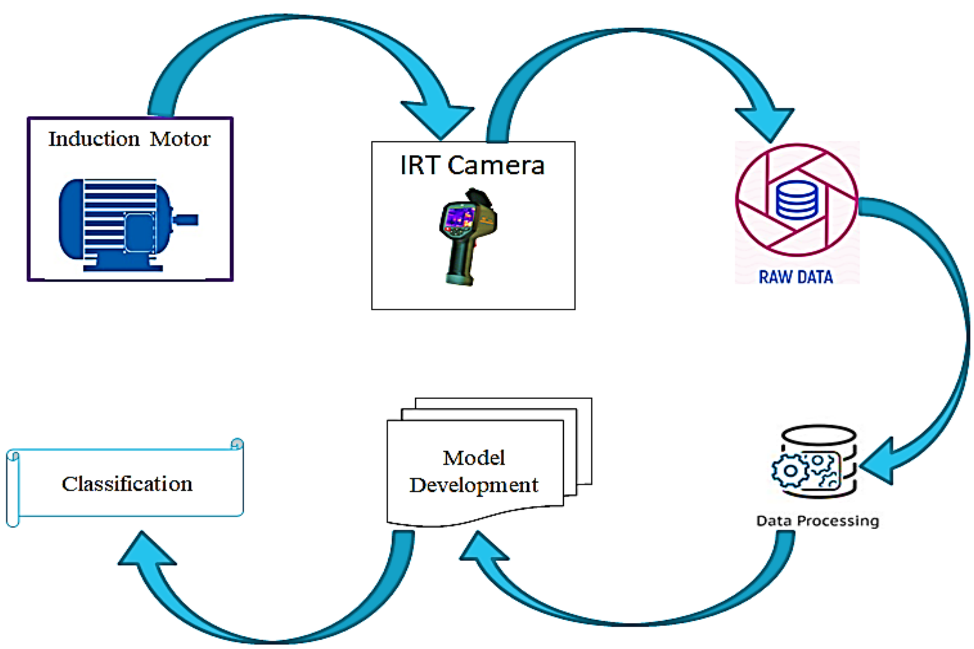

Figure 2: Generalized Block Diagram of the Proposed Approach

The remaining paper is organized as follows: Section 2 summaries and reports the related research works. Section 3 discusses the methods and dataset employed in this research. Section 4 reports and discusses the results obtained in the investigation. Lastly, Section 5 reports the conclusions of this study.

2. Relevant Work

Recently, IRT-based condition monitoring of various industrial systems has become a point of attention for researchers working in the domain. Multiple approaches have been explored for thermal images based condition monitoring of IMs [10, 11]. The traditional approaches do not provide desired results in terms of fault detection accuracy. Thus, researchers are continuing to explore better methods for achieving better diagnosis results. In this direction, Singh, G. et al. [18] have presented research on diagnosing the faults of IM using thermal imaging. The motor conditions included the healthy, inter-turn fault, and cooling system failure. The FLIR-E60 thermal camera was used to capture the machine surface temperature. Then the FLIR software and the MATLAB were used to pre-process and analyse the thermal image data, respectively. Yongbo Li. et al. [19] have conducted an IRT-based investigation of IM. The thermal images of five types of bearing faults were fed to the diagnosis models. The thermal images of IM operated under different speeds were captured by the two cameras, namely Hawk-1384 cameras. The bag-of-visual-word (BoVW) algorithm was first used to extract fault characteristics from the images. The received characteristics were inputted into the SVM classifier. The authors also conducted vibration-based experimentation for comparing the performance results achieved through the IRT-based analysis. The vibration-based approach resulted in test accuracy of 79.11% that is lower than the accuracy projected by the IRT-based method, which achieved 99% accuracy. The study proves the effectiveness of the IRT-based method in condition monitoring of IMs compared to the vibration-based method. In their extended work [15], the authors have performed DL based analysis of a three-phase asynchronous motor with the bearing faults and rotor unbalance faults. They employed DL models including deep NN, CNN, deep belief network (DBN), and stacked auto-encoder (SAE). The comparative analysis proved CNN as the best classifying model with an average accuracy of 98.59%.

The authors of [20] developed a method that identity classifies the region of interest (ROI) of different electrical installation faults using thermal images. The images were pre-processed by using FLIR Thermacam software and those images were exported in MATLAB. SVM, Fuzzy c-mean and Ostu approaches were used for identifying the faults in electrical installations. To evaluate the quality of these techniques, simulation is performed to compare performance between binary images and the achieved results show that the SVM method provides the best detection of faults with minimum loss compared to the Fuzzy c-means and Ostu methods. The authors of [21] proposed an automatic thermal image segmentation-based fault diagnosis method for IM. The work focuses on the faults such as bearing, broken bar fault, shaft misalignment, and healthy condition. The method detected ROI using the Ostu thresholding-based automatic segmentation. The researchers have presented an alternate method to the existing thermal image analysis methods for industrial equipment. The achieved results proved the effectiveness of the proposed method.

Al-Musawi et al. [22] proposed a novel method based on Hue, Saturation and Value (HSV) technique for motor fault diagnosis using thermal images. First, images were transformed to HSV and then segmented using Sobel, Prewitt, Roberts, Otsu, and Canny methods. Through segmentation, different statistical values such as mean, mean square error (MSE), variance, and kurtosis were extracted, which effectively detected various types of bearing faults in the motor from the thermal images. In [23], authors have proposed the method to detect and identify the faults of the IM based on thermal images, which included classes: normal condition, rotor blocking, cooling fan blocking, and short circuit faults. The ROI was detected in each image by using the scale-invariant feature transform (SIFT) method. Hence, extracting the ROI properly and eliminating the background plays an important role in increasing the classification model's accuracy. All of these SIFT-based detected ROIs were resized to 180x127 pixels. Then, the extracted ROIs were characterised based on a pre-trained CNN. The training samples are clustered into two cold and hot clusters by the K-Means model. Then, in each cluster, the Support vector machine (SVM) algorithm is applied to classify the inputted examples. They used K-nearest neighbour (KNN), random forest (RF), and SVM for the classification task. Among these models, the SVM technique was able to classify the faults with 100% accuracy. In [11], the authors have presented the work on the fault simulator (WS-ZHTI multifunctional rotor test ring). The fault trainer was operated to examine various types of faults, including faults in flywheels, bearing, driving motors, rotors, and shafts. Two feature extraction methods (i.e. BoVW and CNN) were individually employed to extract characteristics from the IRT images captured under both transient and steady-state conditions. The results of both the feature extraction techniques were compared on IRT based fault diagnosis techniques using and vibrational signals based fault diagnosis. For the verification of diagnostic performance, these methods were evaluated using various metrics. Experimental findings indicate that the classification accuracy of the CNN model based on the Thermal image dataset is more than the vibration signals based analysis. The relevant literature is summarized in Table 1.

Table 1: Summary of relevant literature

S. No.	References	Year of Research	Types of Faults	Methods	Prominent Results on Thermal Image Dataset
1.	Singh, G. V. Naikan [18]	2017	Healthy condition, inter-turn fault, cooling system failure	FLIR tool and statistical analysis in the Matlab	The faults were detected based on statistical analysis of the motor temperature.
2.	Dit Leksir, Y.L. et al.[20]	2018	Faults in Electrical Installations	Ostu, Fuzzy c-means, and SVM	SVM effectively identified the faults with minimum loss in the range 1.7-1.99%.

3.	Resendiz-Ochoa, E., et al. [21]	2018	Healthy condition, bearing fault, broken bar fault, and shaft misalignment	Ostu thresh holding technique based segmentation	The method proved as a better alternate to classical thermal image-based analysis methods.
4.	Yongbo Li., et al. [19]	2019	Normal, BF, ORF, IRF, CF.	BOVW, SIFT, K-mean, SVM, FLIR IRT camera.	The method achieved maximum accuracy of 99.91%.
5.	Yongbo, L., et al. [15]	2020	Unbalanced rotor faults and bearing faults	CNN, DBN, DNN, and SAE.	CNN achieved average classification accuracy of 98.59%.
6.	Al-Musawi , A.K. [22]	2020	Bearing fault under different load conditions	HSV with Sobel, Prewitt, Roberts, Otsu, and Canny image segmentation techniques	The method effectively segmented the thermal images.
7.	Jia, Z., et al. [11]	2020	UN, IRF, ORF, BF, CF, IRFUN, ORFUN, BFUN, (CFUN).	CNN and BoVW were separately used for feature learning and SVM for fault classification	On the IRT dataset, CNN performed better than the BoVW with 100% accuracy.
8.	Khanjani, M [23]	2021	Normal operation, Blocking the rotor, blocking cooling fan, short circuit faults in the stator winding.	SIFT for ROI feature extraction and SVM for classification	SVM achieved 100% accuracy.

Compared to the existing researches, this work explores two new DL models on the IRT images of three-phase IM. IMs' existing IRT-based fault diagnosis methods rely on manual feature extraction, large datasets, and balanced datasets. Unlike the existing methods, the proposed DL methods can effectively classify the faults of IMs with a small and unbalanced dataset without relying on manual feature extraction techniques.

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3. Methodology

This work explores DL and thermal images based fault detection and identification method. Fig. 3 depicts the flow diagram of the proposed method. In the first step, thermal images of the IM are captured using a FLIR-E4 IRT camera. In the second step, data is pre-processed using FLIR software analysis. Then, the dataset is split into the train, test, and validation sets. Lastly, the DL models are trained, tested, and validated on three sets of data.

The pre-processing step is done by using the desktop application of the FLIR, which allows processing an individual image to get input images of proper sizes. Then, these images are fed to the DL models without any manual feature extraction. These DL models based on convolutional layers, max-pooling, and dense layers can automatically extract complex features from the image data for classification. The DL models, including RESNET-50 (Residual network) and VGG-16 (Visual Geometry Group), are employed for fault classification. These variants of CNN have been widely employed for image data analysis in different fields owing to their unique feature learning capabilities.

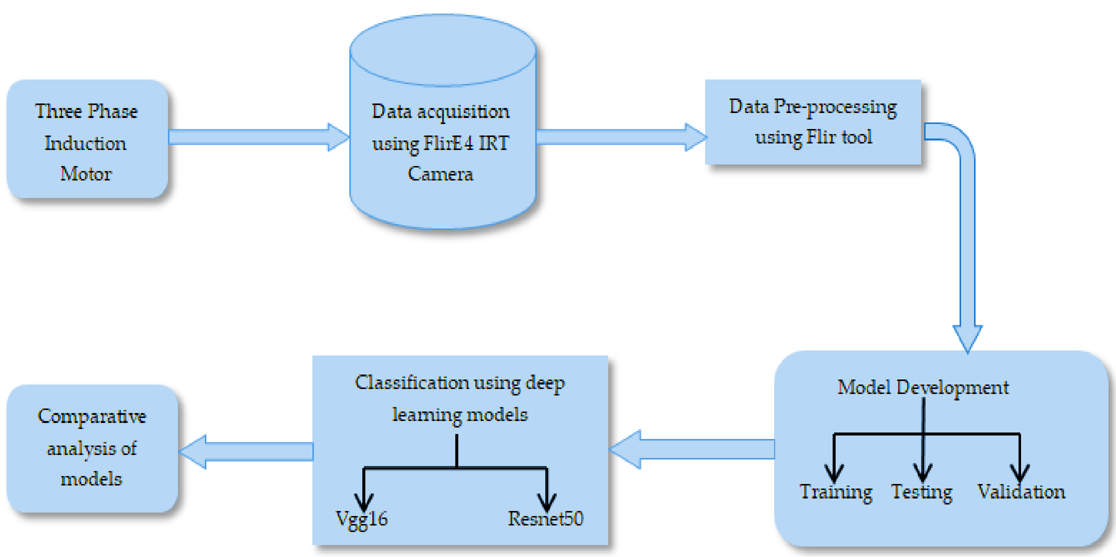

Figure 3: Block diagram of proposed work

Each of these steps is further discussed in the following subsections:

3.1 Dataset and Its Pre-processing

An open-access IRT dataset of the three-phase IM is employed in this research work [24]. The unbalanced dataset used in this investigation comprises five classes of artificially generated faults in IM. The selected dataset comprises only a total of 165

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images. The details of the used subset of the dataset are given in Table 2. The image size used for input to the DL models is set through the FLIR tool, having an image size of 320 x 240 pixels.

Table 2: Details of thermal images dataset

Class Label	Fault Type	No. of images in Training Set	No. of images in Test Set	No. of images in Validation Set
Rotor-0	Stuck Rotor Fault	21	8	2
No-load	Healthy	18	7	2
Fan	Cooling Fan Fault	28	9	2
A&C&B30	Short Circuit Fault in the Stator Winding (30%)	30	10	3
A&C&B10	Short Circuit Fault in the Stator Winding (10%)	25	8	2

3.2 Classification Models

To detect and identify the faults of IMs using thermal images following DL models are explored:

3.2.1 VGG-16

The VGG-16 model is a type of CNN model comprising 16 layers. The model was proposed by K. Simonyan and A. Zisserman, and it has been widely used as one of the most popular DL architecture in different domains [25]. It consists of convolutional layers of 3 x 3 filters having a stride value of 1. It uses the max-pool and padding layers of 2 x 2 with a stride of 2. The VGG-16 model uses these convolutional and max-pool layers constantly, and their output is followed by two fully connected layers in the end. Softmax function is used for the multiclass classification [26]. The structure of the model is depicted in Fig. 4.

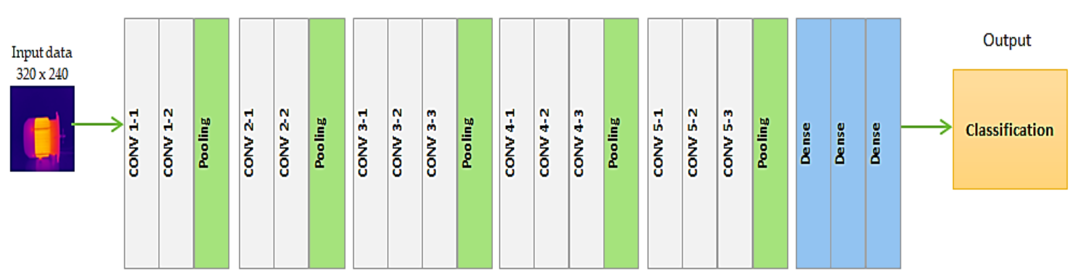

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Figure 4: VGG-16 model

3.2.2 RESNET-50

The Residual network (RESNET) model is an advanced version of CNN which was initiated by Kaiming and his team in the research paper on computer vision titled “Deep residual learning for image recognition” [27]. Different variants of the RESNET-50 model are being explored with different number of layers. The RESNET-50 with the fifty layers of residual blocks improves the model accuracy by skipping the connections of residual units. The main idea was to strengthen the neural network with residual blocks, making the model much simpler for the layers to learn characteristics from the complex data. The residual units make the DL architecture more efficient and decrease the error ratio by using more effective neural networks layers. Skip connections work in a residual model by adding the outputs of earlier layers to the outputs of stacked layers, making it possible to train maximum deeper networks effectively. The skipping connection also addresses the gradient problem. The RESNET-50 model has five stages which contain convolutional and identity blocks on each stage and individual convolutional blocks have three layers. The identity block contains three convolution layers. After that, information is passed through fully connected layers, which provide classification with the best accuracy [28].

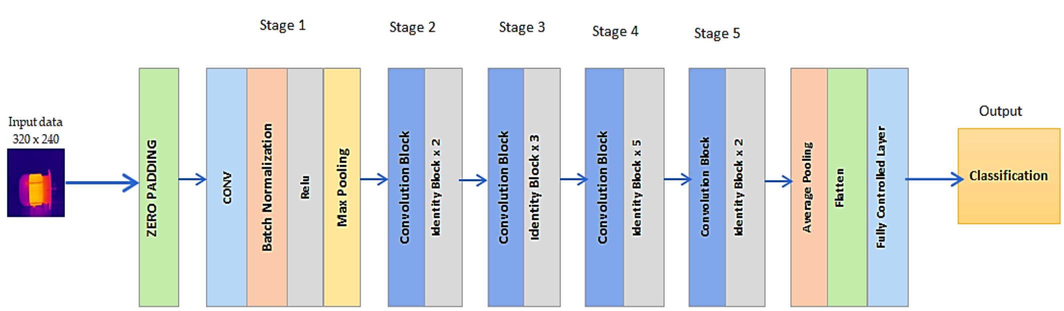

Figure 5: RESNET-50 model

3.3 Experimental Configuration and Evaluation Metrics

Two DL models, namely RESNET-50 and VGG-16, were employed for performing the fault detection and identification analysis. The thermal images of different motor conditions are fed as input to the models. The size of thermal images is 320 x 240 ×3 representing height, width, and the number of channels, respectively. Two DL networks were employed to perform comparative analysis, which were explored in recent works relating to image analysis. The computational hardware used to perform this work includes a GPU (GeForce RTX-2060 model). For programming Python 3.8.1, and DL frameworks including Keras and Tensorflow are used.

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Performance of the DL models is evaluated using the following evaluation indexes [29]:

$$accuracy = \frac{TP+TN}{m} \times 100 \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1 - Score = \frac{2(Precision \times Recall)}{Precision+Recall} \tag{4}$$

TP represents true positives, TN represents true negatives, FP represents false positives, FN represents false negatives, and m is the number of data samples.

4. Results and Discussion

This section presents the performance results of the implemented DL methods based on the IRT image dataset. The diagnosis methods classy IM faults (rotor fault, no-load fault, fault due to fan, A&C&B30 fault, and A&C&B10 fault) using the thermal images as input.

The accuracy curves of the VGG-16 model are depicted in Fig. 6, and the loss that appeared in this model is shown in Fig. 7. The accuracy curve depicts fluctuations till 40 iterations, and then it starts saturating. The confusion matrix of the VGG-16 model is shown in Fig. 8, representing its performance for individual class predictions. The RESNET-50 model achieved better accuracy than the VGG-16 model as shown in the accuracy and loss curves of the RESNET-50 illustrated in Fig. 9 and Fig. 10, respectively. The accuracy of the RESNET-50 model in individual class predictions is shown through the confusion matrix in Fig. 11.

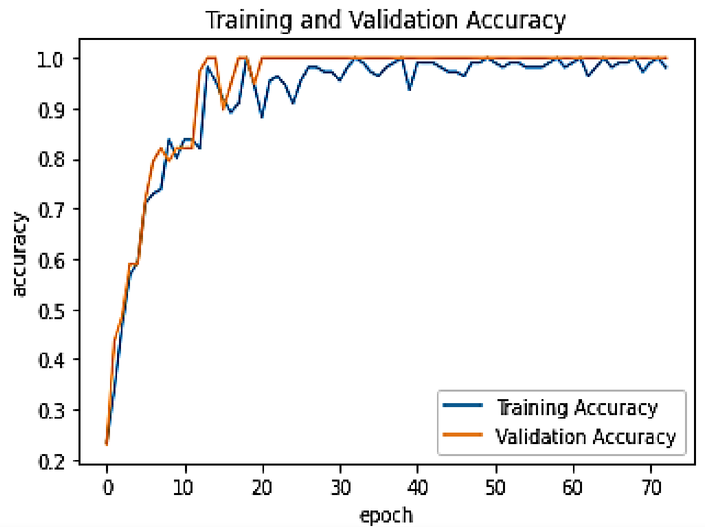

Figure 6: VGG-16 model accuracy

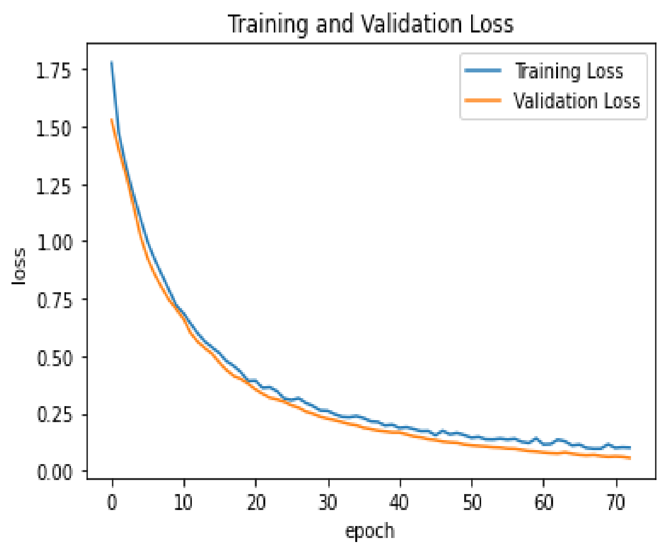

Figure 7: VGG-16 model loss

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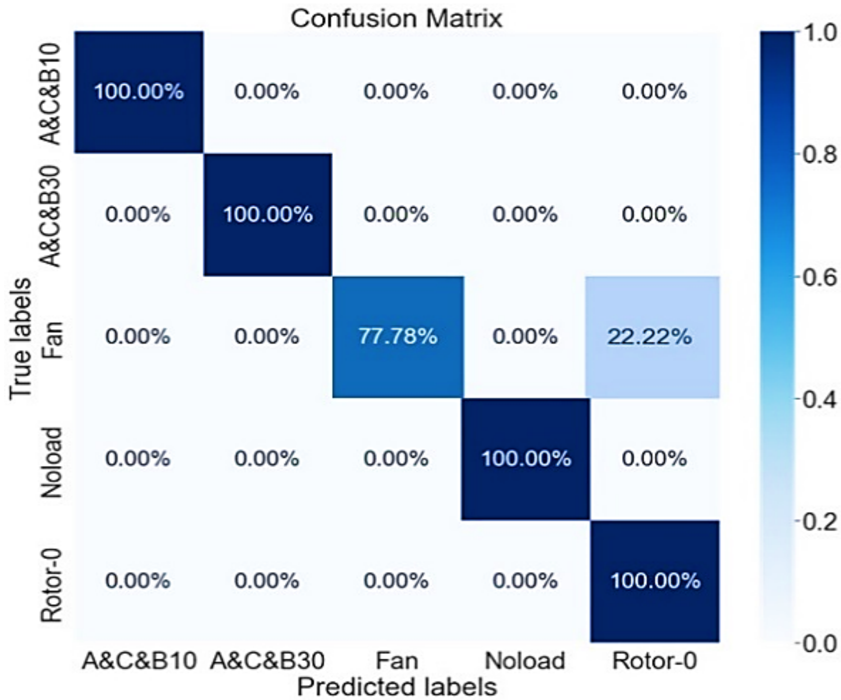

Figure 8: Confusion matrix of VGG-16 model

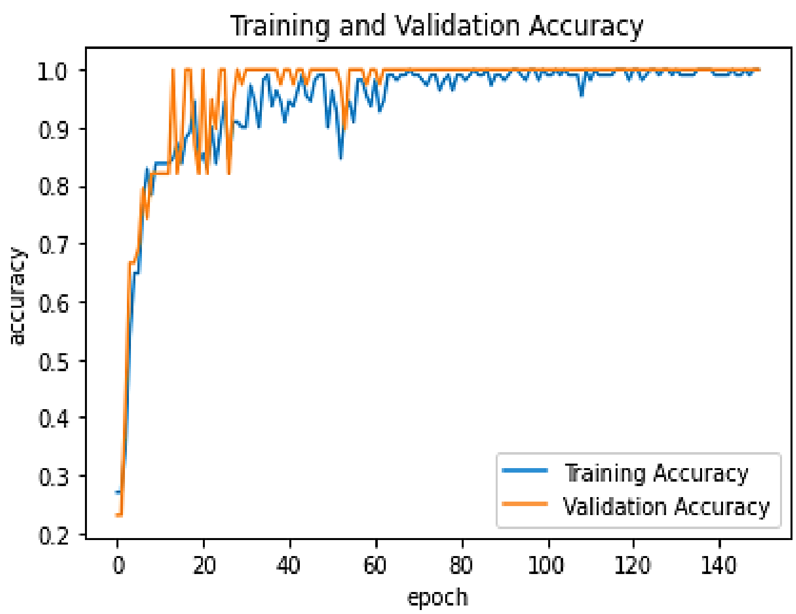

Figure 9: RESNET-50 model accuracy graph

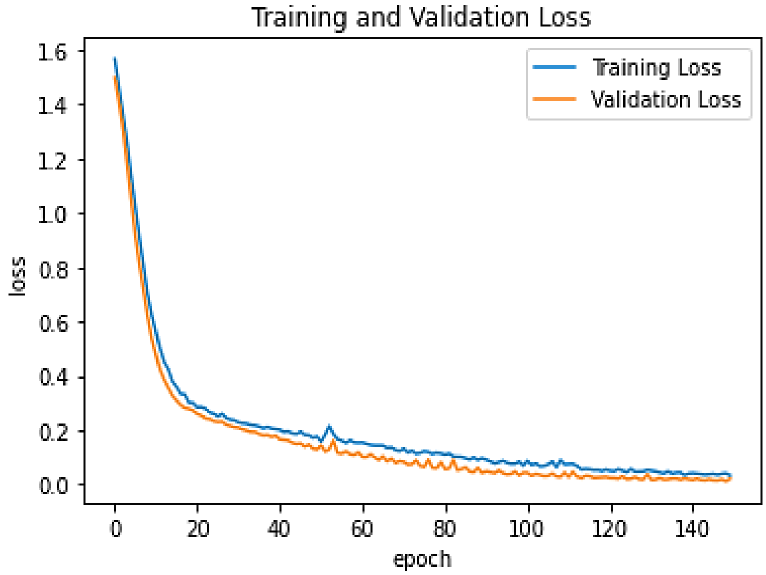

Figure 10: RESNET-50 model loss graph

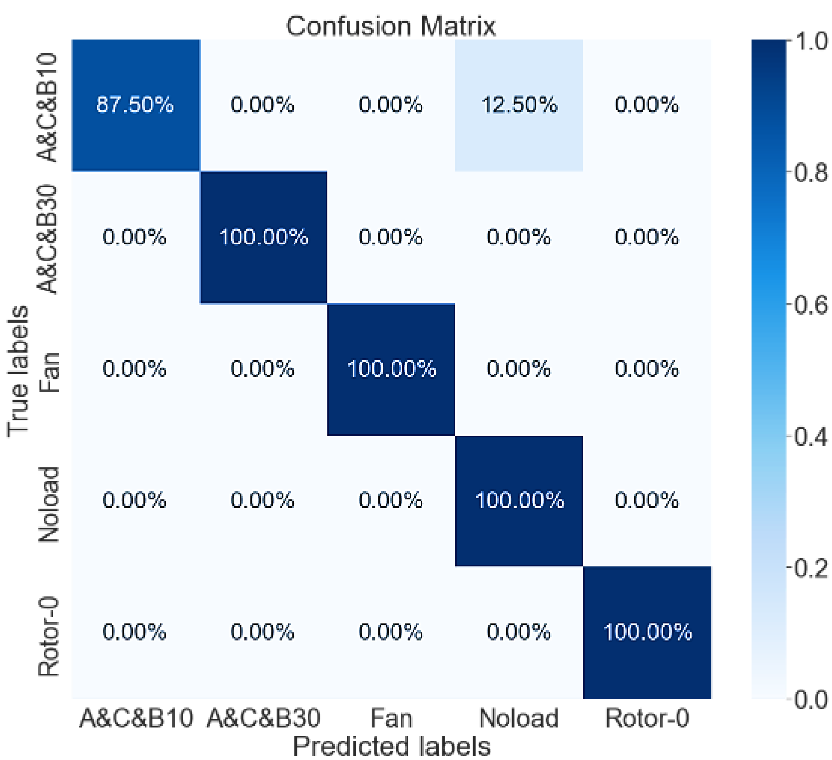

Figure 11: RESNET-50 confusion matrix

Fig. 12 shows the comparative chart of evaluation metrics for both the DL models. The comparative chart clearly depicts the performance superiority of the RESNET-50 model

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concerning to all evaluation indexes, including average accuracy, precision, F1-score, and recall.

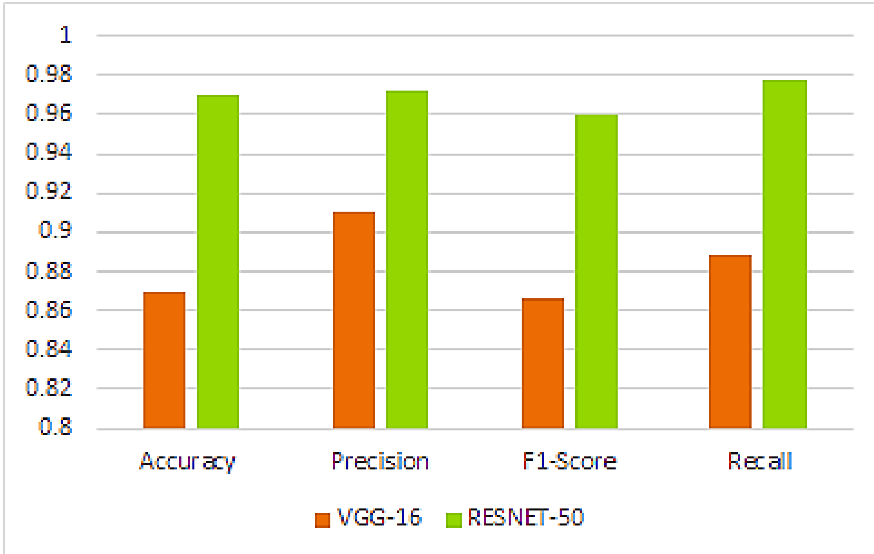

Figure 12: Comparative results of VGG-16 and RESNET-50

From the achieved graphical results, it can be noticed that the RESNET-50 model depicted fluctuations during the training process. Still, it was able to achieve better generalization due to its unique and deep architecture. Its performance becomes smoother after 120 iterations. Moreover, both the DL models achieve effective classification results even with the imbalanced thermal image dataset. Due to their deep hierarchical architecture, the models predicted motor fault classes with high accuracy without any manual feature learning technique.

5. Conclusion

This work proposed the fault diagnosis method based on DL models thermal images of motor. The employed models can directly learn from the fed thermal images without any feature extraction method. The DL models including VGG-16 and RESNET-50 can efficiently classify the motor conditions with high accuracy and lower error rate for the individual classes. The achieved experimental results show that the classification accuracy based on IRT images using RESNET-50 is superior to the VGG-16 model owing to its residual units based architecture with an accuracy of 97%. The results also show that the DL-based methods can efficiently predict the motor conditions, even these models were trained with a small and unbalanced thermal image dataset. In the future, these methods can be explored for an end-to-end motor diagnosis in an industrial rotating machine setup.

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