International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

The High Efficiency of Induction Motor Failure using Predictive Maintenance with Deep Learning Model

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DOI: https://doi.org/10.55248/gengpi.234.5.39749

A B S T R A C T

The rotary parts failure is very common problem in industrial world. It includes induction motors. The damaged induction motors make the industrial process halted. This situation caused the high loses. In order to handle this problem, the implementation of predictive maintenance is one the optimal solution. The predictive maintenance task is able to scheduling optimal maintenance frequency and prevent the incidental unpredicted machine failure, especially induction motors. The various data type have used, such as analog sensor, thermal data, thermal image and so on. Accordingly, the methods also varied such as mathematic computation up to smart or intelligent computation. The proposed method uses a kind of deep learning architecture, Residual Network or Resnet 50 model. The dataset is selected a kind of image, thermal image of damaged induction motor with varied defect rate. It is 10% and 30 % respectively. The obtained prediction accuracy is 100%. It means every prediction is true. Therefore, the proposed method is able to predict the rate of failure of induction motor. It will help the operator to plan the cost of repairing task and the suitable operational duration of induction motor accurately. This method prevent to use many sensors and complicated electronic circuit. This method is easy and accurate to implement in industrial world.

Keywords: Predictive maintenance; deep learning; thermography

1. Introduction

Three phase induction motors are very common used in industrial world, such as woodworking machines, blowers, pump, automotive industries, railway applications, and so on. The induction motors have the main goal to maximize the operational production and quality operation[1]. Nevertheless, at the same time reducing operational cost as low as possible. To reach this goal, the induction motors should be in high efficiency operation[2]. In order to keep the induction motors work in high efficiency, they need maintain properly. There are many different maintenance strategies being used to maintain the efficiency of the induction motor. For any type of induction motors, maintenance effects the costs of output produced. To avoid accidentally failure, maintenance strategies should be planned in such a way the maintenance tasks are done at right time. The non-essential maintenance tasks increase the maintenance cost and also the time required to perform them. Failure of electric motors can be listed as stator faults, rotor electrical faults, rotor mechanical faults, bearing faults and so on. The fault detection and diagnostic (FDD) of induction motor is very important nowadays[3]. However, various failures repeatedly occur in induction motor because of hard working conditions, overload and unexpected conditions and many others. Thus, FFD is useful to prevent the serious failures, high operational cost, shutdown and unsafe operations.

There were several methods to perform FDD of the induction motors. The incipient failure detection of single rotor bar uses cyclostationnaritysignal[4]. This electric signal can classify the incipient failure and the size of cracking that occurs in the single rotor bar even under various loads. The other FDD of induction motor is performed in stator fault detection. This method used motor current signature analysis (MCSA) for stator winding short circuit fault[5]. This short circuit happed because of the destruction of the turn isolation. Further, this problem can make the induction motor shutdown. The other method that uses electric signal to detect the failure of rotor bar and gearboxes is embedded system simulation[6]. The broken rotor bar or gear failure were pointed using the hotspot. Besides, using electric signal to detect the induction motor failure, the appearance of thermal electric signal was very helpful to perform the FDD operation. The thermal signal processing was implemented in fault diagnosis of induction motor[7]. This method used CAPnet to do fault diagnosis of three-phase induction motor.

The use of infrared thermography is very important in areas of maintenance electrical installation. This data can be applied to detect the presence of fault of electrical machinery, such as induction motor[8].There were many methods of FDD induction three-phase motors such as CNN model to detect bearing. failures[9]. Then , the comparison between damaged and normal thermal images of induction motor[1]. Furthermore, the use of YOLO network to detect the anomalies of temperature equipment[10]. This temperature anomaly was predicted as the machinery failures. The deep learning architecture, YOLO was able to predict the temperature anomaly accurately. The fault diagnosis based on thermal images was applied to evaluate the gearbox condition. The procedure was according to multiscales convolutional neural network[11]. The thermal images were applied to detect the failure of bearings using machine learning. It was able to classify the failure of bearing[12]. The thermal image used to detect bearing-lubricant starvation, lack of lubricant. The differencing of sequence images determined the rotor unbalanced. Finally, the method was able to distinguish all eight different conditions with the high accuracy.

Besides diagnosis of induction motor failures the thermal images could be used to classify the faults. The using of HSV color space was able to extract failure features[13][14].

2. Method

The proposed method is a classification of induction motor failures based on deep learning. The method predicts what kind of problem the induction motor has. Through this classification, the maintenance operation can be done more efficient and faster. The classification is done using deep learning method. The ability of deep learning is very powerful in performing classification task[15][16].

The classification of induction three-phase motor can be categorized based on damage percentage. The classification is divided into two categories. The classification is focused on two-phase failure within 10% and 30 % damages[17]. The method uses deep learning with Resnet 50 network. The Resnet 50 network can help to classify accurately the induction motor failure. The accurate classification because of Resnet 50 network is able to maintain the original feature of the input image until the end layers. The architecture is as shown in Fig 1 below., .

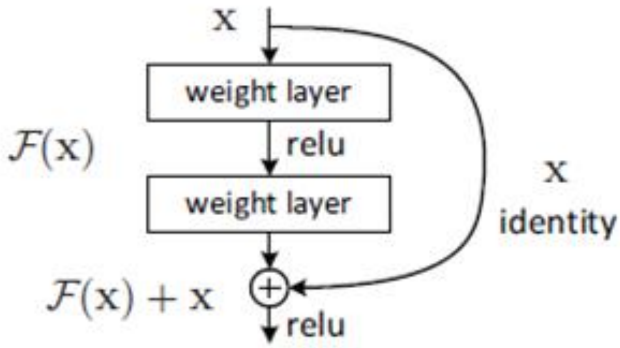
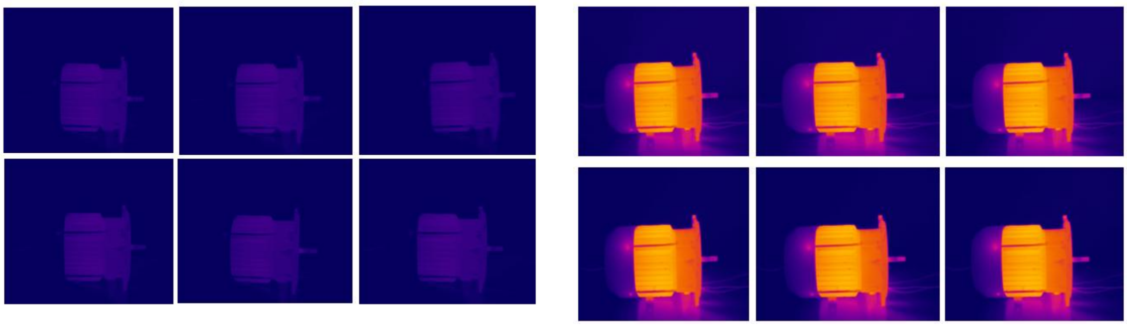


Fig. 1 The building block architecture of Residual Network

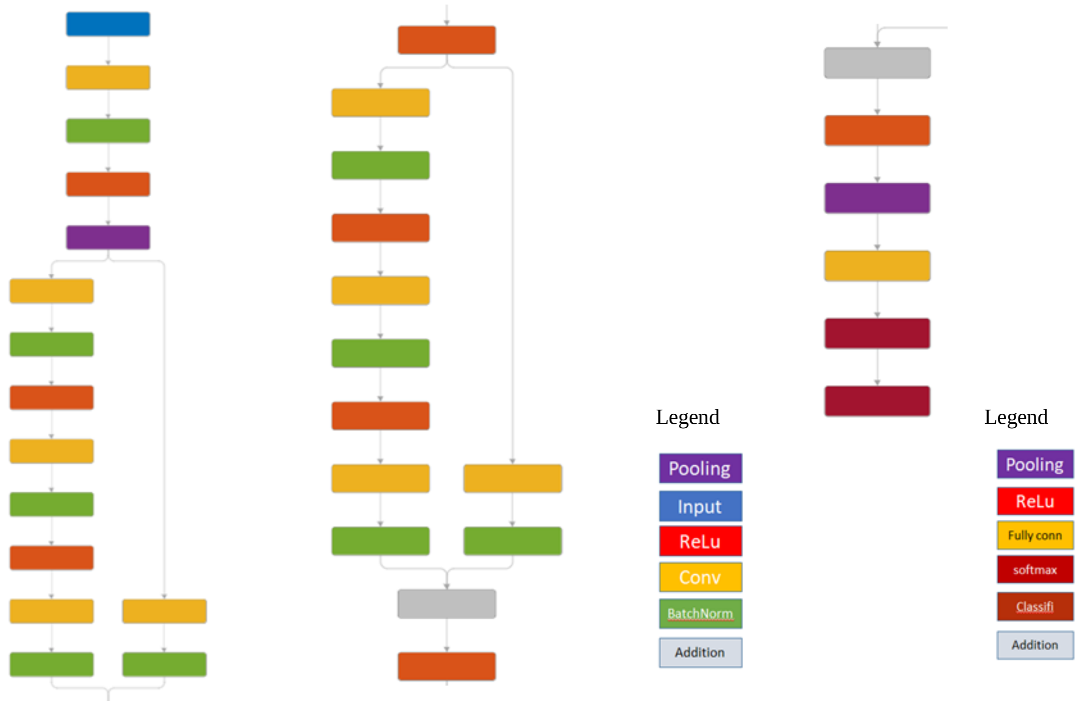
Based on Figure 1, the identity mapping x kept the feature from beginning layer to the end layer[18]. The method uses thermal images of damaged induction three-phase motors. The three phase induction motors have two type of damages with the 10% and 30% respectively. The faults take place in the motor coils. It might be in the form of isolation breakdown or other mechanical problems. This problem generates higher temperature in the region. The hotter temperature can be detected through thermal vision devices. The dataset is divided into training set and validation set. Some of the training set is as shown in Fig.2 below.



(a) (b)

Fig.2 The training set with (a)10% damage rate; 30 % damage rate

Fig.2 shows some samples of thermal images of training set. The training set is used to perform training process to generate a model. Besides available dataset, training process needs some training parameters such as iteration, mini batch size, max epoch and so on. The architecture of beginning layers are as shown in Fig.3 below.



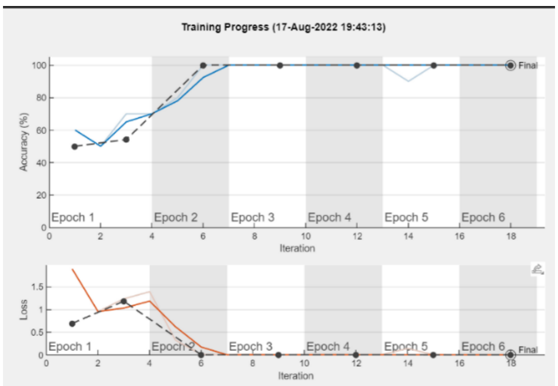
(a) The beginning layers (b) The building block of Resnet (c) The last layers

Fig.3 The beginning layers of Resnet 50

Result

The training process involves dataset with two labels. They are 10% and 30% damaged induction motor respectively. The set up of training hyper parameters such as iteration is 100, minibatch size 4, max epoch 6 and learning rate 0.001. The training process is performed with non-early stopping mode. That, the training process is run according to iteration value. The training needs about 15 minutes to complete. The training progress start with low accuracy. It is about 50%. The next iteration, it increases to 85% accuracy. Finally, It reaches accuracy 100% soon.

Based on the Resnet 50 architecture, the obtained training progress is as shown in Figure 8 below.



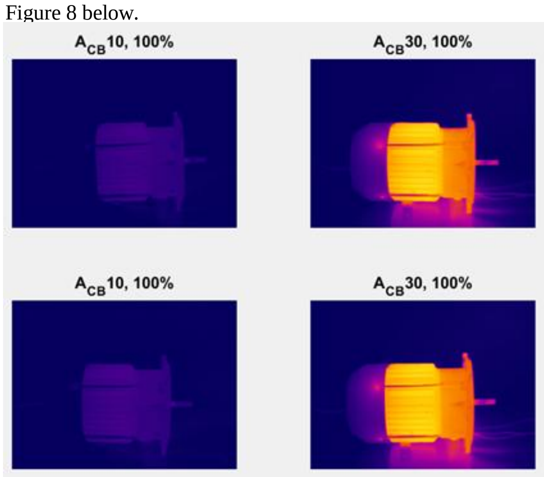


Fig.4 The training progress of proposed method

Fig.5 The accuracy of prediction of the induction motor failures

The generated model is able to produce high accuracy. It reaches 100%. It means all the given input can be predicted with high accuracy. The given inputs or test set are two phase motor with failure rates are 10% and 30% respectively.

The prediction of test set shows the 100% accuracy. It is as shown in Fig.6 below. The test set is predicted 100% accurate. Therefore, it shows that the proposed method is powerful to predict the damage of induction motor. Further, the maintenance and repairing tasks run more efficiently.

In order to ensure that the proposed method is powerful, the other test set is applied to the model. The result of the prediction task is shown in Fig.7

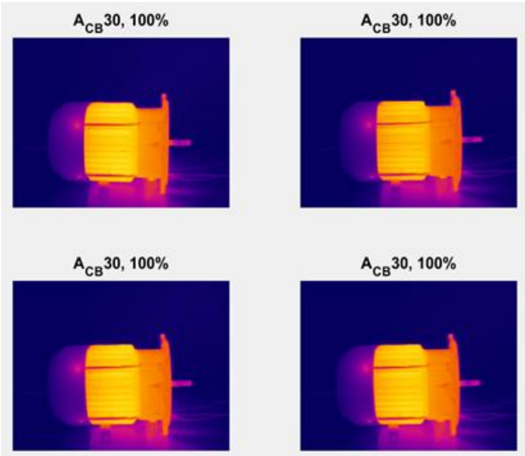


Fig.6 The accuracy of prediction of two phase motor failures

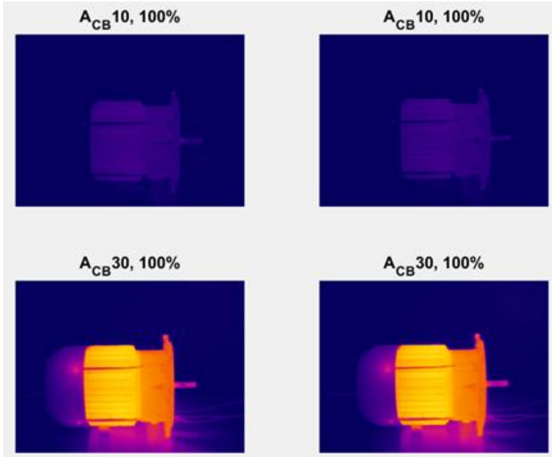


Fig.7 The accuracy of prediction of 10% and 30 % motors failures

Fig.8 and Fig.9 show the prediction accuracy of proposed method with damaged induction motor rate 30%. The obtained accuracy is high, it is 100%.

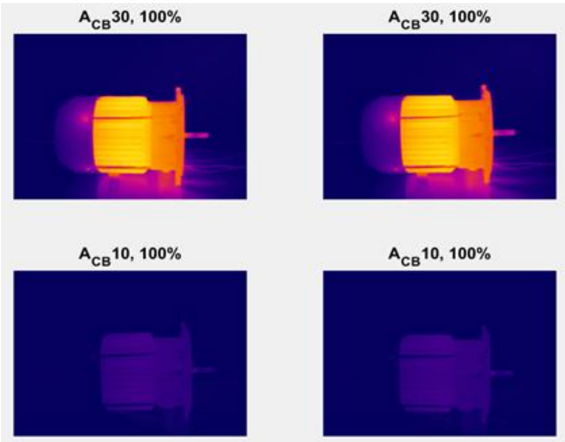


Fig.8 The accuracy of prediction of 10% and 30 % motors failures

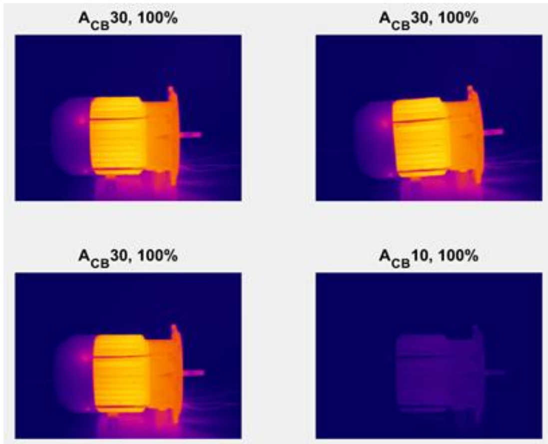


Fig.9 The accuracy of prediction of 10% and 30 % motors failures

All the test set provides accuracy 100%. As the accuracy is high, the proposed method is able to predict the damaged induction motor failure percentage. The accuracy of classification task of damaged induction motor is high. This confidence makes assure that the robustness of proposed method is very powerful. The implementation of this method is guaranteed to work accurately.

4. Conclusion

It is still a challenge to predict efficiently the damaged induction motor in industrial world. The using electrical or analog signal is still very common in the fields. The using thermal image becomes a new challenge in predicting induction motor damage. The thermal image format is ubiquitous nowadays. The implementation thermal image in artificial intelligent algorithm such as deep learning and machine learning is feasible. Since the intelligent computation grow fast, the development of deep learning rise quickly.

The use of intelligent computation in predictive maintenance is very important, because this method is able to predict the failure faster and accurate. Thus, the maintenance task will be in low cost.

In order to reach this goal, this method uses thermal images as dataset. Then, the data processing uses deep learning architecture. It is Resnet 50 model.

Acknowledgements

This article is supported by a competitive grant of DIPA Politeknik Negeri Padang in 2022..

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