Categorization of Internal Fault using Artificial Neural Network

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Abstract - **The main objective of this project is to create an intelligent model using image processing techniques in order to categorize the internal fault to four categories, there are low, intermediate, medium and high. Sample of internal fault location are captured using infrared thermography camera where the RGB color image are stored and processed using matlab. Processing involves impixelregion which includes creating a Pixel Region tool associated with the image displayed in the current figure, called the target image. This information is then being used to train a three layer Artificial Neural Network (ANN) using Levenberg Marquardt algorithm. 168 samples are used as training. While another 168 samples are used for testing. The optimized model is evaluated and validated through analysis of performance indicators frequently used in any classification model.**

Keywords: Artificiel Neural Network, internal fault and cross validation

I. INTRODUCTION

The internal faults are difficult to be penetrated because internal faults are much more complex. To find out the internal faults, one must know the law of the internal faults attribute to the relation of their infrared thermography characteristics. The internal faults of the electrical equipments can be diveded into loose connection or contact of internal conductors and inferiority in insulation and other faults. The internal faults don't have protection system and internal fault can be detected by using infrared thermography camera [1, 2]. People and structure are still exposed to the danger of internal fault result in the need for internal fault prediction system.

In many cases the true source of the temperature rise is not visible either to the human eye or the infrared camera making these measurements indirect. The decision to conduct the corrective actions rests on the maintenance team, taking into consideration other factors, such as equipment's criticality, safety and the availability of parts [1, 2].

Artificial neural network (ANN) is a branch of artificial intelligence (AI). This system based on the operation of biological neural network, in the words, is an emulation of biological neural system. In engineering, neural networks serve two important functions. There are pattern classifiers and as nonlinear adaptive filters. ANN has several advantages. As stated in [3], the advantages of the ANN are it can perform tasks that a linear program cannot and does not need to be reprogrammed. Besides, ANN can be implemented in any application without any problem. But, ANN also comes with several disadvantages such as it needs training to operate and require high processing time for large network. It also need to be emulated due to different architecture with microprocessor.

This Paper present ANN-based technique to categorize the fault system based on temperature and RGB color image data in fault picture. In order to determine the best ANN model, several feed-forward back-propagation ANN designs were constructed and each network performance was evaluated by using cross-validation. ANN model with the best performance was selected as the best design. As a result, the developed fault category system is able to generalize well when presented with new sets of input data [1]. Finally, caterorized the fault to 4 catagori can be successfully done.

II. METHODOLOGY

In general, the research design for categorize fault to 4 caterory system can be grouped into three main stages. They are data collection, data analysis using image processing and development of the ANN.

A. Data Collection

In this project, there are four types internal fault category. These internal faults are low, intermediate, medium and high. From these four category internal fault, there are 84 for low fault, 84 for intermediate fault, 84 for medium fault and 84, for high fault samples of data have been collected. All samples were collected at Grahatech Resourses Sdn. Bhd, Subang and were captured the internal fault using infrared thermography camera [1].

TABLE 1: Internal Fault Category

Low	ΔT < 9°C	Minor Overheating
Intermediate	9°C ≤ ΔT ≤ 19°C	2nd Stage Overheating
Medium	19°C < ΔT ≤ 35°C	Major Overheating
High	ΔT > 35°C	Acute Overheating

From table 1, the internal fault can be divided to 4 categories. There are low, intermediate, medium, and high internal fault. The internal fault can be describe as the different temperature between spot temperature and reference temperature. Figure 1 to figure 5, show the type of internal fault.

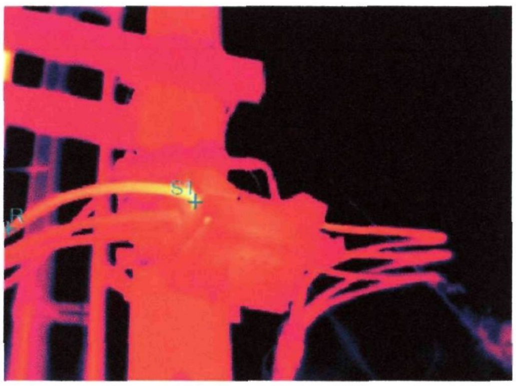

Figure 1: Low Internal fault

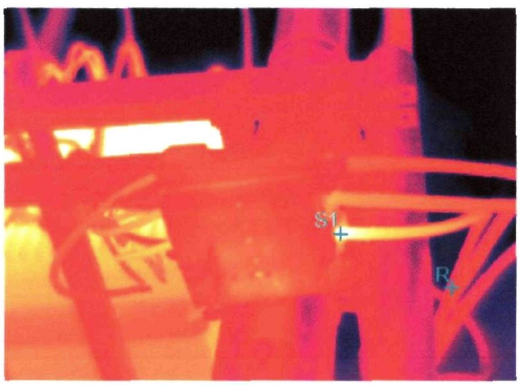

Figure 2: Intermediate Internal fault

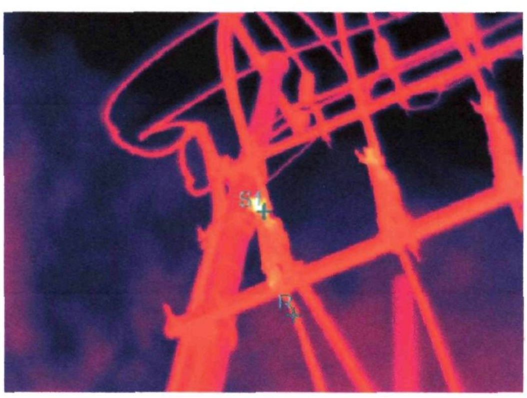

Figure 3: Medium Internal Fault

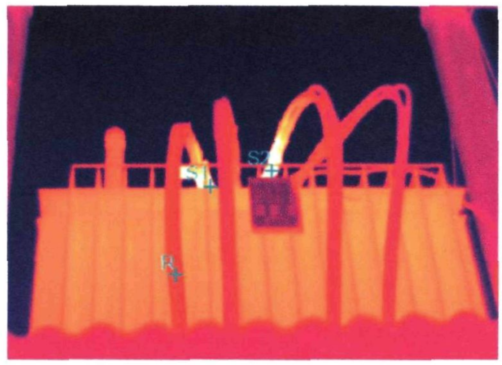

Figure 4: High Internal Fault

B. Data Analysis using Image Processing

Image processing is the most critical part since the RGB component will be used as an input to ANN. If it is done in improper process, the recognition process will becomes inaccurate. Impixelregion one of the command in image processing toolbox. Impixelregion creates a Pixel Region tool associated with the image displayed in the current figure, called the target image. The Pixel Region tool opens a separate figure window containing an extreme close-up view of a small region of pixels in the target image. When use the command impixelregion, the pixel region rectangle will be displayed. The Pixel Region rectangle defines the area of the target image that is displayed in the Pixel Region tool. The pixel region rectangle can be move over the target image using the mouse to view different regions. To get a closer view of the pixels displayed in the tool, use the zoom buttons on the Pixel Region tool toolbar or change the size of the Pixel Region rectangle using the mouse [4].

From figure 5, its show the pixel region rectangle use in the target image. By using this command, the RGB color data can be obtain and use for input ANN. Figure 6 show the scale color, its use to take RGB color data when pixel region rectangle focus at certain temperature level.

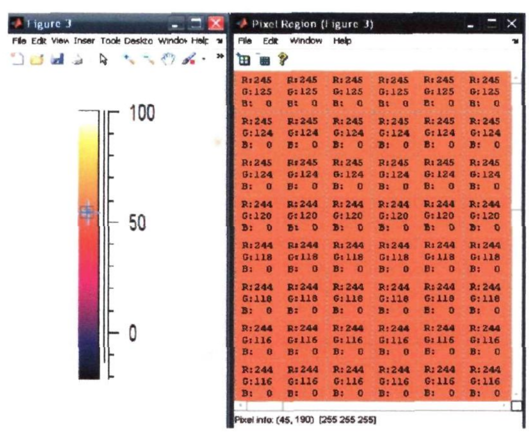

Figure 5: Pixel Region Rectangular

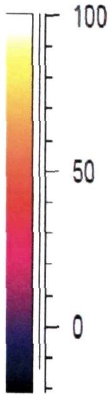

Figure 6: Scale Color

C. *Development of the ANN*

From figure 7, the neural network have three-layer feed-forward backpropagation ANNs are developed in Matlab. There are input layer, hidden layer and output layer. Ach layer consists of one or more nodes, represented in this diagram by the small circles. The lines between the nodes indicate the flow of information from one node to the next. In this particular type of neural network, the information flows only from input to output.

From figure 8, shows the block diagram for categorize fault system. In the block diagram, temperature data and RGB color data are used as the input and categorize internal fault to four categories as the target output to the ANN. The temperature data and color data, a factor that helps in the convergence of ANN training process, to form the overall input data. The developed ANN receives the input data and also the targeted output to produce network output [5].

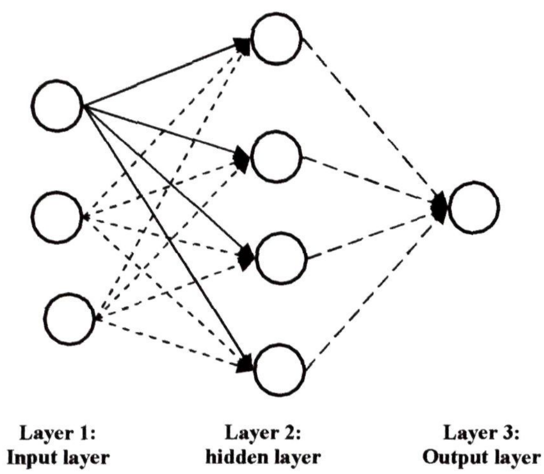

Figure 7: ANN Diagram

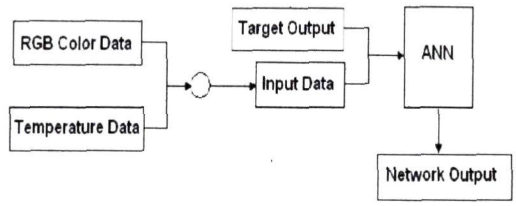

Figure 8: Categorize Fault System Architecture

1) Training Process

In order to determine the best design, each network is trained and tested to estimate its performance and determine which configuration provided the best results. This could be done by using cross validation, a model evaluation method that estimates generalization error based on re-sampling [6]. It is a statistical practice of partitioning a sample of data into subsets where the analysis is performed on a single subset while the other subsets are retained for subsequent use in confirming and validating the initial analysis.

There are two types of cross validation methods that can be considered. They are the holdout cross validation and the K-fold cross validation.The holdout method is the simplest kind of cross validation. The data set is separated into two sets, called the training set and the testing set. The holdout cross validation use the training set only. The errors it makes are accumulated as before to give the mean absolute test set error, which is used to evaluate the model [7, 8]. The advantage of this method is that it is usually preferable to the residual method and takes no longer to compute

In *K*-fold cross-validation, the original sample is randomly partitioned into *K* subset. Of the *K* subset, a single subset is retained as the validation data for testing the model, and the remaining *K* – 1 subset are used as training data. The cross-validation process is then repeated *K* times, with each of the *K* subset used exactly once as the validation data. The *K* results from the folds then can be averaged to produce a single estimation. The advantage of this method over repeated random sub-sampling is that all observations are used for both training and validation, and each observation is used for validation exactly once. Figure 9 show the K – 1 subset is used as a validation set [8, 9].

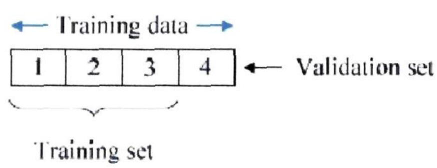

Figure 9: Partitioning of data for K = 4

2) Testing Process

Testing process is carried out to measure the performance of the trained network, which can be measured to some extent by the errors on the training and validation sets and the testing data; or by performing a linear regression analysis between the network response and the corresponding targets. The regression coefficient, R with values close to one indicates that there is a strong correlation between the targeted outputs and network outputs while the values that are close to zero indicates otherwise [10]. In order to measure network performance in terms of its R-value, the best network is trained once again using both training and validation sets as the whole training data. Its performance is then assessed using the testing data. A fully trained network should be able to categorize fault into four categories from this set of unseen data and it is evaluated by measuring the R-value. From figure 10, show the flow chart for ANN algorithm.

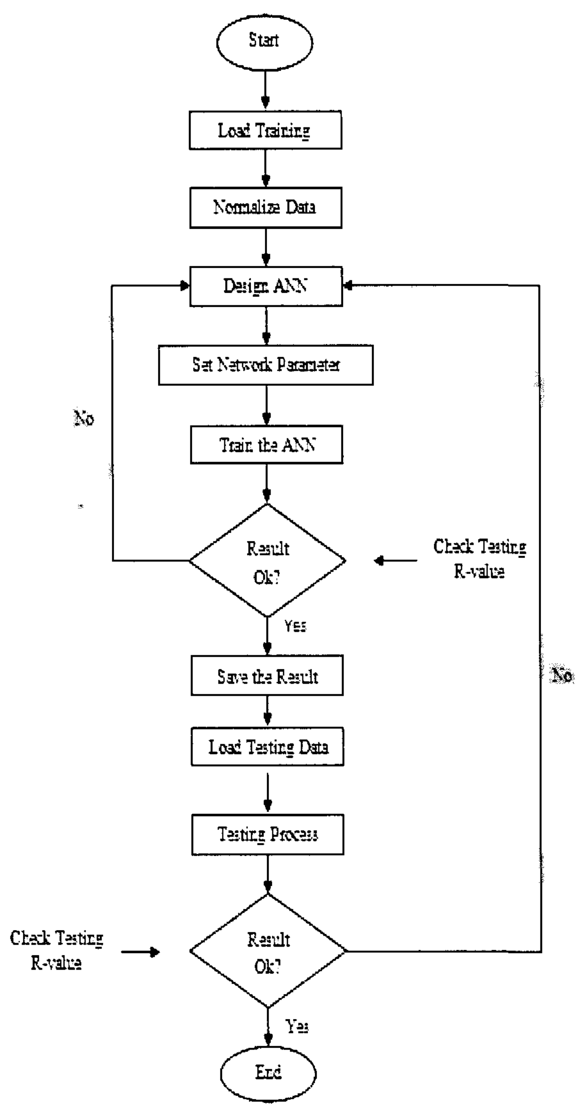

Figure 10: ANN Algorithm

III. RESULT AND DISCUSSION

The data were selected from RGB color and temperature internal fault record. 336 data internal fault is selected, 168 were utilized for trainning network and 168 were employed for the testing process. The developed ANN receives the input data and also the targeted output to produce network input.

The feed-forward back-propagation ANN were developed in matlab. Network configurations such as the number of neurons and transfer functions were determined heuristically. For each network design, the learning rate was chosen to be 0.50 while the momentum constant 0.9 (typical value). The value learning rate and momentum kept constant in the holdout and K-fold validation methods. After finishing the validation method, the number neuron and transfer function is selected depend on the R-value should be close to one.

In the holdout cross validation methods, the training data is subdivided into 2 set data, there are training and validation sets. For this study, the K-fold cross validation have 168 training data and this data subdivide into 4 set. There 3 set for training and 1 set for validation set. However the number of fold is choice depend on the size the data. When the number of fold is large, the result is more accurate.

TABLE 2: Comparison Between Holdout & K-fold validation method

No of Neuron	Transfer Function	R-value	
		Holdout Validation	K-fold Validation
10, 8, 1	Logsig Logsig Purelin	0.97396	0.93426
10, 8, 1	Logsig Tansig Purelin	0.98211	0.97602
10, 8, 1	Tansig Logsig Purelin	0.96934	0.97272
10, 8, 1	Tansig Tansig Purelin	0.90879	0.9879
8, 5, 1	Logsig Logsig Purelin	0.98683	0.97724
8, 5, 1	Logsig Tansig Purelin	0.86111	0,9847
8, 5, 1	Tansig Logsig Purelin	0.9837	0.9688
8, 5, 1	Tansig Tansig Purelin	0.98523	0.9467

The comparison between holdout and K-fold validation method is depend on the value R-value. When the R-value is close to one as that indicates that there is a strong correlation between target output and network output. R-value close to zero indicates otherwise.

From table 2, the best R-value for holdout is 0.98683 as shown in figure 11. The best value, 0.9879 is obtained from an average of K-fold as shown in figure 12 to figure 15. It can also be seen that the network trained in using K-fold cross validation gives better results than that using holdout method. By comparison, between holdout and K-fold cross validation method, the R-value obtained by the network trained using K-fold cross validation method was higher that that using holdout method. Based on these, it can be concluded that K-fold cross validation method gives better than result holdout cross validation method in term R-value. The K-fold cross validation method can be obtain the best R-value when used fix learning rate and momentum constant of 0.5 and 0.9 respectively

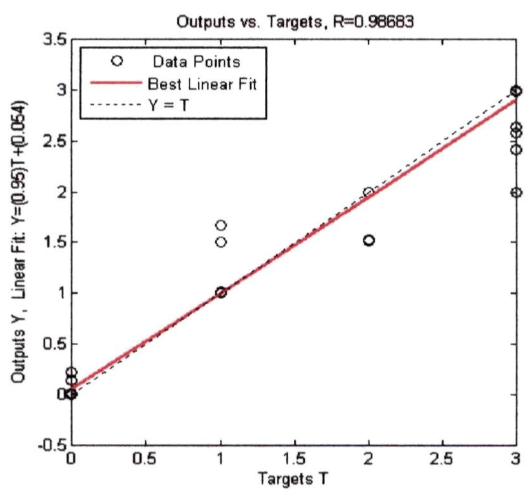

Figure 11: The best R-value for Holdout Cross Validation Method

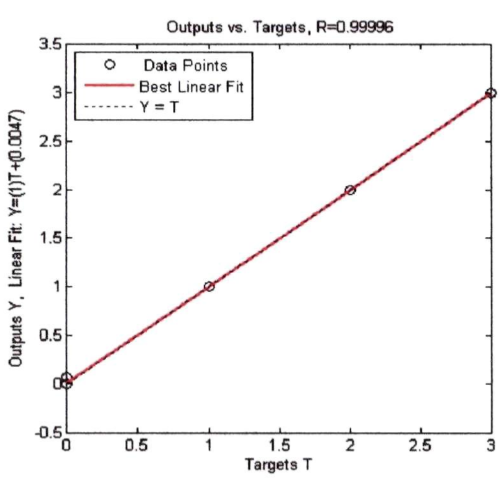

Figure 12: The R-value for partioning of data for K=1

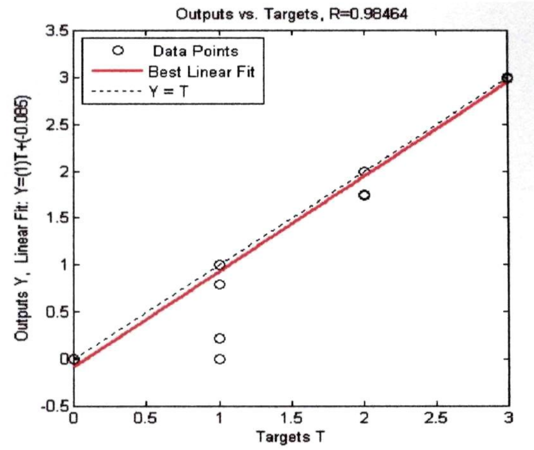

Figure 13: The R-value for partioning of data for K=2

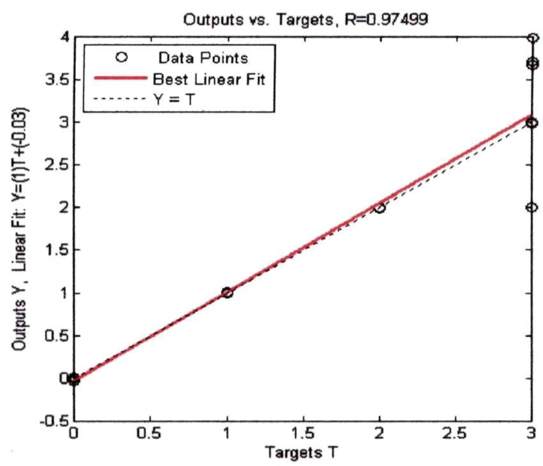

Figure 14: The R-value for partioning of data for K=3

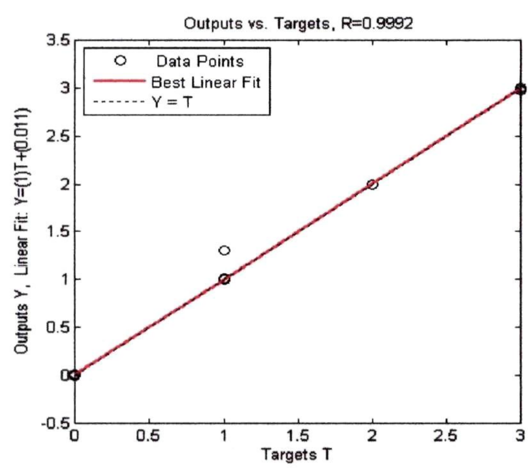

Figure 15: The R-value for partioning of data for K=4

The R-value is change when the value learning rate and momentum varied. The K-fold cross validation method is use to get the best of value learning rate and momentum. From table 3, the best value of learning rate and momentum are 0.1 and 0.5. The R-value obtain by this network is 0.99381 as shown in figure 16.

TABLE 3: Learning Rate and Momentum

Learning Rate	Momentum	R-value
0.1	0.1	0.97948
	0.3	0.97626
	0.5	0.99381
	0.7	0.88871
	0.9	0.96934
0.3	0.1	0.9881
	0.3	0.9872
	0.5	0.96126
	0.7	0.97875
	0.9	0.96669
0.5	0.1	0.97312
	0.3	0.9555
	0.5	0.96131
	0.7	0.97222
	0.9	0.98047
0.7	0.1	0.9783
	0.3	0.97566
	0.5	0.97639
	0.7	0.98777
	0.9	0.97375
0.9	0.1	0.9393
	0.3	0.97556
	0.5	0.98977
	0.7	0.96709
	0.9	0.97337

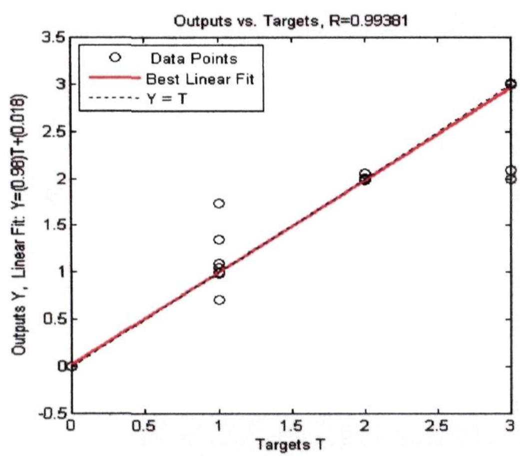

Figure 16: The best of ANN design

TABLE 4: Properties to developed network for categorize internal fault to 4 categories

ANN Properties	Properties
Network Configuration	[10, 8. 1]
Transfer Function	Tansig, tansig, Purelin
Learning Rate	0.1
Momentum Constant	0.5
Training Technique	Lavenberg-Marquardt
Epochs	1000
Regression Coefficient, R	0.99381
Training Pattern	168
Testing Pattern	168
Accuracy Training Data	100 %
Accuracy Testing Data	99.38%

Its can be conclude, the best ANN to categorize internal fault can be divided to four categories as shown in table 4. The accuracy of training and testing depend on the percentage of the R-value.

IV. CONCLUSION

This research mainly presents a contribution in the field of image processing to analysis the internal fault picture and to get the RGB color data. This information is expected then can be used to produce intelligent model system for internal fault classification. The feed-forward back propagation network develop in the ANN model for categorize the internal fault to 4 categories. The development of these network required a certain degree of experience because the network architectures such as the number of neurons and transfer functions needed to be determined heuristically.

From the comparison cross validation method between holdout and K-fold, it can be conclude that, the K-fold cross validation method produce better result for ANN in term R-value. Therefore, based on the result, to categorize internal fault to 4 categories is able to generalize well when presented with new sets of input data. Therefore, the internal fault can be divided to 4 categories can be successfully done.

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