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Determination of Abnormality of IGBT Images Using VGG16

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Abstract: A power device is a semiconductor device for power control used for power conversion such as converting direct current to alternating current and alternating current to direct current. It is widely used such as refrigerators, air conditioners which is implemented electronic components that are closely related to our daily lives. Therefore, high reliability and safety are required, and power cycle tests are conducted for the purpose of evaluating them. In the conventional test, there is a problem that it is difficult to perform analysis because sparks are generated during the test and the device is severely damaged after the test. To solve this problem, a new technology has been developed that adds ultrasonic that enable internal observation during the test. However, there are remains a problem that the method for analyzing the ultrasonic image obtained in the new technology has not been established. Also, few abnormal images are obtained in the test. In this paper, we propose a method for detection of abnormal devices based on CNN. Especially, we implement a Cycle-GAN to extend the abnormal data and classify the known image based on improved VGG16. As an experimental result, classification accuracy of $Precision = 97.06\%$, $Recall = 93.58\%$, $F - measure = 95.17\%$ were obtained.

Keywords: Ultrasound images, Convolutional neural network, Cycle-GAN, Data augmentation, VGG16, Batch normalization, Global average pooling

1. INTRODUCTION

A power device is a semiconductor for power control used for power conversion such as converting direct current to alternating current and alternating current to direct current. It is used in electric vehicles, trains, and is an electronic component closely related to our daily lives. In recent years, awareness of energy saving and power saving has increased. Furthermore, the power devices can accurately rotate motors from low speeds to high speeds, and the electricity generated by solar cells can be sent to the power grid without waste. It is an indispensable electronic component in our daily lives and is used in various environments, so high reliability is required.

Power cycle tests are being conducted to evaluate its reliability. It is a test in which power is applied to a power device and the ON-OFF operation is repeated to confirm the life of thermal fatigue due to local heat generation of the chip. In conventional tests, it is difficult to identify the cause of destruction due to sparks generated at the time of destruction, severe damage to chips, substrates, solder, after destruction, and analysis of the process leading up to destruction. Therefore, a technology has been developed that makes it possible to solve the problem by recording the internal structure in real time by adding ultrasonic observation. At present, the problems of the new technology are that a method for analyzing a huge amount of image data and a method for extracting changes that are difficult for humans to discriminate have not been established [1, 2].

J.K. Chowa et al. [3,4] proposes a method for detecting anomalies in concrete using deep learning. This shows that deep learning is also effective in the field of anomaly detection. We proposed an identification of normal and abnormal devices from ultrasound images using VGG16 [5]. However, high accuracy is still remained. Therefore, in this paper, we propose an analysis method using deep learning. In addition, since the number of images for power device ultrasonic images is insufficient due to experiments, we also propose a data expansion method based on Cycle-GAN [6].

2. METHOD

In this study new CNN model proposed for the detection of abnormalities from the ultrasound images. The structure of the power device is shown in Fig. 1, and the image obtained in the power cycle test is shown in Fig. 2. The overall processing flow is shown in Fig. 3. In this method, Interface3 and Interface4, which change significantly during the test, are used as training data, and the region of interest is specified around the DBC diode

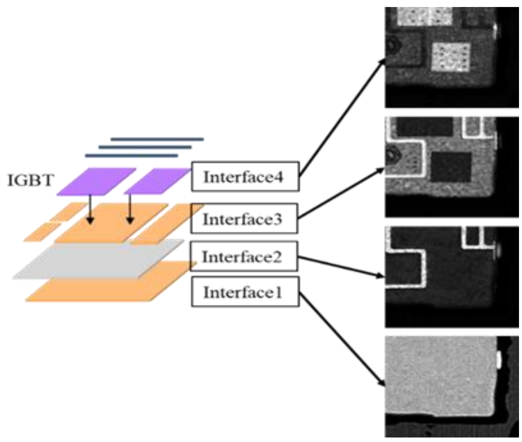
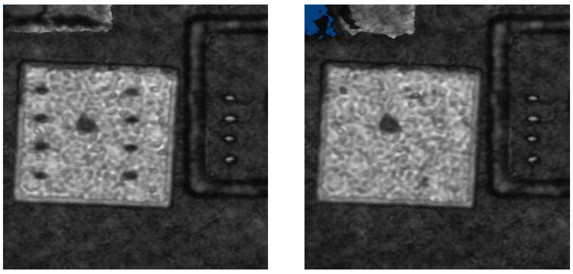


Fig.1 The structure of the power device



(a)Normal (b)Abnormal
Fig.2 Ultrasound image (Interface3)

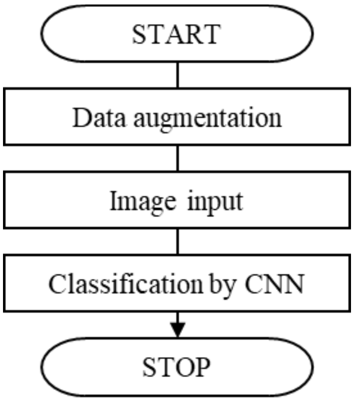


Fig.3 Flowchart

and cut out. As a preprocessing step, noise is removed from the cropped image based on non-local-mean-filter [7] which is described in 2.1. After that, the data is expanded and classified by CNN.

2.1 Non-Local Mean Filter (NLMF)

NLMF is a smoothing filter to remove the image noise without excluding edges information [7]. The formula of the filter is described below. Here, $v(p)$ is the data after filtering, $u(q)$ is the data before filtering, and d is the Euclidean distance between the peripheral pixels and the pixel of interest, respectively.

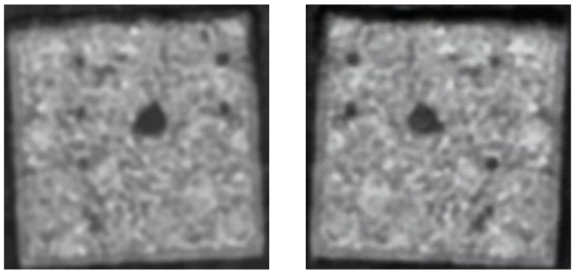
$$v(p) = \sum_{q \in I} \omega(p, q) u(q) \tag{1}$$

$$\omega(p, q) = \frac{1}{Z(p)} exp\left(-\frac{d^2}{\sigma^2}\right) \tag{2}$$

$$Z(p) = \sum_{q \in I} exp\left(-\frac{d^2}{\sigma^2}\right) \tag{3}$$

2.2 Data Augmentation

In this paper, Cycle-GAN, which is a kind of GAN, is used for data expansion. This network can learn without the need for paired images like pix2pix [8]. The function of Cycle-GAN is to convert an image to another image with the characteristics of the original image. In addition, the loss function is calculated using the L1 norm for the image obtained by restoring the input data from the converted image called cycle-loss and the original input data. With this loss calculation method, it is possible to give a cycle property that returns to the original when converted again, and even if learning with an ampere



(a)Original image (b)Created new image
Fig.4 Cycle-GAN results

image, the shape after conversion is hardly changed as when learning a pair image [6]. In this paper, identity loss is also added to the loss function in cycle-GAN. Owing to add this loss function, the invariance / universality of the self-identity common to the image groups can be made robust. By utilizing the above properties, it becomes possible to learn different types of power devices as a pair image and to reproduce a new power device in a pseudo manner. Fig. 4 shows an example of an image converted using Cycle-GAN. From this figure, it can be seen that new image generated without destroying the shape of the original image.

2.3 Convolutional Neural Network (CNN)

In this paper, we use a model of VGG16 with batch normalization (BN) and global average pooling (GAP) [9-11]. This model adds batch normalization after all convolution layers that can reduce data bias, and changes one of the fully coupled layers to GAP to reduce computational complexity. In this paper, we perform binary classification of normal data and abnormal data. The architecture of the model is shown in Fig. 5. The details of the model are shown in Table 1 [9].

3. EXPERIMENT RESULTS AND DISCUSSION

The number of images used in the experiment was 47 abnormal images and 154 normal images. Among them, the number of abnormal images was increased to 94 by data augmentation, and the experiment was conducted.

3.1 Evaluation Method

Three cross-validations were used to evaluate the experiment. The details of the dataset are shown in Table 3. Precision, Recall, and F-measure are used to evaluate the classification accuracy.

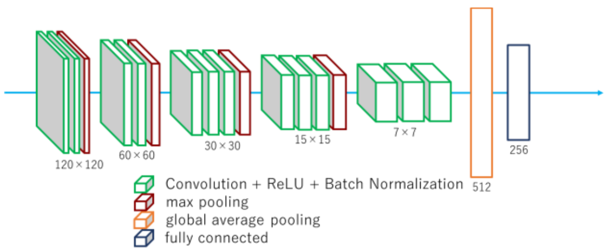


Fig.5 Architecture of CNN

Table.1 Details of the model
(BN: Batch Normalizaiton,
GAP: Global Average Pooling, FC: Fully Connected)

Layer	Kernel	Stride	Remarks
Input	$200 \times 200 \times 3$	-	-
Conv.	$3 \times 3 \times 64$	1	ReLU, BN
Conv.	$3 \times 3 \times 64$	1	ReLU, BN
Pooling	$2 \times 2 \times 64$	2	-
Conv.	$3 \times 3 \times 128$	1	ReLU, BN
Conv.	$3 \times 3 \times 128$	1	ReLU, BN
Pooling	$2 \times 2 \times 128$	2	-
Conv.	$3 \times 3 \times 256$	1	ReLU, BN
Conv.	$3 \times 3 \times 256$	1	ReLU, BN
Conv.	$3 \times 3 \times 256$	1	ReLU, BN
Pooling	$2 \times 2 \times 256$	2	-
Conv.	$3 \times 3 \times 512$	1	ReLU, BN
Conv.	$3 \times 3 \times 512$	1	ReLU, BN
Conv.	$3 \times 3 \times 512$	1	ReLU, BN
Pooling	$2 \times 2 \times 512$	2	-
Conv.	$3 \times 3 \times 512$	1	ReLU, BN
Conv.	$3 \times 3 \times 512$	1	ReLU, BN
Conv.	$3 \times 3 \times 512$	1	ReLU, BN
Pooling	$2 \times 2 \times 512$	2	-
GAP	512	-	-
FC	2	-	Softmax

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F - measure = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{6}$$

3.2 Experimental Result

Table 4 shows the results without data expansion. Table 5 shows the results of data expansion. In each experiment, the classification accuracy of the model used this time is compared with VGG16 and ResNet34 [12].

3.3 Discussion

Comparing Table 4 and Table 5, it can be seen that the classification accuracy is improved by conducting experiments with data augmentation. This is considered to be significant for data augmentation using Cycle-GAN. As mentioned above, Cycle-GAN is a GAN that does not require paired images. Therefore, it is possible to generate an image having the characteristics of the two images. It is considered that by newly adding the image of the power device generated by utilizing this property to the data set, the characteristics of each image could be sufficiently learned while reducing the influence of the bias of the data set.

Although the accuracy could be improved by data expansion, correct identification could not be performed when the original data was small data set. The image that could not be identified is shown in Fig. 6. In the treatise in which the experiment was conducted using only this data, the identification was possible with relatively good accuracy, so it is considered that there is a possibility of overfitting in the treatise. In this paper as well, not only the non-uniformity of the data of the normal image and the abnormal image, but also the bias was observed in the abnormal image. Therefore, it is considered necessary to further expand the data in order to build a model that is versatile for any device.

Table.2 Evaluation criteria

		CNN's prediction.	
		normal	abnormal
Actual Class	normal	TP	FN
	abnormal	FP	TN

Table.3 Summary of dataset

	1	2	3
Normal	51	51	51
Abnormal	32	31	31

4. CONCLUSION

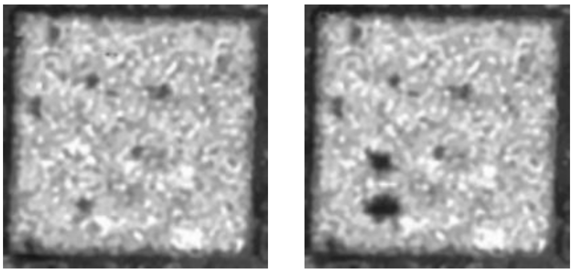
In this paper, we expanded the data on the ultrasonic images output by the power cycle test, enhanced the data set, and constructed a classifier by CNN. As a result, we were able to obtain accuracy of $Precision$ of 97.06%, $Recall$ of 93.58%, and $F - measure$ of 95.17%. In the future, we plan to try new data expansion methods and secure new experimental data to build a new model that incorporates the ResNet [12] skip connection structure used for comparison this time.

Table.4 Experimental results without data augmentation

	$Precision$	$Recall$	$F - measure$
VGG+BN	0.9053	0.8028	0.829
VGG16	0.9188	0.7458	0.8021
ResNet34	1.0	0.8292	0.9046

Table.5 Experimental results with data augmentation

	$Precision$	$Recall$	$F-measure$
VGG+BN	0.9706	0.9358	0.9517
VGG16	0.8986	0.9139	0.8933
ResNet34	0.9792	0.8626	0.914



(a) (b)

Fig.6 Misclassified image

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