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Prediction of warp distortion in circuit board using machine learning

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Abstract. *A convolutional neural network, which reproduce a function by data, was used to predict the amount of warp distortion of a four-layer circuit board in a reflow soldering process. The data used for training are material properties such as Young's modulus, board thickness, and residual copper content as input data, and the predicted warp distortion data is the amount of warpage of the circuit board obtained from the measurement. Since a number of distortion data to be predicted was insufficient to be used for training, a newly proposed data augmentation method used to increase a number of data. The augmentation method is evaluated through the result of the predictions and discussed.*

1 INTRODUCTION

When soldering component terminals to a circuit board, there is a flow soldering process in which melted solder is applied. Lead-free solder has become common as environmental concerns increase. Since the maximum temperature of furnace has been increased by the solder, and the temperature conditions have become strict. Defects of solder joint have increased due to circuit board warp. If the displacement of circuit board warp is predicted, the defects will be decreased by modification of product design. In this study, we'd like to employ a convolutional neural network, characterize the data relations, for the prediction of circuit board warp. The objective is a prediction of the amount of board warp using very limited results of several experimental measurements.

2 CONFIGURATION OF CIRCUIT BORAD AND TRAINING DATA GENERATON

2.1 MEASUREMENT MODEL

The four-layer circuit board model used for measurement is shown in Figure1. In order to make the effect of the circuit board warp, we have prepared four types of the model, which have different copper layer surface areas. All of input data which include material properties and so on are standardized between 0 to 1. The output is standardized warp displacement of 9 points in vertical direction on the substrate.

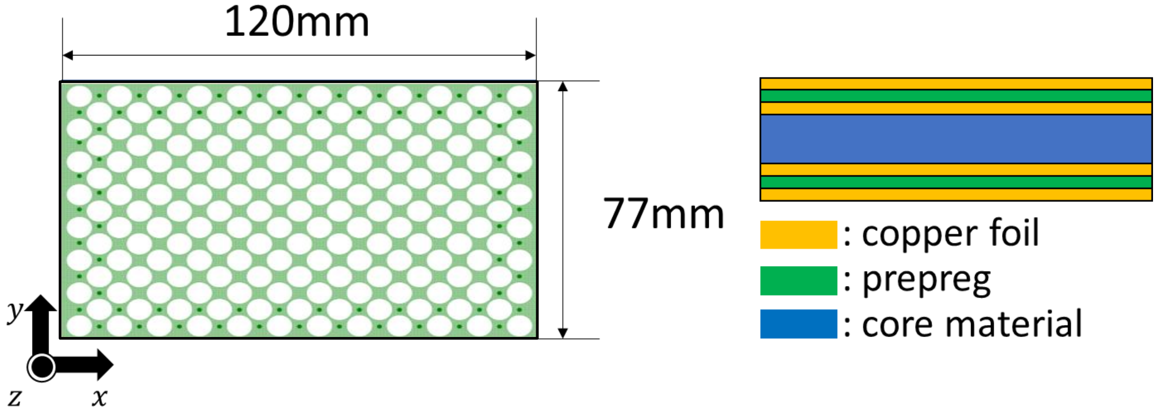

Fig 1 Circuit board model

2.2 Factor levels augmentation

Since a number of original data is very limited, it is necessary to augment training data sets. However, usual augmentation techniques just interpolate closed data in a parameter space. In short, the improvement of the learning accuracy would be limited. We'd like to propose a method called as factor levels augmentation, shown in Figure 2. The midpoint is appropriately chosen for keeping nonlinear relationship between input and output values. The simplest factor levels augmentation is linear interpolation. However, since it assumes linearity, it may not be able to represent actual physical phenomena. The linear interpolation has poor interpolation performance if the relative distances are not far apart in a parameter space. A value to be predicted reproduced in inclination that are not monotonically increasing or monotonically decreasing are not suitable for factor levels augmentation, as shown in Figure3. Keeping nonlinearity of a function to be reproduced, simple linear interpolated augmentation is not appropriate.

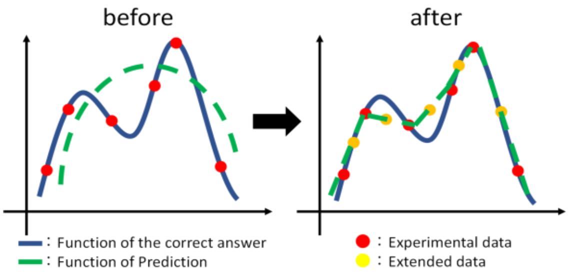

Fig 2 Factor levels augmentation

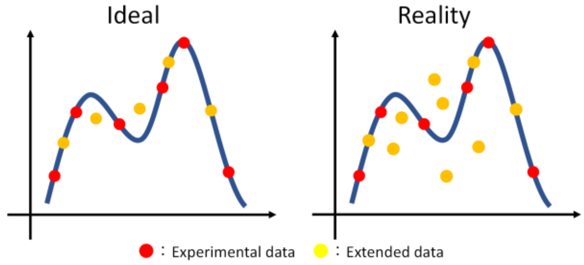

Fig 3 Augmentation method

2.3 Convolutional neural network

Convolutional neural networks are one of the methods commonly used for image recognition in deep learning. It's particularly useful for finding patterns in images to recognize objects, faces, and scenes. It is also an effective method for classifying non-image data such as audio, time series, and signal data. It adds a structure that a convolutional layer and a pooling layer to a neural network. The role of the convolutional layer is filter image features that represented as the theory in Equation 1. The pooling layer reduces the size of the feature map by a predetermined calculation while retaining the important information in the image. These characteristics make it possible to extract the characteristics of influencing factors for numerical engineering problems, and we consider it an effective method. In this study, we used convolutional neural network of the structure shown in Figure 4.

$$y_{ij} = \sum_{s=0}^{m-1} \sum_{t=0}^{n-1} w_{st}^{k} x_{(i+s)(j+t)} + b^{k} \tag{1}$$

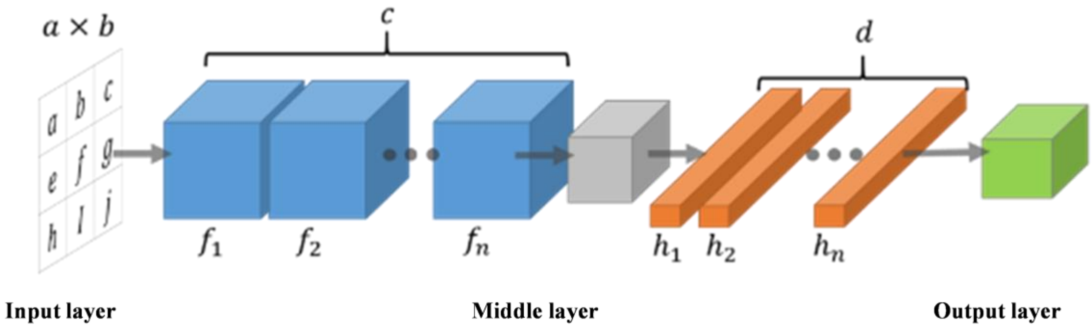

Fig 4 Convolutional Neural Network Configuration Diagram

2.4 Data visualization

To solve the problem of section 2.2, improper interpolation, data visualization is necessary. The amount of circuit board displacement as a standard deviation value to check for improper interpolation is visualized in Fig5. Comparing the cases which only the value of each upper layer copper foil changes that a quadratic inclination confirmations. Figure 6 shows linear interpolation for all points in the green area of Figure 5. By factor levels augmentation, an original quadratic inclination changed to a linear inclination. Must been returned to original inclination for high precision results. Therefore, removing the reinforcement points that were inhibit the inclination, the interpolation can be based on physical phenomena. It's important to confirm the dataset that when the interpolation is base on physical phenomena.

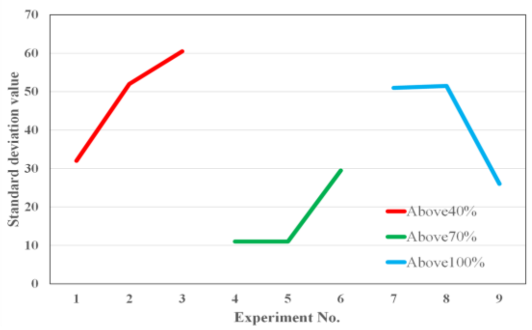

Fig 5 Standard deviation mean value

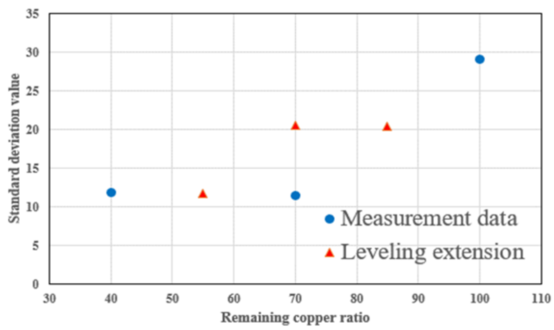

Fig 6 All intermediate points

2.5 K-fold cross-validation

It is common to divide the data set during model creation into training and validation. When we divide whole data sets into small subsets, the accuracy will be reduced. Therefore K-fold cross-validation, which randomly divides the dataset into k pieces, is used. As shown in Figure 7, each is used in turn as validation data, and the rest are used as training data to fit the model. The computed performance index, in the k-fold cross validation is the average of the values compute within the loop. Although the method is computationally expensive, but all data can be effectively utilized. This is a great advantage for problems with very small sample sizes.

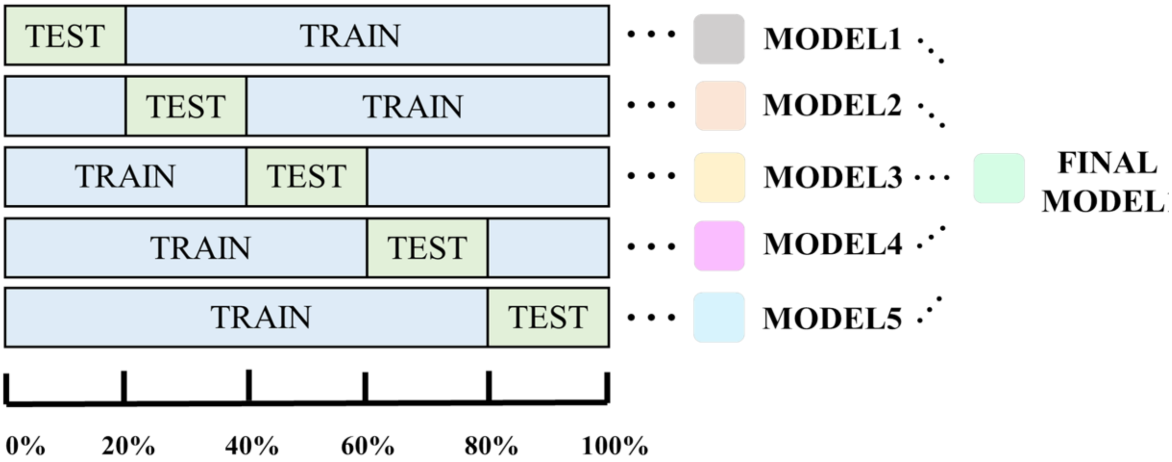

Fig 7 K-fold Cross-validation

3 RESULTS AND DISCUSSION

3.1 Significance of factor levels augmentation

To confirm validity, prediction accuracies between no augmentation data and factor levels data augmentation is compared. The loss function for no augmentation is shown in Figure 8. The loss function for factor levels augmentation is shown in Figure 9. Figures 8 and 9 also both show a decrease in losses. Losses are reduced in Figure 9 than in Figure 8. The errors predicted and correct values when no augmentation occurred more than 20 percent. In contrast, augmentation introduced that could be reduced to less than 1 percent. This is because patterns could be recognized even with inadequate data by factor levels augmentation.

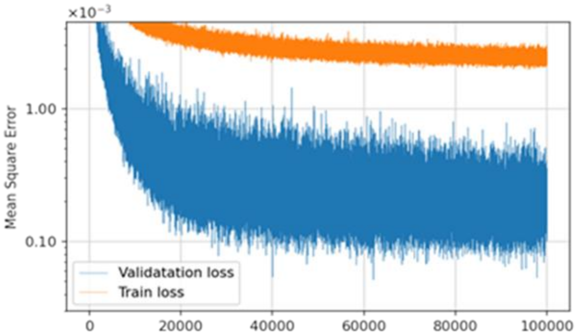

Fig 8 loss function with no augmentation

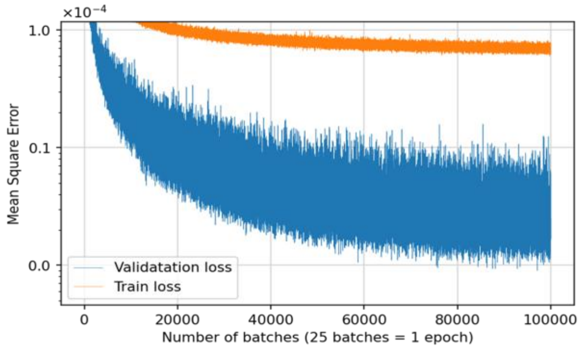

Fig 9 loss fanction with factor levels data augmentation

3.2 Cross-validation results

Since the results in section 3.1 were not divided into training and validation, cross-validation was performed. 90 data were divided into 9 parts so that the frequency of occurrence in the data would be the same. The loss for learning with identical frequencies is shown in Figure 10, and the regression line is shown in Figure 11. Figure 10 shows that losses do not increase and are the same in all cases. From Figure 11,768 points in all 810 points occurrence measurement error 5 percent or less. But 8 points occurrence error 20 percent or more. This is because the distribution in the data set is not uniform. To improve learning accuracy which less distribution data must fixed for training data.

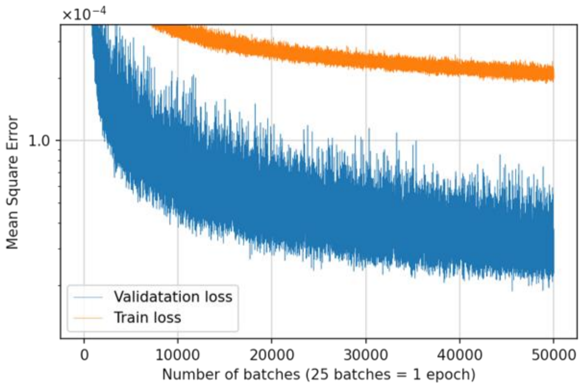

Fig 10 loss function with Cross-validation

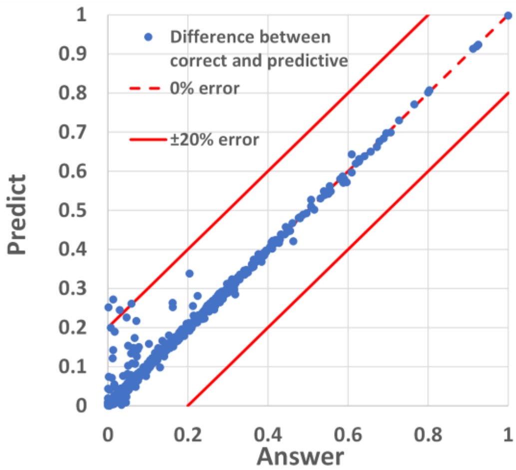

Fig 11 Regression line

3.3 Confirmation of generalization performance

Because highly accurate results have been obtained in the section 3.2 , the generalization performance should be verified. For the new data, 64 patterns of boards were measured, 8 patterns were extracted and used as verification data. When using factor levels augmentation, visualization was performed by standard deviation values as in section 3.2.To make the data distribution uniform, the low frequencies as fixed in the training data. Two validation data were created and trained it.The resulting loss function is shown in Figure 12 and 13, and the error in Table 1. From Figure 12,13, the loss initially increased but decreased in the result. Table 1 shows that the error was within 10 percent for all 16 patterns of validation data.But one pattern resulted in a loss of accuracy.By using it, prediction of new distortion warp became possible, and generalization performance is confirm.

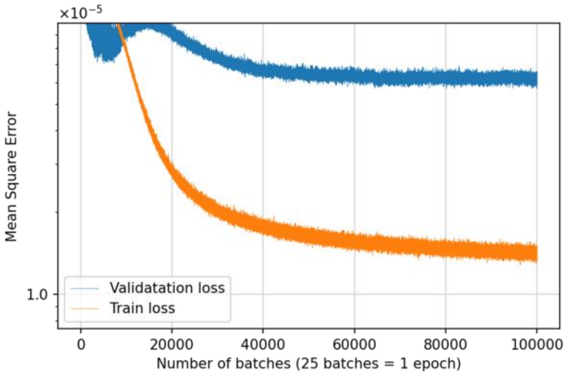

Fig 12 New data with loss function

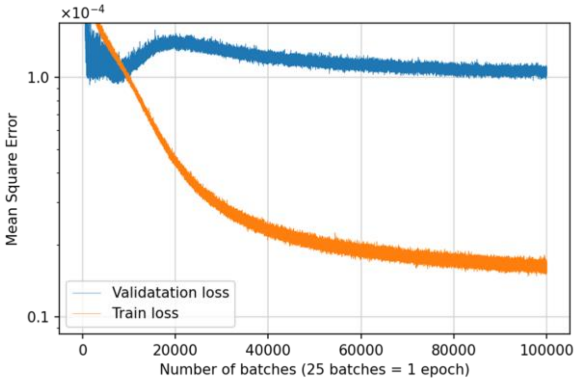

Fig 13 All intermediate points

Table 1

First time mean error	4.33%	First time minimum error	0.02%
First maximum error	7.84%	Second time mean error	5.19%
Second time minimum error	0.01%	Second maximum error	6.71%

4 CONCLUSIONS

From the section 3.1,3.2 results, we confirm the effectiveness of the method for engineering problems for small amount of data. Also, the method is verified for generalization performance from section 3.3 result. It is important to keep the characteristics of a function to be expected using factor levels augmentation. To ensure that points with different slopes are not taken. But try and error is needed to require which physical phenomenon to display when visualizing data.

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