Development of an AI Model for Defect Detection Considering Manufacturing Variability

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Abstract

To evaluate the risk points and levels of display panels caused by manufacturing variations, a numerous number of simulations are required. Traditional reliability assessment method, such as Finite Element Analysis (FEA) are time-consuming for this purpose. Therefore, this study has developed an AI-based model that can predict panel defects, enabling efficient simulations for numerous scattered cases within a short timeframe, serving as a practical alternative to FEA. Initially, structural analysis are conducted following the reliability evaluation technique through conventional FEA simulations. The likelihood and location of defects are determined by examining strain contours derived from the FEA results. In the panel layout, manufacturing tolerances that may occur include critical dimension (CD), overlay, thickness, and taper angle. To secure data, all manufacturing tolerances are assumed to randomly occur in each layer, and 100 cases of panel structures are modeled and analyzed. The solving time for a FEA simulation takes about 3 hours. The finite element (FE) model used in FEA simulation is preprocessed to be input data into the neural network model. And strain contours derived from FEA simulation results are preprocessed to be output data into the neural network model. We developed and optimized an AI model capable of taking input from the preprocessed data. Input and output data are high-dimensional, and a fully convolutional network (FCN) model is employed to handle these data. After completing the training of the AI model, we input a panel with a new structure into the AI model and predicted the strain contour. We compared the predicted contours with the ground truth strain contours by performing FEA on a panel of the same structure. The results revealed an inference accuracy of 92.02% for the AI model, with a prediction time of around 17 seconds. This indicates a significant time-saving effect of 99.84% compared to FEA. It is expected that a faster structural reliability assessment will be conducted through this method.

Author Keywords

Artificial intelligence (AI); Fully convolutional network (FCN); Display panel; Defect; Manufacturing variability; Finite element analysis (FEA)

1. Introduction

With the increasing versatility and diversity in the utility and design of smartphones, there is a growing demand for various forms of displays. Due to their high mechanical flexibility, displays experience diverse loads in both usage environments and manufacturing processes. These loads, especially repetitive ones, can lead to defects such as cracks and delamination. Additionally, displays, with their extremely intricate structures, are susceptible to even infinitesimal manufacturing tolerances causing defects. Therefore, for a proper evaluation of the structural reliability of displays, simulations reflecting manufacturing tolerances need to be conducted during the design phase. While finite element analysis (FEA) serves as the predominant and effective simulation method for structural reliability assessment, it requires extensive modeling and computing time for the analysis of complex panel structures. Consequently, utilizing FEA to perform simulations considering a sufficient number of manufacturing tolerances within a limited development period becomes challenging.

Since the remarkable success of AlexNet in the 2012 ImageNet competition and the subsequent proven performance of neural networks in various fields, these algorithms have begun to be applied to predict physical phenomena. Although neural networks may exhibit slightly lower accuracy compared to FEA, they provide a significantly faster and more efficient solution. In this study, we applied neural networks to analyze the reliability influenced by manufacturing tolerances in display panels, demonstrating the feasibility of incorporating AI techniques in structural reliability analysis.

2. Overview of Research Methodology

The workflow of this study is illustrated in Fig. 1. Initially, structural analyses are conducted following the reliability evaluation technique through conventional FEA simulations. The likelihood and location of defects are determined by examining strain contours derived from the analysis results. In the panel layout, manufacturing tolerances that may occur include critical dimension (CD), overlay, thickness, and taper angle. The manufacturing variability arising from these parameters is of very small magnitude, and simultaneously, manufacturing variability can occur across multiple parameters. To account for such variability, the layout data must be configured with a very high resolution, encompassing information on various parameters such as structure, properties, initial stress, and others. To address this, in this study, we have developed preprocessing techniques tailored to our AI model, and established a computing environment capable of accommodating training with very large datasets.

All manufacturing tolerances are assumed to randomly occur in each layer, and 100 cases of panel structures are modeled and analyzed. The solving time for structural analysis takes about 3 hours. Upon securing the data, the following processes were employed to develop and train/optimize the AI model.

A. Input Data Preprocessing: The finite element (FE) model used in structural analysis is preprocessed to be input into the neural network model.

B. Output Data Processing: Strain contours derived from structural analysis results are preprocessed to be input into the neural network model.

C. AI Model Training: We developed and optimized an AI model capable of taking input from the preprocessed data. Input and output data are high-dimensional, and a fully convolutional network (FCN) model is employed to handle these data.

D. Trained Model: We input the structure of a panel with new manufacturing tolerances into the well-trained AI model and predicted the corresponding strain contour.

3. Data Collection and Preprocessing

The structural reliability of display panels is generally pre-assessed

ISSN 0097-996X/25/5603-1602-$1.00 © 2025

through structural analysis. When modeling the panel structure and applying boundary and load conditions, areas exhibiting excessive strain are evaluated as high-risk for defect. In this structural analysis, the input data consist of the display panel's structure, boundary conditions, and load conditions, while the output data are represented by strain contours. Since the AI model developed in this study aims to replace this structural analysis, we designated the panel's structural data as the input data for the AI model and the strain contour as the output data. We assumed that the load and boundary conditions remain constant and thus did not include them as variables.

Display panels are composed of multiple thin sheets layered together. The combination and layout of each layer, as well as their thickness, material properties, and initial stress, all influence defect. Therefore, effectively inputting this complex data into the AI model is crucial for achieving high accuracy. Because the display panel structure can be closely approximated by stacking top view images of each layer, we developed a method where the top view images of each layer are layered and input directly. By distinguishing between filled and empty regions in these top view images, converting filled pixels to 1 and empty pixels to 0, we can input the layout of each layer into the AI model with high precision. Since this method lacks thickness, material properties, and initial stress information, we multiply each element of the 2D array (composed of 0s and 1s) by a 1D array containing three elements: [thickness, material properties, initial stress]. This produces a 3D array containing all necessary information for each layer. Finally, by stacking these 3D arrays according to the actual layering order of the panel, we create a 4D input data array that encompasses all information of the entire panel, as illustrated in Fig. 2. The W and H dimensions must be configured with sufficiently high resolution to capture fine variations, with each data point corresponding to an area of 0.01μm x 0.01μm. The D dimension represents the number of layers, and the C dimension holds three values: thickness, material properties, and initial stress. For instance, to evaluate the reliability of a 100μm x 100μm area in a panel composed of 20 layers, the entire input data would be a 4D array with a size of 10,000 x 10,000 x 20 x 3.

The output data from the structural analysis, which are strain contours, are produced in the same 3D structure as the input data. However, identifying areas at risk of defect quickly and easily with 3D data is challenging for engineers. By generating a single top view image of the strain contour across the entire display panel, where each pixel represents the maximum strain value across all layers at that location, weak points can be identified more quickly and easily. We developed a method to input this single image as the AI model's output data.

If the output data resolution is too high, it becomes difficult to visually identify defects. Therefore, we configured each pixel to correspond to an area of 1μm x 1μm. For example, creating an output strain contour for a 100μm x 100μm area results in a 2D array of size 100 x 100, with each pixel value representing the maximum strain within a 1μm x 1μm area. The configured output data is illustrated in Fig. 3.

To acquire data for training and validation, we applied 100 different combinations of manufacturing tolerances (CD, overlay of each layer) to the layout of sample panels, performed structural analyses, and preprocessed the input/output data for input into the AI model.

4. AI Model Development

In Chapter 3, we created 4-dimensional input data and 2-dimensional output data. Given that both the input and output are high-dimensional data, we determined that an FCN (Fully Convolutional Network) model would be the most suitable AI model. After configuring a basic FCN model, we optimized the number of layers and the number of channels in each layer. As shown in Fig. 4, we finalized an FCN model composed of six layers. Batch normalization techniques were applied to each layer.

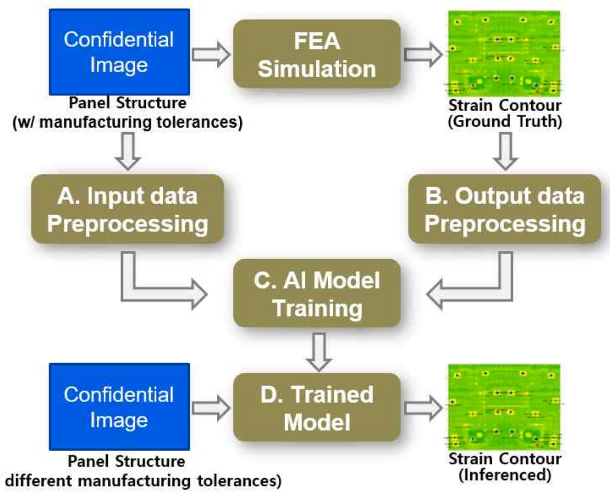

Figure 1. Diagram of the FCN based display panel defect detection model. (In compliance with company security regulations, certain parts of the image are kept confidential)

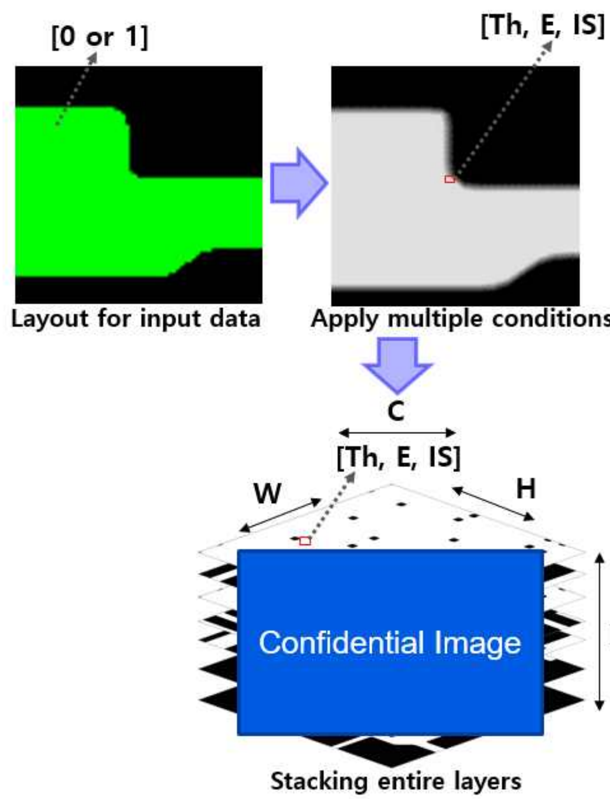

Figure 2. Input data preprocessing

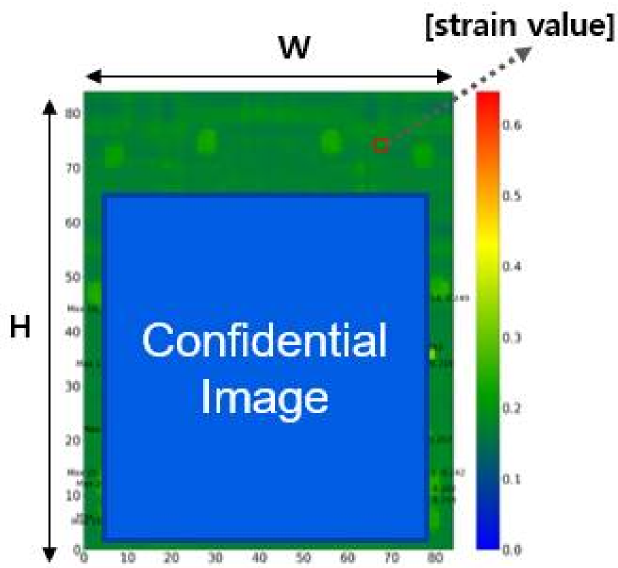

Figure 3. Output data preprocessing

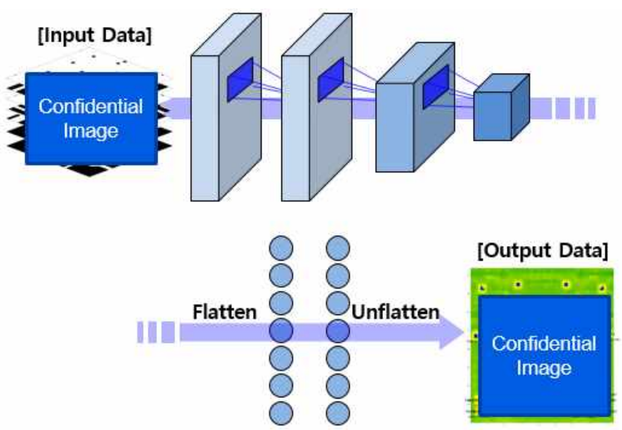

Figure 4. FCN model

5. Training and Inference

We trained our developed AI model using the prepared input/output data. The model was configured to minimize the error between the predicted and actual strain values at all locations in the output data. Of the total available data, 70% was used for training and 30% for validation. The training process was conducted over 1,000 epochs, taking approximately 20 hours to complete.

Upon completing the training, we input data from a panel structure with a new combination of manufacturing tolerances to predict the strain contour and compared it with the structural analysis results. The comparison results are illustrated in Fig. 5. In the figure, the left side shows the actual strain contour obtained through structural analysis, and the right side shows the predicted strain contour generated by the AI model. It can be observed that the predicted image closely resembles the actual image. The actual and predicted strain values at all pixels are compared in Fig.6. The predictive accuracy was evaluated using the R-squared metric, achieving an accuracy of approximately 92.02%. Extracting the strain contour from this input data using structural analysis took about 3 hours, whereas predicting the strain contour using the AI model took approximately 17 seconds as shown in Fig.7. This demonstrates a time reduction of approximately 99.84% in structural reliability evaluation.

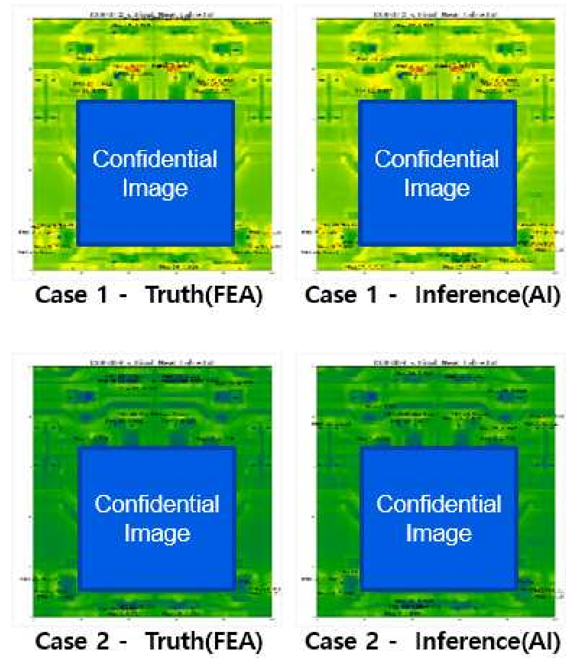

Figure 5. Comparison result of prediction and truth

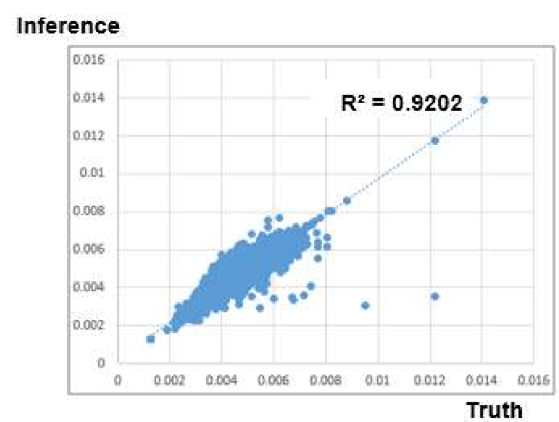

Figure 6. Evaluation predictive accuracy(R-squared)

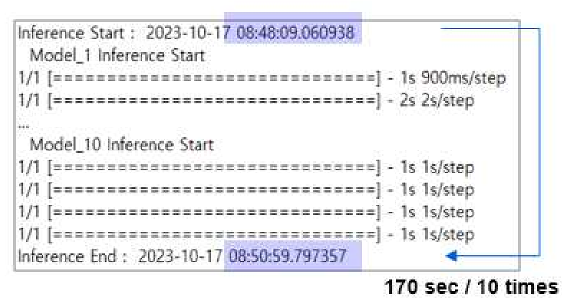

Figure 7. Required time to inference

In this study, we developed an AI model that can effectively replace structural analysis for evaluating structural reliability. Using this methodology, structural analysis results can be predicted in a very short time. To assess structural reliability considering manufacturing tolerances, evaluations of at least 10,000 cases are necessary. Since structural analysis takes about 3 hours per evaluation, evaluating 10,000 cases would take 30,000 hours, making it time-prohibitive. With our methodology, after conducting 100 structural analyses in 300 hours and training the AI model for 20 hours, it would be possible to evaluate structural reliability for thousands of cases per day. If inference is performed in parallel, tens of thousands of cases could be evaluated in a single day. This makes it practically feasible to consider manufacturing tolerances in structural reliability evaluations. Consequently, the structural quality of display panels is expected to improve significantly.

7. References

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