[Anomaly Detection of SEM images by using DeepLearning - Ryosuke Kurosawa]

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INTRODUCTION

As for semiconductor manufacturing plants, production efficiency and quality control in the manufacturing process are becoming increasingly important in accordance with the demands for products with high performance. Under these circumstances, the development of sensing technology and the advancement of information infrastructure have led to the construction of a network environment called the “Internet of Things” (IoT), which makes it possible to collect and accumulate manufacturing data. At the manufacturing site, this so-called “big data” is being used for analysis with the aim of improving productivity, maintaining quality, and increasing yield [1]. As for the inspection process using various images, technology using machine learning to automatically detect defects is being developed. A case study on establishing and implementing a model using “deep learning” for automatically detecting pattern anomalies in scanning electron microscope (SEM) images is reported hereafter.

MODEL

The image data used in the case study were SEM images taken after processes that is related to the characteristics of products (Figure 1). Accordingly, we set out to build a detection model using deep learning and apply it to those SEM images.

The main network structure uses a convolutional neural network (CNN) and an autoencoder. In this case study, when images acquired during mass production were learned, the number of images have pattern anomalies was extremely small compared to the number of images acquired, so the network was constructed by using the autoencoder.

Regardless of the method or the form of the data, formatting and sample size are essential when making judgments based on the data. Obstacles to learning and inference include noise in the image, differences in the appearances of images due to differences in equipment or maintenance status of the measurement device, and marks on the image. To overcome these obstacles, noise reduction using filters, normalization, and removal of areas in images other than the detection target are used. At such times, to prevent loss of information, pre-processing should be minimized. On the contrary, to secure sufficient sample size, image augmentation is used to expand the sample. As shown in Fig. 2, these processes were executed in series by using Neural Network Console [2] and the programming language Python.

The characteristics of the data greatly influence the process of constructing the network. An example is relative positional variation of elements in an image (Figure 3). Convolution, which is used for encoding, conveys locally filtered output values for an image to the next layer, so it can respond to variations in the position of the image. It is therefore effective to encode images by using convolution only for images with positional variations. On the contrary, if the positional variation of each image is small, an affine layer is inserted between encoding and decoding. This configuration allows the positional information of the image to be fixed, thereby increasing reproducibility and improving detection accuracy. A schematic diagram of the respective networks is shown in Figure 4.

The images may change due to variability concerning the measurement device, and such changes may cause fluctuations in brightness and positioning. As a result, it is difficult to handle all situations by only using training images. To address that situation, noise and luminance variations are added to the image during the learning phase with the aim of making learning robust (Figure 5).

SYSTEM

To perform inferencing on images by deep learning, we implemented a system by using the Python library Neural Network Libraries (Figure 6). Moreover, by visualizing the detection results linked to history information on the Web and via sending e-mails, the system enables prompt detection of abnormalities and reduces the workload of engineers.

RESULTS AND DISCUSSION

As a result of implementing the constructed SEM-image automatic-detection model as the above-described system, it is possible to detect changes in the state of the measurement device by capturing changes in the values output by the model (Fig. 7).

CONCLUSIONS

A deep-learning-based anomaly-detection model was developed and applied to pattern anomalies in SEM images. It is thus now possible to detect pattern anomalies that could not be detected by the conventional method.

REFERENCES

[1] M. Ikeda et al., EPC-O-19, AEC/APC Symposium Asia 2019
[2] https://dl.sony.com/ja/

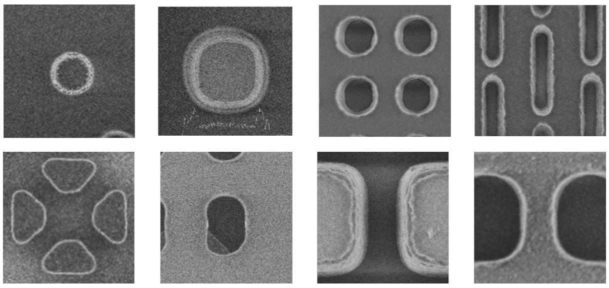

Figure 1: Examples of SEM images

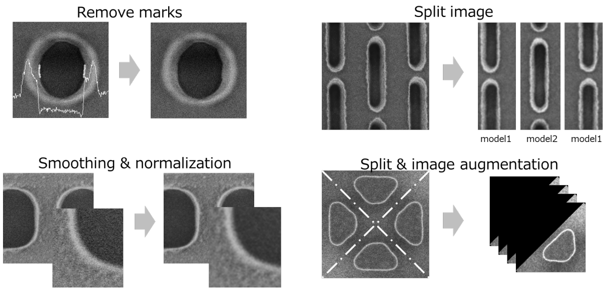

Figure 2: Preprocessing of images

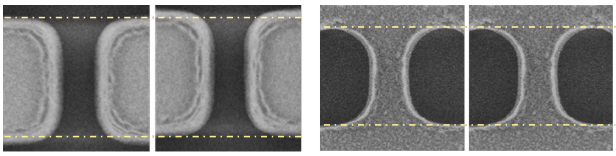

Figure 3: Left: process with misalignment of element in each image; right: process with minimal misalignment of element in each image

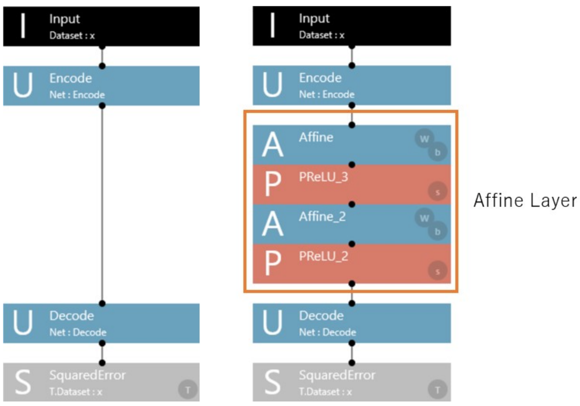

Figure 4: Example of autoencoder configuration in Neural Network Console

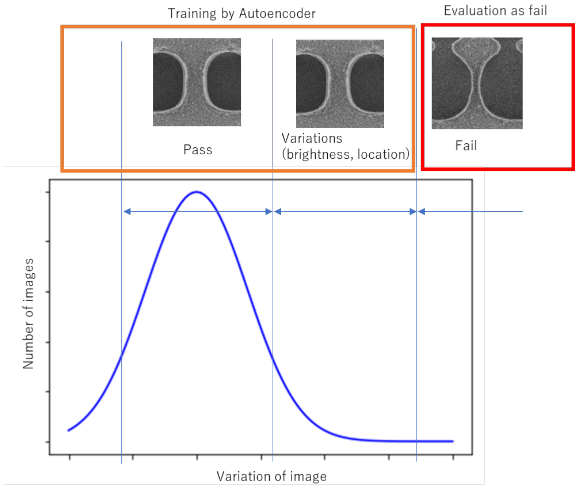

Figure 5: Using images for learning robust against image variability

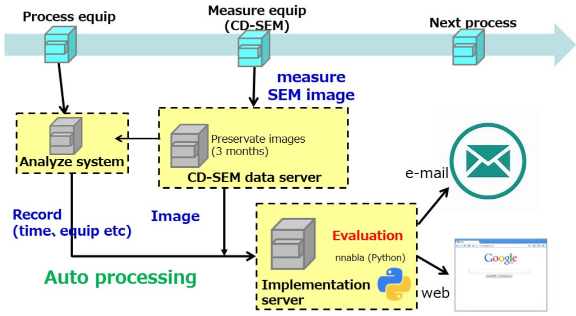

Figure 6: Example of system configuration and means of outputting results

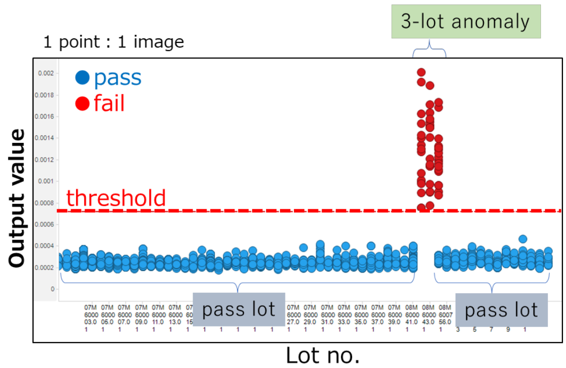

Figure 7: Change in network output values during detection of anomalies