Evaluation of Image Data Augmentation using Generative Adversarial Network (GAN)

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ABSTRACT – This paper presents the use of Generative Adversarial Networks (GAN) to incorporate domain knowledge in image data augmentation and overcome class imbalance problems in semiconductor packaging crack defect classification. A Mask GAN is used to generate images of defect mask label when bounding box information is supplied. The artificial defect masks are used by a Defect Image GAN to "paint" defects onto non-defect images. The performance of defect classifier trained on real defect images and artificial defect images generated through this two-step process is compared. McNemar's test is used to validate the findings in this paper.

1. INTRODUCTION

In defect classification problems, non-defective samples are usually more abundant than defective samples. This phenomenon is also known as the class imbalance problem. As a result, the distribution of the minority class will be misrepresented, and the number of false negatives will increase [1]. False negatives are especially critical in the case of defect classification as mislabeling defect as non-defect will result in decreased quality of a production.

Deep convolutional neural network performs well in classification problem as long as the data used for training is similar to actual data found in its application [2]. However, data of outliers may not be easily acquired for use in classifier training so that it may detect such images. Hence, GANs are proposed to integrate domain knowledge in generating artificial data to improve classifier performance on detecting defects that are expected to occur.

2. METHODOLOGY

The proposed system which consists of Mask GAN and Defect Image GAN is outlined in Figure 1.

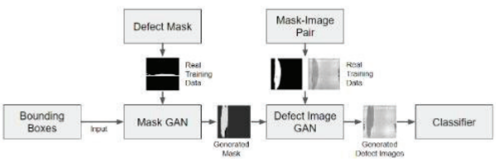

Figure 1 Overview of proposed system

2.1 Dataset

The crack defect dataset consists of 15 non-defect images and 19 defect images. 7 out of 19 defect images are outlier that look drastically dissimilar to the others. The training data set is organized by taking 10 non-defect images and 5 defect images. Test data set consists of 5 non-defect images and 14 defect images which includes all the outlier images. The decision to not include outlier defect images in the training set is done to verify the efficacy of GAN in generating outlier defect images from only bounding box information as input.

2.2 Mask GAN

Multi-Scale Gradients architecture [3] is used for the Mask GAN. Intermediate output of the generator network at each resolution is passed as input to the discriminator. This ensures stability in the training process as the generator network is forced to output visually similar images at each upsampling step.

2.3 Defect Image GAN

The network architecture from [4] is used for the Defect Image GAN. The generator network takes in mask label image, background image, and random noise as the input. In the case of this paper, non-defect images are used as background image for the network, on which defects are "painted" onto. The generated defect will take on the shape of the mask label provided as input.

2.4 Testing and Evaluation

The duration of training and hyperparameters for both the Mask GAN and Defect Image GAN are determined through manual inspection. Quantitative evaluation such as Fréchet Inception Distance (FID) [5] cannot be applied due to the limitation in the data quantity.

ResNet50 network is used as the classifier for evaluating the efficacy of GAN-based image data augmentation. Transfer learning and fine-tuning process is performed by replacing the output layer of the classifier with a custom layer to fit the purpose of this paper which is binary classification of defect images. Only the output layer is trained for the first 30 iterations while the whole model is trained for the subsequent 270 iterations.

In each iteration, 8 non-defect images and 8 defect images are passed to the classifier network. Random rotation and flipping is applied to the non-defect images in addition to shuffling the order of the images.

As a baseline for comparison, traditional data augmentation in the form of random rotation and flipping is applied to the defect images. The classifier is trained on this defect image data as the first case.

In the second case, artificial image data is generated using the proposed GANs with only bounding box images as input. To imitate domain knowledge of expert, bounding box information of all defect data, including those of the test data set is used. This artificial image data is used to train the classifier network. In both cases, non-defect data used to train the classifier is treated the same.

3. RESULTS AND DISCUSSION

Figure 2 shows the output of Mask GAN and Defect Image GAN. It can be seen that the Mask GAN generates convincing mask images with some variety between each output. On the other hand, Defect Image GAN replicates the tone of the actual image but there is no texture in the generated defects.

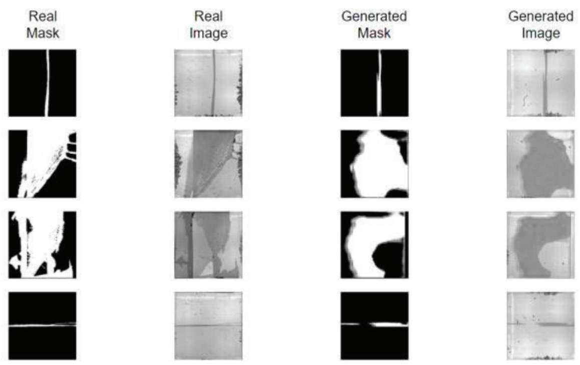

Figure 2 Comparison of actual images and GAN generated images

Table 1 outlines the performance of classifier on real and generated data. Training on real data results in false negatives due to the training data not reflecting data from the test set. On the other hand, the proposed system is able to infer the outlier images from given bounding box information, which allows the classifier to perform well.

Table 1 Performance of classifier on real and generated data.

Data	False Negatives	False Positives
Real	6	0
Generated	0	0

Applying McNemar's Exact Test on the classifier results, it is shown at confidence level of 95% that there is a significant improvement between the performance of classifier trained on generated data over classifier trained on real data, with a p-value of 0.03125.

In addition, it is noted that classifier loss function converges slower when trained on generated data, due to the larger variety of defect data provided.

4. CONCLUSIONS

Domain knowledge from experts can be incorporated into classifier training data sets through the use of GAN-based data augmentation. The use of GAN generated defect images has shown a significant improvement over random rotation and flipping data augmentation. Further refinements can be made to the Defect Image GAN in order to produce variations within the defect itself. In addition, the proposed system can be applied in other data set by training both GANs on new data.

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