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Effectiveness Study of Generative Model Augmentation Techniques for Internal Defect Data in SFR

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1. Introduction

The technology of object detection using AI (artificial intelligence) is widely utilized across various industries, and the quality of the dataset is crucial for enhancing the performance and reliability of this technology. SFR (sodium-Cooled Fast Reactors) pose challenges in measuring structural defects, and research is underway to apply object detection technology based on AI (artificial intelligence) in the development of defect monitoring techniques for structural materials. However, the unique internal environment of SFR presents difficulties in obtaining sufficient training data for AI.[1] There are limitations in securing optical images in SFR, and C-Scan data produced through ultrasonic has limitations in expressing the various types of defects that will actually occur. This can lead to data imbalance, and in the field of artificial intelligence vision, augmentation techniques based on image processing are mainly used to compensate for this. This is a method of applying transformations such as rotation and distortion to the original data. If the absolute quantity of original data is low, it can be somewhat challenging to rectify data imbalances.

This study explored the use of generative models in artificial intelligence to produce data similar to the original data, aiming to enhance the diversity of the dataset. In particular, we applied the Stable-Diffusion model[2] which demonstrates higher performance compared to traditional GAN (generative adversarial network) models, using a distinctive training approach. By employing this model in the augmentation technique for image data, we endeavored to secure diversity within the dataset. Furthermore, we validated the effectiveness of the augmentation techniques studied in this paper based on the suitability assessment approach of the Image Type Balance dataset proposed by TTA (Telecommunications Technology Association of Korea).[3]

2. Background

The augmentation technique applied in this study is based on the Diffusion model, which is one of the deep learning generative models. The characteristic feature of the Diffusion model is derived from the phenomenon of diffusion in liquids or gases, where molecules dispersed in a confined space gradually spread out until they are evenly distributed throughout the entire space. And then, reversing the diffusion process causes the molecules to return to a concentrated state in a single space. In the context of images, pixels represent the molecules, and the diffusion process corresponds to the gradual addition of noise to the image.

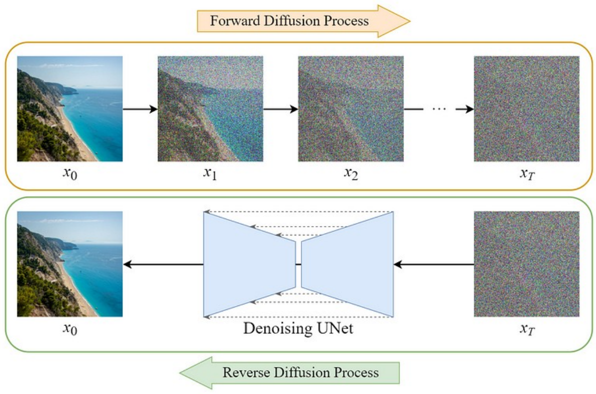

Fig. 1. Diffusion Model Processing

Fig. 1, visualizes the process of image data using the Diffusion Model. The Forward Diffusion process adds noise generated from a normal distribution to the image, and the Reverse Diffusion process removes noise generated from a learned normal distribution to make it similar to the probability distribution of the input image. Each process can be expressed as a formula as follows.[2]

$$(1)\ q\left(X_t \vee X_{t-1}\right) = N\left(\sqrt{1-\beta_t}X_{t-1}, \beta_t I\right)$$

$$(2)\ p_\theta\left(X_{0:T}\right) = p\left(X_T\right)\prod_{t=1}^{T} p_\theta\left(X_t \vee X_{t-1}\right)$$

Equation (1) represents the Forward Diffusion process. Given the previous state X_{t-1} the probability distribution for X_t denoted as$q$ follows a N(normal distribution), In this equation, I(image) selects different pixels by β and chooses the previous pixel value by $\sqrt{1-\beta_t}$.

Equation (2) represents the Reverse Diffusion process, which formalizes the problem of finding the probability distribution $p_\theta$that best models the given probability distribution q from Equation (1). Here, $p_\theta\left(X_t \vee X_{t-1}\right)$ serves as the target for the Diffusion model's training, repeating the Reverse Diffusion

Process to learn the distribution of the data. Subsequently, the Diffusion model utilizes the learned probability distribution to generate a complete image x_0 by inputting the randomly generated noise X_T. Through this approach, the Diffusion Model is capable of generating images with higher quality and diversity compared to other generative models such as GAN (Generative Adversarial Network) or image processing algorithms.

3. Experiment

3.1 Stable-Diffusion Text-To-Image Generative

The Stable-Diffusion model is a Text-To-Image model that applies the user-inputted text as conditioning for image generation. By concretizing the correlation with the original data as prompts during image generation, it can create more diverse and higher-quality images.

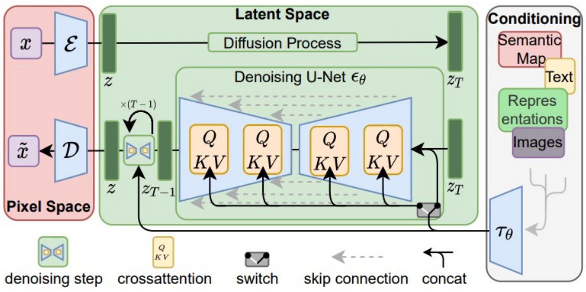

Fig. 2. Stable Diffusion Model Architecture.

Fig. 2, illustrates the internal structure depicting the data flow of Stable Diffusion. The Pixel Space comprises an Auto Encoder for applying the condition, where the input condition undergoes Cross Attention operations in the Latent Space.

It receives Text-form conditions through a Text Encoder of a Pretrained Large Language Model (LLM). Subsequently, Cross Attention is employed to calculate the correlation with the existing input image, thereby generating an image that reflects the condition information with weighted factors. These generated images exhibit diversity in forms based on the prompts applied in the conditioning, maintaining correlation with the original data.[4][5]

3.2 Augmentation data comparison and balance dataset suitability evaluation

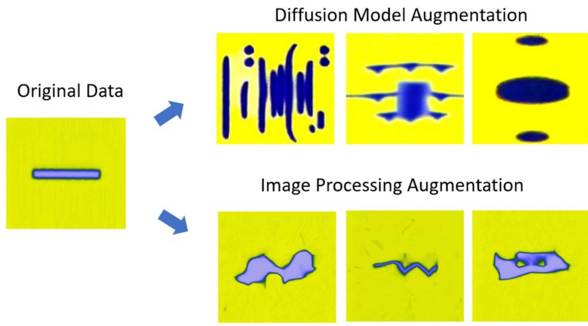

Fig. 3. Comparison of generated data in terms of data augmentation

Fig. 3, displays the Original Data, which consists of simulated defect images obtained in an environment similar to the invisible interior of SFR. Using this as a basis, we generated data applying the Stable Diffusion Model for Data Augmentation, as well as data employing image processing techniques. The Augmentation Data utilizing the Diffusion Model demonstrated diverse forms while maintaining correlation with the Original Data. However, it was observed that the Augmentation data applying Image Processing techniques exhibited limitations in representing various defects beyond single slit forms, such as multiple slits, circular shapes, and multiple scratches, showing a significant dependency on slit shapes.

The TTA (Telecommunications Technology Association) defines standards for evaluating the reliability of artificial intelligence software and provides guidelines for designing image type-balanced datasets. When the balance of image datasets is not appropriate, sampling bias and errors can occur, leading to a degradation in the accuracy and reliability of the software. Therefore, it is necessary to secure a balanced dataset to evaluate whether the software can handle various forms of data. The suitability assessment of balanced datasets is achieved by evaluating the distribution level of the dataset, serving as a preventive measure against dataset imbalance.[3] And The suitability evaluation of the augmentation dataset was performed by setting the following Method (Diversity, Cosine Similarity, Histogram Distribution Score).

Table I. Measurement of dataset distribution according to augmentation technique

Method	Diversity (entropy) Score	Cosine Similarity Score	Distribution (Histogram) Score
Diffusion Model AD	**2.550**	**0.754**	**0.723**
Image Processing AD	2.064	0.923	0.089

Table I. presents measurements of the distribution level of data according to augmentation techniques from the perspective of dataset balance suitability. A higher score in Diversity (entropy) and Distribution (Histogram) indicates a higher diversity in the dataset. Cosine Similarity measures the similarity between data points, where a lower score suggests a dataset with greater diversity. As a result, it can be seen that the diffusion model AD has higher diversity than the image processing AD in all scores in Table I.

4. Conclusion

In this study, we explored the application of augmentation techniques in dataset acquisition to enhance the performance and reliability of Artificial Intelligence Object Detection models. Following the standards provided by TTA, we measured the level of dataset distribution, and the results indicated that the Stable-Diffusion model is effective in obtaining a diverse dataset compared to image processing algorithms-based Augmentation techniques.

SFR pose significant challenges in acquiring defect data due to the unique nature of their environment, which could potentially lead to dataset imbalance. However, by utilizing the Stable-Diffusion model introduced in this study, it is possible to address the issue of dataset imbalance by constructing balanced datasets as recommended by TTA. Building suitable datasets is a crucial factor in improving the performance and reliability of Artificial Intelligence models. Therefore, our research is expected to positively impact the future adoption of Artificial Intelligence technology in the nuclear power industry in the future.

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