Deep Learning-based Data Augmentation for Display Defect Detection

Changheon Lee[1], JoonKyu Kim[2] and Suk-Ju Kang[3]

[2]sjkang@sogang.ac.kr
[1,2]Department of Electronic Engineering, Sogang University, Seoul 04107, Republic of Korea
Keywords: Anomaly detection, Generative models, Conditional Diffusion models.

ABSTRACT

This paper presents a deep learning-based data augmentation method for generating defect data. The generated data are to be used for training an anomaly detector for the purpose of detecting display defects. By comparing the generated data with those generated from previous methods we find that the deep learning-based data augmentation outperforms previous methods by producing photorealistic data covering a diverse range of real-world defects.

1 Introduction

The objective of anomaly detection is to detect defect data from defect-free normal data. Unsupervised anomaly detection [1,2] aims to detect defect data without any prior knowledge of possible anomalies. A natural solution to the challenge of detecting anomalies without labeled data is to take a supervised or weakly-supervised approach by providing a limited number of labeled defect data to improve the detection accuracy [3]. However, due to the scarce nature of anomaly occurrence in the manufacturing environment, it is extremely difficult to obtain real-world anomaly data. Therefore, alternative methods [4,5] use data augmentation to creating anomalies within normal data. These methods take a two-stage approach of first generating defect data and then learning a classifier to differentiate between normal data and augmented data. These easy-to-implement and powerful methods can create a diverse range of defects however the created anomalies are unnatural due to the difference between the domain of where the patch was taken from and the domain of the region where the patch is pasted to. Moreover, the behavior of taking a patch from the background and pasting it to another position in the background causes a discrepancy between the label and the data as the augmented data is labeled as a defect while actually being normal. Due to this reason when the augmentation strategies from [4,5] are applied to the manufacturing data from [6] the anomaly detection performance for classes where the object only occupies a small proportion of the image fails to match with the performance for standard classes. To address this issue, we take conditional diffusion models [7], a generative model for conditional image synthesis. The conditional diffusion model [7] is capable of generating high-quality synthetic images with the strategy of using the embedding of the condition as guidance for the reverse diffusion process. Specifically, by making use of the conditional diffusion model fine-tuned to perform an image-to-image translation we generate realistic defects in normal data while preserving the domain of the ground truth data.

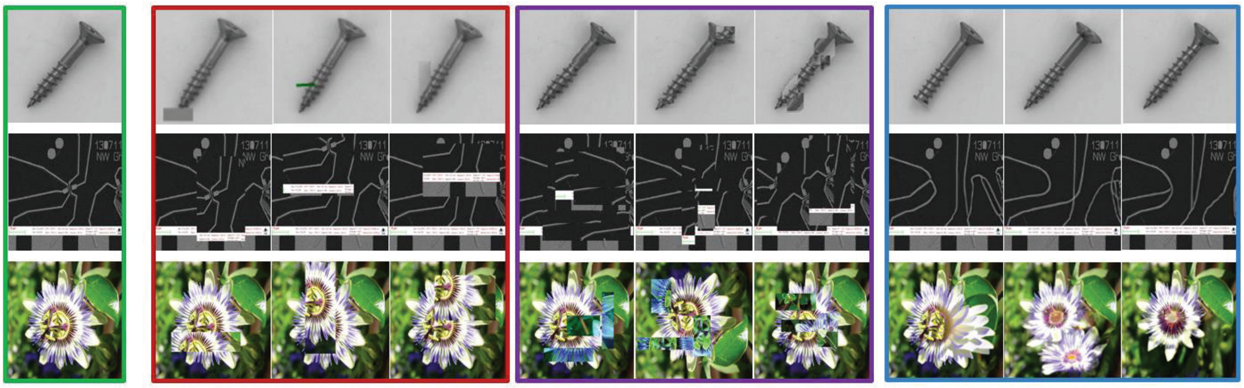
2 Method

Previous works for generating defect data with data augmentation take the form of cutting a patch of data and pasting it to a random region in the same data [4]. Similarly, the work of [5] uses seamless cloning augmentation which takes a patch of data from a data A and pastes it to a random position in another data B. Through these methods have proven to be effective for generating defect data and training anomaly detectors. The unrealistic nature of the generated defect data limits the performance of anomaly detectors and whether the method can be applied to more complex domains like display defects is questionable.

The proposed method of using a deep learning-based data augmentation or a conditional diffusion model is no different from the previous methods in the sense that it generates anomalies within a randomly chosen area of the normal data. Given defect-free data, positional information of the mask, and a condition, the diffusion model performs a image-to-image translation by filling in the masked region with the guidance from the conditional embedding. Empirical experiments on the manufacturing dataset [6], SEMS dataset [8], and the Oxford flower dataset [9] demonstrate that the trained conditional diffusion model can generate realistic defects without extra finetuning on the specific datasets.

3 Results and Discussion

In this section, we evaluate our method by comparing the generated defect data with those generated from previous works. To confirm that the validity of the proposed method is not domain-specific we experiment on the MVTec dataset [6], the SEMS dataset [8], and the Oxford flower dataset [9] each representing manufacturing data, microscope data, and natural image data. The experiment results presented in Fig 2. show that the proposed method generates defect data that are



(a) Normal (b) CutPaste [4] (c) NSA [5] (d) proposed method

Fig. 2 Visualization of augmented normal samples in three different domains

realistic regardless of the data's domain. In addition, while the previous data augmentation methods struggle to preserve the domain of the original data the proposed method succeeds in producing photorealistic data. When training the anomaly detector these photorealistic data will act as hard samples that are difficult to differentiate from normal data and possibly boost the detection performance as the more challenging objective will train the anomaly detectors to detect a wider range of real-world defects.

4 Conclusions

In this paper, we demonstrate the advantage of using deep learning-based data augmentation for generating defect data. Experimental results confirm that the proposed method outperforms previous methods in terms of fidelity and diversity. Furthermore, the proposed method proves to be effective in multiple domains of data including complex domains where previous methods fail to generate realistic defects.

5 Acknowledgment

This work is supported by the Korea Agency for Infrastructure Technology Advancement(KAIA) grant funded by the Ministry of the Interior and Safety (Grant 22PQWO-C153369-04) and National R&D Program through the National Research Foundation of Korea(NRF) funded by Ministry of Science and ICT(2021M3H2A1038042).

References

[1] Zorriassatine, Farbod, Amin Al-Habaibeh, R. M. Parkin, M. R. Jackson, and J. Coy. "Novelty detection for practical pattern recognition in condition monitoring of multivariate processes: a case study." The International Journal of Advanced Manufacturing Technology 25, no. 9, pp. 954-963 (2005).

[2] Moya, Mary M., Mark W. Koch, and Larry D. Hostetler. "One-class classifier networks for target recognition applications." NASA STI/Recon Technical Report N 93 (1993).

[3] Pang, Guansong, Chunhua Shen, Huidong Jin, and Anton van den Hengel. "Deep weakly-supervised anomaly detection." arXiv:1910.13601 (2019).

[4] Li, Chun-Liang, Kihyuk Sohn, Jinsung Yoon, and Tomas Pfister. "Cutpaste: Self-supervised learning for anomaly detection and localization." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 9664-9674. 2021.

[5] Schlüter, Hannah M., Jeremy Tan, Benjamin Hou, and Bernhard Kainz. "Self-supervised out-of-distribution detection and localization with natural synthetic anomalies (nsa)." arXiv:2109.15222 (2021).

[6] Bergmann, Paul, Michael Fauser, David Sattlegger, and Carsten Steger. "MVTec AD--A comprehensive real-world dataset for unsupervised anomaly detection." In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pp. 9592-9600. 2019.

[7] Dhariwal, Prafulla, and Alexander Nichol. "Diffusion models beat gans on image synthesis." Advances in Neural Information Processing Systems 34 pp. 8780-8794. (2021).

[8] Aversa, Rossella, Mohammad Hadi Modarres, Stefano Cozzini, Regina Ciancio, and Alberto Chiusole. "The first annotated set of scanning electron microscopy images for nanoscience." Scientific data 5, no. 1 (2018): 1-10.

[9] Nilsback, Maria-Elena, and Andrew Zisserman. "Automated flower classification over a large number of classes." In 2008 Sixth Indian Conference on Computer Vision, Graphics & Image Processing, pp. 722-729. IEEE, 2008.

[10] Tewel, Yoad, Yoav Shalev, Idan Schwartz, and Lior Wolf. "Supplementary Material: ZeroCap: Zero-Shot Image-to-Text Generation for Visual-Semantic Arithmetic." In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2022.