Flaw Detection in LCD Manufacturing Using GAN-based Data Augmentation

Jingyi Li[1], Yan Li[1], Zuyu Zhang[1], Byeongseok Shin[1,*]
[1]Department of Electrical and Computer Engineering, Inha University

Abstract

Defect detection during liquid crystal display (LCD) manufacturing has always been a critical challenge. This study aims to address this issue by proposing a data augmentation method based on generative adversarial networks (GAN) to improve defect identification accuracy in LCD production. By leveraging synthetically generated image data from GAN, we effectively augment the original dataset to make it more representative and diverse. This data augmentation strategy enhances the model's generalization capability and robustness on real-world data. Compared to traditional data augmentation techniques, the synthetic data from GAN are more realistic, diverse and broadly distributed. Experimental results demonstrate that training models with GAN-generated data combined with the original dataset significantly improves the detection accuracy of critical defects in LCD manufacturing, compared to using the original dataset alone. This study provides an effective data augmentation approach for intelligent quality control in LCD production.

Keywords: Defect Detection; Generative Adversarial Networks; Data Augmentation

1. Introduction

Defect detection in industrial manufacturing is crucial for quality control and production monitoring. However, imbalanced datasets where normal images dominate make accurate classification challenging [1]. The scarcity of images containing defects limits the training of high-performance models, directly impacting product quality and efficiency. Previous studies on imbalanced classification [2] and image enhancement highlight the importance of addressing this issue. However, existing methods are insufficient for industrial image classification tasks, as they overlook domain-specific constraints and challenges. Recent advances in deep learning provide new opportunities through generative models like generative adversarial networks (GANs) [3-4]. By generating realistic defect images, GANs can augment imbalanced datasets effectively. However, the application of GANs in industrial contexts remains limited. Most studies concentrate on natural images and lack considerations of industrial data characteristics.

This study proposes a GAN-based data augmentation approach tailored for defect detection in liquid crystal display (LCD) manufacturing. By generating synthetic yet realistic samples, the augmented dataset mitigates data imbalance and enhances model training. Comprehensive experiments demonstrate the effectiveness of the proposed approach in boosting defect detection accuracy under varying data imbalance ratios.

2. Method

The training procedure, as illustrated in Fig. 1, follows two key steps: 1) Generate synthetic defective images using the GAN and add them to the real minority class samples. 2) Train the classification model on the augmented dataset with weighted loss.

To address the challenge of imbalanced datasets, we propose a data augmentation approach using a Generative Adversarial Network (GAN) to synthesize additional defective images. We adopt the original GAN architecture consisting of a generator and discriminator network. Unlike typical GAN training involving both positive and negative samples, our approach only leverages defective images as the negative class. This guides the generator to produce realistic synthetic defects to augment the minority class. For the classification model training, we assign higher weights to the defective class to counteract the dominance of normal images. The weight coefficients are proportional to the relative sample sizes of the two classes. By penalizing misclassifications of the minority instances more, their influence in optimizing the classifier is balanced with the majority. Overall, the augmented data provides more defect patterns to improve detection accuracy, while the weighted loss balances the impact between the two classes. Our approach is tailored for industrial panel images by leveraging domain-specific data characteristics.

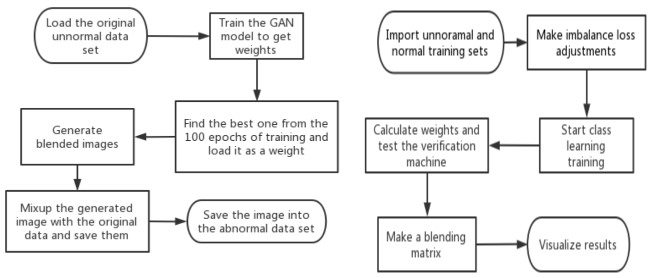
3. Experiments

3.1 Datasets

This study utilizes an industrial panel image dataset containing both normal and defective samples. This dataset is real data extracted from the production process of the company GSI Co., Ltd. The dataset reflects the diversity and complexity of real-world industrial scenarios. However, due to the large size of individual images, we adopt the following approach to augment the data while reducing sample volume.

* Corresponding author. E-mail address: bsshin@inha.ac.kr (B. Shin)
This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (No.NRF-2022R1A2B5B01001553 & 2022R1A4A1033549). This research was supported by the Korea Institute for Advancement of Technology (KIAT) grant funded by the Kore a Government (MOTIE) (P0017157-World Class Plus Project).

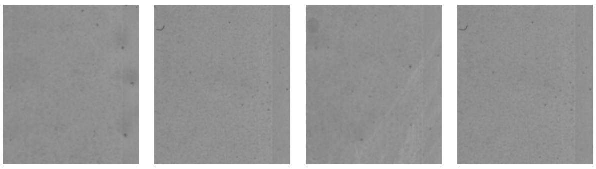
We crop the original oversized image samples into multiple smaller 512x512 squares. We then classify square patches containing defect traces as abnormal samples and categorize the remaining patches as normal data.



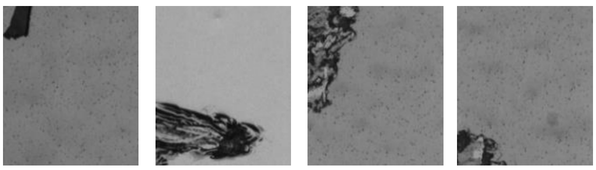
(a)Unnormal data Generation (b) Classification model flow chart

Fig.1. Overall procedure of proposed method

The constructed dataset contains 132 abnormal samples and 5,705 normal samples. This imbalance reflects real-world industrial scenarios where normal images dominate production. The limited defective instances may impede model training. Table I shows example normal and defective images after pre-processing. The imbalance ratio of 1:43 poses challenges for identifying rare anomalies amidst abundant normal patterns. Data augmentation is necessary to supplement the minority class and mitigate the imbalance.



(a) normal training sample



(b) Unnormal training

Fig.2 Data situation

< Table I> Dataset statistics

	val	train	all
unnormal	55	92	147
normal	1650	5096	6746

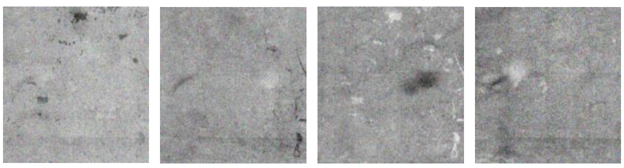


Fig.3. Enhanced mixed data sample

3.2 Implementation Details

This section provides experiment details for reproducibility. Key parameters used include ResNet-18 [5] as the model architecture with a learning rate of 0.001 and momentum of 0.9. A batch size of 16 was chosen to balance computational efficiency and model performance. ResNet-18 was trained on the preprocessed data for defect classification.

3.3 Experimental Results

We evaluated model performance with varying amounts of GAN-generated defective samples added to the minority class. Specifically, 0.1x, 0.2x, 0.4x, 0.8x, and 1.0x the original abnormal set size was augmented. Table II presents the experimental results on overall and defective sample accuracy. Detailed analyses reveal the impact of generated image multiples on model training. Adding too few synthetic images fails to address the severe imbalance, while excessive samples lead to overfitting. An optimal balance must be achieved through sufficient augmentation while preventing redundancy. Our experiments quantify the trade-offs and provide insights on proper minority over-sampling rates.

<TABLE II> The impact of the number of enhanced images o n model performance.

Rate	TP	FP	TN	FN	Neg. Acc	Total Acc
0	1650	0	47	8	85.45%	99.53%
0.1	1650	0	49	7	89.09%	99.94%
0.2	1650	0	51	4	92.73%	99.77%
0.4	1647	3	52	3	94.55%	99.65%
0.8	1647	3	52	3	94.55%	99.65%
1	1647	3	52	3	94.55%	99.65%

From the results, we can observe that as the data enhancement factor increases, the target recognition accuracy shows a steady upward trend. This shows that data augmentation techniques can effectively improve the performance of the model, making it better capture the characteristics of normal and abnormal images.

4. Conclusion

This research provides a method for defect detection in LCD manufacturing and has achieved significant improvement through the application of data enhancement and GAN technology.

Reference:

[1] Qi, S., Yang, J., & Zhong, Z. (2020, September). A review on industrial surface defect detection based on deep learning technology. In Proceedings of the 2020 3rd International Conference on Machine Learning and Machine Intelligence (pp. 24-30).
[2] Kotsiantis, S., Kanellopoulos, D., & Pintelas, P. (2006). Handling imbalanced datasets: A review. GESTS international transactions on computer science and engineering, 30(1), 25-36.
[3] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial nets. Advances in neural information processing systems, 27.
[4] Back, M. K., Yoon, S. W., Lee, S. B., & Lee, K. C. (2019). Perceptual Generative Adversarial Network for Single Image De-Snowing. KIPS Transactions on Software and Data Engineering, 8(10), 403-410.
[5] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).