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Accelerating solder joint classification using generative artificial intelligence for data augmentation

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ABSTRACT

Despite advancements in computer vision, deploying deep learning algorithms for automated optical inspection (AOI) in printed circuit board (PCB) manufacturing remains challenging due to the need for large, diverse, and high-quality training datasets. AOI programs must be developed quickly, often as soon as the first PCB is assembled, to meet tight production timelines. However, deep learning models require extensive datasets of defect images, which are both scarce and time-consuming to collect. As a result, AOI software developers frequently resort to traditional rule-based methods. This study introduces a novel framework that leverages generative AI and discriminative AI to address dataset limitations. By applying a diffusion model to systematically add and remove Gaussian noise, the framework generates realistic defect images, expanding the available training data. This data augmentation accelerates the learning process of deep learning models, enhancing their robustness and generalizability. Experimental results demonstrate that this approach improves AOI system performance by producing balanced datasets across various defect classes. The framework shortens training times while maintaining high inspection accuracy, facilitating faster deployment of AOI systems in manufacturing. This advancement enhances quality control processes, contributing to more efficient, and reliable mass production of PCBs.

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1. INTRODUCTION

The domain of computer vision, particularly in machine inspection has experienced significant advancements with the advent of deep learning algorithms [1]–[4]. In the context of printed circuit board (PCB) manufacturing, automated optical inspection (AOI) system has become a widely accepted standard for vision-based inspection fully integrated into the manufacturing lines [5], [6]. However, the vision system continues to face challenges in achieving accurate inspections in real-world industrial settings due to the highly specular nature of solder joint surfaces [7], [8].

To address these concerns, researchers have proposed numerous innovative machine learning approaches [9]–[12]. Among them, convolutional neural networks (CNN) are highly recommended for solder joint defect detection tasks due to their efficient spatial processing capabilities [13]–[21]. Despite the promising developments, the industrial application of CNN-based algorithms for solder joint quality inspection in AOI systems remains limited. The primary hurdle is due to defective samples are significantly fewer than good ones, leading to an imbalanced dataset, significantly affect the classification accuracy [22]–[25].

Numerous studies have been proposed to mitigate this issue of imbalanced dataset due to limited defective samples [26]–[28]. However, risk of bias and overfitting caused by imbalanced dataset remains unresolved. Generative artificial intelligence (Gen AI) has recently emerged as powerful tool across various domains for content creation. However, its application in creating synthetic datasets for AOI model training remains underexplored. Techniques such as diffusion models offer vast potential for augmenting training dataset, particularly the scarcely available defective data [29]–[31].

This study aims to tackle the challenge of data imbalance by proposing a novel approach inspired by the diffusion process used in Gen AI for defective data augmentation. The method involves progressively adding noise to original images (forward diffusion) and then denoising them (reverse diffusion) to generate synthetic images that closely match the desired data distribution. This approach accelerates training process without sacrificing classification accuracy, facilitating rapid model deployment in the industrial aligned with the practical requirements.

In industrial PCB assembly manufacturing, ensuring the effectiveness of AOI for solder joint quality is crucial during mass production. While CNN-based algorithms offer advanced defect detection capabilities, their development requires extensive and balanced datasets across various defect categories to perform reliably. During early AOI program development phase, defective samples are often limited as compared to good ones, resulting in an imbalanced dataset. Training CNN models on such dataset could compromise generalization and increase the risks of bias and overfitting. To meet the stringent time-to-market demands, AOI programs often developed using rule-based approaches, which do not require large and balanced training datasets but sacrifice the advanced learning capabilities of deep learning algorithms. This study aims to address the key challenge posed by the scarcity of defective sample data.

This research intents to address the following gaps:

- Limited availability of defect data. In real-world industrial environments, particularly in PCB assembly, defective solder joint images are scarce. Deep learning models rely on large, well-balanced datasets, which are often unavailable, leading to bias and overfitting.
- Reliance on rule-based approaches. Due to the limited availability of defect data, AOI systems in manufacturing often depend on traditional rule-based methods instead of more advanced deep learning-based approaches. These rule-based systems lack flexibility and robustness.
- Underexplored application of Gen AI for data augmentation. Although Gen AI, particularly diffusion models, have proven effective for data augmentation across various domains, their applications in solder joint inspection remains largely unexplored. This study aims to address this gap by demonstrating the potential of generative AI in creating synthetic defect images to enhance deep learning model performance.

2. METHOD

The proposed technique is evaluated through five sequential stages, as depicted in Figure 1. The process begins with data preparation, followed by model training, data augmentation and data synthetization, then concludes with performance evaluation. Each of these stages will be described in detail in the subsequent sections.

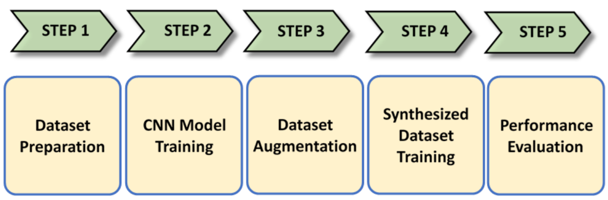

Figure 1. Step-by-step evaluation of the proposed technique

2.1. Dataset preparation (step 1)

In order to ensure transparency and reproducibility, this study utilizes an open-source public dataset obtained from the Kaggle repository at https://www.kaggle.com/datasets. In this paper, the downloaded dataset is referred as “Data_Origin_1”. It contains 323 images of good solder leads and 30 images of defect solder leads. These images are segmented region-of-interest focus on the solder joint leads of surface-mount devices, typically found in packages like small outline integrated circuit (SOIC), small outline package

(SOP), and quad flat package (QFP). Figure 2 presents sample images from “Data_Origin_1,” while Figure 3 provides a closer view of the solder joints on the component leads.

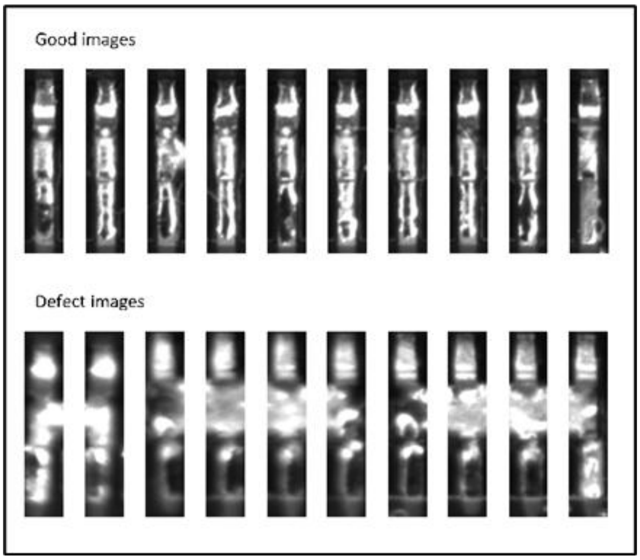

Figure 2. Examples of good and defect images from “Data_Origin_1” dataset

Figure 3. Close-up view of solder joints at leads

To construct the testing dataset, referred as “Data_Test”, three good images and three defect images were randomly sampled from the “Data_Origin_1” dataset downloaded from the repository. The remaining images, comprising 320 good images and 27 defect images, are called “Data_Origin_2”. The dataset partitioning is illustrated in Figure 4.

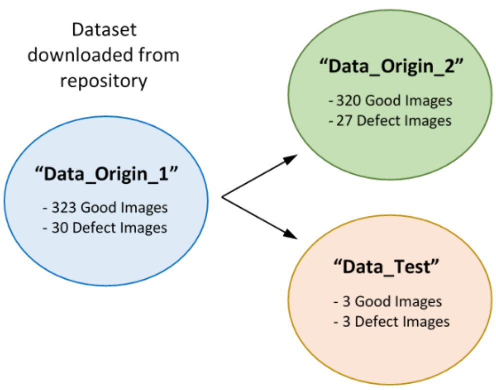

Figure 4. Downloaded dataset is divided into training and testing datasets

2.2. CNN model training (step 2)

Given that the "Data_Origin_2" dataset is a collection of grayscale images with dimensions of 179×38 pixels, a simple CNN-based algorithm with a linear structure was chosen. A Python script, using OpenCV and TensorFlow libraries, was developed for image loading and model training. The "Data_Origin_2" dataset was used for training. After 10 epochs, the model achieved a test accuracy of 98.57% with a test loss of 2.18%.

2.3. Dataset augmentation (step 3)

Many techniques were reported suitable for data augmentation [32]–[34]. Common augmentation methods are rotation, scaling, flipping, and cropping. However, as "Data_Origin_2" dataset consists of only segmented images, hence the most relevant image augmentation will be pixel value modification. To address the imbalance in "Data_Origin_2" (320 good images versus 27 defect images), data augmentation was performed exclusively on the defect images. Five defect images were randomly sampled and their synthesized counterparts were generated progressively based on a diffusion model. The synthesized image from each augmentation loop is loaded to the trained CNN model from step 2 to evaluate the classification results. Synthesized images with a confident level under 95% were discarded. Figure 5 shows original and synthesized images after augmentation process. Through experimentation, it was found that applying Gaussian noise with a mean of 0 and a standard deviation up to 40 preserved key image features, achieving confidence levels above 95%.

Each defect image was synthesized five times to generate in a total of 25 synthesized images. To preserve the consistency of ratio between good and defect images, three synthesized images were deliberately excluded. The final set of 22 synthesized images, along with the original 5 defect and 320 good images from "Data_Origin_2", constituted a new dataset labelled "Data_Syn_A". The composition of this dataset is summarized in Figure 6.

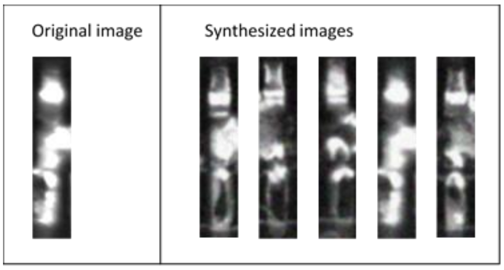

Figure 5. Original image is augmented to five synthesized images

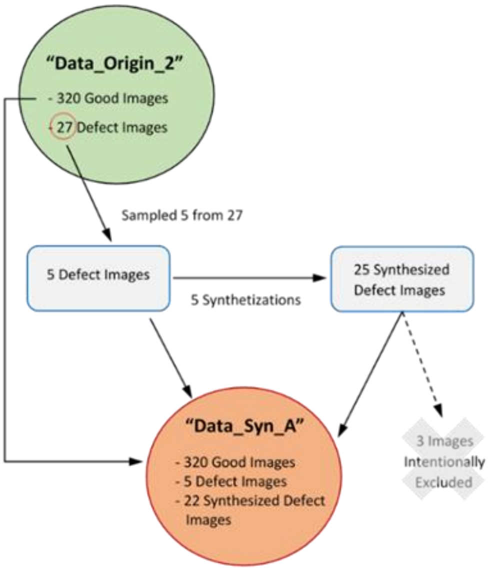

Figure 6. Forming a new dataset from original and synthesized images

2.4. Synthesized dataset training (step 4)

In this step, the CNN model was trained using the "Data_Syn_A" dataset. To ensure repeatability and reproducibility, the same training procedure described in step 2 was applied. Upon completion of 10 epochs, the model achieved a test accuracy of 100% with a corresponding test loss of 1.60%.

2.5. Performance evaluation (step 5)

To compare the classification performance, both models trained on "Data_Origin_2" and "Data_Syn_A" were tested using a synthesized testing dataset, "Data_Test_Syn," created through augmentation of the original "Data_Test". The augmented "Data_Test_Syn" dataset comprised 15 synthesized images each for the good and defect classes, in addition to the original three good and three defect images. Figure 7 illustrates this augmentation process.

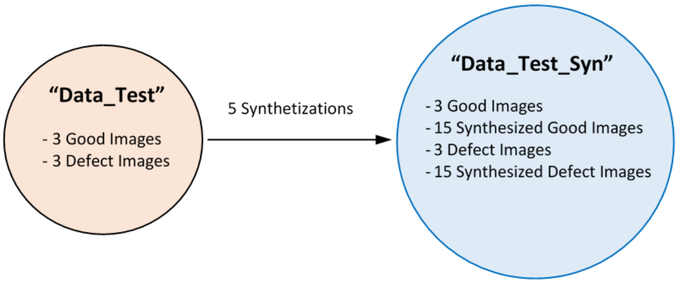

Figure 7. Data augmentation of the testing dataset

The CNN model operates under a two-class classification framework, categorizing predictions as positive (P) or negative (N). Classification outcomes include: i) true positive (TP) the model correctly predicts P for an actual P sample; ii) false positive (FP) the model incorrectly predicts P for an actual N sample; iii) true negative (TN) the model correctly predicts N for an actual N sample; and iv) false negative (FN) the model incorrectly predicts N for an actual P sample. Performance was evaluated using accuracy, precision and recall defined as follows:

– Accuracy: proportion of correctly predicted samples among all samples.

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{1}$$

– Precision: proportion of TP predictions among all positive predictions.

$$Precision = \frac{TP}{(TP+FP)} \tag{2}$$

– Recall: proportion of TP predictions among all actual positives.

$$Recall = \frac{TP}{(TP+FN)} \tag{3}$$

3. RESULTS AND DISCUSSION

Table 1 presents the performance of CNN models trained on different datasets. Although the results reveal only minor differences overall, the model trained on "Data_Syn_A" demonstrates a noticeable bias towards the good class. Specifically, 2 out of 18 defect images were misclassified as good, while all 18 good images were correctly classified with a very high confidence level. This bias is likely attributed to the dataset's imbalance, where the ratio of good to defect images is 12:1.

To verify whether the issue is caused by dataset imbalance, defect images in "Data_Origin_2" were synthesized five times using the procedure similar to that described in step 3. This process resulted in an expanded dataset referred to as "Data_Syn_B". Figure 8 illustrates the dataset expansion process in detail. Following the data augmentation, the ratio of good to defect images was adjusted to 2:1.

Table 1. Comparing performance of "Data_Origin_2" against "Data_Syn_A" dataset

	Accuracy (%)	Precision (%)	Recall (%)
Model trained by "Data_Origin_2"	100	100	100
Model trained by "Data_Syn_A"	94.4	100	90

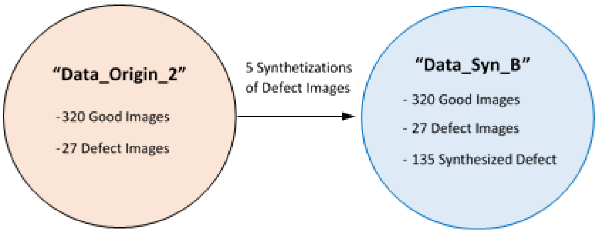

Figure 8. Data augmentation of defect images to balance the dataset

The "Data_Syn_B" dataset was then loaded into the same CNN model for training and evaluated using the same test image dataset, "Data_Test_Syn". The results indicate that accuracy, precision and recall indicators achieved having the level equivalent to those with "Data_Origin_2". In addition, the average classification confidence level showed a notable improvement. Table 2 provides a summary of the performance metrics of "Data_Syn_B" compared to those of "Data_Origin_2".

Table 2. Comparison of "Data_Origin_2" against "Data_Syn_B" datasets

	Accuracy (%)	Precision (%)	Recall (%)	Average confidence level (%)
Model trained by "Data_Origin_2"	100	100	100	96.33
Model trained by "Data_Syn_B"	100	100	100	99.99

4. CONCLUSION

This study presents an innovative framework leveraging generative AI, specifically the diffusion model, to address the inherent challenge of limited defect image data in AOI systems. By augmenting the dataset with synthesized images, the proposed approach enhances the performance of CNN-based classifiers, yielding a more balanced and representative training set. The diffusion model enables progressive image synthesis through the addition and removal of Gaussian noise, thereby enriching the dataset while maintaining characteristics to the original defect distribution. This process ensures the preservation of critical visual features, which is essential for achieving robust classification performance. The experimental outcomes validate the efficacy of this generative approach, demonstrating classification results that are comparable to models trained on real-world defect data. The methodology supports rapid dataset preparation, facilitating the deployment of CNN-based models in industrial settings where reduced time-to-market is a strategic priority. Moreover, it underscores the complementary role of generative learning in augmenting traditional discriminative methods, especially during the early phases of mass production when defect samples are scarce. This study used a manual and iterative approach for image synthesis, which inherently limited the exploration of diverse noise models and augmentation techniques. There is a need for comprehensive software tools capable of supporting various noise modeling techniques, automating simulation processes and optimizing the selection of noise types and intensities. Developing such advanced software solution in the future will be crucial to streamline and enhance dataset augmentation. Meanwhile, this paper focuses exclusively on a single type of soldering defect. In practical, a wider spectrum of soldering-related anomalies, such as solder bridging, nonwetting, excessive solder, and disturbed solder joints are commonly encountered but not addressed in the present study. Future research should extend the framework to include these additional defect types, thereby improving the generalizability and industrial relevance of the findings. Lastly, scaling the dataset size is recommended to reinforce the robustness and reliability of the model performances.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Teng Yeow Ong	✓	✓	✓	✓	✓	✓		✓	✓		✓			
Ping Chow Teoh	✓	✓						✓		✓		✓	✓	
Koon Tatt Tan	✓						✓			✓				✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

DATA AVAILABILITY

The data that support the findings of this study are openly available dataset in the Kaggle repository at https://www.kaggle.com/datasets under the name “lead-legs-on-chipset”.

REFERENCES

[1] A. Prakash and S. Chauhan, “A comprehensive survey of trending tools and techniques in deep learning,” in *2023 International Conference on Disruptive Technologies*, IEEE, May 2023, pp. 289–292, doi: 10.1109/ICDT57929.2023.10151083.

[2] N. Hütten, M. A. Gomes, F. Hölken, K. Andricevic, R. Meyes, and T. Meisen, “Deep learning for automated visual inspection in manufacturing and maintenance: a survey of open- access papers,” *Applied System Innovation*, vol. 7, no. 1, Jan. 2024, doi: 10.3390/asi7010011.

[3] P. Klco, D. Koniar, L. Hargas, K. P. Dimova, and M. Chnapko, “Quality inspection of specific electronic boards by deep neural networks,” *Scientific Reports*, vol. 13, no. 1, Nov. 2023, doi: 10.1038/s41598-023-47958-0.

[4] M. Dol and A. Geetha, “A learning transition from machine learning to deep learning: a survey,” in *2021 International Conference on Emerging Techniques in Computational Intelligence*, IEEE, Aug. 2021, pp. 89–94, doi: 10.1109/ICETCI51973.2021.9574066.

[5] A. A. R. M. A. Ebayyeh and A. Mousavi, “A review and analysis of automatic optical inspection and quality monitoring methods in electronics industry,” *IEEE Access*, vol. 8, pp. 183192–183271, 2020, doi: 10.1109/ACCESS.2020.3029127.

[6] M. Michalska, “Overview of AOI use in surface-mount technology control,” *Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska*, vol. 10, no. 4, pp. 61–64, 2020.

[7] W. Dai, A. Mujeeb, M. Erdt, and A. Sourin, “Soldering defect detection in automatic optical inspection,” *Advanced Engineering Informatics*, vol. 43, Jan. 2020, doi: 10.1016/j.aei.2019.101004.

[8] V. Reshadat and R. A. J. W. Kapteijns, “Improving the performance of automated optical inspection (AOI) using machine learning classifiers,” in *2021 International Conference on Data and Software Engineering*, IEEE, Nov. 2021, pp. 1–5, doi: 10.1109/ICoDSE53690.2021.9648445.

[9] I.-C. Chen, R.-C. Hwang, and H.-C. Huang, “PCB defect detection based on deep learning algorithm,” *Processes*, vol. 11, no. 3, Mar. 2023, doi: 10.3390/pr11030775.

[10] G. Lakshmi, V. U. Sankar, and Y. S. Sankar, “A survey of PCB defect detection algorithms,” *Journal of Electronic Testing*, vol. 39, no. 5–6, pp. 541–554, Dec. 2023, doi: 10.1007/s10836-023-06091-6.

[11] Z. Zhang, W. Zhang, D. Zhu, Y. Xu, and C. Zhou, “Printed circuit board solder joint quality inspection based on lightweight classification network,” *IET Cyber-Systems and Robotics*, vol. 5, no. 4, Dec. 2023, doi: 10.1049/csy2.12101.

[12] F. Ulger, S. E. Yuksel, and A. Yilmaz, “Anomaly detection for solder joints using β -vae,” *IEEE Transactions on Components, Packaging and Manufacturing Technology*, vol. 11, no. 12, pp. 2214–2221, Dec. 2021, doi: 10.1109/TCPMT.2021.3121265.

[13] M. B. Akhtar, “The use of a convolutional neural network in detecting soldering faults from a printed circuit board assembly,” *HighTech and Innovation Journal*, vol. 3, no. 1, pp. 1–14, Mar. 2022, doi: 10.28991/HIJ-2022-03-01-01.

[14] Y. Tian, “Artificial intelligence image recognition method based on convolutional neural network algorithm,” *IEEE Access*, vol. 8, pp. 125731–125744, 2020, doi: 10.1109/ACCESS.2020.3006097.

[15] Y.-G. Kim and T.-H. Park, “SMT assembly inspection using dual-stream convolutional networks and two solder regions,” *Applied Sciences*, vol. 10, no. 13, Jul. 2020, doi: 10.3390/app10134598.

[16] B. Cai, “Fully connected convolutional neural network in PCB soldering point inspection,” *Journal of Computer and Communications*, vol. 10, no. 12, pp. 62–70, 2022, doi: 10.4236/jcc.2022.1012005.

[17] Q. Zhu and X. Zu, “Fully convolutional neural network structure and its loss function for image classification,” *IEEE Access*, vol. 10, pp. 35541–35549, 2022, doi: 10.1109/ACCESS.2022.3163849.

[18] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, “A survey of the recent architectures of deep convolutional neural networks,” *Artificial Intelligence Review*, vol. 53, no. 8, pp. 5455–5516, 2020, doi: 10.1007/s10462-020-09825-6.

[19] Z. Li, F. Liu, W. Yang, S. Peng, and J. Zhou, “A survey of convolutional neural networks: analysis, applications, and prospects,” *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 12, pp. 6999–7019, Dec. 2022, doi: 10.1109/TNNLS.2021.3084827.

[20] M. Krichen, “Convolutional neural networks: a survey,” *Computers*, vol. 12, no. 8, Jul. 2023, doi: 10.3390/computers12080151.

[21] J. Lian, L. Wang, T. Liu, X. Ding, and Z. Yu, "Automatic visual inspection for printed circuit board via novel mask R-CNN in smart city applications," *Sustainable Energy Technologies and Assessments*, vol. 44, Apr. 2021, doi: 10.1016/j.seta.2021.101032.
[22] A. I. M. Schwebig and R. Tutsch, "Compilation of training datasets for use of convolutional neural networks supporting automatic inspection processes in industry 4.0 based electronic manufacturing," *Journal of Sensors and Sensor Systems*, vol. 9, no. 1, pp. 167–178, Jul. 2020, doi: 10.5194/jsss-9-167-2020.
[23] Y. Liu, H. Wu, Y. Xu, X. Liu, and X. Yu, "Automatic PCB sample generation and defect detection based on controlnet and swin transformer," *Sensors*, vol. 24, no. 11, May 2024, doi: 10.3390/s24113473.
[24] S.-H. Tsang, Z. Suo, T. T.-L. Chan, H.-T. Nguyen, and D. P.-K. Lun, "PCB soldering defect inspection using multitask learning under low data regimes," *Advanced Intelligent Systems*, vol. 5, no. 12, Dec. 2023, doi: 10.1002/aisy.202300364.
[25] R. Ding, C. Zhang, Q. Zhu, and H. Liu, "Unknown defect detection for printed circuit board based on multi-scale deep similarity measure method," *The Journal of Engineering*, vol. 2020, no. 13, pp. 388–393, Jul. 2020, doi: 10.1049/joe.2019.1188.
[26] T.-C. Tsan, T.-F. Shih, and C.-S. Fuh, "TsanKit: artificial intelligence for solder ball head-in-pillow defect inspection," *Machine Vision and Applications*, vol. 32, no. 3, May 2021, doi: 10.1007/s00138-021-01192-8.
[27] Y. Wan, L. Gao, X. Li, and Y. Gao, "Semi-supervised defect detection method with data-expanding strategy for PCB quality inspection," *Sensors*, vol. 22, no. 20, Oct. 2022, doi: 10.3390/s22207971.
[28] J. Zhou, G. Li, R. Wang, R. Chen, and S. Luo, "A novel contrastive self-supervised learning framework for solving data imbalance in solder joint defect detection," *Entropy*, vol. 25, no. 2, Jan. 2023, doi: 10.3390/e25020268.
[29] F.-A. Croitoru, V. Hondru, R. T. Ionescu, and M. Shah, "Diffusion models in vision: a survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 45, no. 9, pp. 10850–10869, Sep. 2023, doi: 10.1109/TPAMI.2023.3261988.
[30] L. Yang *et al.*, "Diffusion models: a comprehensive survey of methods and applications," *ACM Computing Surveys*, vol. 56, no. 4, pp. 1–39, Apr. 2024, doi: 10.1145/3626235.
[31] H. Cao *et al.*, "A survey on generative diffusion models," *IEEE Transactions on Knowledge and Data Engineering*, vol. 36, no. 7, pp. 2814–2830, Jul. 2024, doi: 10.1109/TKDE.2024.3361474.
[32] L. Nanni, M. Paci, S. Brahnam, and A. Lumini, "Comparison of different image data augmentation approaches," *Journal of Imaging*, vol. 7, no. 12, Nov. 2021, doi: 10.3390/jimaging7120254.
[33] T. Kumar, R. Brennan, A. Mileo, and M. Bendechache, "Image data augmentation approaches: a comprehensive survey and future directions," *IEEE Access*, vol. 12, pp. 187536–187571, 2024, doi: 10.1109/ACCESS.2024.3470122.
[34] M. Xu, S. Yoon, A. Fuentes, and D. S. Park, "A comprehensive survey of image augmentation techniques for deep learning," *Pattern Recognition*, vol. 137, May 2023, doi: 10.1016/j.patcog.2023.109347.

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