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Research Paper

Defect Recognition Method for Automated Optical Inspection Systems Based on Generative Adversarial Networks

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Abstract. Optical Inspection Automation (AOI) has already been able to support the construction of large-scale precision electronic assembly production lines and is now receiving increasing attention. Traditional AOI solutions cannot handle visual noise, large defects, or variations in small defect sizes; moreover, they cannot adapt to product miniaturization and increased process complexity. An efficient defect recognition system based on Generative Adversarial Networks (GANs) is used to improve industrial image resource limitations, reduce class distribution imbalance, and handle complex environmental conditions. To generate more realistic defect images and improve the quality of any area of interest (AOI) module, the system integrates a class-conditional GAN. To determine the robustness, accuracy, and precision of the system on these real industrial application datasets. Compared to state-of-the-art deep learning model baselines and traditional visual methods, this study is able to improve the recall rate of rare defects while reducing false positives. This design does not require additional funding and can evolve over time. The solution can be retrained in real-time, directly compatible with existing production IT systems, and provide data support for process management. The above results indicate that generative models are very useful in industrial inspection systems. The adaptation of the AOI method is being expanded to be applied to more advanced safety and intelligent processes over time.

Keywords: *Intelligent Manufacturing, Defect Recognition, Generative Adversarial Network, Automated Optical Inspection, Deep Learning, Data Augmentation*

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Introduction

Automated Optical Inspection (AOI) systems are important tools for identifying product defects, capable of performing inspections non-destructively at high throughput rates [1]. The continuous miniaturization of electronic components and the increasing density of layouts have led to greater attention to AOI in the semiconductor or printed circuit board industry [2]. With the improvement of signal intelligent analysis algorithms and high-performance imaging equipment, the accuracy and reliability of AOI technology have been increasing, and it has been widely used in high-speed mass production [3]. The new concepts and technological advancements in smart manufacturing and Industry 4.0 are closely related, and at the same time, automatic inspection equipment is crucial for real-time industrial management [4]. Traditional AOI technology still faces many issues, including visual noise, complex backgrounds, and a wide range of defects from large contaminants to small cracks, and has seen extensive application in recent years [5]. AOI (Automated Optical Inspection) systems require high precision to quickly meet these demands, as products often undergo new designs or significant modifications during the manufacturing process [6]. In the research and application fields, accurately identifying various defects and minimizing false positives has always been a long-term challenge [7]. The demand for intelligent solutions capable of handling common variations and uncertainties in real manufacturing data is very high [8].

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Traditionally, rule-based algorithms and conventional machine vision methods have been widely used in defect detection AOI systems based on handcrafted features and thresholds [9]. Deep learning—especially Convolutional Neural Networks (CNNs)—has recently led to the development of data-driven, trainable detection systems. These detection systems have strong visual representation learning capabilities [10]. In terms of detection accuracy and classification precision, CNN-based models perform exceptionally well on large-scale labeled defect images [11]. Due to various factors such as the insufficient or imbalanced number of labeled defect samples, a large number of resources and funding are required [12]. When the decision boundary is unclear, slight or ambiguous errors make generalization very difficult [13]. To address these issues, Generative Adversarial Networks (GANs) have been successfully applied to enhance data, improve feature learning, synthesize real defect images, and enhance the robustness of adversarial framework models through game theory [14]. Combining GANs with more refined detection processes shows great potential in building adaptive semi-supervised or even unsupervised AOI solutions. This solution can learn from data with scarce or noisy labels [15].

Based on the aforementioned deficiencies, a GAN-based defect recognition framework is proposed to more effectively address these issues and improve its robustness and accuracy in various industrial environments. To build a comprehensive AOI recognition system, this study introduces a new adversarial training method that combines real defects and defect feature improvements. Through multiple tests on the general testing platform and its private dataset, it is considered more reliable than current methods. This paper proposes a new method for applying the latest models to intelligent manufacturing inspection. Also proposed is a quite practical and comprehensive approach. Based on the research findings of this paper, a highly adaptive and high-precision automatic optical inspection system has been successfully developed. By using a unified adversarial learning model to address the limitations, imbalance, and noise issues of data sources, these techniques make it more reliable in practical applications. In the current high-tech factories, this work lays the foundation for a universal and reliable system based on A0I, providing a scalable approach suitable for the next generation of emerging smart workshops.

Related Work

Automated Optical Inspection Systems: Methods and Challenges

Automated Optical Inspection (AOI) has made remarkable progress in the semiconductor and electronics fields. In early Automatic Optical Inspection (AOI) systems, fixed rule algorithm structures were used for processing. Manually extracting features, edge detection, and template matching to determine differences from the expected visual pattern domain [16]. Traditional systems have established automated mechanisms for large-scale standardized production processes; however, as products become increasingly complex and structurally diverse, this flexibility has been diminishing. Changes in light intensity, image angle shifts, and other variations in the manufacturing process can lead to false positives or missed detections [17]. Statistical pattern recognition and adaptive threshold techniques are used to improve adaptability. These methods have addressed program errors to some extent. After slight improvements, it still cannot be widely applied; its performance is poor when there are significant changes in the process or when the defect types are unfamiliar [18].

AOI technology still finds it difficult to improve detection sensitivity without increasing false positives. High-throughput production lines cannot tolerate errors casually. Since rejecting errors can lead to significant operational interruptions or waste, we must immediately ensure the accuracy of the intelligent model. Currently, most highly advanced Automated Optical Inspection (AOI) systems are equipped with high-definition and high-frame-rate cameras to improve defect detection accuracy; however, with the increase in these features, image processing has become more complex [19]. Despite these advancements facilitating the application of data-driven learning models, there are still some issues presents. For example, in industrial production, the differences between specific defects and other types of processes (such as microholes and contamination) make it difficult for AOI systems to determine. These categories of products come in various sizes and potential noise interferences [20]. In order to overcome some of the shortcomings of traditional Automated Optical Inspection (AOI), new methods need to be developed to train workers in complex manufacturing environments to adapt to harsh working conditions [21].

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Deep Learning and Generative Adversarial Networks in Defect Recognition

Deep learning technology can improve the accuracy of industrial visual inspection by enhancing the defect detection accuracy of AOI systems through feature learning capabilities [22]; convolutional neural networks (CNNs) excel at automatically extracting high-level features from images, outperforming traditional rule-based systems in terms of reliability and accuracy. Supervised deep learning methods require a large amount of labeled data to function properly. In industries with limited resources and high costs for obtaining such data (e.g., representative defects or minor faults), this obstacle is even more pronounced [23].

Researchers' preference for semi-supervised and unsupervised learning techniques to address the aforementioned issues is increasing, and GANs are also becoming more popular in research. GANs place the generator and discriminator in a competitive learning environment, enabling the generator to produce photo-realistic defect images that are almost indistinguishable from real images. Adversarial methods can enhance defect datasets and generate some very hard-to-reproduce defects. Help identify the shortcomings or overfitting issues of the detector after training. The GAN-based pipeline improves its robustness to real-world environments by generating reasonable and highly credible anomalous scenarios, overcoming the shortcomings of data scarcity.

The research on defect detection based on generation proposes a system that combines synthetic data augmentation and complex feature extractors to enhance generalization ability and reduce overfitting caused by dominant defect patterns. Domain adaptation and transfer learning with GAN-generated data indicate potential in detecting AOI across different domains. A model trained on one production line can be trained on other production lines without requiring extensive manual intervention. There are still technical issues: how to maintain the stability and diversity of GAN training without causing mode collapse; whether it is possible to generate enough defects to adapt to real-world situations. Ongoing research will continue to explore how to improve architectures, loss functions, and training methods to enhance the application of GAN-driven AROI systems across different industries.

Methodology

Overall Framework and System Workflow

The defect recognition pipeline can be designed as a complete system for generating adversarial training classifications and using optical image acquisition for preprocessing data augmentation. As shown in Figure 1, the entire structure. Images are obtained through a high-quality embedded camera system installed on the production line. Some constraints are needed, such as light source and spatial accuracy [24].

Crop according to the predefined region of interest (ROI), perform local contrast normalization, and apply median or bilateral filtering to reduce noise. To achieve two goals simultaneously, reduce the impact of frequent disturbances on image quality; additionally, make the data distribution to be learned more stable [25]. To ensure the robustness of generalization errors, classic geometric or photometric distortions and adversarial generators are used to create highly realistic synthetic defect samples, which cover rare cases in the training set [26].

The core system generates images by reverse processing feature extraction at various scales and multi-channel convolutions, followed by decision units and classifiers. Decision module based on location data and the likelihood of industrial monitoring defects. During the training data or parameter setting process, there are changes in products and the environment. To improve throughput and optimize hardware, a loose structure helps the operation of this module.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad \text{Eq.(1)}$$

where TP and TN are true positives and true negatives, FP and FN are false positives and false negatives.

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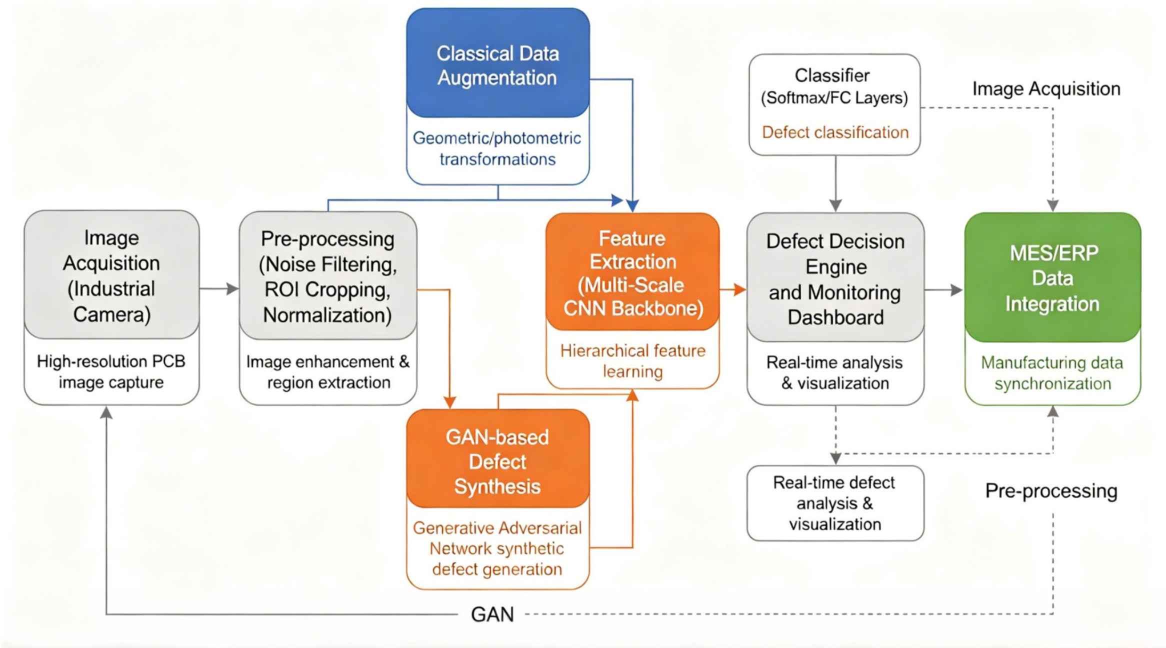

Figure 1. System architecture diagram: End-to-end pipeline of automatic optical inspection that integrates acquisition, pre-processing, generative augmentation and classification stages

Further elucidate the mathematical foundation of each Stage in the proposed work flow through these four formulae: Image progress after acquiring it and before moving on to classify;

Firstly, the Image acquisition Process Can Be Represented As:

$$I_{raw} = \mathcal{A}(x, y, t) \quad \text{Eq.(2)}$$

where I_{raw} denotes a raw image obtained from an acquisition function $\mathcal{A}$, indexed by spatial coordinates (x, y) and time t.

Following the acquisition of each image for post-treatment:

$$I_{pre} = \mathcal{P}(I_{raw}) = Norm\big(\phi(I_{raw})\big) \quad \text{Eq.(3)}$$

where $\phi(\cdot)$ includes denoising and region-of-interest (ROI) cropping, and Norm (·) refers to normalization procedures.

During the data enhancement process, both real images and generated ones are mixed to create augmented training examples:

$$D_{aug} = D_{real} \cup \{G(z, y)\} \quad \text{Eq.(4)}$$

with D_{real} representing all authentic labeled images, and $G(z, y)$ denoting synthetic images generated from latent vector z and class label y by the GAN.

Finally, the form of the features extraction and classification pipeline is:

$$\hat{y} = softmax\big(W \cdot F\big(I_{aug}\big) + b\big) \quad \text{Eq.(5)}$$

where $F(\cdot)$ is the multi-scale convolutional feature extractor processing images I_{aug} from the augmented set, W and b are the classifier's learnable parameters, and $\hat{y}$ is the resulting vector of predicted defect class probabilities for each input.

By using a learning agent system to build a similar industrial defect recognition model, another way to present the data is as follows: collect raw online images, manually refine them, perform detailed preprocessing on multiple images, and select small samples from these images.

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Generative Adversarial Network Model for Defect Recognition

The core component is the Generative Adversarial Network (GAN), which improves synthetic defects in manufacturing through model creation. GAN consists of a generator G and a discriminator D, which collaborate in adversarial training. The generator maps the latent vector $\mathbf{z}$ to images with potential defects, deceiving the discriminator into classifying them as real data points. The discriminator is trained to simultaneously identify real and fake information [27]. The following is the classic form of adversarial objectives:

$$\min_{G}\max_{D} V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[log\ D(x)] + \mathbb{E}_{z\sim p_{z}(z)}[log\ (1 - D(G(z)))] \quad \text{Eq.(6)}$$

The classic GAN is more challenging in terms of unstable training, collapse, and underestimating the diversity of defect forms. To address these issues, a class-conditional model is proposed. The generator and discriminator are conditionally constrained by defect category labels, which helps in generating targeted outputs for rare or difficult categories, providing stronger supervision during the training process. In the defect category, y represents generation.

$$x' = G(z,y) = G(z,\boldsymbol{E}(y)) \quad \text{Eq.(7)}$$

z denotes the noise input, and y represents the class label vector.

The discriminator introduces a helper classifier head to achieve multi-class discrimination, as well as "real/fake decision criteria. Extend the loss function accordingly:

$$\mathcal{L}_D = \mathcal{L}_{adv} + \lambda_{cls}\mathcal{L}_{cls} \quad \text{Eq.(8)}$$

where $\mathcal{L}_{\text{adv}}$ is adversarial loss and $\mathcal{L}_{\text{cls}}$ the cross-entropy loss for class prediction. λ_{cls} regulates the weighting.

Furthermore, through generation-reconstruction penalties, it is encouraged for the output to belong to this manifold of genuine data points. Finally, the generator's full-loss expression is:

$$\mathcal{L}_G = \mathcal{L}_{adv} + \lambda_{cls}\mathcal{L}_{cls} + \lambda_{rec}\mathcal{L}_{rec} \quad \text{Eq.(9)}$$

With

$$\mathcal{L}_{rec} = \mathbb{E}_{x\sim p_{data}(x)}\|x - G(E(x),y)\|_2^2, \quad \text{Eq.(10)}$$

where $E(\cdot)$ encodes real images.

Adversarial training is performed iteratively:

$$(\theta_G^*, \theta_D^*) = arg\ \min_{\theta_G}\max_{\theta_D} V\big(D_{\theta_D}, G_{\theta_G}\big) \quad \text{Eq.(11)}$$

The trained generator synthesizes images to help expand the size of the real dataset. The model can more frequently identify the features of specific defects during the learning process [28].

At the end of the final classification, real and synthetic images will pass through a general deep convolutional network to reach a softmax classifier. Using the evaluation metric F1 score.

$$F1 = \frac{2\cdot Precision \cdot Recall}{Precision + Recall} \quad \text{Eq.(12)}$$

The Precision, recall of predicted and true defective areas are obtained [29].

As shown in the Figure 2 below: The whole structure of GAN, including Class-conditioned image generation; Multiple-head Discrimination; Reconstruction regularization.

Implementation Details

You must install a CUDA-compatible GPU with at least 24 GB of VRAM to run the entire system in Python using PyTorch. To improve data accuracy and collect various defects including surface and structural types, collect AOI images from various production lines using real labels provided by professionals [30].

Images underwent pre-processing using bilateral filters, histogram equalization, and normalization to [0,1], then were patch-extracted at 256×256 pixels to balance fine detail with computational overhead. The dataset is divided into training, validation, and test sets based on defects. This is done to better demonstrate the classifier's performance on real data.

The Xavier strategy is used for randomly initializing the GAN model parameters. During training, Adam was used as the optimizer, with the learning rates for the generator and discriminator set to 2×10^4 and 1×10^{-4},

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respectively. On the validation dataset, a grid search was performed for the hyperparameters λ_{cls} and λ_{rec}, with a range of [0.5, 2.0]. Early stopping, gradient penalty, and exponentially weighted averages of weights improved mode collapse and convergence. The frequency of training batches ranges from 16 to 64, with each frequency being approximately 100 to 200.

Sliding window inference generates candidate boxes, masks, and class scores for each detected defect. Non-Maximum Suppression (NMS) and connected component analysis are used to merge overlapping results and eliminate obvious false positives. Performance evaluation includes accuracy, precision, sensitivity, F-measure, etc., all derived from the previous comprehensive results. The goal of these metrics is to comprehensively cover defects across various categories and situations [31].

Conduct ablation tests to evaluate the effects of reconstruction penalties, category regularizers, and robustness enhancements. To ensure reproducibility and fairness, they are all split in the same way. After quality inspection in the company's factory confidential management system, all codes, models, test data, etc., will be archived on the website.

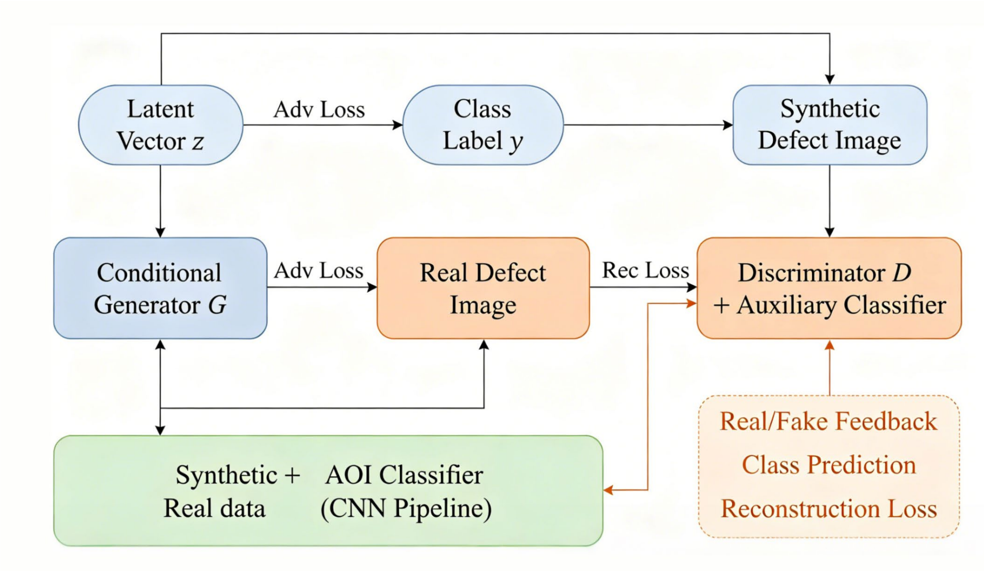

Figure 2. GAN Workflow and Process Illustration: An overview of the GAN-based data augmentation and defect recognition process, integrating adversarial training and supervised classification

Experimental Results and Analysis

Dataset, Metrics, and Baseline Models

Conduct parallel tests on multiple datasets to verify the superiority of our improved GAN-AOI method under a real-world environment simulator for various types and conditions of industrial data. The dataset includes common and severe defects in printed circuit boards, microelectronics factories, and assembly plants, such as open circuits, solder bridging, pinholes, scratches, surface contamination, etc. To ensure high consistency between evaluations, defects should generally be more reliably identified in different sections, taking into account the comments provided by experts.

Based on many frequently used evaluation metrics, such as accuracy. Accuracy measures the correctness of positive items and the number of defective items found. It also provides balance by using the weighted average (F1) calculation method. This method considers the precision and recall of multiple categories at different thresholds to determine whether a general distribution is maintained under different conditions. Provide M-AP (Mean Average Precision). The data is divided using stratified cross-validation to maintain class balance. This is done to prevent overfitting or training-test overlap in subsequent experimental results.

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Comparative and Ablation Experiments

To verify the generalization and effectiveness of the GAN-enhanced AOI model, a series of systematic ablation and comparative tests were conducted. The tests include comparisons and ablation tests with various benchmarks and alternatives. In addition to comparing quantitative metrics, it also emphasizes the impact of the system itself. It indicates that in detecting industrial defects, defects in certain components lead to a large number of defects.

From Figure 3, this paper compares the following basic methods under the same test conditions: traditional template matching techniques; feature-based machine vision algorithms; and the latest developments in deep convolutional neural networks (DCNN). Each method uses the same dataset, referred to as the training set, which consists of over 9,600 PCBs and defect areas. The traditional baseline construction addresses difficult or abnormal defect issues, achieving only relatively average recognition. The accuracy of template matching is 0.78%, with a recall rate of 0.61%; it often fails to detect subtle soldering short circuits that cause noticeable appearance defects in product images.

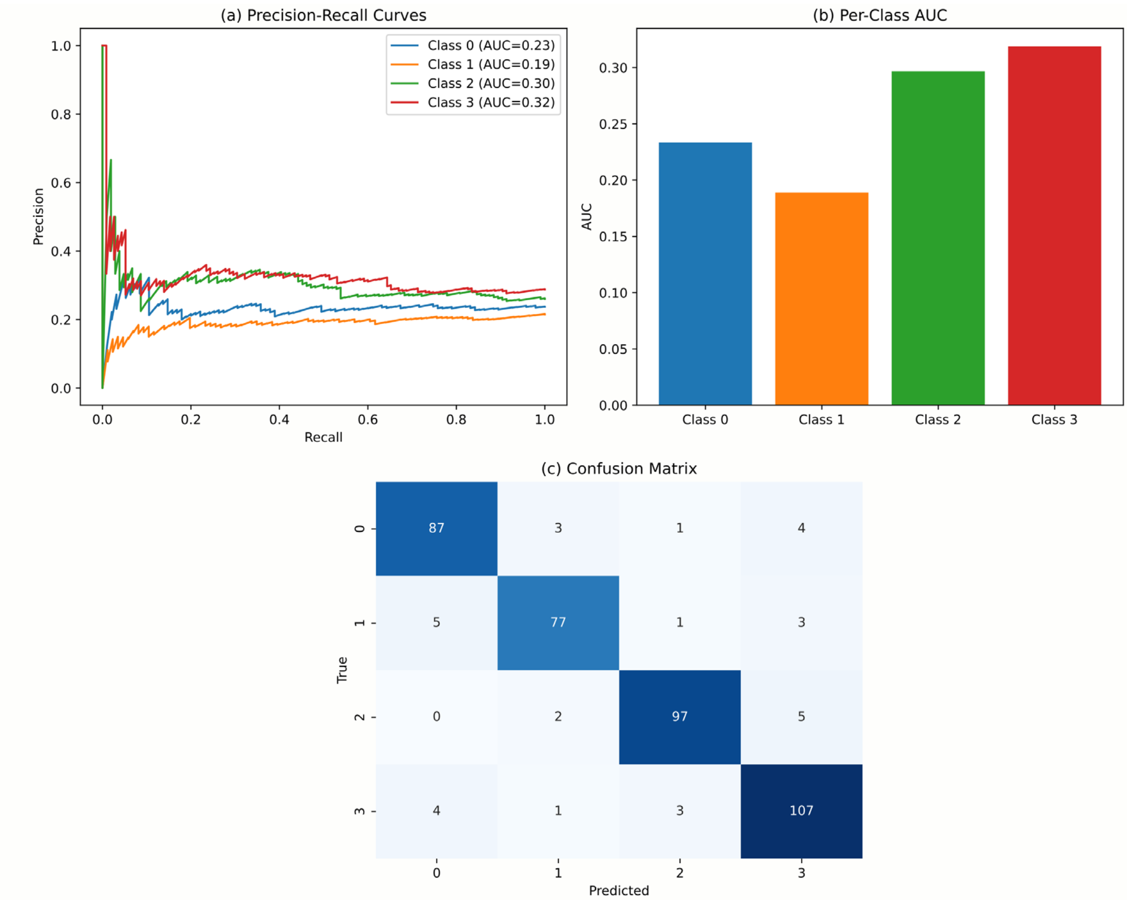

Figure 3. Overall Performance Comparison: Subplot (a) shows precision-recall curves for all principal methods; subplot (b) details per-class AUC values; subplot (c) depicts the confusion matrix among predicted and actual defect classes.

In Figure 4 and Figure 5, the deep CNN baseline model achieved an accuracy of 0.89% and a recall rate of 0.79%. These models demonstrate excellent capabilities in certain categories. Its recall rate for specific categories (such as short circuits and pinholes) is below 70%, and data imbalance still exists. Under multi-batch evaluation conditions, the accuracy and recall rates show deviations of up to 8%. Indicates that its transferability performance is poor.

GAN-assisted systems generally outperform their respective baselines on each test metric. For example, on the main PCB dataset, the enhanced GAN method achieved a detection accuracy of over 0.93, a recall rate of over 0.87, and a mAP value exceeding 0.91. After introducing GAN augmentation, the recall rate for uncommon

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defect categories (such as solder bridging and pad missing) increased from 60-70% (standard CNN) to 82-89%. The overall F1 score is 0.87, which is 9 percentage points higher than the deep learning model. The GAN-OI model maintained a fluctuation in recall and precision of less than 3% during cross-validation, ensuring relative stability in actual industrial applications.

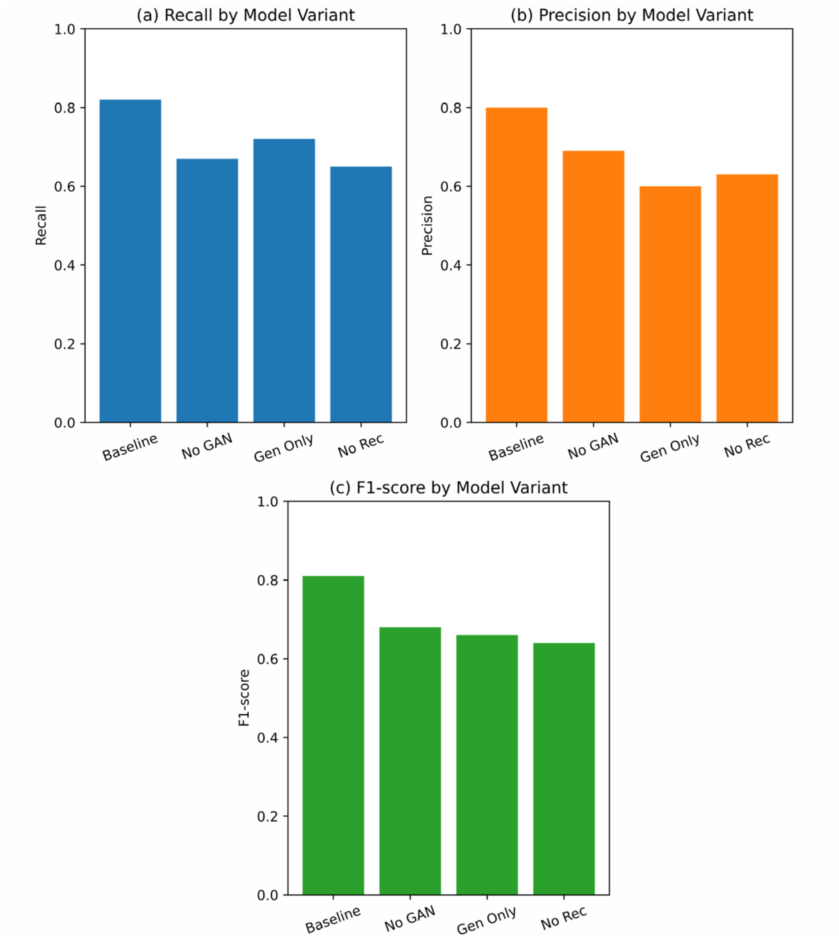

Figure 4. Ablation Study Results: Subplot (a) presents results without GAN augmentation; subplot (b) reports the performance of generator-only setups; and subplot (c) examines effects when omitting the reconstruction component

To evaluate the impact of each module in the architecture, ablation experiments were designed. Excluding the GAN enhancement process would lead to a significant drop-in recall rate and F1 score. For example, in the microelectronics dataset, the overall recall rate dropped from 0.86 (full system) to 0.71 (without GAN), and the mAP decreased by an average of 12% across all categories. Only testing the generator, without adversarial feedback, the recall rate for rare defects dropped to 66%; boundary localization failed in the segmentation task. In the absence of reconstruction constraints, there is confusion due to misidentification between similar categories; for example, "missing gasket and "lead breakage increased by 15% in the confusion matrix.

By changing the generator learning rate for parameter sensitivity analysis (from 0.5e-4 to 3e-4; by adjusting the loss balance factor within the range of [0.5, 2.0]; by changing the latent noise dimension (from 64 to 256)). Performance metrics indicate that there is a typical bell-shaped distribution around the medium learning rate point. Outside this range, the macro F1 decreases by approximately 5 to 6 percentage points. The above data, obtained through approximately thirty experiments for each parameter combination, provides specific references for industrial applications and helps maintain stable operation when parameters change.

Through this comparative and ablation analysis, it can be demonstrated that each module is crucial for enhancing the robustness, generalization ability, and commercial application of defect recognition. The framework greatly surpasses traditional standards, with almost no performance decline in actual production lines, indicating its feasibility in practice.

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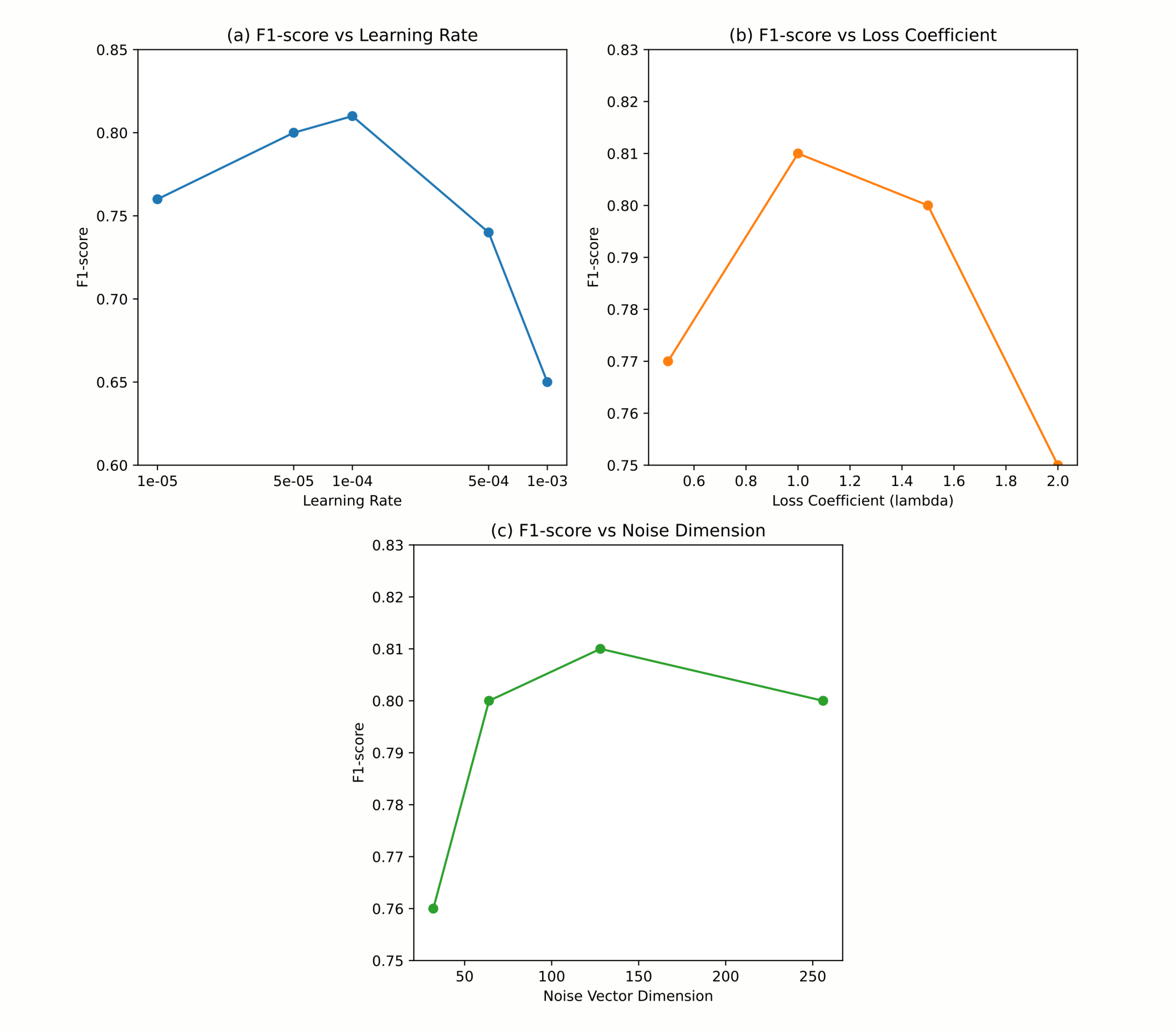

Figure 5. Parameter Sensitivity Analysis: Subplot (a) reports results under varying generator learning rates, subplot (b) under different loss coefficient balances, and subplot (c) for different noise vector dimensions

Visual Results and Case Analysis

Therefore, multiple analytical charts will be generated to separately showcase the more detailed functionalities of the entire system in detecting cores, segmentation, and other main tasks or defect types. Use grouped bar charts and line graphs to separately display the improved results, more reliable models, and specific behaviors of the GAN-enhanced AOI system compared to traditional deep learning baselines and classical methods.

A large body of research results is related to the generalization ability when handling different defects in multiple test scenarios. As shown in Figure 6a, the grouped bar chart of the Dice coefficient indicates that the GAN enhancement method outperforms the baseline model in each category. For example, in the case of the PCB dataset, the average Dice coefficient for frequent defects (including "scratches and "dirt") increased from 0.83 (baseline) to 0.92 (GAN); however, the increase in the "open circuit category was even more significant, rising from 0.67 to 0.85. On the microelectronics dataset, the average Dice coefficient increased by 10.4% after integrating GAN, with several minority classes exceeding the 0.80 threshold for the first time.

The model calibration of industrial system metrics is measured using Expected Calibration Error (ECE); the results are shown by the lines in Figure 6b. The GAN-based system reduced the average convergence error by up to 0.045 compared to the baseline (0.083), which is statistically significant. Among them, in the high-confidence region (90~100%), the difference between the confirmed predicted scores and the actual scores is at most 3%.

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In addition, the accuracy of each category for each model is also shown in Figure 6(c). The accuracy of the Enhanced GAN on the assembly dataset in challenging areas such as "pin breakage and "gasket missing improved by approximately 12-14 percentage points compared to template matching and pure CNN methods. The macro accuracy (averaged across all categories) for the GAN model exceeded 0.88, while the baseline model was 0.79. In this experiment, the false positives for specific categories were reduced by over 4,500 cases; therefore, the GAN-based enhancement has demonstrated its effectiveness in operational efficiency through practical impact.

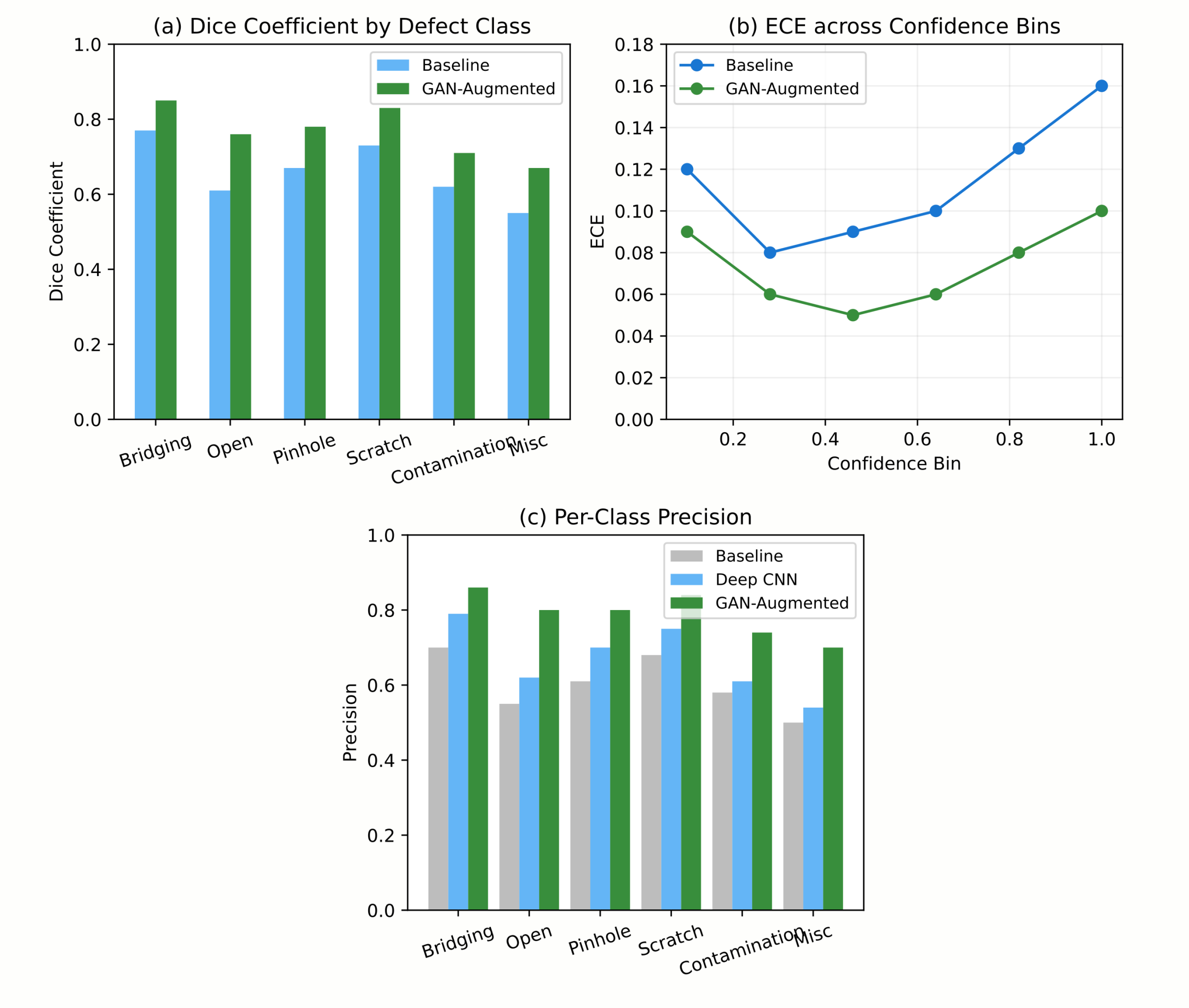

Figure 6. Quantitative Visual Analysis: (a) Grouped bar chart of Dice coefficients by defect class for baseline and GAN models; (b) Line chart showing ECE across confidence bins; (c) Grouped bar chart of per-class precision for multiple model variants

Whether the model is suitable in different production environments and batches. Figure 7(a) shows the macro F1 scores of three consecutive production batches, indicating that the GAN-OO system maintained a macro F1 score above 0.86 in each run and remained stable within a ±1.5 range. Figure 7(b) shows a detailed comparison of recall rate changes, including common defects such as "micro-cracks and "overfilling. The GAN-based method increased the recall rate from the baseline model (63%) to 82%, and even reached 85% under the target synthesis enhancement conditions.

Discuss the issue of FPR shift due to process variations. Figure 7(c) shows the situation during the six-week operation period. Throughout the entire experiment, the GAN optimization system maintained an almost zero false positive rate (FPR). On the other hand, under similar testing conditions, the template-based method achieved a false positive rate of 14.5%.

Based on over 12,000 labeled test images covering all defect categories in the industry, combined with display GAN enhancement, users can identify defects in different operational environments.

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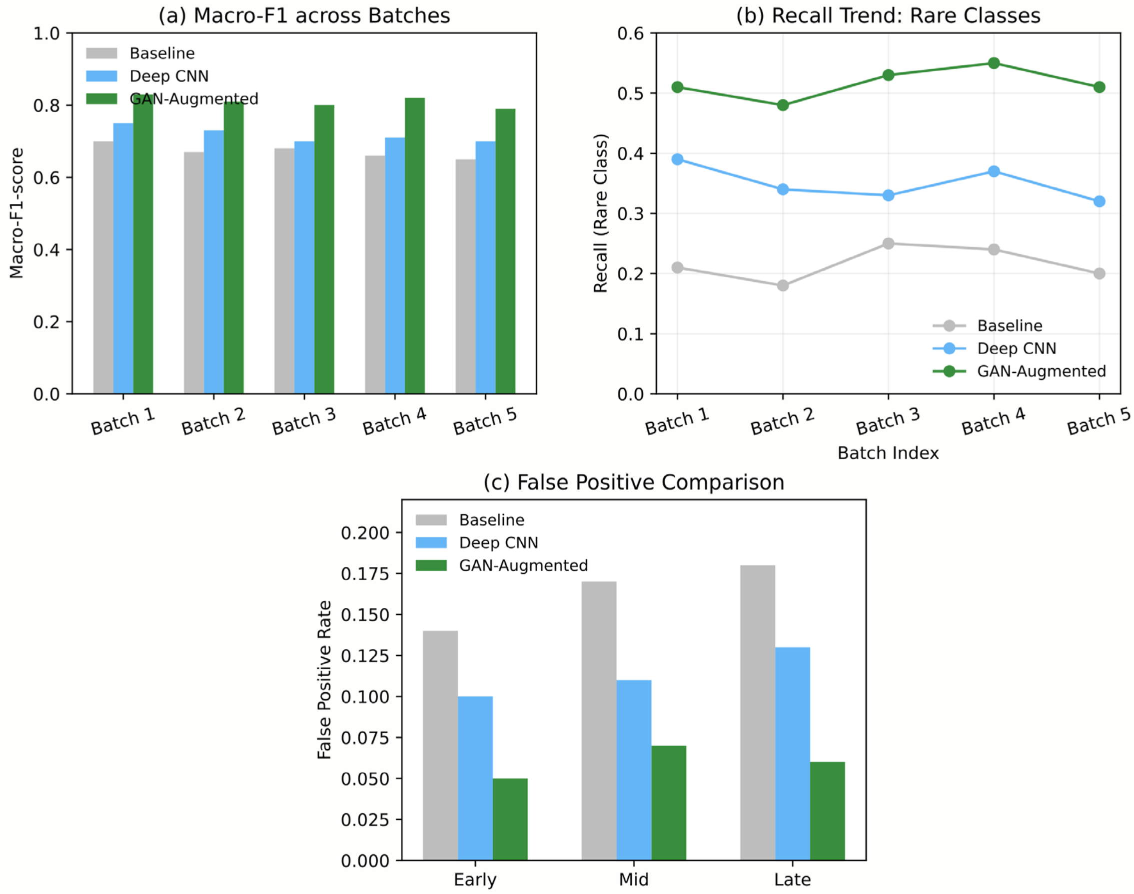

Figure 7. Comprehensive Performance Analysis: (a) Macro-F1-score bar chart across production batches and models; (b) Recall trends for rare classes; (c) False positive rate comparison between models and shifts

Conclusion

This paper proposes a stable and adaptable automatic optical measurement system based on a generative adversarial network structure. This system can comprehensively identify defects in advanced industrial production lines. Through rigorous validation, it was found that the proposed system significantly outperforms both traditional AOI methods and mainstream deep learning platforms in cases of high variance or low defect detection rates due to noise-induced rare defects.

Key innovations include enhancing data from certain categories and combining it with multi-objective adversarial learning to address the long-standing issue of distribution imbalance in industrial datasets. Unified design has higher defect localization accuracy, false alarm suppression capability, and action feedback functionality performance, and it can be compatible with existing production lines, reducing infrastructure changes. A comprehensive approach will be able to monitor changes in adaptive manufacturing equipment in real-time.

This advanced hierarchical learning system for the manufacturing field helps with continuous process optimization and can reduce defect rectification time. Its modularity and flexibility can adapt to various manufacturing systems, products, and defects. Batch processing and real-time online additions can be performed simultaneously; it can adapt to changes in production status, such as reducing the extent of defective parts when deployed at multiple locations, and it can accommodate the extent of defective parts that appear when deployed at different locations.

In different environments, the implemented plans can provide improvements to varying degrees. To ensure the normal operation of the continuous casting machine and quickly identify any new defects or parameter

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adjustments during this process. The experimental results using generative adversarial enhancement technology indicate that it can improve the accuracy of identifying rare defects; maintain more reliable model stability during calibration; reduce operational risks; and provide a realistic basis for quality inspection and decision support. Therefore, this adaptive feature can respond to environmental changes during the production process while maintaining high accuracy.

To further promote the integration of intelligent manufacturing systems, this approach will be extended to multimodal sensing technologies, continuous learning mechanisms, and strong integration with digital twin platforms. The second generation AOI has improved self-balancing capabilities and enhanced stability through real-time detection and predictive maintenance. This result indicates that the generator recommendation method overall improves the detection accuracy of industrial equipment inspection items. The current high-quality standards required by industry regulations, along with changes in the work environment and requirements, make the stability of industrial applications over time more complex. Different environments enhance the universality and scalability of system fault detection. These benefits will lay the foundation for further research in the intelligent industry and high automation.

Author Contributions

Michał Tomasz Dąbrowski contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision. Magdalena Król contributes to conceptualization, methodology, software. All authors have read and agreed with the manuscript before its submission and publication.

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References

[1] A Zheng, X., Zheng, S., Kong, Y., & Chen, J. (2021). Recent advances in surface defect inspection of industrial products using deep learning techniques. The International Journal of Advanced Manufacturing Technology, 113(1), 35-58. https://doi.org/10.1007/s00170-021-06592-8

[2] Bhattacharya, A., & Cloutier, S. G. (2022). End-to-end deep learning framework for printed circuit board manufacturing defect classification. Scientific reports, 12(1), 12559. https://doi.org/10.1038/s41598-022-16302-3

[3] Wang, Q., Yang, R., Wu, C., & Liu, Y. (2021). An effective defect detection method based on improved Generative Adversarial Networks (iGAN) for machined surfaces. Journal of Manufacturing Processes, 65, 373-381. https://doi.org/10.1016/j.jmapro.2021.03.053

[4] Zhang, L., Jin, Y., Yang, X., Li, X., Duan, X., Sun, Y., & Liu, H. (2018). Convolutional neural network-based multi-label classification of PCB defects. The Journal of Engineering, 2018(16), 1612-1616. https://doi.org/10.1049/joe.2018.8279

[5] Chen, Y., Ding, Y., Zhao, F., Zhang, E., Wu, Z., & Shao, L. (2021). Surface defect detection methods for industrial products: A review. Applied Sciences, 11(16), 7657. https://doi.org/10.3390/app11167657

[6] Chen, J., Wang, C., Hong, Y., Mi, R., Zhang, L. J., Wu, Y., ... & Zhou, Y. (2024, November). A survey on anomaly detection with few-shot learning. In International Conference on Cognitive Computing (pp. 34-50). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-77954-1_3

[7] Simmler, N., Sager, P., Andermatt, P., Chavarriaga, R., Schilling, F. P., Rosenthal, M., & Stadelmann, T. (2021, June). A survey of un-, weakly-, and semi-supervised learning methods for noisy, missing and partial labels in industrial vision applications. In 2021 8th Swiss conference on data science (SDS) (pp. 26-31). IEEE. https://doi.org/10.1109/SDS51136.2021.00012

[8] Hsieh, C. C., Hsu, T. Y., & Huang, W. H. (2022). An online rail track fastener classification system based on YOLO models. Sensors, 22(24), 9970. https://doi.org/10.3390/s22249970

[9] Jain, S., Seth, G., Paruthi, A., Soni, U., & Kumar, G. (2022). Synthetic data augmentation for surface defect detection and classification using deep learning. Journal of Intelligent Manufacturing, 33(4), 1007-1020. https://doi.org/10.1007/s10845-020-01710-x

[10] Prunella, M., Scardigno, R. M., Buongiorno, D., Brunetti, A., Longo, N., Carli, R., ... & Bevilacqua, V. (2023). Deep learning for automatic vision-based recognition of industrial surface defects: A survey. IEEE Access, 11, 43370-43423. https://doi.org/10.1109/ACCESS.2023.3271748

[11] Wu, J., Zhao, Z., Sun, C., Yan, R., & Chen, X. (2020). Few-shot transfer learning for intelligent fault diagnosis of machine. Measurement, 166, 108202. https://doi.org/10.1016/j.measurement.2020.108202

[12] Wei, R., & Bi, Y. (2019). Research on recognition technology of aluminum profile surface defects based on deep learning. Materials, 12(10), 1681. https://doi.org/10.3390/ma12101681

[13] Ashurov, A., & Qu, H. (2025). An efficient industrial defect detection based on hybrid residual attention with modified generative adversarial network and convolutional neural network model. Computers and Electrical Engineering, 127, 110580. https://doi.org/10.1016/j.compeleceng.2025.110580

[14] Chen, X., Wu, Y., He, X., & Ming, W. (2023). A comprehensive review of deep learning-based PCB defect detection. IEEE Access, 11, 139017-139038. https://doi.org/10.1109/ACCESS.2023.3339561

[15] Khanam, R., Hussain, M., Hill, R., & Allen, P. (2024). A comprehensive review of convolutional neural networks for defect detection in industrial applications. IEEE Access, 12, 94250-94295. https://doi.org/10.1109/ACCESS.2024.3425166

[16] Wen, L., Zhang, Y., Gao, L., Li, X., & Li, M. (2023). A new multiscale multiattention convolutional neural network for fine-grained surface defect detection. IEEE Transactions on Instrumentation and Measurement, 72, 1-11. https://doi.org/10.1109/TIM.2023.3271743

[17] Singh, S. A., & Desai, K. A. (2023). Automated surface defect detection framework using machine vision and convolutional neural networks. Journal of Intelligent Manufacturing, 34(4), 1995-2011. https://doi.org/10.1007/s10845-021-01878-w

[18] Long, C., Tan, C., Li, Q., Tan, H., & Duan, L. (2024). Industrial CT image reconstruction for faster scanning through U-Net++ with hybrid attention and loss function. Nondestructive Testing and Evaluation, 39(8), 2646-2665. https://doi.org/10.1080/10589759.2024.2305329

[19] Behera, S., Misra, R., & Sillitti, A. (2023). GAN-based multi-task learning approach for prognostics and health management of IIoT. IEEE Transactions on Automation Science and Engineering, 21(3), 2742-2762. https://doi.org/10.1109/TASE.2023.3267860

[20] Zhao, C., Xue, W., Fu, W. P., Li, Z. Q., & Fang, X. (2023). Defect sample image generation method based on GANs in diamond tool defect detection. IEEE Transactions on Instrumentation and Measurement, 72, 1-9. https://doi.org/10.1109/TIM.2023.3284139

[21] Swathi, B., Polyakov, S. V., Kandavalli, S. R., Singh, D. K., Murthy, M. Y. B., & Gopi, A. (2024). Enhancing hybrid manufacturing with AI-driven real-time adaptive process control: integrating machine learning models and robotic systems. The International Journal of Advanced Manufacturing Technology, 1-9. https://doi.org/10.1007/s00170-024-14155-w

[22] Rippel, O., Müller, M., & Merhof, D. (2020, September). GAN-based defect synthesis for anomaly detection in fabrics. In 2020 25th IEEE international conference on emerging technologies and factory automation (ETFA) (Vol. 1, pp. 534-540). IEEE. https://doi.org/10.1109/ETFA46521.2020.9212099

[23] Liu, Y., & Gao, Y. (2025). Multi-Modal Dynamic Fusion for Defect Detection in Electronic Products: A Novel Approach Based on Energy and Deep Learning. IEEE Access. https://doi.org/10.1109/ACCESS.2025.3584551

[24] Guo, R., Liu, H., Xie, G., & Zhang, Y. (2021). Weld defect detection from imbalanced radiographic images based on contrast enhancement conditional generative adversarial network and transfer learning. IEEE Sensors Journal, 21(9), 10844-10853. https://doi.org/10.1109/JSEN.2021.3059860

[25] Zajec, P., Rožanec, J. M., Theodoropoulos, S., Fontul, M., Koehorst, E., Fortuna, B., & Mladenić, D. (2024). Few-shot learning for defect detection in manufacturing. International Journal of Production Research, 62(19), 6979-6998. https://doi.org/10.1080/00207543.2024.2316279

[26] Rezaei, A., Richter, J., Nau, J., Streitferdt, D., & Kirchhoff, M. (2022, October). Transparency and traceability for ai-based defect detection in pcb production. In International Conference on Modelling and Development of Intelligent Systems (pp. 54-72). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-27034-5_4

[27] Saiz, F. A., Alfaro, G., Barandiaran, I., & Graña, M. (2021). Generative adversarial networks to improve the robustness of visual defect segmentation by semantic networks in manufacturing components. Applied Sciences, 11(14), 6368. https://doi.org/10.3390/app11146368

[28] Ferguson, M., Ak, R., Lee, Y. T. T., & Law, K. H. (2018). Detection and segmentation of manufacturing defects with convolutional neural networks and transfer learning. Smart and sustainable manufacturing systems, 2(1), 137-164. https://doi.org/10.1520/SSMS20180033

[29] Jang, J., Tang, Q., & Jung, H. (2024). PCB defect classification with data augmentation-based ensemble method for sustainable smart manufacturing. Sustainability, 16(23), 10417. https://doi.org/10.3390/su162310417

[30] Tao, X., Gong, X., Zhang, X., Yan, S., & Adak, C. (2022). Deep learning for unsupervised anomaly localization in industrial images: A survey. IEEE Transactions on Instrumentation and Measurement, 71, 1-21. https://doi.org/10.1109/TIM.2022.3196436

[31] Han, Y., Qi, Z., & Tian, Y. (2024). Anomaly classification based on self-supervised learning and its application. Journal of Radiation Research and Applied Sciences, 17(3), 100918. https://doi.org/10.1016/j.jrras.2024.100918