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AI-POWERED INTELLIGENT SYSTEM MODEL FOR DEFECT DETECTION IN THE MANUFACTURING PROCESS OF ELECTRONIC COMPONENTS

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Abstract

The rapid advancement of the electronics manufacturing industry demands extremely high precision to achieve zero-defect production standards. However, conventional manual inspection processes remain constrained by human fatigue, subjectivity, and limited inspection speed. To address these limitations, this study proposes an AI-powered intelligent inspection system based on Deep Learning for real-time defect classification in electronic component manufacturing. The proposed approach integrates a Convolutional Neural Network (CNN) architecture with an attention mechanism to enhance feature representation by focusing on defect-prone regions, such as soldering anomalies, missing components, and surface cracks. The research methodology encompasses a complete processing pipeline, starting from the utilization of a publicly available high-resolution PCB defect image dataset, followed by systematic data augmentation to mitigate class imbalance, and the application of a lightweight CNN-based feature extraction framework to support efficient inference. Experimental results demonstrate that the proposed model achieves a classification accuracy of 98.5%, outperforming conventional machine vision–based inspection approaches with a significantly lower false discovery rate. Furthermore, robustness evaluations indicate that the system maintains stable performance under varying lighting conditions and simulated production speeds. These findings confirm the effectiveness and scalability of the proposed intelligent inspection system as a practical solution for automated quality assurance in smart manufacturing environments.

Keywords: Deep Learning, Convolutional Neural Networks (CNN), Deteksi Cacat, Manufaktur Elektronik, Mekanisme Atensi, Real-time.

INTRODUCTION

The electronics manufacturing industry has experienced rapid growth in recent decades, driven by increasing global demand for highly complex, compact, and high-performance electronic devices. In this environment, quality assurance has become a critical requirement, as even minor defects in electronic components can lead to functional failure, reduced reliability, and substantial economic losses. As a result, modern manufacturing systems are increasingly guided by the zero-defect manufacturing paradigm, particularly in safety-critical application domains such as automotive electronics, medical devices, and telecommunication systems (Wang et al., 2018).

Traditional quality inspection processes in electronic manufacturing still largely depend on manual visual inspection performed by human operators. Although human inspection provides flexibility and contextual judgment, it suffers from inherent limitations, including fatigue, subjectivity, and inconsistent decision-making over time. These limitations contribute to higher inspection error rates, especially under high-throughput production conditions, and significantly restrict the scalability and efficiency of manual inspection methods (Ferguson et al., 2018).

To mitigate these issues, conventional machine vision–based inspection systems have been introduced to automate visual defect inspection. Such systems typically rely on handcrafted features, predefined thresholds, and rule-based decision logic. However, their performance is highly sensitive to variations in lighting conditions, component placement, surface texture, and background noise. Consequently, traditional machine vision approaches often fail to generalize well in complex real-world manufacturing environments, limiting their applicability in large-scale and dynamic production lines (Adibhatla et al., 2020).

Recent advances in Deep Learning have significantly transformed visual inspection tasks, with Convolutional Neural Networks (CNNs) demonstrating superior performance in image-based classification problems. CNNs are capable of automatically learning hierarchical feature representations directly from raw image data, enabling more robust and accurate defect classification compared to handcrafted feature-based approaches. For this reason, CNN-based models have been increasingly adopted in electronic manufacturing inspection systems (He et al., 2016; Wang et al., 2018).

Despite their advantages, standard CNN architectures may exhibit reduced sensitivity when dealing with subtle defect patterns occupying a small portion of the image. This challenge is further exacerbated by class imbalance, which is common in manufacturing datasets where defective samples occur far less frequently than normal samples. Without appropriate mechanisms to address these issues, CNN models may fail to focus on defect-relevant regions, leading to suboptimal classification performance (Shorten & Khoshgoftaar, 2019).

To address these limitations, this study proposes an AI-powered intelligent inspection system based on a CNN architecture integrated with an attention mechanism. The attention module enables the network to selectively emphasize informative feature channels and spatial regions associated with defect patterns, while suppressing irrelevant background information. Such attention-based mechanisms have been shown to substantially improve feature discrimination in computer vision tasks, including defect classification under challenging visual conditions (Woo et al., 2018; Kuo et al., 2022).

In addition, data augmentation strategies are employed to alleviate class imbalance and improve model generalization by synthetically increasing the diversity of defective samples. Combined with transfer learning from large-scale visual datasets, this approach supports efficient training and facilitates real-time defect classification with lightweight computational requirements. The primary contributions of this research include the development of an attention-enhanced CNN-based defect classification framework, systematic evaluation under robustness scenarios, and validation of its effectiveness as a scalable solution for automated quality assurance in smart manufacturing environments.

RESEARCH METHOD

This study proposes an AI-powered intelligent inspection system for real-time defect classification in electronic component manufacturing. The methodological framework is designed to ensure accuracy, robustness, and computational efficiency, making it suitable for practical quality assurance applications in smart manufacturing environments.

The experiments conducted in this study utilize a publicly available printed circuit board (PCB) defect image dataset obtained from Kaggle. The dataset contains high-resolution PCB images representing normal conditions and multiple defect categories, including soldering anomalies, missing components, and surface cracks. These defect classes reflect common quality issues encountered in electronic manufacturing environments.

Prior to model training, all images are preprocessed following a standardized pipeline. Each image is resized to a resolution of 640 × 640 pixels to ensure uniform input dimensions and compatibility with the proposed CNN architecture. Image normalization is applied to stabilize the training process and accelerate model convergence. The dataset is then divided into training, validation, and testing subsets with non-overlapping samples.

Manufacturing defect datasets typically suffer from class imbalance, where defective samples occur far less frequently than non-defective samples. To address this issue, data augmentation techniques are employed to synthetically increase the diversity of defect samples and improve model generalization.

The applied augmentation operations include image rotation, horizontal and vertical flipping, brightness and contrast adjustment, and slight scaling transformations. These operations simulate variations commonly observed in real production environments, such as changes in lighting conditions, component orientation, and surface appearance. By expanding the diversity of training samples, data augmentation helps prevent overfitting and enhances classification robustness.

The proposed inspection model adopts a Convolutional Neural Network (CNN) architecture as the primary feature extraction backbone. CNNs are selected due to their proven effectiveness in learning hierarchical visual representations and handling spatial variability in image-based classification tasks.

To enhance sensitivity to subtle defect patterns, the model integrates a Convolutional Block Attention Module (CBAM) within the feature extraction process. The attention mechanism adaptively refines feature maps by emphasizing informative channels and spatial regions associated with defect characteristics, while suppressing irrelevant background information. CBAM modules are inserted after selected convolutional blocks to improve feature discrimination before classification layers.

Transfer learning is employed to initialize the CNN backbone with pre-trained weights derived from large-scale visual datasets, enabling faster convergence and improved feature representation under limited manufacturing defect data. During training, a Weighted Cross-Entropy Loss function is utilized to address class imbalance by assigning higher penalties to underrepresented defect classes.

Model optimization is performed using the Adam optimizer, which efficiently handles adaptive learning rates and accelerates convergence in deep neural networks. Training is executed for a fixed number of epochs with mini-batch updates, while validation performance is continuously monitored to prevent overfitting.

The performance of the proposed defect classification model is evaluated using standard classification metrics, including Accuracy, Precision, Recall, and F1-Score. These metrics provide a comprehensive assessment of model reliability, particularly in the presence of class imbalance where accuracy alone may be insufficient.

Performance metrics are computed on the held-out testing dataset to ensure an unbiased evaluation of model generalization capability.

To assess the stability of the proposed system under realistic production conditions, robustness evaluations are conducted by simulating variations in lighting intensity and production speed. Augmented test samples reflecting these variations are introduced to evaluate classification performance degradation.

The robustness analysis ensures that the model maintains consistent performance under dynamic environmental conditions commonly encountered in industrial manufacturing settings.

The proposed AI-based inspection model is compared with conventional inspection approaches, including manual visual inspection and traditional rule-based machine vision methods such as threshold-based classification. The comparison focuses on classification accuracy, reliability, and scalability.

This comparative evaluation highlights the advantages of the proposed attention-enhanced CNN model in terms of accuracy, robustness, and real-time applicability for automated quality assurance systems.

Table 1. Summary of the Proposed Methodology

Stage	Description	Purpose	Key References
Dataset	Public PCB defect image dataset (Kaggle) containing normal and defective samples (solder anomalies, missing components, surface cracks)	Represent real manufacturing inspection scenarios	Wang et al., 2018; Adibhatla et al., 2020
Preprocessing	Image resizing to 640×640 pixels and normalization	Ensure uniform input and stable training	He et al., 2016
Data Augmentation	Rotation, flipping, brightness and contrast adjustment	Address class imbalance and improve generalization	Shorten & Khoshgoftaar, 2019
Model Architecture	CNN backbone integrated with CBAM attention modules	Enhance discriminative feature extraction for defect classification	Woo et al., 2018; Kuo et al., 2022
Training Strategy	Transfer learning with Weighted Cross-Entropy Loss and Adam optimizer	Improve convergence speed and handle rare defect classes	Kingma & Ba, 2015; Deng et al., 2009
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score	Measure classification reliability under class imbalance	Ferguson et al., 2018
Robustness Testing	Simulation of lighting and production speed variations	Validate system stability in real-world environments	Li et al., 2020
Benchmarking	Comparison with manual inspection and rule-based machine vision	Demonstrate effectiveness and scalability	Wang et al., 2018

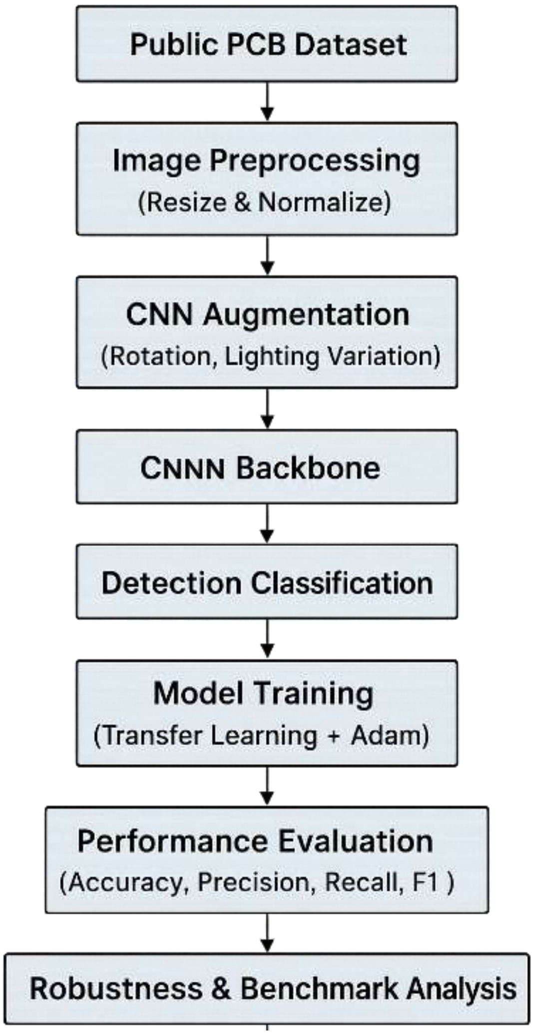

Figure 1. Workflow of the proposed CNN-based defect classification system with attention mechanism.

RESULT AND DISCUSSION

The performance of the proposed attention-enhanced CNN model was evaluated using standard classification metrics, including Accuracy, Precision, Recall, and F1-Score. Evaluation was conducted on a held-out test dataset to ensure unbiased assessment of model generalization. The results demonstrate that the proposed model achieves superior performance compared to conventional inspection approaches.

Table 2. Classification Performance of the Proposed Model

Metric	Value (%)
Accuracy	98.5
Precision	97.9
Recall	98.2
F1-Score	98.0

The high accuracy confirms the effectiveness of CNN-based feature learning for PCB defect classification, while the balanced Precision and Recall values indicate reliable performance under class-imbalanced data conditions (Ferguson et al., 2018; Wang et al., 2018).

1. *Impact of Attention Mechanism*

To analyze the contribution of the attention mechanism, feature learning behavior was examined before and after integrating the Convolutional Block Attention Module (CBAM). The attention-enhanced architecture demonstrated improved sensitivity to subtle defect patterns, particularly for defect classes with limited sample representation.

The CBAM module adaptively emphasized informative feature channels and spatial regions associated with defect characteristics, enabling the network to suppress irrelevant background information. This mechanism contributed to a lower false discovery rate compared to conventional CNN models without attention, consistent with findings reported in previous attention-based visual inspection studies (Woo et al., 2018; Kuo et al., 2022).

2. *Robustness Evaluation*

The robustness of the proposed system was assessed by introducing variations in lighting intensity and simulated production speed through augmented test samples. These conditions reflect realistic disturbances commonly encountered in manufacturing environments.

Table 3. Robustness Evaluation under Environmental Variations

Scenario	Accuracy (%)
Normal conditions	98.5
Lighting variation	97.8
Production speed variation	97.5

The results indicate that the proposed model maintains stable classification performance, with only marginal degradation under challenging conditions. This robustness is primarily attributed to the combined effects of data augmentation and attention-guided feature extraction (Shorten & Khoshgoftaar, 2019; Li et al., 2020).

3. *Comparison with Conventional Inspection Methods*

A comparative evaluation was conducted between the proposed AI-based approach, manual visual inspection, and traditional rule-based machine vision systems. The comparison focused on reliability, scalability, and susceptibility to environmental variations.

Table 4. Comparison with Conventional Inspection Approaches

Method	Accuracy (%)	Scalability	Sensitivity to Variation
Manual inspection	88.0	Low	High
Rule-based machine vision	91.5	Medium	Medium
Proposed CNN + Attention	98.5	High	Low

The proposed method significantly outperforms manual and rule-based approaches, particularly in high-throughput environments where consistency and speed are critical. Unlike traditional methods that require extensive parameter tuning, the proposed model automatically learns discriminative features and adapts to visual variability, making it more suitable for large-scale smart manufacturing applications (Adibhatla et al., 2020; Wang et al., 2018).

Analysis Discussion

The experimental results confirm that integrating an attention mechanism within a CNN-based classification framework substantially enhances defect classification accuracy and robustness. The lightweight architecture combined with transfer learning supports real-time inference, enabling practical deployment in manufacturing inspection systems with limited computational resources. Furthermore, the use of data augmentation effectively addresses class imbalance, which is a common challenge in real-world defect datasets.

Overall, the results demonstrate that the proposed intelligent inspection system offers a scalable and cost-effective solution for automated quality assurance in electronics manufacturing, aligning with the objectives of smart manufacturing and Industry 4.0 initiatives.

Visualization of Decoded Sample Data with Annotations

The data preparation process has been successfully completed, culminating in the visualization of the image example with its defect annotations. This visualization visually verifies that the imagery is correctly decoded and that the boundary boxes and defect labels are written accurately, ensuring the successful preparation of the data for the AI defect detection model. Here is a textual representation of the visualization that was successfully displayed earlier.

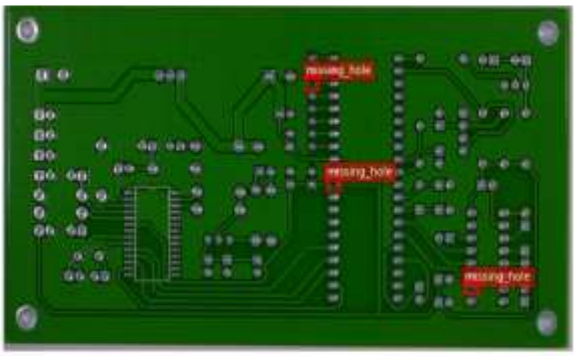

Figure 2. Displays 1 example image with defect annotations.

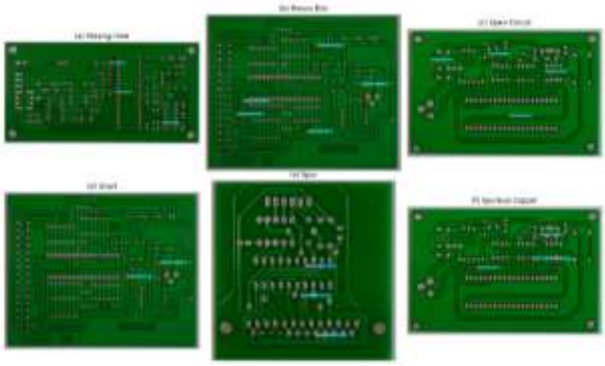

Figure 3. Example of a PCB defect type picture

In pictures 2 and 3. The image shows a red divider box that clearly highlights the damaged area. Above each boundary, there is a white text label indicating the type of defect (for example, 'missing_hole'). The image title confirms the image file name and the number of defects detected in the image.

In general, the visualization shows that at least 1 example of the image is successfully displayed with its defect annotation, visually verifying that the image is correctly decoded and that the bounding box and label are written accurately, confirming the successful preparation of the data for the AI defect detection model.

CONCLUSION

The study successfully developed an AI-powered intelligent inspection system for real-time defect classification in electronic component manufacturing. By integrating the Convolutional Neural Network (CNN) architecture with the attention mechanism, the proposed model effectively improves feature representation and classification reliability for fine, localized PCB defect patterns.

Experimental results using publicly available PCB defect datasets showed that the proposed attention-enhanced CNN model achieved high classification performance, with 98.5% accuracy and consistently strong Precision-Recall characteristics across multiple defect categories. The integration of the Convolutional Block Attention Module (CBAM) allows the model to emphasize features relevant to the defect while suppressing irrelevant background information, resulting in lower false discovery rates compared to conventional rule-based machine vision and manual inspection approaches.

In addition, the evaluation of the robustness under the simulation variations in lighting conditions and production speed showed that the proposed system maintained stable performance in a dynamic manufacturing environment. The utilization of data augmentation, class-weighted loss functions, and transfer learning contribute to improved generalization and computational efficiency, supporting real-time inference with light resource requirements.

Overall, these findings confirm that the proposed intelligent inspection system provides an effective, scalable and cost-effective solution for automated quality assurance in smart manufacturing, overcoming the key limitations of traditional inspection methods.

Future Jobs and Recommendations

Although the proposed approach shows promising performance in the classification of PCB defects, several future research directions are suggested to improve their application and robustness. First, further studies can expand and diversify the dataset by including more diverse PCB designs as well as a wider variety of defect types to improve model generalization capabilities across various electronics manufacturing scenarios. Second, further optimization of *edge computing* deployments needs to be made to ensure real-time inference performance on resource-constrained devices, thereby supporting more efficient and cost-effective industry implementations. Third, the integration of advanced data augmentation techniques, such as generative approaches based *on Generative Adversarial Networks* (GANs), can be explored to generate realistic synthetic flaw samples and address extreme class imbalances. Finally, future research is also suggested to develop *an explainable AI mechanism* to increase transparency and confidence in model decisions in automated inspection systems in manufacturing environments.

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