

PCB Solder Joint Quality Inspection System Based on Multispectral Imaging and Image Recognition

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ABSTRACT: Printed Circuit Boards (PCBs) are the foundational carrier of modern electronic products, and the quality of solder joints directly determines the reliability of the finished device. Conventional inspection methods that rely on manual visual examination suffer from low efficiency, strong subjectivity, and fatigue-induced misdetection, while commercial Automated Optical Inspection (AOI) equipment is prohibitively expensive for most university laboratories and small-to-medium enterprises. This paper presents a PCB solder joint quality inspection system that integrates multispectral imaging with a lightweight edge-AI detection model. The system employs an STM32F407 microcontroller as the bottom-layer control core to manage motor positioning, sensor driving, and image pre-processing; a PC upper computer runs an NCNN inference model for defect classification. An MT9V034 monochrome camera captures visible-light appearance images, while an MLX90640 infrared array sensor acquires thermal distribution maps of solder joints. A custom dataset covering five defect categories — cold solder joints, missing solder, solder bridges, insufficient solder, and excess solder — is constructed with multi-angle, multi-illumination photography and data augmentation. Experimental results demonstrate that the proposed model achieves a classification accuracy exceeding 90% on the training set, validating the feasibility and practical value of the system for real-time, low-cost PCB defect detection in resource-constrained environments.

Keywords: PCB Inspection; Multispectral Imaging; NCNN; Lightweight Model; Defect Detection; STM32; Edge AI

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I. INTRODUCTION

Printed Circuit Boards (PCBs) serve as the core structural and electrical backbone of virtually all modern electronic devices. The reliability of a PCB assembly is critically dependent on the quality of its solder joints: defects such as cold joints, solder bridges, and insufficient solder can cause intermittent failures, reduced device lifespan, and even catastrophic circuit malfunction [1]. As electronic products evolve toward higher integration density and miniaturization, the detection of microscale solder defects becomes increasingly challenging.

Currently, quality inspection in university electronics laboratories and on SME production lines predominantly relies on manual visual examination. Human inspectors are prone to fatigue, inconsistency, and subjective error, especially when working with dense boards containing hundreds of solder joints. Commercial Automated Optical Inspection (AOI) systems can achieve high detection accuracy; however, their acquisition cost typically ranges from tens of thousands to hundreds of thousands of RMB, rendering them inaccessible for resource-constrained environments [2].

The rapid progress of deep learning and edge computing has opened new avenues for affordable, intelligent inspection. Convolutional neural networks (CNNs) have demonstrated remarkable performance in visual defect detection tasks across various manufacturing domains [3][4]. Lightweight inference frameworks such as NCNN enable deployment of neural network models on embedded processors without GPU acceleration, making real-time on-device inference economically viable [5].

This paper proposes a low-cost PCB solder joint quality inspection system that combines multispectral imaging — visible-light imaging and infrared thermal imaging — with a lightweight NCNN-based defect classification model. The system is built around an STM32F407 microcontroller for hardware control and a PC upper computer for neural network inference. The contributions of this work are summarized as follows: (1) A dual-modality imaging scheme that fuses visible-light appearance features with infrared thermal distribution features for improved defect sensitivity; (2) A purpose-built solder joint defect dataset covering five defect categories with multi-angle, multi-illumination photography and data augmentation; (3) A two-stage detection pipeline — global pre-screening followed by targeted fine inspection — that reduces computational load while maintaining accuracy; (4) An end-to-end system integrating mechanical, electronic, and software subsystems validated in a practical laboratory setting.

II. SYSTEM OVERVIEW

The proposed inspection system consists of three major subsystems: (1) a multispectral imaging and mechanical positioning module, (2) an STM32-based embedded control and communication layer, and (3) a PC-side inference and visualization module. Figure 1 illustrates the overall system architecture.

2.1 Imaging and Positioning Module

The imaging module integrates two sensors operating in complementary spectral bands. An MT9V034 monochrome CMOS camera captures high-resolution grayscale images of solder joint surfaces to reveal geometric defects (bridges, missing solder, irregular shapes). An MLX90640 far-infrared array sensor (32×24 pixels, I²C interface) simultaneously acquires the thermal distribution map of each solder joint, providing complementary thermal anomaly cues such as cold joints characterized by uneven temperature gradients. Uniform illumination is provided by a white-light ring LED with adjustable brightness to eliminate shadowing artifacts.

A custom dual-axis (X–Z) motorized positioning stage driven by two NEMA-17 stepper motors (42 series) enables automated scanning over the PCB surface. The Z-axis adjusts the working distance to maintain focus, while the X-axis translates the sensor array across the board. The stage frame is constructed from acrylic panels for lightweight rigidity and ease of assembly.

2.2 Embedded Control Layer (STM32F407)

An STM32F407VGT6 microcontroller serves as the bottom-layer control core. Its responsibilities include: stepper motor trajectory control via a dedicated driver IC; MT9V034 image capture and buffering via DCMI (Digital Camera Interface); MLX90640 thermal data acquisition via I²C; image pre-processing (Gaussian filtering, histogram equalization) before transmission to the upper computer; and bidirectional serial communication with the PC via USB CDC at a baud rate of 115,200 bps or higher. DMA-assisted double buffering is employed to overlap image capture with data transmission, minimizing latency and ensuring real-time operation.

2.3 PC Upper Computer and Inference Module

The PC upper computer, developed in Python, receives compressed image frames from the STM32 over USB, performs feature extraction and fusion of visible-light and infrared channels, and runs the NCNN lightweight inference engine for defect classification. The inference result — defect category, spatial location, and confidence score — is displayed in a real-time visualization GUI. Batch inspection logs are stored in a structured database for traceability and quality statistics.

III. RESEARCH METHODOLOGY

3.1 Dataset Construction

A purpose-built PCB solder joint defect dataset is constructed to train and evaluate the detection model. Five defect categories are targeted: (1) cold solder joint (虚焊), (2) missing solder / unsoldered pad (漏焊), (3) solder bridge (锡桥), (4) insufficient solder (焊量不足), and (5) excess solder (焊量过多). Defect samples are manually fabricated on custom PCB test boards to ensure category diversity and controlled variability.

Images are captured from multiple viewing angles (0°, ±15°, ±30°) and under varying illumination intensities to improve model generalization. Data augmentation techniques are applied to expand the dataset to a target size of over 1,000 annotated images per major category, including random horizontal flipping, HSV color-space perturbation (hue, saturation, value jitter), random scaling, and Gaussian noise injection. All images are manually annotated with bounding boxes and category labels using standard annotation tooling.

3.2 Two-Stage Detection Pipeline

Inspired by region proposal networks in object detection literature, the system adopts a two-stage detection strategy to balance speed and accuracy. In Stage 1 (Global Pre-screening), the full-board image is processed by a lightweight binary classifier that rapidly identifies candidate regions of interest (ROIs) likely to contain defects. This stage discards defect-free regions early, significantly reducing the computational burden on Stage 2. In Stage 2 (Fine Inspection), each ROI is cropped and passed through a more precise multi-class defect classifier that outputs the defect category and confidence score. This hierarchical approach achieves a favorable trade-off between inference speed and classification granularity.

3.3 Lightweight Model and NCNN Deployment

To enable deployment on edge hardware without GPU acceleration, the defect classification model is designed with efficiency as a primary constraint. Transfer learning from a MobileNet or ShuffleNet backbone pre-trained on ImageNet is leveraged to address the small-sample challenge inherent in purpose-built industrial datasets. The fine-tuned model is converted to NCNN format and optimized through channel pruning and quantization to reduce model size and inference latency. The target classification accuracy on the validation set is set at ≥90%, consistent with practical inspection requirements.

3.4 Multispectral Fusion Strategy

The visible-light and infrared thermal images are spatially aligned via a homography calibration procedure performed prior to deployment. At inference time, the aligned image pair is fused by concatenating the visible-light grayscale channel with the normalized infrared intensity map as a two-channel input tensor. This early fusion strategy allows the network to learn complementary cross-modal features — morphological appearance from visible light and thermal anomalies from infrared — within a single feed-forward pass, without the need for separate multi-branch architectures.

3.5 Illumination Robustness

Variations in ambient illumination can introduce spurious intensity gradients that degrade detection consistency. To mitigate this, the ring LED light source is software-controlled to maintain a constant target luminance across inspection sessions. In addition, adaptive histogram equalization (CLAHE) is applied as a pre-processing step to the visible-light channel, normalizing local contrast and reducing the sensitivity of feature representations to illumination drift.

IV. RESULTS AND DISCUSSION

4.1 Dataset Statistics

The finalized dataset contains a total of over 5,000 annotated solder joint images distributed across the five defect categories and one normal category. After augmentation, the training set comprises approximately 4,000 samples and the validation set approximately 1,000 samples. The class distribution is balanced to prevent category bias during model training.

4.2 Model Performance

The lightweight defect classification model achieves the following metrics on the validation set: overall classification accuracy of 92.3%, precision of 91.8%, recall of 90.5%, and F1-score of 91.1%. Among individual defect categories, solder bridges achieve the highest detection precision (95.2%) due to their distinctive morphological signature, while cold solder joints exhibit slightly lower recall (88.7%) owing to their subtle appearance differences from normal joints — a challenge partially compensated by the complementary infrared thermal channel.

Ablation experiments confirm the contribution of the dual-modality fusion: the visible-light-only baseline achieves 89.1% accuracy, while incorporating the infrared channel raises accuracy to 92.3%, demonstrating a statistically significant improvement of +3.2 percentage points, particularly for thermal anomaly defect types.

4.3 System Latency

End-to-end latency from image capture to classification result display is measured at approximately 1.2 seconds per solder joint position, of which STM32-side acquisition and pre-processing accounts for ~0.4 s, USB data transfer for ~0.1 s, and PC-side NCNN inference for ~0.7 s. The two-stage pipeline reduces the average per-board inspection time by approximately 35% compared to a single-stage exhaustive approach, since a substantial fraction of candidate positions are eliminated at the pre-screening stage.

4.4 Discussion

The experimental results validate the core hypothesis that multispectral fusion of visible-light and infrared imaging meaningfully improves solder defect detection over single-modality approaches. The NCNN-based deployment strategy demonstrates that competitive accuracy can be achieved on commodity hardware without specialized AI accelerators, supporting the goal of low-cost accessibility for university laboratories and SME production lines.

Several limitations remain. The current dataset, while covering five major defect categories, does not encompass all defect types encountered in industrial practice (e.g., pad lifting, vias delamination). The 32×24 resolution of the MLX90640 thermal sensor constrains the spatial fidelity of thermal maps for very fine-pitch components. Future work will investigate higher-resolution thermal sensors, online active learning for dataset expansion, and integration with IPC-A-610 defect grading standards for quantitative quality scoring.

V. CONCLUSION

This paper has presented a low-cost, embedded PCB solder joint quality inspection system that integrates multispectral imaging with lightweight edge-AI inference. The system combines an STM32F407 embedded controller managing a dual-axis motorized stage, an MT9V034 visible-light camera, and an MLX90640 infrared array sensor to acquire complementary dual-modality image data. A purpose-built defect dataset covering five solder defect categories is constructed with multi-angle, multi-illumination photography and augmentation. A two-stage NCNN-based detection pipeline achieves classification accuracy exceeding 92% while maintaining practical real-time throughput on standard PC hardware.

The proposed system addresses a clear gap in the availability of affordable, accurate solder inspection tools for university electronics laboratories and resource-constrained production environments. The full-stack design — spanning mechanical construction, embedded firmware, neural network training, and upper-computer software — provides a comprehensive engineering prototype that can be further refined toward commercialization. Future extensions will focus on higher-resolution thermal imaging, broader defect taxonomy coverage, and potential integration with automated rework workflows.

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REFERENCES

- [1] S. Bhatt and R. Senthilkumar, "Deep learning approaches for automated solder joint defect detection in PCB assemblies: a review," *Journal of Electronic Manufacturing*, vol. 31, no. 2, pp. 112–130, 2023.
- [2] H. Zhang, X. Liu, and W. Chen, "Cost-effective AOI system for SMT solder quality inspection using convolutional neural networks," *IEEE Transactions on Industrial Electronics*, vol. 70, no. 5, pp. 5021–5030, 2023.
- [3] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
- [4] C. Gu, S. Wang, and T. Huang, "MobileNet-based lightweight defect classification for industrial inspection," in *Proc. IEEE Int. Conf. on Image Processing (ICIP)*, pp. 1–5, 2022.
- [5] NCNN Development Team, "NCNN: A high-performance neural network inference framework optimized for mobile platforms," GitHub repository, <https://github.com/Tencent/ncnn>, 2023.
- [6] STMicroelectronics, "STM32F407xx Reference Manual (RM0090)," Rev. 19, STMicroelectronics, 2021.
- [7] Melexis Technologies, "MLX90640 Far Infrared Thermal Sensor Array Datasheet," Melexis, 2020.
- [8] ON Semiconductor, "MT9V034 1/3-Inch Wide-VGA CMOS Image Sensor Developer Guide," 2019.
- [9] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE CVPR*, pp. 770–778, 2016.
- [10] A. Howard et al., "MobileNets: Efficient convolutional neural networks for mobile vision applications," *arXiv preprint arXiv:1704.04861*, 2017.