Machine Vision-based Defect Inspection Model for Plated Through Hole Components in Large-Scale PCB Manufacturing Industries

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ABSTRACT
In contemporary Printed Circuit Board Assembly (PCBA) operations, to ensure high-quality and efficient manufacturing processes is critical. The optimization of process conformance in PCBA lines presents significant challenges to production efficiency. Detailed process mining analyses of actual PCBA lines have revealed substantial deviations from ideal processes at the Plated Through Hole (PTH) stage, resulting in elevated rework rates post-wave soldering due to component placement issues. The primary root causes include component misalignment, missing components, and incorrect polarity at the manual insertion station preceding wave soldering. This research paper introduces an innovative machine vision-based inspection framework to address the above-mentioned critical issues for large-scale PCBA operations. The developed framework employs a three-phase computational approach wherein Phase 1 includes calibrated image acquisition with reduced radial distortion. Next, Phase 2 defines Region of Interest (ROI) using advanced template extraction algorithms that precisely isolate component templates, locations, and sizes. Finally, Phase 3 consists of a multiscale template matching algorithm that employs a hybrid multichannel approach to enhance light and color sensitivity. The proposed multiscale template matching algorithm employs a hybrid multichannel approach to enhance light and color sensitivity, integrating color-based matching with luminance information to improve defect detection. This approach utilizes a three-tiered strategy incorporating Hue, Saturation, Value (HSV), which separates image color components for precise hue detection; Blue, Green, Red (BGR), which captures standard color information; and grayscale, which focuses on luminance for detailed texture and edge detection. Additionally, bilateral filtering and Gaussian blur are applied to reduce noise and enhance edge detection, further maximizing the accuracy and reliability of the defect identification process. By systematically addressing these root causes identified through process mining, the system significantly enhances process conformance by reducing the number of defective PCBs entering the wave soldering stage and subsequently lowering the rework rate. The proposed methodology provides a robust solution to common manufacturing challenges, ensuring higher process adherence and operational efficiency.

Index Terms— Computer Vision, Template Matching Algorithms, Filtering Techniques, Defect Detection, Component Placement Issues, Plated Through Hole Components, Industry 4.0

INTRODUCTION
The PCBA process is a critical aspect of the electronics manufacturing industry, involving the mounting of electronic components onto a PCB to create functional assemblies. This process encompasses two primary technologies: Surface Mount Technology (SMT) and Plated through Hole (PTH) assembly. SMT is widely used for its efficiency and ability to handle high-density and miniaturized components, making it essential for modern electronic devices. This technology involves steps such as solder paste printing, high-speed component placement, and reflow soldering [1]. PTH technology is preferred for components that require strong mechanical bonds, such as connectors and large capacitors [2]. Initially, component placement is performed both automatically and manually to accommodate various component requirements. The board then undergoes wave soldering, where it passes over a wave of molten solder, forming electrical connections between the components and the board. This is followed by a touch-up stage to manually correct any soldering defects and to clean flux residues, ensuring the integrity of the solder joints. Subsequently, manual visual inspection is conducted to identify any visible defects or issues not addressed during the touch-up stage. For a more thorough inspection, particularly for hidden or complex solder joints, X-ray inspection is utilized. Then the board proceeds through several testing stages, including In-Circuit Testing (ICT), Functional Board Testing (FBT) to verify its electrical and functional integrity [3]. The significance of the PTH process is evident in its ability to handle high-power components and its robustness under physical stress [4]. While SMT benefits from advanced inspection systems such as Automated Optical Inspection (AOI) and Solder Paste Inspection (SPI), which detect defects early in the manufacturing process, PTH inspection systems are less advanced. The higher cost and complexity of implementing AOI for through-hole components result in PTH assemblies often relying on manual Visual Inspections (VI) or post-wave soldering X-ray inspections [5]. During a comprehensive process mining analysis at a case-study electronics manufacturing plant, investigation revealed significant

deviations between the actual processes and ideal processes in the PTH stage. A detailed root cause showed PCBAs exhibit defects for PTH components at VI and X-ray inspection stations, necessitating these assemblies to be redirected for rework. Root cause analysis identified that the predominant defects were due to missing components, misalignment, and incorrect polarity. These findings underscore the necessity for an advanced solution aimed at early defect detection (before the wave soldering stage) within the PTH assembly process to effectively mitigate failure rates and enhance overall efficiency and reliability in the PCBA process.

In PCBA process, various challenges such as thermal management, surface modifications, material selection, and progressive designs have been approached over the years to enhance assembly quality [6] [7] [8] [9]. As challenges persist, effective inspection method becomes crucial to make sure defect-free production. In recent years, machine learning and deep learning have enabled design and optimization of complex to improve their performance [10] [11]; similarly these methods can be employed for effective defect inspection [12] [13] [14].Barbosa et al. employed a one-shot learning method using a Siamese Neural Network (SNN) to detect defects in PTH electronic components. The SNN model compares sample and reference images, generating vector representations for defect classification, making it flexible and scalable for real-time inspection [12]. Building on these advancements, Li et al. proposed a lightweight Convolutional Neural Network (CNN) for semantic segmentation, combined with a rule-based defect recognition algorithm. Their method segments PCBA images and compares them with contour maps to detect defects. The efficiency and high-speed suitability of this approach make it particularly valuable for industrial applications, ensuring that large-scale production lines can maintain high standards of quality without compromising on throughput [13]. Combining the strengths of machine learning and machine vision, Zhang et al. developed a method that integrates template matching for defect detection with an optimized Support Vector Machine (SVM) classifier for classification. This hybrid approach uses gray histogram features and geometric features to describe defect regions, achieving a recognition rate of over 96% [14]. Le et al. took a different approach by developing an AOI system that utilizes image processing techniques to inspect PCBA for missing components. Their system captures images of standard and defective boards, applies Gaussian filters for noise reduction, and uses histogram comparison for defect identification [15]. Daniel et al. introduced a novel method using background subtraction with the Mixture of Gaussian (MoG) model to detect missing or misaligned components on PCBAs. By capturing reference and test images and applying median filtering, their method highlights defects through image subtraction [16]. The domain of pure machine vision for PCB defect detection has seen significant advancements as well. Prachi P. et al. and S. A. Chavan employed image processing techniques in Matlab to detect and classify 14 types of PCB defects. Their system utilizes image subtraction, feature extraction using the region props function, and a k-Nearest Neighbors (KNN) classifier for defect classification. This method showcases MATLAB's potential for developing robust PCB inspection systems, particularly suited for various defect types [17]. Similarly, Vikas et al. focused on a referential approach, employing image registration, preprocessing, and segmentation to detect and classify PCB defects. Their method is robust to variations in rotation, scale, and translation, making it suitable for real-world applications [18]. T. J. Mateo al. developed a system combining a modified subtraction method with a particle classification algorithm using light intensity measures to improve defect detection resolution and speed. Their system pre-processes images, applies particle analysis, and uses light intensity measures for defect classification, offering a significant improvement in resolution and speed over traditional methods [19]. F. Raihan et al. utilized OpenCV for defect detection through image subtraction and binary large object detection. Their system preprocesses images, applies Gaussian blurring and thresholding, and uses XOR operations to highlight defects [20]. The study underscores the significance of identifying key factors and optimizing process variables to enhance production efficiency. Though significant advancements have been made to identify PTH components defects, current survey of respective literature showed the following limitations:

- Many existing methods predominantly rely on grayscale images for defect detection, which limits the ability to capture and utilize color information that can enhance defect identification.
- The lack of multi-channel template matching techniques (e.g., HSV, BGR) in defect detection application, which leads to comparatively lower accuracy.
- Machine learning approaches often become complex and less effective in absence of extensive training data.
- The high searching time for defining the region of interest (ROI) in many methods leads to inefficiency.
- Many existing methods do not support real-time defect detection, which is crucial for large-scale manufacturing processes.

The present research endeavors to bridge existing gaps and evaluate advanced strategies for addressing critical issues in PTH components such as missing components, misalignment, and incorrect polarity. By harnessing cutting-edge machine vision technologies, this study aims to develop and implement sophisticated image processing methodologies to mitigate these challenges. The research introduces the following advancements:

- Incorporates three templates (HSV with bilateral filter, BGR with bilateral filter, and grayscale with Gaussian blur) to improve defect detection accuracy.
- By defining the ROI with location and size, the search time is reduced, enhancing computational efficiency.
- Overcomes limitations of grayscale imaging by incorporating color scales, enhancing detection of subtle defects.
- The system is designed for real-time performance, improving production line efficiency.

The structure of this paper is designed as follows: Section II outlines a high-level overview of the methodological approach employed in this study. Section III delves into the proposed machine vision system, detailing both the development and practical implementation of the defect inspection model tailored for PTH components. Results and discussions are elaborated in Section V. Section VI concludes the paper, summarizing key insights and suggesting avenues for future research and development.

METHOD OVERVIEW

Figure 1 provides a high-level overview of the proposed computational pipeline tailored to the development of machine vision-based approach by leveraging template-matching technique to enhance process conformance PCBA lines. There are three primary phases delineated within the outlined computational framework:

Phase I - Image Capturing: This initial phase focuses on calibration to minimize radial distortions in captured images. This is crucial for maintaining the integrity of visual data, which is essential for accurate analysis in subsequent phases. The calibrated images ensure that any geometric distortions are corrected before further processing.

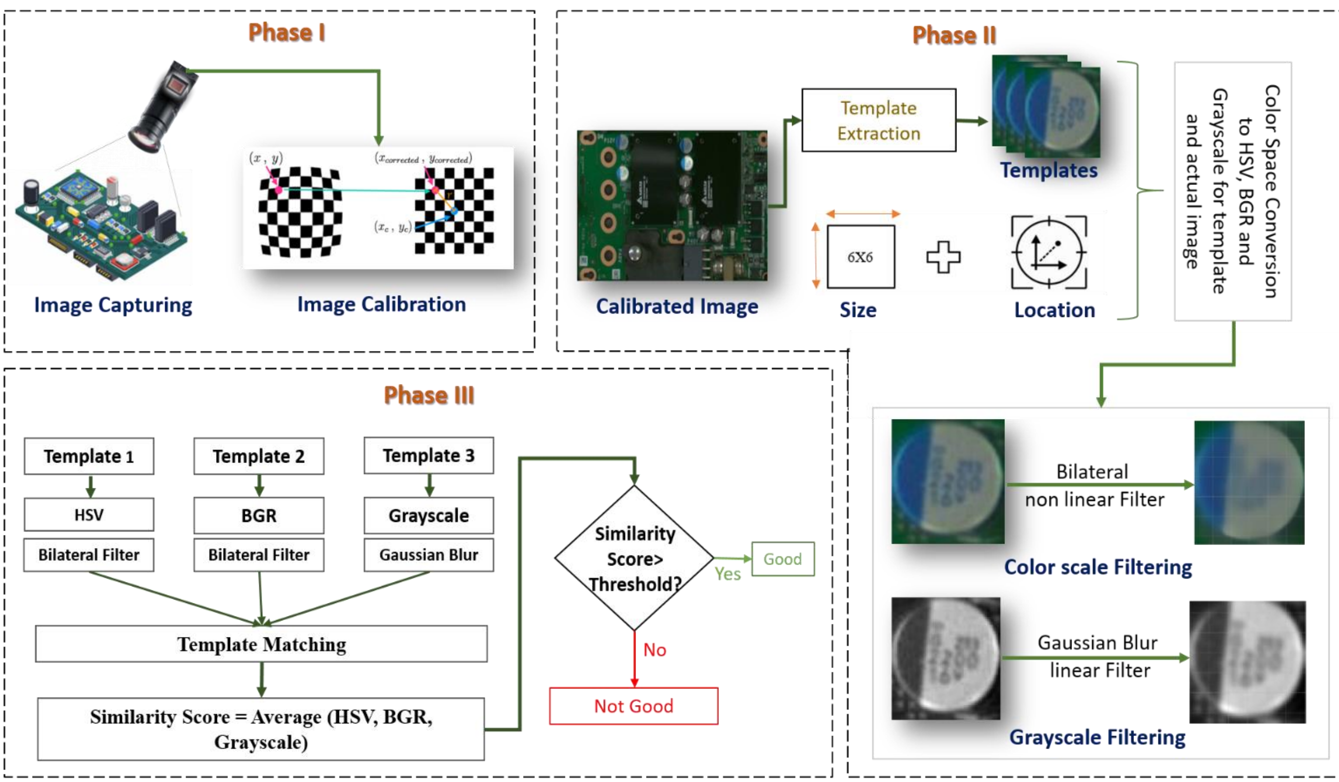

Figure 1. High-level overview of the proposed computational pipeline outlining three important phases: (a) Phase I – Image Capturing, (b) Phase II – Defining the Region of Interest, and (c) Phase III – Multi-scale Template Matching.

Phase II - Defining the ROI: This second phase involves employing template extraction algorithms to isolate key image features. This includes identifying component templates, their precise locations, and dimensions. By defining the ROI, this phase significantly reduces the computational load required for the intensive image analysis that follows. This setup is critical for targeting the specific areas of the PCB where defects are most likely to occur, thus optimizing the inspection process.

Phase III - Multi Scale Template Matching: Phase 3 depicts a proposed multichannel approach that integrates color-based matching and luminance information while reducing noise, thereby increasing both the robustness and precision of the template matching process. The inspection system employs a three-tiered template matching strategy to maximize feature detection and accuracy. The system simultaneously applies template matching across multiple scales: the HSV with a bilateral filter to enhance feature discernment within the ROI, the BGR scale with bilateral filtering for further refinement, and a grayscale input coupled with a Gaussian blur filter at the ROI. The maximum similarity score obtained from these three scales is compared to a predefined threshold value. Failure to meet the similarity score triggers defect detection, ensuring thorough inspections and minimizing missed defects. The above-mentioned three phases of computational pipeline led to developing an innovative machine-vision based solution to detect PTH defects namely missing components, incorrect polarity, and components misalignment before the wave soldering stage to mitigate failure rates and high rework costs in the PCBA process.

METHODOLOGY

This section outlines the methodology employed to implement and deploy a machine vision system for defect inspection in large-scale PCB manufacturing, as illustrated in Figure 2.

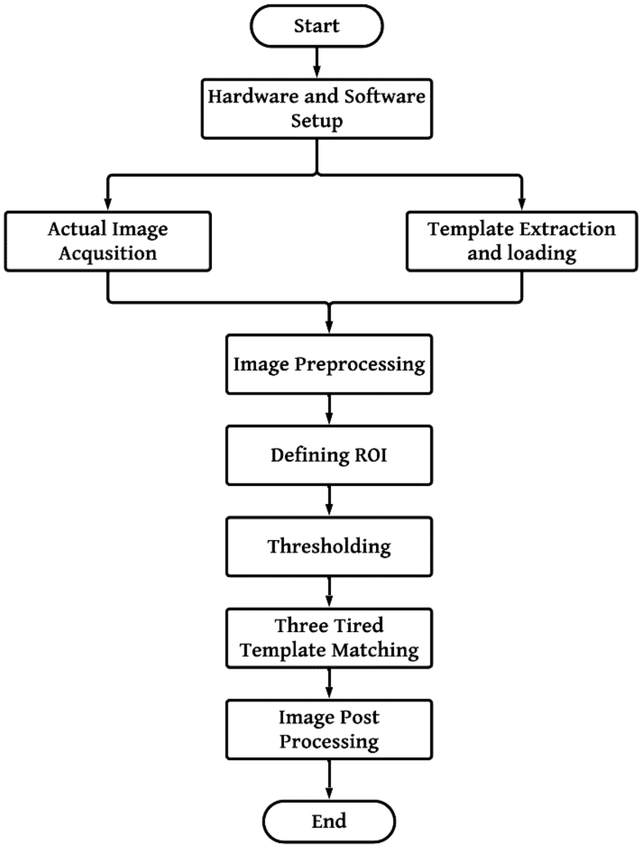

Figure 2. Flow chart of step-by-step methodology

Hardware and software setup: A robust hardware and software system was developed to ensure precise and reliable defect detection. The hardware setup consists of a Basler camera mounted above a conveyor system holder, ensuring stability, precise alignment, and minimal vibration for consistent high-resolution imaging. The conveyor halts when a PCB is positioned under the camera, eliminating motion blur and ensuring sharp image capture. Uniform lighting is utilized to enhance image clarity, with software algorithms normalizing any variations. The software leverages Python and its extensive libraries, particularly OpenCV, to facilitate robust image processing tasks such as filtering, template matching, and defect detection. A meticulous camera calibration process was conducted using a chessboard pattern to mitigate radial distortion. Multiple images of the chessboard were captured from various angles and distances, then converted to grayscale for improved corner detection. The chessboard's interior corners were accurately identified, and these 2D image points were matched with their corresponding 3D world coordinates on a Z=0 plane. This data was used in the calibration process, where OpenCV computed the camera's intrinsic parameters and distortion coefficients. The result was accurately calibrated to get the distortion-free images. Following calibration, feature extraction is pivotal for accurate defect identification. The full PCB image is acquired into memory, resized to fit display dimensions while maintaining aspect ratio, and analyzed through a Graphical User Interface (GUI) that enables manual delineation of ROIs, particularly focusing on PTH components. Bounding boxes are drawn and adjusted around PTH components, by marking them as ROIs and verifying these selections in real-time. Finalized ROI dimensions, spatial coordinates, and templates are extracted from the high-resolution image and stored as discrete template files for consistency in future inspections. These templates are systematically stored in designated directories and named with integer-valued filenames for accurate sorting and loading. Real-time high-resolution PCB images are captured using Basler cameras, with the system continuously displaying the latest image to verify PCB presence and alignment through precise coordinates. Calibration corrects lens distortions, and PCB presence is confirmed by template matching against the stored CPU component template, visually indicating alignment status for immediate operator intervention.

Image Preprocessing: In the image preprocessing phase, advanced techniques are employed to enhance the quality and consistency of both real-time captured images and pre-loaded template images, ensuring accurate defect detection. Key steps include resizing and scaling, color space conversions, and filtering.

Resizing and Rescaling: To ensure dimensional alignment between template and captured images, resizing and scaling are fundamental. The dimensions of the captured images are analyzed to serve as the reference for resizing the templates. Templates are adjusted using interpolation methods designed for effective downscaling by averaging pixel values, which helps preserve image integrity and quality. Proper scaling maintains the aspect ratio, preventing deformation that could compromise defect detection accuracy.

Color Space Conversions: Color space conversions are integral to interpreting and analyzing image data through various perspectives. The BGR color space, the default format in OpenCV, is useful for basic image representation and processing tasks, representing images with blue, green, and red components. The HSV color space separates chromatic content (hue and saturation) from intensity (value), providing robust color-based analysis by isolating color information from brightness variations. Meanwhile, the grayscale color space simplifies images by removing color information and retaining only luminance or intensity. This conversion is advantageous for tasks focused on structural details like edge detection and texture analysis. By converting images between these color spaces, the inspection model leverages each space's strengths, enhancing defect detection accuracy.

Filtering Techniques: Filtering techniques are crucial for enhancing image quality by reducing noise and preserving important details. Gaussian Blur applies a Gaussian function to the image, reducing high-frequency noise and enhancing overall image quality by averaging pixel values with their neighbors. This technique is particularly effective in grayscale images, simplifying data and highlighting structural features. The Gaussian blur works by convolving the image with a Gaussian function G(x,y), defined as:

$$G(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$

Where, x and y are the distances from the origin in the horizontal and vertical axes, and σ is the standard deviation of the Gaussian distribution. On the other hand, Bilateral Filtering, a non-linear, edge-preserving, and noise-reducing filter, maintains sharp edges while smoothing the image by applying Gaussian filters in both the spatial and intensity domains. This is particularly useful in color images where preserving the integrity of color boundaries is critical for accurate defect detection. The bilateral filter for a pixel I(x) is given by**:**

$$I_{filtered}(x) = \frac{1}{W(x)} \sum_{y \epsilon \Omega} I(y) . e^{\frac{||x-y||^2}{2\sigma_s^2}} . e^{\frac{||I(x)-I(y)||^2}{2\sigma_r^2}}$$

where, x and y are pixel coordinates, σ_s is the spatial standard deviation, σ_r is the intensity standard deviation, and W(x) is a normalization factor ensuring the sum of weights is 1. These filtering techniques ensure that images are free of noise and retain essential details, preparing them for precise template matching and defect detection. By meticulously applying these preprocessing techniques, the inspection model achieves high-quality, consistent images, enhancing the robustness and reliability of defect detection in PCB manufacturing.

Defining ROI and Thresholding: Defining the ROI is paramount for focusing computational resources on critical areas, thus enhancing both accuracy and efficiency in PCB defect detection. The system dynamically delineates the ROI for each component using coordinates and dimensions derived during feature extraction. This process involves cropping captured images based on predefined parameters, resulting in sub-images that contain only the targeted components. This targeted method allows for the application of intensive image processing techniques, such as filtering and template matching, significantly reducing false positives and negatives. By isolating relevant areas for analysis, this focused approach enhances computational efficiency and accuracy. Furthermore, thresholding is a vital image processing technique used in PCB inspection to distinguish components from the background. Threshold values are predefined based on component size to ensure optimal detection sensitivity and accuracy for each specific component type: higher thresholds are assigned to smaller components, such as capacitors and resistors, while lower threshold values are designated for larger components. During inspection, the predefined threshold values are compared with the actual similarity scores determined using a template matching algorithm. For single-channel in grayscale images, pixel intensities are directly compared to the threshold. In multi-channel color spaces (e.g., RGB and HSV), each channel is processed independently, and the final similarity score is derived by averaging the scores across all channels. This approach enhances detection robustness and accuracy, ensuring precise component detection under diverse conditions.

Inspection using Template Matching: The inspection is carried out using template matching, which is central to this process, by comparing predefined component templates against actual PCB images to identify anomalies like misalignment, missing components, and incorrect polarity. Here, template matching has been chosen for several compelling reasons, including its resistance to rotation, which is crucial for identifying polarity. Polarity determination relies on the direction of color information, and template matching can effectively handle rotational variations, ensuring accurate polarity detection. Additionally, template matching is robust to scale variations, noise, and partial occlusions, making it ideal for identifying a wide range of defects in PCB inspection. The adoption of a multichannel approach further enhances the inspection accuracy, as color information is critical for differentiating and identifying incorrect polarity. Utilizing multiple color channels, specifically RGB and HSV, allows for a more comprehensive analysis. Furthermore, Template matching, a foundational technique in computer vision, involves identifying regions in a target image that closely match a template image. This process starts with a template image T of size m x n pixels and a target image I of size **M×N** pixels, where the target image represents the entire PCB being inspected, and the template image represents the specific component or feature being compared. The goal is to locate the sub-region in the target image that best matches the template, achieved by sliding the template across the target image and computing a similarity measure at each position. While common similarity metrics include Sum of Squared Differences (SSD) and Cross-Correlation (CC), this application employs Normalized Cross-Correlation (NCC) for its robustness to variations in lighting and contrast. The mathematical representation for NCC is:

$$NCC(i,j) =$$

$$\frac{1}{m.n} \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} \frac{(I(i+x,j+y)-\bar{I}).(T(x,y)-\bar{T})}{\sqrt{\sum_{x=0}^{m-1} \sum y = 0^{n-1} (T(x,y)-\bar{T})^2} . \sqrt{\sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (I(i+x,j+y)-\bar{I})^2}}$$

where, x, y represent the coordinates within the template image T(x,y), and m, n denote the width and height of the template, respectively. The intensity value of the pixel at position (i,j) in the target image I is denoted by I(i,j). The coordinates i and j correspond to the top-left corner of the sub-region in the target image where the template is being compared. As the window shifts across the target image, i and j help in positioning the template for comparison. Overall, x and y are used within the template, i and j are used within the target image, and m and n define the dimensions of the template. I(i,j) and T(x,y) represent the pixel intensities in the target image and the template, respectively. By normalizing the correlation, NCC becomes robust to changes in brightness and contrast, making it more reliable in real-world scenarios.

Implemented Approach: To enhance the inspection process for PTH components, a three-tiered, multichannel, multi-filter methodology has been adopted. This approach integrates multiple color spaces—HSV, BGR, and Grayscale—to achieve comprehensive and precise defect detection. In the HSV color space, the image is decomposed into three orthogonal channels: Hue, Saturation, and Value. Each channel undergoes bilateral filtering to effectively reduce noise while preserving critical edge details. Subsequently, template matching is executed on each channel utilizing NCC, and the resulting matching scores from the Hue, Saturation, and Value channels are averaged to derive a composite score:

$$S_{HSV} = \frac{S_H + S_S + S_V}{3}$$

S_H, S_S, S_V denote the matching scores for the Hue, Saturation, and Value channels, respectively. In the BGR color space, the image is processed through its blue, green, and red channels. Each channel is subjected to bilateral filtering to minimize noise while retaining edge integrity. Template matching is performed on each channel using NCC, and the scores are averaged to produce a composite score:

$$S_{BGR} = \frac{S_B + S_G + S_R}{3}$$

S_B, S_G, S_R represents the matching scores for the blue, green, and red channels, respectively. For grayscale images, Gaussian blur is applied to smooth the image by averaging pixel values with a Gaussian kernel, thereby reducing high-frequency noise while maintaining essential structural information. Template matching is subsequently carried out using NCC:

$$S_{Gray} = NCC_{Gray}$$

The final decision for each component is derived from the highest matching score among the HSV, BGR, and Grayscale analyses. The overall matching score is computed by averaging the scores from these three-color spaces:

$$S_{Final} = \frac{S_{BGR} + S_{HSV} + S_{Gray}}{3}$$

If the overall matching score meets or exceeds the predefined threshold, the component is classified as having passed the inspection. This multichannel approach leverages the individual strengths of the HSV, BGR, and Grayscale channels while mitigating the limitations inherent in any single channel. By integrating these color spaces and applying bilateral filtering and Gaussian blur, this methodology effectively accounts for variations in color and intensity, thereby providing a robust and accurate defect detection mechanism. The use of robust NCC template matching techniques ensures comprehensive and precise analysis, which is critical for maintaining high-quality standards in large-scale PCB production.

Duplicate Removal: During template matching, multiple detections often occur due to minor variations in matched features, resulting in redundant or closely spaced detection points. These duplicates can obscure true defects and inflate defect counts, leading to false positives. An algorithm is employed to identify and eliminate duplicates by calculating the Euclidean distance between detected points:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

where (x_1, y_1) and $(x_2, y_2)$are coordinates of detected points. Points within a predefined threshold distance are considered duplicates, with one point retained to ensure unique defect locations. This threshold is set based on the imaging system's resolution and component sizes, balancing the removal of duplicates with the retention of genuine detections. Eliminating duplicates enhances the clarity of inspection results and reduces false positives, thus improving the overall accuracy and computational efficiency of the defect detection system.

User Interface and Data Tracking: The user interface (UI) and data tracking components are crucial for effective post-processing and comprehensive analysis. The UI, developed with the Tkinter library, facilitates operator interaction, providing visual feedback and control options, including fields for work order and serial numbers, camera operation buttons, and status displays. Data tracking meticulously logs inspection times, serial numbers, and related metadata in structured CSV files, ensuring traceability and accessibility for future analysis. Storing inspection results in directories named by work order numbers and timestamps enables precise documentation. By monitoring serial numbers, the system can distinguish between system and human errors, facilitating targeted maintenance and quality improvements. This integration of a user-friendly interface with robust data tracking enhances the inspection process's efficiency and reliability, enabling accurate defect detection and comprehensive documentation. This system ensures thorough monitoring and addressing of all factors impacting solder quality.

RESULTS AND DISCUSSION

The proposed machine vision-based defect inspection model was deployed for detecting PTH components, such as PE connectors, capacitors, switches, DIMMs, ICs, and power modules, in a large-scale PCB manufacturing environment. The system demonstrated high accuracy in identifying defects, including missing components, misalignments, and incorrect polarities. Figure 3 shows an illustrative example of the system's capability to correctly identify these defects, showcasing its robustness in real-time inspection scenarios. Upon implementation on the production line, the system underwent continuous feedback and iterative adjustments to threshold values and parameters. Key parameters optimized included template quality, filter settings, and the sensitivity of the detection algorithms. These adjustments ensured the system's adaptability to varying lighting conditions and component variations, leading to improved detection rates. The system's accuracy was rigorously evaluated through a series of controlled tests where components were deliberately removed or incorrectly positioned, with the accuracy analysis depicted in Figure 4. Further comparative analysis of the proposed

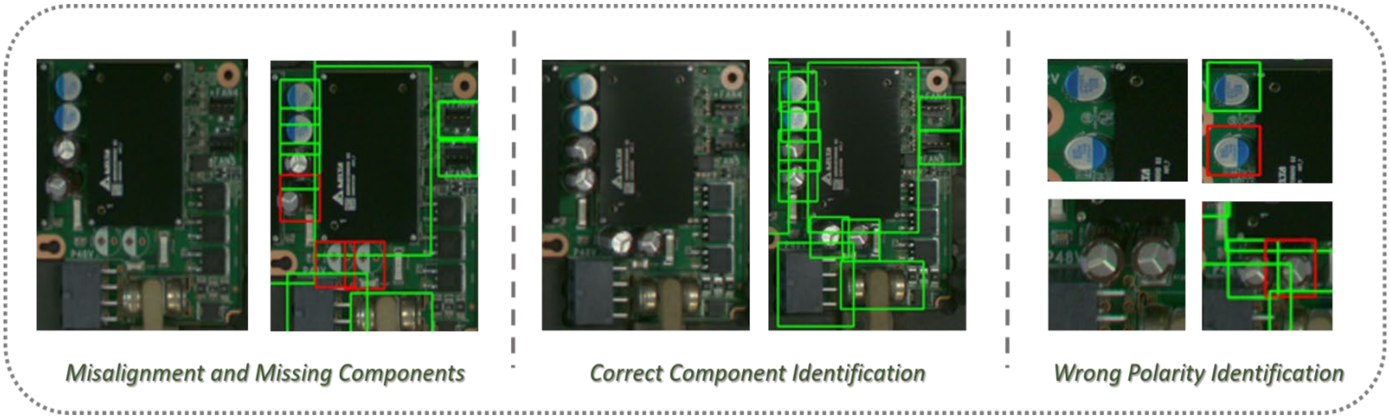

Figure 3. (Confidential) Results of PTH component identification and defect inspection

algorithm's accuracy was conducted across different detection scales for ten samples, including grayscale mode, BGR, HSV, and the hybrid BGR-HSV-grayscale approach. The hybrid approach demonstrated a higher detection accuracy by significantly outperforming the individual scales as shown in Figure 5(1). Comparative false call rates for each mode further underscored the hybrid approach's performance. To validate the system's efficacy on a larger scale, the hybrid algorithm was tested on 100 PCB boards where false calls rate was observed and achieved 98.5% detection accuracy. The detection accuracy was calculated as:

$$Detection\ accuracy = \left(1 - \frac{Total\ false\ calls}{Total\ components\ Inspected}\right) * 100$$

Moreover, as depicted in Figure 5(2), the frequency of false calls was analyzed across a sample size of 100 boards. The results indicate a higher occurrence of boards with zero or one

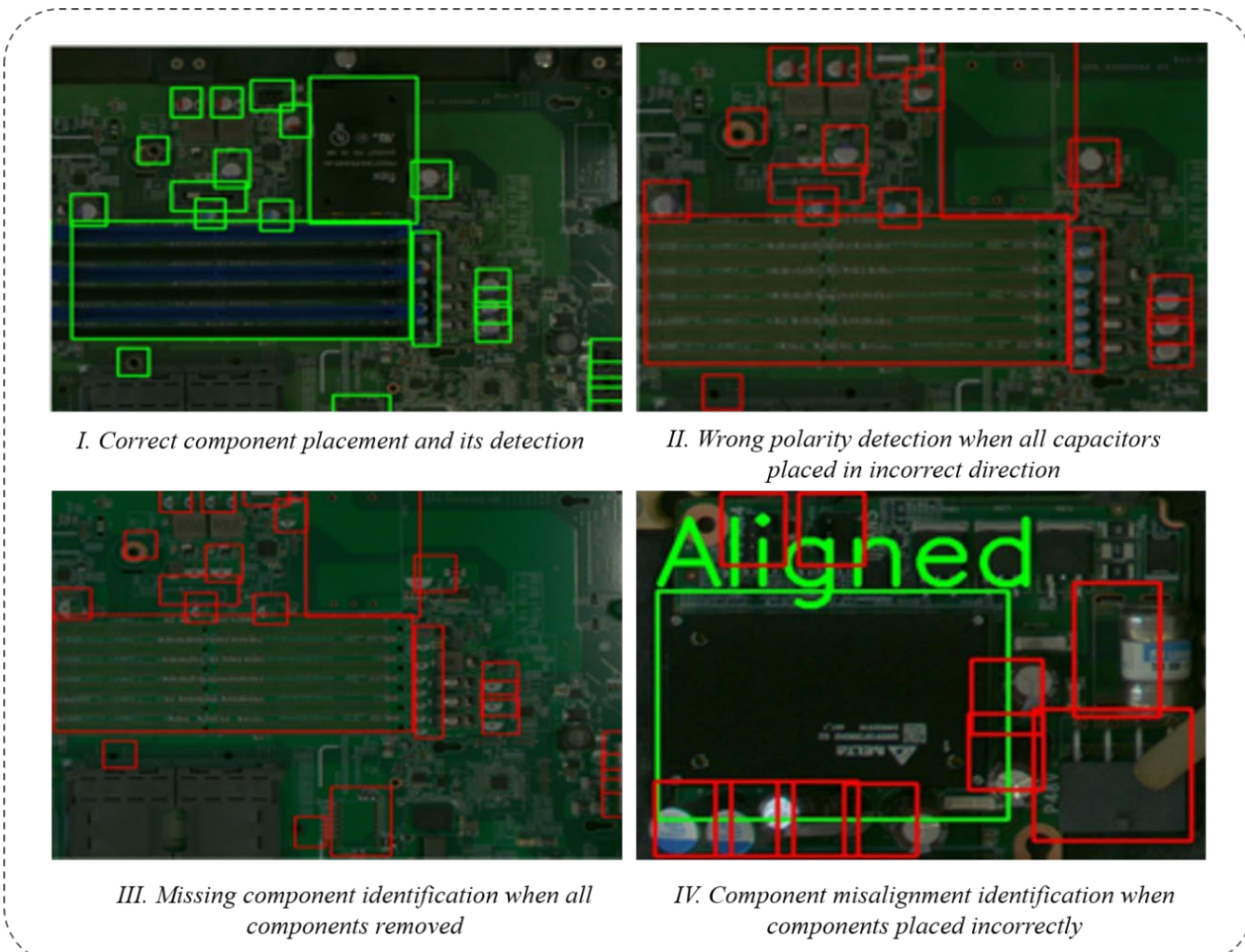

Figure 4. (Confidential) Verification of detection accuracy

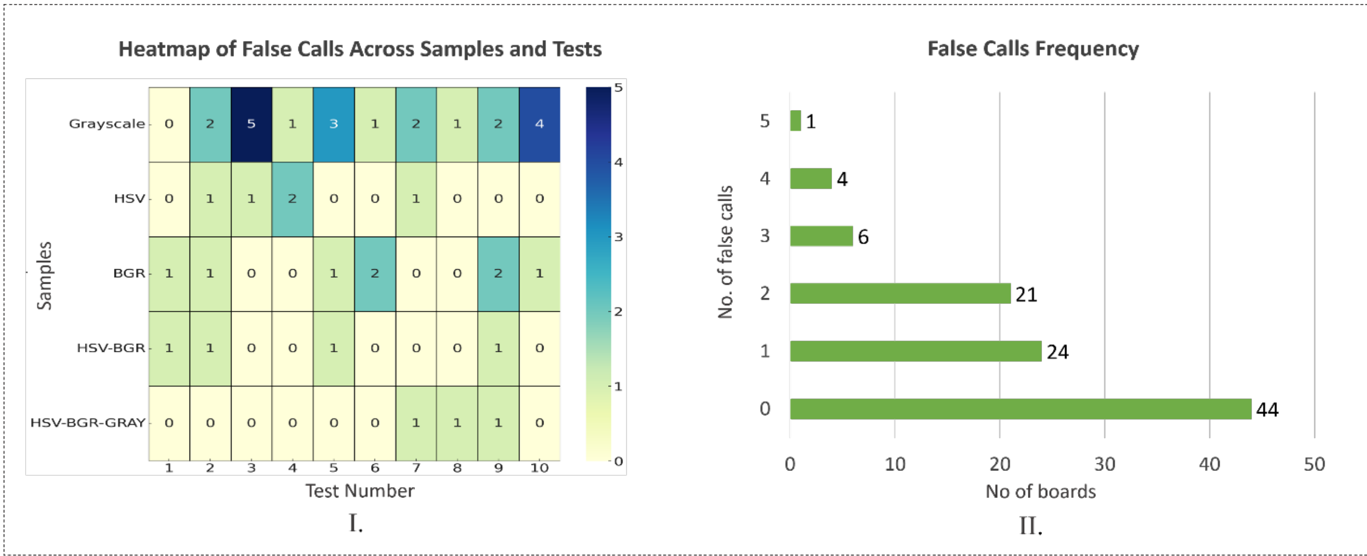

Figure 5. (I) Comparison of different scales using heat map of false-call distribution, (II) Frequency of false calls vs number of boards indicating less boards with false calls

false call, suggesting a minimal rate of false detections. Following the attainment of high accuracy levels in detecting defects on the primary PCB assemblies, the inspection system was also deployed for secondary PCB assemblies. This expansion validated the system's modular standardization by ensuring comprehensive defect detection across various PCB types.

The results underscore the efficacy of the machine vision-based defect inspection model in augmenting quality control within PCB manufacturing processes. By effectively addressing prevalent challenges such as lighting variations and component discrepancies, the system significantly reduces the incidence of defective PCBs advancing to the wave soldering stage, thereby minimizing rework rates, and enhancing overall production efficiency.

CONCLUSION AND FUTURISTIC APPROACH

In the dynamic and increasingly complex domain of PCB assembly, the assurance of PTH component integrity is paramount to upholding rigorous production standards. This study delineates the conceptualization and implementation of a machine vision-based defect inspection model, meticulously engineered to confront the intricacies of high-throughput PCB assembly environments. The framework of the proposed system is underpinned by three phase computational framework, which synergizes precision image acquisition, exacting region of interest delineation, and an innovative multiscale template matching methodology. This integration facilitates a robust and comprehensive defect detection process, significantly improving the system’s diagnostic acuity. The primary phase includes the acquisition of high-resolution PCB imagery under rigorously controlled lighting conditions to mitigate the potential confounding effects of reflections and shadows, which could compromise the accuracy of defect identification. The subsequent phase is devoted to ROI definition, where targeted regions, particularly those encompassing PTH components, are isolated for focused analysis. The final phase implements multiscale template matching, a method that juxtaposes multiple template scales with the target images, ensuring precise defect detection across varying component sizes and orientations.

The efficacy and robustness of the inspection system were validated through rigorous empirical evaluations, encompassing both main and system PCB assemblies. Iterative optimizations of the detection algorithms were conducted to refine system performance, culminating in an exceptional detection accuracy rate of 98%. This precision is attributed to a hybrid inspection approach that leverages the synergistic capabilities of multiple color spaces—HSV, BGR, and grayscale—coupled with advanced filtering techniques. These methodological improvements enable the system to maintain heightened sensitivity to minute lighting variations and subtle color discrepancies, which are frequently overlooked by conventional inspection systems. The successful deployment of this system across diverse PCB assembly environments underscores its scalability and robustness, marking a significant advancement in PCB assembly industries. By substantially reducing rework rates and mitigating defect occurrences, the system not only optimizes production throughput but also elevates the overall quality of the manufactured products.

Looking ahead, the future of defect inspection for PCB manufacturing lies in embracing digital transformation and advanced AI technologies to push the current detection capabilities. One promising direction seems an integration of transformational AI, particularly attention-based models like Vision Transformers (ViTs), which focus on local patches, as it processes entire images which makes them ideal for identifying defects across PCBs. By learning both global and local dependencies, ViTs can dynamically optimize their detection accuracy in real-time as they deal with new defect patterns and adapt to production conditions. Apart from that, incorporating self-supervised learning that allows the inspection models to continuously learn from new defect patterns and dynamically optimize the detection accuracy, even in the absence of labeled data. This adaptability, paired with continuous learning, must drive inspection systems toward achieving detection accuracy of 99.99%, significantly surpassing current industry standards. Further than AI, advancements in imaging technologies are also pivotal. The inclusion of hyperspectral imaging and exploration of color spectrums such as CIELAB color space, YUV (Luminance, Blue Projection, Red Projection), which separates brightness from color information can enhance the detection which can facilitate detection of some anomalies which might be not captured earlier. Furthermore, the application of multi-dimensional (X-D) imaging, such as 4D or 5D techniques, could also provide insights into component structure by ensuring smallest deviations are identified from multiple perspectives. To accommodate holistic automation, Co-bots (collaborative robots) in conjunction with machine vision systems can improve real-time defect detection. Co-bots with high-precision actuators can assist in repositioning components. By integrating sensor feedback loops with AI decision-making models, the system can respond dynamically to detected defects without halting production which is crucial for systematic integration. Such seamless, end-to-end integration of AI models, imaging systems, and robotic assistance into the PCB manufacturing process will streamline operations and improves the overall product quality.

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