Volume 94, No. 4, 2025

Automated Optical Inspection For Assembled Printed Circuit Boards : A Simple and Effective Image Processing Approach

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ABSTRACT

A simple yet effective image processing method is employed in this work to improve AOI performance in detecting soldering defects on assembled PCBs. a machine learning (ML)-based technique is integrated into the automated optical inspection (AOI) system to address soldering challenges. a tailored dataset, curated from raw images of populated PCBs along with annotation files, forms the foundation of this approach. a sophisticated transform algorithm is used to categorize soldered components as either proper or defective. features extracted from this labelled dataset enable the system to detect issues such as incorrect component orientation and missing parts. this additional layer of analysis enhances the robustness of defect detection, ensuring a more comprehensive evaluation of the assembly process. the results are visually represented using a color-coded scheme: red rectangles highlight defective soldering, while green rectangles denote correctly soldered components. this streamlined approach improves detection accuracy and makes result interpretation more accessible and efficient. overall, this work offers PCB manufacturing a reducing reliance on manual inspection, lowering

https://doi.org/10.5281/zenodo.15854565

operational costs, and providing an intuitive, efficient solution for defect detection in the assembly process.

Keywords: automated optical inspection; image processing; machine learning; PCB assembly; defect detection; soldering faults.

INTRODUCTION

AOI is a crucial technology in PCB design and manufacturing, ensuring product quality and operational efficiency. It can detect defects such as soldering issues, component misplacements, and open circuits, preventing their propagation throughout the assembly line. AOI's strategic placement in the production line enhances its impact on the manufacturing process [1]. Overall, AOI's importance in the PCB design and manufacturing field cannot be overstated, as it detects defects, prevents their propagation, and optimizes operational efficiency, making it an indispensable technology for high-quality standards and cost-effective production in the electronic devices industry.

The AOI tools are widely used in the electronics manufacturing industry to detect defects and ensure the quality of PCBs and other electronic components. There are various AOI commercial tools available, each with its own features and capabilities. Some of types of AOI tools commonly used in the industry:

- Inline AOI Systems: These systems are seamlessly integrated into production lines, facilitating real-time inspections of PCBs during the manufacturing process. Inline AOI systems effectively identify various defects, including soldering issues, missing components, and incorrect component placements.
- Offline AOI Systems: Unlike inline systems, offline AOI systems are used for inspections conducted after production. PCBs are extracted from the manufacturing line and examined separately, allowing for

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more detailed analysis and in-depth evaluations of potential defects.

- Co-Planar Light Inspection (CLI): Traditional AOI systems primarily provide two-dimensional inspections. In contrast, three-dimensional (3D) AOI systems offer additional depth information, which is particularly advantageous for evaluating complex components, solder joints with height variations, and detecting issues such as lifted leads or tombstoning.
- Solder Paste Inspection (SPI) Systems: Though not strictly classified as AOI, SPI systems are closely related and often incorporated into the overall inspection process. SPI systems assess the quality of solder paste deposition prior to the placement of components on the PCB.
- Automated X-Ray Inspection (AXI) Systems: Utilizing X-ray technology, AXI systems enable the inspection of concealed solder joints and the detection of defects that may not be visible through conventional optical inspection methods. AXI is especially valuable for inspecting Ball Grid Arrays (BGAs) and other intricate components.
- Desktop AOI Systems: These compact AOI systems are designed for benchtop or desktop use, catering to smaller-scale electronics manufacturing and research and development applications.
- High-Speed AOI Systems: Engineered for high-throughput production environments, these systems provide rapid inspection capabilities, ensuring the manufacturing process keeps pace with modern production demands.

RELATED WORK

https://doi.org/10.5281/zenodo.15854565

The active learning framework for automatically classifying defects in solder joints for Automatic Optical Inspection of Soldering (AOI) for PCBs [17]. The framework starts with a small labelled dataset and expands using K-means clustering and user input. Evaluations show high accuracy with minimal user input, outperforming random and representative sampling by 3.2% and 2.7%, respectively, and uncertainty sampling by 0.5%.

Improving accuracy of automatic optical inspection with machine learning implies the assembly of PCB in electronic devices often faces welding issues, particularly for SMD resistors [3]. The method uses an adjacent pixel RGB value-based method to pre-process images and build a customized deep learning model for image classification. This method reduces the rate of misjudgement from 0.3%-0.5% to 0.02%-0.03%, significantly impacting thousands of PCBs with electronic components.

Colour intensity analysis for defect detection

YOLOv4-based PCB detection framework for detecting six types of defects in printed circuit board manufacturing [16]. The framework uses the Intel Open VINO toolkit to optimize models, achieving production-ready capability. Experiment results show good accuracy and significant execution speed on low-power embedded platforms, addressing image mismatch and high computation time and processing power.

The analytical scheme for designing realistic metal gratings for wide-angle engineered reflection, utilizing a closed-form formalism [13]. This innovative approach addresses challenges with conventional meta surfaces and gradient meta surfaces. The methodology, validated through commercial solvers, enables researchers to progress from theoretical design to synthesis of a complete physical structure, eliminating the need for time-consuming numerical optimizations. This

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demonstrates the practicality and efficiency of the proposed analytical scheme.

Machine learning for AOI

Soldering defect detection in automatic optical presents an integrated detection framework for solder joint defects in AOI of PCB [4]. It uses a generic deep learning method for localization, providing real-time speed and high accuracy. An active learning method is proposed for classification, reducing labelling workload when a large labelled training database is unavailable. The localization method is fast and accurate, while the classification framework achieves high accuracy with minimal user input. The method outperforms three other active learning benchmarks, demonstrating its potential in the PCB inspection process.

The Printed Circuit Board Assembly (PCBA) Solder Joint Defects Inspection System Based on Deep Learning proposes a deep learning-based method for inspecting solder connection flaws in PCBA is presented in this research. A camera module, AI edge computing module, conveyor, and PCBA quality control platform comprise the system [2]. The camera takes photos of PCBAs on the conveyor, which are subsequently transferred to the AI edge computing module for fault identification. The system can detect three common faults in 1.2 seconds with average accuracy, recall, and precision scores ranging from 72.3% to 100.0%, 0.98 to 1.00, and 0.98 to 0.99, respectively.

PCB manufacturing and quality control

The novel framework for automatic solder joint classification using Convolutional Neural Networks (CNN) [14]. The framework uses existing deep learning network architectures for region of interest detection on 2D grayscale images, comparing it with product-related meta-data. Data augmentation ensures sufficient input features. The results show a

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significant reduction in false call rate compared to commercial X-ray machines and reduced product-related optimization iterations. This approach improves the manufacturing process of SMD electronics production.

An approach to quality prediction using intelligent SMT solder joint inspection through the use of Machine Learning is an approach aimed to optimize electronic assembly manufacturing processes for modern global competition [6]. It focuses on reducing non-value-adding processes without compromising error rates. The method uses inspection data from solder paste inspection to predict X-ray process quality. Optical measurements and quality labels are used to establish a relationship between solder paste printing and inspection results.

The development of a low-cost Automated Optical Inspection (AOI) system for detecting defects in Printed Circuit Boards (PCBs) during the rapid prototyping stage[18]. The system uses commercial off-the-shelf components and a non-reference defect detection algorithm based on mathematical morphology-based image processing techniques. This AOI system can quickly detect and classify defects as either fatal or potential, enabling early detection and reducing prototyping costs. In this approach, fatal defects lead to immediate board rejection, while potential defects trigger alerts for further operator evaluation. The classification process enhances quality assurance during prototyping by supporting timely decision-making and minimizing resource waste.

EXPERIMENTAL SETUP

The proposed AOI methodology for PCB assembly quality control operates through a comprehensive two-stage process: the training phase and the testing phase. In the training phase, a diverse PCB image dataset is acquired and subjected to augmentation techniques for improved model robustness. MATLAB-based image pre-processing follows, involving noise reduction, sharpness enhancement, resizing for

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consistency, gamma correction, and saturation adjustment. The Hough Line Transform is then employed for soldering classification, involving grayscale conversion, edge detection, Hough Transform, accumulator thresholding, and line extraction. Extracted components are labelled based on solder joint orientation, forming the groundwork for a deep learning model [19]. In the testing phase, a specialized dataset is acquired, and components are extracted for defect identification. The system identifies missing and misaligned components, providing a comprehensive output visualization to facilitate effective defect detection.

Training phase

The flowchart on figure 1 is an overview of a process for creating a training dataset for an AOI system for PCBs. The process starts with acquiring a dataset of PCB images. Augmentation is then performed on the images to increase the variety of the data. Next, component extraction is performed to identify and isolate the individual components on the PCBs. The component classification block uses the extracted components to train a classifier to identify the type of component. The Hough line transform block is then used to identify any lines or edges on the PCB. Finally, image processing is performed on the images to prepare them for training the AOI system.

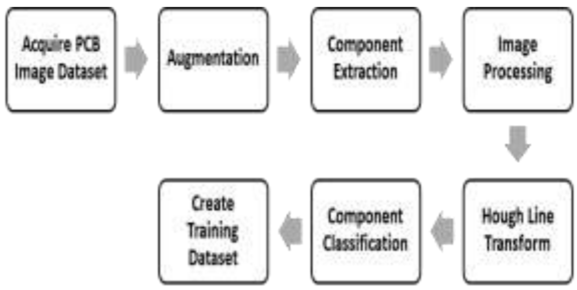

Figure 1: Flow chart of training phase

Acquiring PCB image dataset

The initial step in constructing the training dataset for the AOI project involves the acquisition of a comprehensive PCB image dataset. This foundational dataset forms the

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basis for subsequent analysis and model training, capturing the diverse array of populated PCB scenarios encountered in real-world manufacturing processes.

Augmentation techniques

Figure 2 shows the dataset acquisition, the images undergo augmentation, a critical process that involves applying various transformations to enhance dataset diversity and improve the model's robustness. Augmentation techniques, such as rotation, flipping, and scaling, are employed to simulate different perspectives and orientations, ensuring that the trained model can effectively generalize to a wide range of scenarios.

Figure 2: Image of dataset with annotation file

Image pre-processing

Image processing using MATLAB involves a series of strategic steps aimed at enhancing the visual quality and characteristics of the images is illustrated as a flowchart in figure 3.

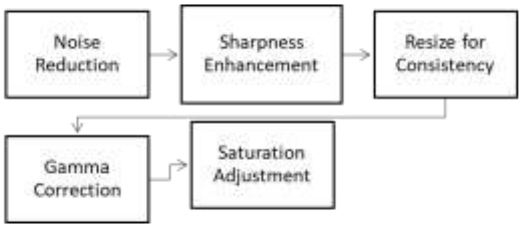

Figure 3: Flow chart of image pre-processing

Each step contributes to the overall improvement of the images, making them more suitable for subsequent analyses, such as defect identification in populated PCB.

1. Noise reduction

The first step in the image processing pipeline is noise reduction. This involves employing MATLAB's noise reduction techniques to diminish or eliminate unwanted artifacts or irregularities in the images. By minimizing noise, the clarity of the components within the images is improved, laying a solid foundation for

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accurate and reliable analysis, some of the examples that Pre-processing image of cropped components are shown in the figure 4.

Figure 4: Pre-processing image of cropped components

2. Sharpness enhancement

Following noise reduction, the images undergo sharpness enhancement. MATLAB's tools for sharpness enhancement are employed to accentuate the edges and finer details of the components[11]. This step ensures that subtle features critical for defect identification, such as solder joint boundaries, are more clearly defined, contributing to the precision of subsequent analyses.

3. Resize for consistency

Consistency in image size is essential for effective analysis and comparison. Resizing the images to a uniform dimension ensures that each component is represented in a standardized manner. This step aids in creating a consistent dataset, facilitating the training of models and algorithms for AOI purposes.

4. Gamma correction

Gamma correction is applied to adjust the luminance levels of the images. This step helps in correcting for variations in brightness and contrast, ensuring that the components are represented in a visually balanced manner. Gamma correction contributes to the overall visual fidelity of the images, providing a more accurate representation of the components.

5. Saturation adjustment

The saturation levels of the images are adjusted to enhance or tone down the colour intensity. This adjustment can be particularly useful in scenarios where colour information plays a role in defect

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identification. Fine-tuning the saturation levels contributes to a more visually appealing and informative representation of the components.

Therefore, the image processing steps with MATLAB form a comprehensive pipeline, addressing various aspects such as noise reduction, sharpness enhancement, size consistency, gamma correction, and saturation adjustment. These collectively contribute to the creation of high-quality images that are well-suited for subsequent analyses in the context of defect identification in populated printed circuit boards.

Hough line transform

The Hough Line Transform is crucial for soldering classification. It is utilized to identify lines in the image, corresponding to the orientation of solder joints in the populated printed circuit board [12]. Peaks in the Hough transform matrix are identified, and lines are extracted based on these peaks. The orientation of each line is then analysed. If the angle exceeds a specified threshold, the component is flagged as defective. This method effectively leverages the Hough Line Transform to classify components based on the orientation of solder joints, a critical step in the AOI process for PCB manufacturing as illustrated in flowchart in the figure 5 below.

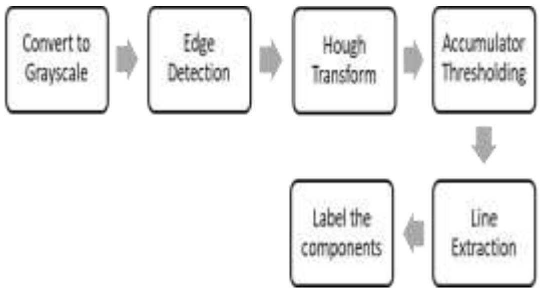

Figure 5: Flow chart of Hough line transform

The process unfolds in following key stages:

1. Convert to grayscale

The initial step involves converting the component images to grayscale. This simplifies the image to a single channel, enhancing computational efficiency and

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laying the groundwork for subsequent analyses.

2. Edge detection

Edge detection techniques are then applied to the grayscale images. MATLAB's edge detection algorithms identify significant changes in intensity, highlighting the edges of the solder joints within the component images. This step is crucial for isolating the key features that determine the soldering orientation.

3. Hough transform

The heart of the process lies in the application of the Hough Transform. This mathematical technique excels in detecting lines within the edge-detected images [7]. The Hough Transform accumulates information about the presence of lines, revealing patterns that correspond to the orientation of solder joints in the component images.It works by accumulating information about the presence of lines in various orientations, forming a "peak map" in the accumulator matrix. These peaks correspond to the dominant orientations of lines present in the image, and for our application, they align with the orientations of solder joints in the component images. This peak map is generated based on the formula[20],

$$\rho = x * \cos(\theta) + y * \sin(\theta)$$

where ρ represents the distance from the origin to the line, θ represents the angle of the line with respect to the x-axis, and (x, y) are the coordinates of a point on the line.

4. Accumulator thresholding

The Hough Transform generates an accumulator matrix containing the frequency of lines at different orientations. To identify significant orientations and potential solder joint positions, systems employ accumulator thresholding. This technique involves setting a threshold value and identifying peaks in the matrix that exceed that threshold [15]. These peaks indicate statistically significant orientations

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that are more likely to represent actual solder joints.

The specific threshold value chosen depends on the expected variability in solder joint orientation and the desired level of sensitivity. The threshold is set to ceil (0.3 * max(H(:))), where peaks that have at least 30% of the maximum value in the entire accumulator matrix. This thresholding can be implemented using a formula like:

Threshold = k * max(H(:))

where:

- H is the accumulator matrix
- k is a thresholding constant between 0 and 1 (typically around 0.3)
- max(H(:)) represents the maximum value in the accumulator matrix.

By analysing the orientation of each detected line and comparing it to the threshold angle (8 degrees), the algorithm can identify potential defects in solder joint orientation. This approach effectively utilizes the power of the Hough Transform and accumulator thresholding to extract valuable information about solder joint characteristics from edge-detected images.

5. Line extraction

Building upon the identified peaks, lines are extracted from the Hough Transform space. These lines represent the orientations of solder joints within the component images. The extraction process involves decoding the accumulator matrix to obtain precise information about the orientation and location of the lines.

6. Label the components

Upon successful line extraction, the components are labelled based on the analysis of the identified lines. The orientation information obtained through the Hough Line Transform is used to categorize components as either properly or improperly soldered. This labelling process forms the basis for defect classification and plays a crucial role in the overall AOI system. The figure 6 shows the Image of components classification with Hough line transform. Right side image shows the properly aligned component Left side image shows the improperly aligned component.

The Hough Line Transform, when applied to the soldering classification process, involves converting component images to grayscale, detecting edges, performing the Hough Transform to identify lines, thresholding the accumulator matrix, extracting lines, and finally, labelling the components based on the extracted orientation information. This intricate process contributes to the accurate classification of solder joints, facilitating effective defect identification in populated printed circuit boards.

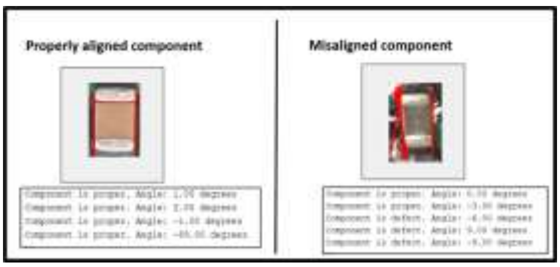

Figure 6: Image of components classification with Hough line transform.

(a) Right side image shows the properly aligned component (b) Left side image shows the improperly aligned component

Labelling the extracted component

After extracting lines using the Hough Line Transform, components are labelled as either "proper" or "defective" based on their orientation relative to expected angles. This binary classification forms the foundation for a deep learning model that automates defect identification in the AOI system. The model leverages the extracted line features and additional image information to classify components with greater accuracy and nuance.

The deep learning model is built upon the ResNet architecture, known for its effectiveness in image classification tasks. We experimented with three ResNet variants: ResNet-18, ResNet-34, and ResNet-50 [5] [8]. Each variant possesses the same underlying structure but with varying layer depths. Utilizing a machine learning toolkit, we constructed a small output network consisting of two fully-connected layers containing two nodes

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each. This network receives features extracted by the chosen ResNet model as input.

Rectified Linear Unit (ReLU) activation function is applied to the first fully-connected layer, accelerating the training process. Softmax cross-entropy serves as the loss function, while the second fully-connected layer outputs the probability of each class (proper or defective). While our dataset only contains two classes, the trained model effectively learns transferable features applicable to other PCB types. This allows our method to be generalized and utilized for classifying components on various PCB layouts.

Testing phase

The testing phase involves the acquisition of a specialized dataset, extraction of components, classification based on pre-established features, and visualization of results as shown in flowchart figure 7. This systematic approach ensures a thorough assessment of the AOI system's performance in identifying soldering issues in populated printed circuit boards. The visual output aids in quick and effective evaluation, facilitating potential improvements to the system based on testing outcomes.

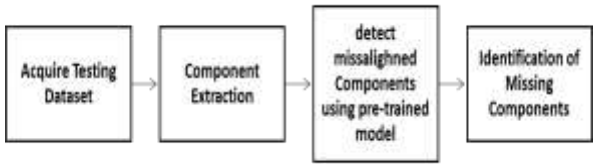

Figure 7:Flow chart of testing phase

The testing phase involves a systematic evaluation of the AOI system for populated PCB.The process encompasses the following key steps:

Acquire testing dataset

A curated dataset of PCB images, specifically collected for testing, is acquired. This dataset includes images of populated PCBs along with corresponding annotation files, providing essential information for subsequent analyses.

Component extraction

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During the testing phase, components are accurately extracted from the testing dataset[9][10]. This process involves leveraging the information derived from annotation files, ensuring that individual components are isolated for detailed analysis.

Identification of missing components

A specialized method is employed to identify missing components. By comparing the colour intensity of the entire PCB board with the colour intensity of annotated regions, discrepancies are detected. Missing components are highlighted with distinctive visual indicators, such as red rectangle boxes, facilitating efficient defect detection.

Identification of misaligned components

In addition to identifying missing components, the system assesses component alignment. Misaligned components are detected through advanced techniques, potentially involving Hough Line Transform or other orientation analysis methods[17]. These components are flagged for further inspection and highlighted for visual evaluation.

Output visualization

The results of component extraction, identification of missing components, and identification of misaligned components are visualized comprehensively. The output visualization provides a clear representation of potential defects. Missing components are highlighted with red rectangle boxes, misaligned components are indicated, and properly soldered components are denoted with green rectangle boxes. This visual feedback aids in a quick and effective evaluation of the AOI system's performance. The figure 8 shows the images which are highlighted for misaligned components and missing components. The images (a) & (d) are properly aligned components with green highlights and the images (b) & (c) are improperly aligned components and missing components.

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Figure 8: Image of highlighted misaligned components and missing components. (a) &(d) Properly aligned component with green highlighted (b) & (c) Improperly aligned component and missing components.

RESULTS AND DISCUSSION

The fundamental role of PCB in ensuring the structural integrity of electronic devices is indispensable. However, soldering issues with electronic components particularly SMD components might occur throughout the assembly process. The proposed method takes a novel approach to address these issues by employing AOI techniques. To ensure precise orientation alignment of the components, a tailored dataset has been created from the set of raw images of populated PCB boards with annotation files. By utilizing the line transform algorithm, the proper and improper soldering components were labelled as proper and defective. Subsequently, for testing purposes a dataset PCBs images with annotation file were collected and by utilizing the pre-established dataset the features are extracted to identify component orientation and applied for the test dataset. The improperly soldered components will be highlighted with red rectangle boxes, while properly soldered components are denoted by green rectangle boxes. In figure 9 and 10 shown a few examples Result images highlighting the misaligned components, missing components and properly solder components. To further enhance the system, it also assesses the presence of the component within the annotated region by comparing colour intensity with surrounding regions. The implementation of the proposed method holds promising implications for PCB manufacturing companies. By reducing the need for manual inspection, it not only curtails costs but it also provides a user-friendly and efficient solution to detect defects in the assembly process. This automated methodology, leveraging line transform,

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stands as a significant advancement in the realm of Automated Optical Inspection, providing a precise and consistent way of assessing the quality of assembled printed circuit boards.

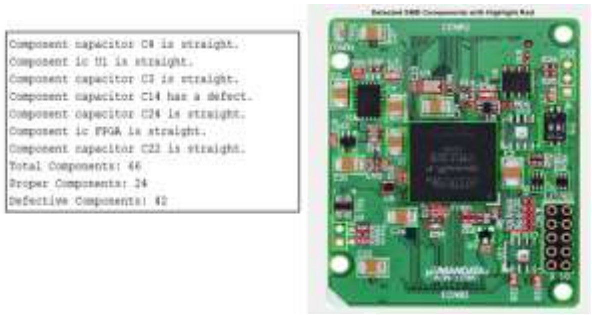

Figure 9: Result image shows highlighted misaligned components, missing components and properly soldered components

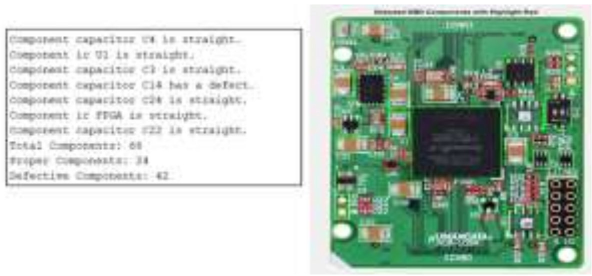

Figure 10: Result image shows highlighted misaligned components, missing components and properly soldered components.

CONCLUSION

In conclusion, the impact of AOI showcased in this project transcends its application in assembled PCB and extends to a wide array of industries relying on electronics manufacturing. Object Oriented Inspection (OOI) is a versatile solution for defect detection in electronic devices, benefiting consumer electronics, aerospace, medical devices, and automotive electronics. It reduces manual inspection requirements and offers high-speed, high-precision inspection methods. AOI aligns with industry visions for streamlined production processes and enhanced product quality, while also reducing material wastage and environmental footprint. Its broad applicability contributes to product reliability and supports sustainable production practices. As technology advances, AOI will shape the future of quality assurance practices, ensuring reliable and flawless electronic devices across various sectors. Its adaptability and efficiency gains make it a catalyst for positive change, fostering innovation and excellence in electronic manufacturing globally. As a future extension of this work, developing an AOI mobile application for

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PCB manufacturers with real-time image processing, user-friendly interfaces, continuous learning with AI implementation, cloud storage connectivity, in industry standards with user training and robust security measures.

REFERENCE:

Chang Y.-M., Wei C.-C., Chen J., Hsieh P., 2019. An implementation of health prediction in SMT solder joint via machine learning. In: Proceedings of the 2019 IEEE International Conference on Big Data and Smart Computing (BigComp), Kyoto, Japan, 1-4.

Chen M.-C., et al., 2023. A PCBA solder joint defects inspection system based on deep learning technology. In: Proceedings of the 2023 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 1-3.

Dai W., Mujeeb A., Erdt M., Sourin A., 2018. Towards automatic optical inspection of soldering defects. In: Proceedings of the 2018 International Conference on Cyberworlds (CW), 375-382.

Dai W., Mujeeb A., Erdt M., Sourin A., 2020. Soldering defect detection in automatic optical inspection. Advanced Engineering Informatics 43, 101004.

Du T.B., Shen G.H., Huang Z.Q., Yu Y.S., Wu D.X., 2020. Automatic traceability link recovery via active learning. Frontiers of Information Technology & Electronic Engineering 21, 1217-1225.

Euro Circuits, 2020. Function of PCBs. Available at: www.eurocircuits.tv/PCBassembly-x-ray-inspection.

Ferri M., 2003. Generalized Hough Transform: A useful algorithm for signal path detection. Available at: http://www.dm.unibo.it/~ferri/hm/pubbl/iaf2003.pdf.

Huang J.H., Di X.G., Chen A.Y., 2020. A novel convolutional neural network method for crowd counting. Frontiers of Information Technology & Electronic Engineering 21, 1043-1057.

Liu X., Chen S., Liu J., Qu W., Xiao F., Liu A.X., Liu J., 2021. Accurate localization of tagged objects using mobile RFID-augmented robots. IEEE Transactions on Mobile Computing 20, 1273-1284.

Liu X., Zhang J., Jiang S., Yang Y., Li K., Cao J., Liu J., 2020. Fast and accurate detection of unknown tags for RFID systems—hash collisions are desirable. IEEE/ACM Transactions on Networking 28, 126-139.

MathWorks, 2025. Image filtering and enhancement. Available at: https://www.mathworks.com/help/images/image-enhancement-and-restoration.html.

OpenCV, 2019. Hough Line Transform. Available at: https://docs.opencv.org/3.4/d9/db0/tutorial_hough_lines.html.

Rabinovich O., Epstein A., 2018. Analytical design of printed-circuit-board (PCB) metagratings for perfect anomalous reflection. IEEE Transactions on Antennas and Propagation 66, 4086-4095.

Schmidt K., et al., 2020. Enhanced X-ray inspection of solder joints in SMT electronics production using convolutional neural networks. In: Proceedings of the 2020 IEEE 26th International Symposium for Design and Technology in Electronic Packaging (SIITME), Pitesti, Romania, 26-31.

Shmueli G., 2025. Mastering peaks-over-threshold in actuarial science. Available at: https://www.numberanalytics.com/blog/peaks-over-threshold-method-acts-4302.

Tham M.-L., Chong B.Y., Tan Y.H., Wong Y.K., Chean S.L., Tan W.K., 2022. Optimizing deep learning inference to detect PCB soldering defects. In: Proceedings of the 2022 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET), Kota Kinabalu, Malaysia, 1-5.

Tong X., Liu K., Tian X., Fu L., Wang X., 2018. Fineloc: A fine-grained self-calibrating wireless indoor localization system. IEEE Transactions on Mobile Computing 18, 2077-2090.

Tong X., Yu Z., Tian X., Ge H., Wang X., 2022. Improving accuracy of automatic optical inspection with machine learning.

Frontiers of Computer Science 16, 161101.

Vaidya S.R., 2024. Automatic optical inspection-based PCB fault detection using image processing. Michigan Technological University, Digital Commons @ Michigan Tech, Available at: https://digitalcommons.mtu.edu/etdr/1602.

Yeh C.-H., 2022. Deep learning based solder joint defect detection on industrial printed circuit boards. Complex & Intelligent Systems 8, 65-74.

Zill D.G., 2023. Manifolds, vector fields, and differential forms. Springer, 978-3-031-25408-6, 296 pp.

 https://doi.org/10.5281/zenodo.15854565