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Leveraging Defect Trend Analysis for Sustainable Printed Circuit Board and Assembly (PCBA) Quality Assurance: A Low-Cost Portable Smart Inspection Solution for Small-Scale Electronics Manufacturers

Meynard H. Samson[1], **Francis Balahadia**[2]
College of Computer Studies, Laguna State Polytechnic University, Siniloan, Laguna, 4019, Philippines [1,2]
meynardsamson@gmail.com; balahadiafrancis@gmail.com

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ABSTRACT

This research addresses the challenges in quality assurance (QA) for low-volume Printed Circuit Board and Assembly (PCBA) production, where manual inspection often leads to inconsistencies, limited traceability, and delays. Analyzing defect trends from 2019 to 2024 across six suppliers, the study identified common issues such as missing components, misalignment, and solder defects. This defect analysis introduces the concept of developing a low-cost, portable, AI-driven PCBA QA inspection system that would utilize a high-resolution microscope, Python-based computer vision, and object detection tools like YOLO to provide an affordable, scalable, and customizable solution ideal for small-scale manufacturers, SMEs, and research environments. This conceptual system is intended to enhance inspection efficiency, accuracy, and traceability while promoting sustainable engineering practices. Future research would focus on developing and implementing this system, including AI-based defect classification and conducting pilot studies to validate its performance in real-world settings. This system has significant implications for SMEs in electronics manufacturing, providing an accessible, cost-effective solution to improve product quality and support the digital transformation of manufacturing operations.

Keywords: *Printed Circuit Board and Assembly, defect analysis, quality assurance inspection, Artificial Intelligence, computer vision*

Introduction

Quality assurance (QA) in Printed Circuit Board and Assembly (PCBA) production is crucial, particularly for small-scale manufacturers involved in engineering development board prototyping and low-volume batch production. The inspection process plays a vital role in determining whether a product meets quality standards, leading to its acceptance or rejection (Sundaram et. al., 2023). Large manufacturers often rely on high-speed Automated Optical Inspection (AOI) systems to detect solder defects, missing components, and polarity issues. However, such systems can be prohibitively expensive for startups and small-to-medium enterprises (SMEs). With limited resources, smaller manufacturers, especially those in low-cost labor markets, find it challenging to invest in AOI technology due to its high upfront and maintenance costs (Kerstin, 2023). As a result, many low-volume producers continue to use manual visual inspection, which, while more accessible, is labor-intensive, inconsistent, and prone to human error (Goti, 2025). Furthermore, manual inspection lacks traceability, contributing to variability in judgment (Ebayyeh et. al., 2020) and increasing the risks of product quality issues (Arumugam, 2025).

For companies like Antech Enviro Philippines, which manage both in-house and offshore PCBA production, the absence of a standardized, automated inspection process exacerbates these risks. Offshore-produced boards must undergo manual inspection before shipment, relying on softcopy images and Certificates of Compliance (COCs) for validation. Internally produced prototypes and test boards also require inspection, but the manual approach significantly slows down iteration cycles and adds operational overhead.

Despite the growing use of AI-powered visual inspection systems driven by cost reductions in embedded imaging solutions (Acuity Vision, 2025), these technologies are largely tailored for large-scale production. They often demand specialized equipment, infrastructure, and trained personnel, making them unsuitable for small-scale operations. There remains a significant gap in the development of cost-effective, portable, and scalable inspection solutions that small electronics manufacturers can adopt without the need for high-end industrial resources. This research aimed to address this gap, firstly, by providing a unique dataset of PCBA defects that sheds light on persistent quality issues in low-volume production contexts. Secondly, it introduces a sustainable, smart QA system that is both affordable and adaptable to low-volume production environments, offering a solution that enhances inspection time, accuracy, and traceability without requiring expensive infrastructure, subsequently addressing UN SDGs 9 and 12.

Methods

Research Design

This study adopted a mixed-methods approach combining quantitative analysis of defect trends with a proposed design and development of a low-cost, portable smart QA inspection system for PCBA. The quantitative part of the study was based on a six-year inspection data analysis in which recurring defects were identified, while the design part focused on conceptualizing and designing; no functional testing or performance evaluation was conducted at this stage. Instead, the study focused on system architecture, workflow design, and tool integration, laying the groundwork for future testing and validation.

Locale of the Study

This study was conducted in the Test and Development Division of Antech Enviro Philippines, an engineering solutions provider located in First Cavite Industrial Estate, Dasmarinas, Cavite. The company handles both local in-house PCBA prototyping as well as offshore production from PCBA partners. Its dual operations, characterized by small-batch and custom assemblies with varied inspection workflows, provided an ideal setting for the development and implementation of a flexible inspection system for resource-limited environments.

Research Instruments

The research utilized the following instruments:

1. Incoming and Outgoing QA Inspection Logs (2019–2024): Inspection reports from 6 PCBA partners were compiled and categorized by defect type, quantity of affected boards, and assembly method (manual, automated, semi-automated). A total of 18 defect types were analyzed.
2. Data Visualization Tools: Microsoft Excel and Microsoft Power BI were employed to prepare, analyze, and visualize the defect trends. These tools supported the creation of dynamic dashboards and trend-based insights that directly influenced system requirements and features.
3. System Design Artifacts: The design of the proposed Portable Smart Inspection System was guided by literature, trend analyses, and current manual inspection processes. Key design elements comprised of live camera mode with real-time inference and annotation; batch upload mode for image-based inspection; detection of PCBA defects using pretrained or custom YOLO; export options for JSON, CSV, annotated images, and log files; and lightweight and portable application suitable for field or office use.

Data Collection Procedure

Historical defect data spanning from 2019 to 2024 were gathered from the QA archives of Antech Enviro Philippines. Each record included year of inspection, supplier identifier (A to F), number of boards inspected, and defect counts categorized by fabrication and assembly method.

The compiled data were organized in Excel and loaded into Power BI for analysis, which allowed investigation of which defect types were most prevalent and which assembly methods were most prone to error, thus suggesting the inspection system's key features and focus areas.

Data Preprocessing and Analysis

Data cleaning and preprocessing were performed using Microsoft Excel to standardize defect categories according to fabrication and assembly type (manual, automated, or semi-auto), '1' for defect presence and '0' for absence, and normalize terminology between suppliers. Missing or ambiguous entries were reconciled through cross-checking with the original inspection forms.

Quantitative data were analyzed through trend visualization, enabling the identification of high-frequency defect types and their variations over time. Graphs, heatmaps, and dashboards were used to track annual defect rates by assembly type, prioritize defects according to their frequency and criticality, illustrate defect concentration across suppliers and years, and determine quality patterns specific to PCBA partners/suppliers

These insights contributed to the functional design of the system, emphasizing the importance of component presence checks, solder and PCB defect detection, and the provision of batch documentation support. Power BI was utilized for defect filtering and comparative analysis, which suggested the intended usability and reporting outputs of the system.

YOLO-Based Detection Model Preparation

Although the actual model training was not conducted at this stage, below is the preparation process. This includes:

1. Dataset planning and AI-powered computer vision integration using Roboflow for dataset versioning, annotation standardization (YOLO txt format), dataset augmentation (flip, rotate, brightness adjustment), train/validation, and dataset export to YOLO formats (Ahmed, 2024).
2. Image preprocessing and annotation procedures that will include capturing high-resolution top and bottom view images, annotating defects using bounding boxes, applying augmentations to simulate real-world inspection conditions, and standardizing label schemas based on defect categories (Roboflow, Inc., 2024).
3. The proposed model training configuration will include batch size, learning rate, epochs, and image size (Torres, 2024).

Ethical Considerations

All historical defect data were used with permission from Antech Enviro Philippines Inc. All data used were anonymized to ensure that neither PCBA partner names nor specific personnel were identifiable. Human participants were not involved, and no sensitive or proprietary technical designs were disclosed.

The design of the proposed system was intended to enhance the existing QA inspection process rather than replace manual inspection staff, aligning with sustainable engineering practices that emphasize human-technology collaboration.

Results and Discussion

This section presents the findings of the study, derived from the six-year (2019-2024) PCBA defect dataset collected from six PCBA partner/suppliers (A-F). The analysis aligns with the research objectives by identifying critical defect patterns, evaluating defect prevalence by assembly method, and informing the conceptualization of the proposed Portable Smart PCBA QA Inspection System. The discussion integrates literature support, interprets observed trends, and explores broader implications and applications of the results.

Key Findings from Defect Trend Analysis

An analysis of defect data revealed significant patterns that recommended the design requirements of a more sustainable and efficient inspection solution. The dataset included over 3,000 board inspections and documented 18 distinct fabrication and assembly defect types, such as uneven solder masks/plating, broken traces, scratches on boards and pads, component not installed, wrong orientation, polarity, misalignment, and tombstoning. These were classified according to their source: manual, automated, and semi-automated processes and fabrication issues. PCB fabrication cosmetic issues, including uneven/discolored solder masks, scratches on boards, and broken traces, are among the highest defect concerns. But certainly, the other PCB quality issues like exposed copper, dents on pads, and uneven plating should not be ignored, as these defects pose functionality considerations.

Assemblies with manual processes, like Manual and Semi-automated, accounted for the highest concentration of critical defects, where reliance on human inspection and manual soldering remains prevalent. By contrast, automated lines reported fewer errors but still experienced issues related to component orientation, polarity, and alignment. Moreover, there is an upward and downward trends in fabrication and assembly-related issues since the annual production output of Antech Enviro Philippines depends on the volume of orders received each year.

Microsoft Power BI was used for the visualization, which enabled the generation of the trend charts, defect frequency heatmaps, and assembly-type-specific breakdowns, which collectively supported the identification of defect patterns. These insights helped define the functional requirements for a portable, technology-driven quality assurance system designed for low-volume environments. Table 1 summarizes the number of PCB fabrication defects recorded per supplier. C, D, and A are the top 3 suppliers with the highest fabrication defects.

Table 1. Summary of Supplier PCB Fabrication Defects (2019–2024)

Supplier	Broken Traces	Expose Copper	Scratches/ Dents on Pads	Scratches on Boards	Uneven Plating	Uneven/ Discolored Solder mask	Total
C	75	57	62	78	60	76	408
D	56	71	66	69	54	67	383
A	54	46	48	46	47	60	301
E	52	30	32	46	46	45	251
F	39	30	24	48	42	48	231
B	38	45	39	38	31	36	227
Total	**314**	**279**	**271**	**325**	**280**	**332**	**1801**

Table 2 summarizes the number of PCB Assembly defects recorded per supplier. D, C, and A are the top 3 suppliers with the highest assembly defects.

Table 2. Summary of Supplier PCB Assembly Defects (2019–2024)

Supplier	Uninstalled Component	Flipped/ Inverted Component	Lacking Mechanical Screws	Misaligned Components	No Pem nuts
D	48	59	52	53	43
C	55	54	69	48	42
A	37	48	38	47	43
E	43	39	40	38	26
F	37	37	25	38	29
B	19	33	28	27	26
Total	**239**	**270**	**252**	**251**	**209**

Supplier	Shorted Pins	Tombs toning	Wrong/ Mismatched MPN	Wrong Pin1 Orientation	Wrong Polarity (+/-)	Total
D	71	80	47	81	63	653
C	64	74	41	75	60	630
A	52	61	49	52	56	522
E	56	69	40	53	57	506
F	42	47	31	48	44	415
B	47	33	31	36	34	347
	332	**364**	**239**	**345**	**314**	**3073**

Visual Analysis and Interpretation

Visual dashboards created using Power BI provided clear insights into the distribution and recurrence of defects. Figures 1 and 2 show the annual PCB fabrication and assembly defect trends from 2019 to 2024.

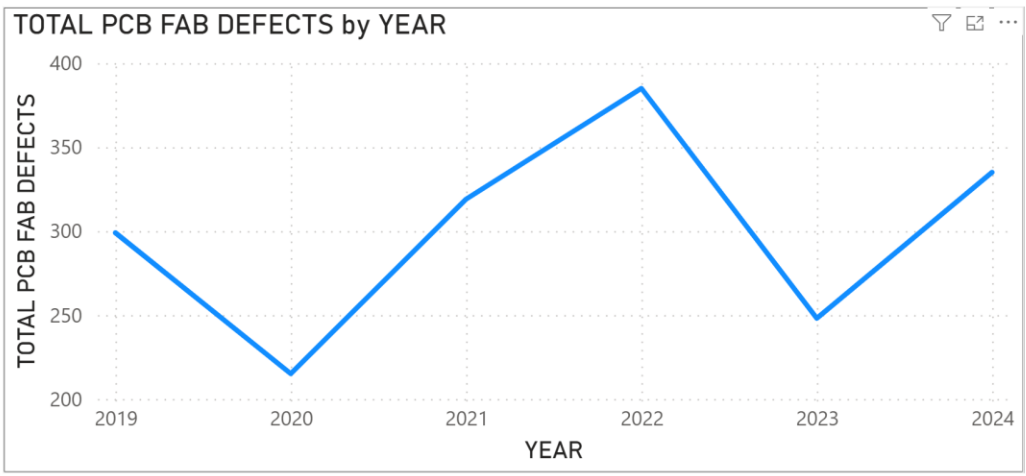

Figure 1. *PCB Fabrication Defects Trend (2019-2024)*

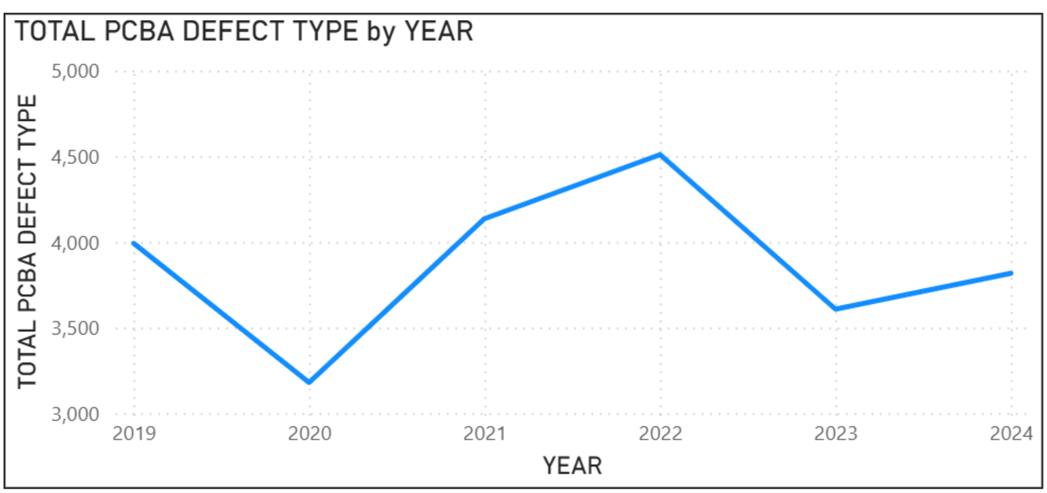

Figure 2. *PCB Assembly Defects Trend (2019-2024)*

Figure 3 shows the total PCB fabrication defect count comparison by supplier from 2019 to 2024.

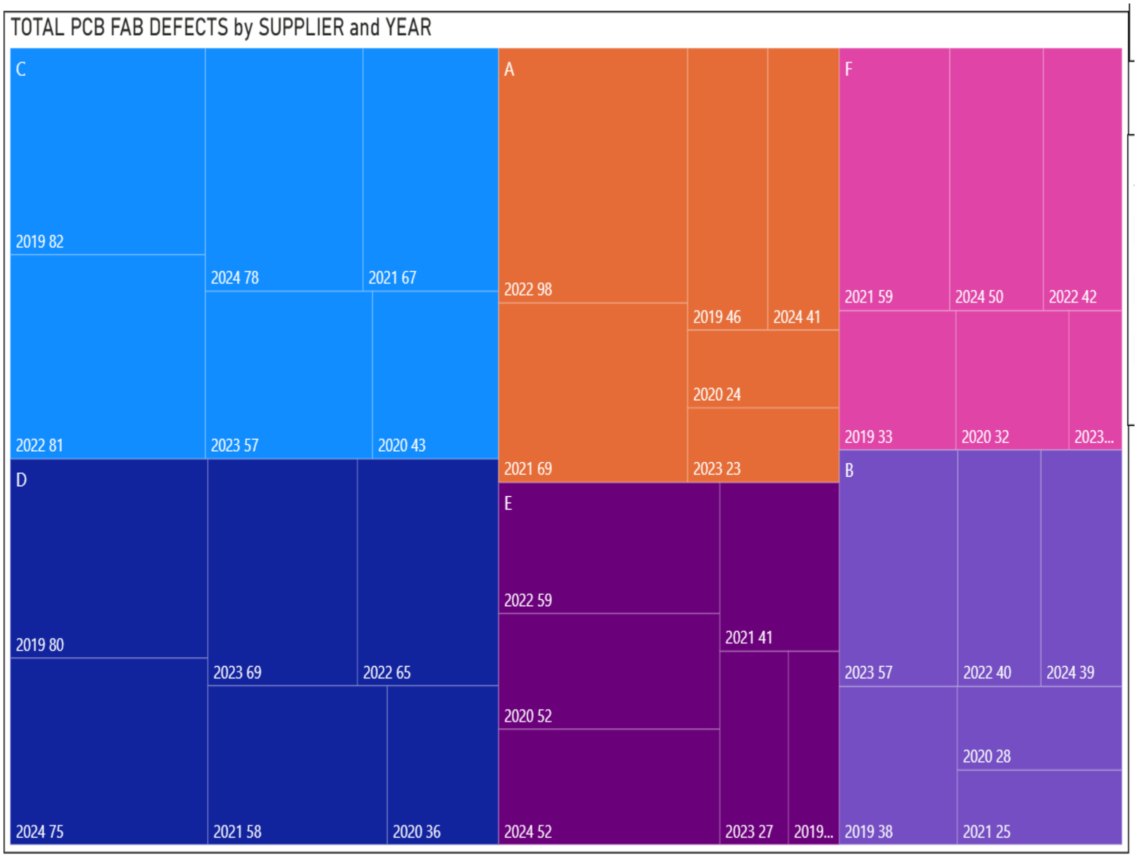

Figure 3. *PCB Fabrication Defects Supplier Comparison (2019-2024)*

Figure 4 shows the total PCB assembly defect count comparison by supplier across assembly types.

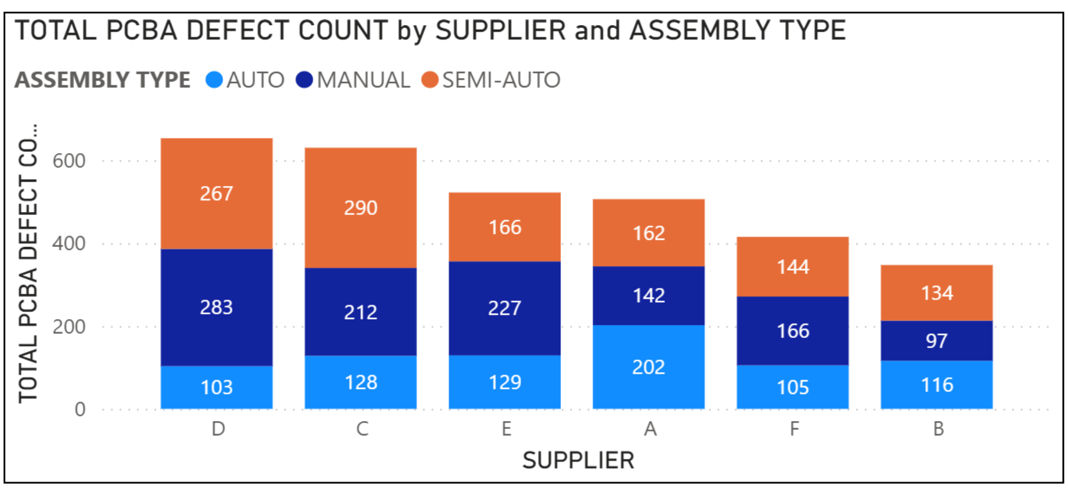

Figure 4. *PCB Assembly Defects Comparison by Supplier and Assembly Type*

Figure 5 shows which PCB fabrication defect types dominate per year.

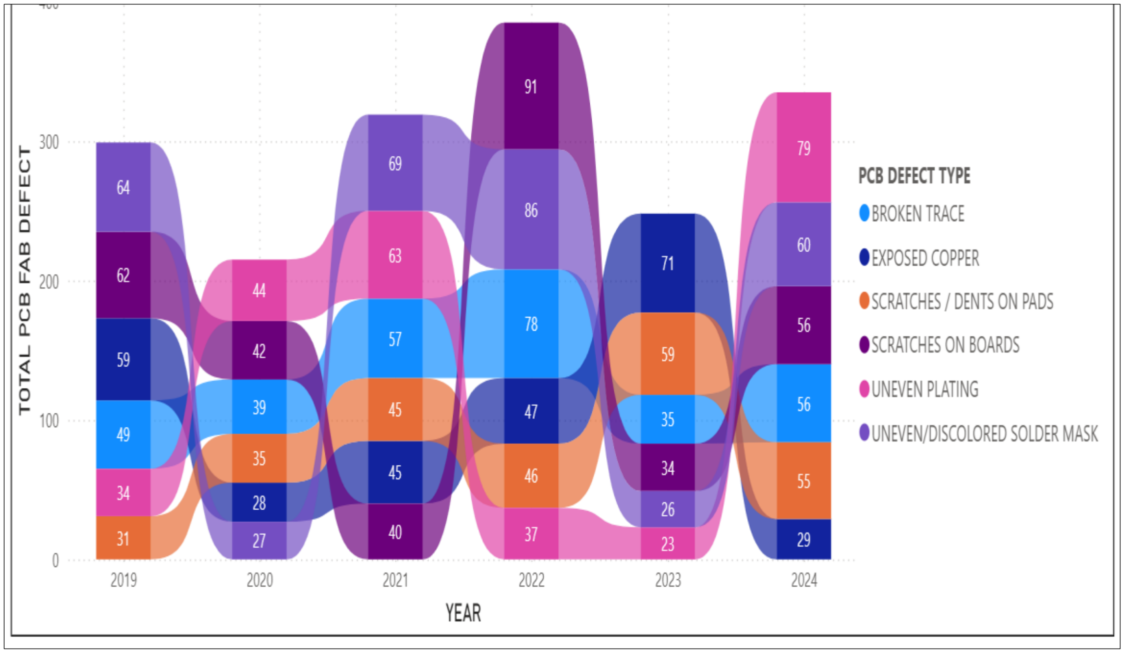

Figure 5. *PCB Fabrication Defect Types Distribution by Year*

Figure 6 shows which PCB Assembly defect types dominate per year.

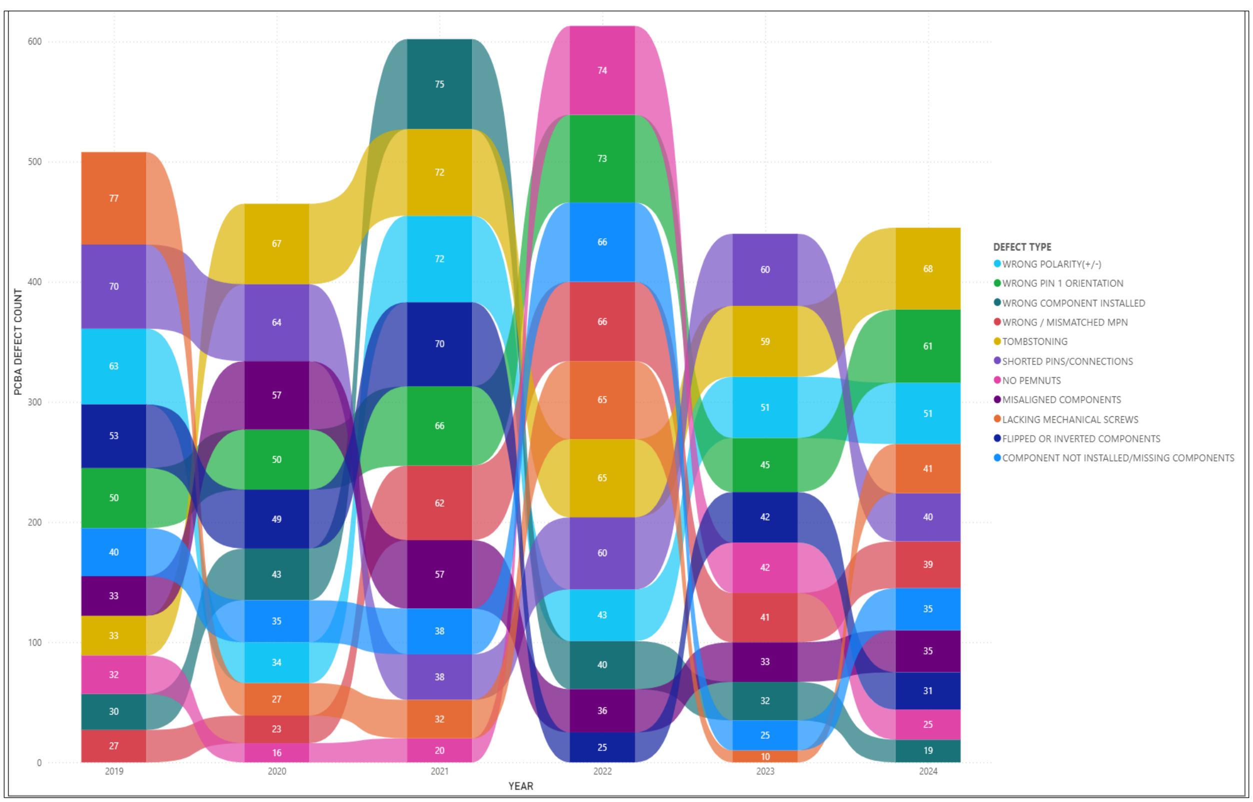

Figure 6. *PCB Assembly Defect Types Distribution by Year*

Implications of Defect Pattern Analysis for PCBA Manufacturers

The analysis implies several broader implications that directly inform quality control, process improvement, and the need for advanced inspection technologies in low-volume electronic industries. Recurring PCB fabrication concerns point to weaknesses in supplier capability and process stability, copper and surface plating, and masking treatment controls. Assembly-caused defects reveal the limitations of purely manual inspection, which is prone to fatigue, visual checking inconsistency, and limited traceability. The increasing complexity of PCBA designs suggests that visual inspection must adapt to handle smaller components, tighter tolerances, and high-density boards.

These implications align with global studies that demand digital transformation and low-cost automation in resource-constrained SMEs (Koumas et. al., 2021). Several studies, such as Modrak et al. (2025) and Park et. al. (2022), highlight the gap between high-end inspection smart manufacturing and the limited capabilities of small-scale manufacturers, further supporting the need for a portable, scalable solution.

Design Implications for the Proposed Inspection System

The observed defect trends directly influenced the architecture and features of the Portable Smart QA Inspection System. Frequent assembly defects like solder shorts, misalignment, polarity errors, and missing or uninstalled components guided the inclusion of a YOLO-based object detection model (Bandukwala et al., 2022). PCB fabrication defects, such as broken traces, uneven plating, scratches, and exposed copper, stressed the need for integration of a camera-based computer vision image capture and tagging. Variability among suppliers justified the design of a centralized logging system capable of tracking defect patterns over time, thus addressing the traceability and documentation gaps highlighted in the defect records.

Development of the Portable Smart QA Inspection System

In response to the trends identified through defect analysis, the study proposed the development of a Portable Smart QA Inspection System, which is a compact, cost-effective platform designed to augment or partially automate the visual inspection of PCBAs in small manufacturing operations. This system will be designed with sustainability, affordability, and traceability as guiding principles.

Several alternative low-cost automated inspection solutions have been explored in recent studies, like the use of Raspberry Pi microcontroller boards employed with cameras and classical computer vision methods; however, inconsistent lighting, limited image detection, and low accuracy for micro-defects have been their limitations. The proposed YOLO-based model will provide a significant performance upgrade through deep-learning (Adeyemi, 2024) feature extraction and Roboflow-assisted (AI) dataset management (Ciagla, 2022), allowing the detection of complex, non-uniform defects.

System Architecture and Components

The proposed system consists of the following core components:

- A high-resolution USB camera or microscope mounted on a foldable rig, providing adjustable focus and consistent lighting;
- A standard laptop or desktop computer, running an open-source software suite developed in Python using OpenCV for real-time image analysis and defect highlighting;

- A graphical user interface (GUI) that allows inspectors to capture board images, mark defect areas, select defect types, and automatically generate inspection reports; and
- Local file storage or optional cloud export for archiving inspection data, annotated images, and summary reports per batch or board ID.

The software is modular, allowing future upgrades to include AI-based classification, barcode/QR integration, or database connectivity.

Proposed Future Testing and Validation

To ensure system reliability and technical robustness, future evaluations will implement the following validation strategies:

1. The inspection system will undergo functional testing to ensure GUI elements, image capture, defect detection, and report generation will work correctly, user acceptance testing for QA inspectors, and stress testing to assess performance during high-volume image processing.
2. YOLO model performance validation will be evaluated using the maP (mean average Precision) for detection accuracy, precision, and recall to assess false positives or negatives, Inference speed (FPS) to confirm real-time capability, and confusion matrices to visualize detection reliability. Roboflow and YOLO training logs will assist in monitoring model metrics (Ultralytics, 2023).
3. Cross-platform validation, meaning the system will be tested on different laptops with varying CPU/GPU capabilities, different lighting conditions, different PCB types, and surface finishes.

Design Considerations and Sustainability Goals

The system was designed to address several key limitations identified during the trend analysis and stakeholder interviews:

1. Time Efficiency: Streamlines the inspection process by consolidating image capture, annotation, and documentation into a single workflow.
2. Cost Accessibility: Built entirely using off-the-shelf components and open-source tools, with an estimated cost under ₱25,000.00, making it affordable for startups, schools, and small-scale fabricators.
3. Portability: Unlike traditional AOI systems, the setup is compact and can be transported or deployed on workbenches without specialized infrastructure.
4. Documentation and Traceability: Automatically stores defect records with timestamps and image references, improving traceability and supporting continuous quality improvement initiatives.

The conceptual system supports the goals of sustainable engineering by reducing dependency on manual documentation, minimizing human error, and enabling faster identification and classification of common defect types. This aligns with broader objectives in SDG 9 (Industry, Innovation, and Infrastructure) and SDG 12 (Responsible Consumption and Production).

Relevance to Small-Scale Manufacturing

For small manufacturers who cannot afford industrial AOI systems, the proposed Portable Smart Inspection System will provide a viable alternative that scales with production volume and budget. It supports low-volume, high-mix production environments common in prototyping, product development, and academic labs, contexts where traditional automation is neither practical nor economical.

By basing the system's design on empirical defect trends, the research ensures that the tool addresses real-world inspection pain points and adapts to evolving manufacturing conditions (Adeyemi, 2024; Islam et al., 2024).

Conclusion and Future Works

This study addressed the quality assurance challenges in low-volume Printed Circuit Board Assembly (PCBA) production by analyzing defect trends from 2019 to 2024 across six suppliers. The analysis revealed critical quality concerns, including issues with pads, plating, solder mask, and assembly, particularly in boards produced with full or semi-manual processes. These findings highlight the need for more cost-effective and efficient inspection solutions for small-scale manufacturers, who often lack access to expensive Automated Optical Inspection (AOI) systems.

In response, this research proposes a Portable Smart PCBA QA Inspection System, a low-cost, modular solution designed to automate visual inspection using open-source software and readily available hardware. The system integrates image capture, real-time defect tagging, and automated report generation, offering a practical alternative to manual inspection for small-scale manufacturers where AOI systems are often cost-prohibitive.

In addition, this study establishes a foundational framework for the system's architecture, design workflow, and tool integration, which serves as a significant starting point for the development of this inspection system. To strengthen the proposed systems' technical robustness, future efforts may focus on comprehensive testing and validation, which includes system functionality evaluation, user acceptance testing to ensure QA inspectors' usability, and stress testing to assess performance during high inspection loads. The YOLO-based defect detection model may undergo performance validation using precision and recall metrics, inference speed, and confusion matrix analysis supported by Roboflow and YOLO training logs to monitor model behavior. Furthermore, a cross-platform validation can be adapted to ensure the system's robustness across different laptop hardware configurations, PCBA types, and lighting environments. These planned evaluations could provide the necessary evidence of reliability, accuracy, and scalability, paving the way for future prototyping and deployment of the system.

A key strength of the proposed system lies in its scalability and future applications. The system's modular design allows for easy customization to suit different manufacturing environments and production volumes, making it adaptable for both small and medium-sized enterprises. Future work could also focus on integrating AI-based defect classification to further enhance the system's capabilities, aligning with current trends in automated manufacturing. Such integration would enable the system to learn from inspection data, improving its accuracy and efficiency over time. Additionally, the system could be expanded to incorporate machine learning algorithms and be integrated into broader smart manufacturing ecosystems.

The findings have broad implications for the fields of electronics manufacturing, quality assurance, and sustainable engineering. The study demonstrates that low-cost, modular solutions can substantially improve inspection traceability and reduce error rates in resource-limited environments. By making quality assurance tools more accessible, the proposed system can be adopted in educational, prototyping, and startup contexts.

Future research can expand on this work by evaluating the system in a wider range of PCB technologies and integrating AI-driven defect classification (Ghelani, Trans, 2024). These advancements would not only improve both accuracy and automation capabilities but further support broader initiatives in smart manufacturing and the global transition toward Industry 4.0 (Elahi et al., 2023; Javaid et al, 2022).

Overall, this research offers a scalable and adaptable solution for enhancing quality assurance in small-scale PCBA production. By providing an affordable, efficient, and customizable tool for defect detection and reporting, the proposed system enables manufacturers to improve quality assurance processes without increasing production complexity or cost. Future applications could involve deploying the system in larger-scale production environments and other industries, helping to drive the digital transformation of quality infrastructure. Future research may also include long-term pilot studies and performance evaluation to further validate the system's effectiveness, including additional key performance indicators (KPIs) such as defect reduction rates and user feedback to assess its impact on real-world manufacturing environments.

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Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Artificial Intelligence (AI) Declaration Statement

During the preparation of this work, the authors used ChatGPT-4, OpenAI, and Google AI for initial literature review, grammar checking, and text summarization. After utilizing this service, the authors reviewed and edited the content as necessary and take full responsibility for the content of the publication, ensuring all facts and conclusions are accurate and align with the original research.