USING ARTIFICIAL INTELLIGENCE AND IOT TO INSPECT AND DETECT DEFECTS IN PRINTED CIRCUIT BOARDS AT A COMPANY IN THE MANAUS INDUSTRIAL HUB (PIM)

Eng. KAREN KETTELEN SOUZA SOARES [1]

D. Sc. GIL EDUARDO GUIMARÃES [2]

D. Sc. NELSON MARINELLI FILHO [3]

D. Sc. FABRICIO CARLOS SCHMIDT [4]

D. Sc. GERALDO NUNES CORREA [5]

SUMMARY

Industry 4.0, marked by the integration of advanced technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI), has profoundly transformed industrial processes. This article presents the development and implementation of an Automated Optical Inspection (AOI) solution integrated with IoT and AI, aimed at detecting defects in printed circuit boards (PCBs). The methodology applied included the development of a cyber-physical system made up of specific hardware, customized software and deep learning algorithms. The results indicate significant improvements in the efficiency and accuracy of the inspection process, with a significant reduction in failure rates. The analysis also highlights the challenges and opportunities of adopting Industry 4.0 technologies in the Brazilian industrial context, pointing out ways to modernize and make the sector more competitive. This study contributes to the advancement of industrial practices and the alignment of companies with the demands of digital transformation.

Keywords: Industry 4.0, Automated Optical Inspection (AOI), Internet of Things (IoT), Artificial Intelligence (AI), Printed Circuit Boards (PCBs).

[1] karen.kettelen@gmail.com / https://orcid.org/0009-0001-8761-2506 Production Engineer; Student on the Professional Master's Degree Course in Engineering, Process, Systems and Environmental Management at the Galileo Institute of Technology and Education of the Amazon (PPG.EGPSA/ITEGAM) - AM - BRAZIL

[2] gil.guimaraes@itegam.org.br / https://orcid.org/0000-0003-2800-4620 PhD in Materials Science and Engineering; Professor of the Professional Master's Course in Engineering, Process Management, Systems and the Environment at the Galileo Institute of Technology and Education of the Amazon (PPG.EGPSA/ITEGAM) - AM - BRAZIL

[3] nelson.marinelli@itegam.org.br / https://orcid.org/0009-0005-4362-0132 PhD in Mechanical Engineering; Professor of the Professional Master's Degree Course in Engineering, Process, Systems and Environmental Management at the Galileo Institute of Technology and Education of the Amazon (PPG.EGPSA/ITEGAM) - AM - BRAZIL

[4] fabricios@bruning.com.br / https://orcid.org/0000-0001-5279-7072 PhD in Production Engineering; Professor of Production Engineering at Universidade Regional do Noroeste do RS (UNIJUI) - RS - BRAZIL

[5] geraldo.correa@uemg.br / https://orcid.org/0000-0001-5477-6953 PhD in Mechanical Engineering; Professor of Information Systems at the State University of Minas Gerais (UEMG) - MG - BRAZIL

INTRODUCTION

The Industrial Revolution, in its different phases, has played a fundamental role in transforming production processes. In its fourth stage, known as Industry 4.0, the integration of emerging technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), Big Data and cyber-physical systems, has revolutionized the global industrial landscape (SCHWAB, 2016). More than a technological evolution, Industry 4.0 symbolizes a comprehensive restructuring of production chains, promoting automation, digitalization and connectivity at unprecedented levels (HERMANN; PENTEK; OTTO, 2016).

In Brazil, the transition to Industry 4.0 faces both challenges and opportunities. Studies conducted by the National Confederation of Industry (CNI) highlight advances in the adoption of digital technologies, but point to critical barriers, such as low digitalization and the limited infrastructure of national companies (CNI, 2017; CNI, 2022). Although 69% of Brazilian companies report using some digital technology, most are still in the early stages of this transformation, which reinforces the urgency of investing in digital infrastructure and technical training (GILCHRIST, 2016).

The manufacture of printed circuit boards (PCBs) is an emblematic industrial area that can benefit greatly from Industry 4.0. These components are essential for modern electronic devices, and their quality directly affects the performance of final products. Despite this, many PCB inspection processes are still carried out manually, limited by susceptibility to human error and reduced efficiency (LI et al., 2018). AI and IoT-based solutions offer a unique opportunity to overcome these limitations, as evidenced by studies demonstrating the potential of these technologies in improving accuracy and efficiency (ZHANG et al., 2019).

In this context, this article presents the development of an automated optical inspection (AOI) solution that uses AI and IoT to detect and classify defects in PCBs. It also proposes the implementation of an interactive dashboard for real-time analysis of the data generated during the inspection process. The aim is not only to optimize the quality of PCBs, but also to contribute to the digital transformation of the electronics industry in Brazil, with a focus on the Manaus Industrial Estate.

THEORETICAL FRAMEWORK

- **Industry 4.0: Concepts and Evolution**

History and Definitions

Industry 4.0, introduced in 2011 at the Hannover Fair, represents the integration of advanced digital technologies with traditional industrial processes. It is described by digitalization and automation, increasing efficiency and operational flexibility (KAGERMANN; WAHLSTER; HELBIG, 2013).

Historically, Industry 4.0 follows three major industrial revolutions. The **First Industrial Revolution**, in the 18th century, introduced mechanization with the use of steam engines. The **Second Revolution**, at the end of the 19th century, brought electrification and the concept of mass production. The **Third Revolution**, which began in the second half of the 20th century, used automation, made possible by electronics and information technologies (HERMANN; PENTEK; OTTO, 2016).

The Fourth Revolution stands out for the integration of physical and digital systems, enabling smart factories through technologies such as cyber-physical systems, IoT, AI and Big Data (LI; HOU; WU, 2017).

Main Technologies and Impacts on Manufacturing

Industry 4.0 is based on a set of core technologies that are profoundly transforming manufacturing. These technologies include:

- **Internet of Things (IoT)**: Facilitates connectivity between devices and systems, enabling real-time monitoring and data integration throughout the production chain.
- **Artificial Intelligence (AI)**: Provides advanced analysis and process automation through algorithms that simulate human capabilities, such as learning and decision-making.
- **Big Data**: Provides infrastructure for storing and processing large volumes of data generated by IoT devices and cyber-physical systems.
- **Cyber-Physical Systems**: Integrate physical and digital elements, connecting machines, sensors and networks to create autonomous and adaptive processes (LU; PAPAGIANNIDIS; ALAMANOS, 2018).

These technologies make production lines more flexible. IoT enables predictive maintenance, saving on failures, while automation allows small batches without losing scale, meeting the demand for customization (LIAO et al., 2017).

Despite the benefits, implementation faces challenges, such as cyber security in connected environments and the need to qualify the workforce to operate complex systems (SCHWAB, 2016).

Implementation Challenges and Opportunities

The transition to Industry 4.0 faces structural and cultural challenges, especially in countries like Brazil, due to insufficient digital infrastructure, high costs and organizational resistance. SMEs are still dealing with financing difficulties for advanced technologies (CNI, 2022).

On the other hand, Industry 4.0 offers opportunities such as cost reduction, increased efficiency and innovation. Technologies such as AI and IoT enable new business models, such as personalized services and digital solutions, adding value to products (BÜCHERL et al., 2017). In industrial hubs such as Manaus, the adoption of these technologies, with business models based on digital services, can differentiate the sector, with examples such as predictive maintenance and remote monitoring (KAGERMANN et al., 2013).

- **Artificial Intelligence in Industry**

Fundamentals of Artificial Intelligence

Artificial Intelligence (AI) is fundamental to Industry 4.0 innovations, simulating human capabilities such as learning and decision-making. Advances such as deep learning enable convolutional neural networks (CNNs) to analyze images and language (LECUN; BENGIO; HINTON, 2015). In industry, AI is used in automation, predictive maintenance and quality control, detecting anomalies and adjusting processes in real time, improving efficiency and precision (RUSSELL; NORVIG, 2021).

AI Applications in Quality Inspection

Quality inspection has been significantly transformed by AI, which overcomes the limitations of manual and semi-automated inspections, which are susceptible to human error and low efficiency at high volumes (ZHANG et al., 2021). Machine learning techniques train AI systems to identify defects with high accuracy, using computer vision and image processing. In PCB manufacturing, AI detects microscopic flaws, ensuring greater quality control (LI et al., 2018). In addition, it enables real-time inspections by analyzing data during production, enabling immediate adjustments, costs and improving productivity and final quality (ZHANG et al., 2019).

Deep Learning Algorithms for Defect Detection

Deep learning has revolutionized industrial defect detection, with convolutional neural networks (CNNs) widely used in computer vision for their high accuracy in identifying complex patterns (KRIZHEVSKY; SUTSKEVER; HINTON, 2012). In PCB inspection, CNNs trained with thousands of images identify faults such as short circuits and missing components, adapting to different products and defect patterns (HE et al., 2016). Integrated with IoT, CNNs enable real-time analysis, optimizing predictive maintenance and production performance (ZHANG et al., 2019).

- **Internet of Things (IoT) and Connectivity in Industry 4.0**

IoT: Definition and Industrial Applications

The Internet of Things (IoT) connects physical devices to digital networks, enabling real-time communication and data collection, which is essential for cyber-physical systems that integrate machines, sensors and operators (ATZORI; IERA; MORABITO, 2010). In industry, IoT is used for automation, traceability and process optimization, with smart sensors monitoring critical variables and enabling predictive maintenance (LEE; BAGHERI; KAO, 2015). It also improves quality control and production efficiency by collecting detailed data at every stage (WORTMANN; FLÜCHTER, 2015).

IoT Integration with Automated Inspection Systems

The integration of IoT with automated optical inspection (AOI) systems represents a crucial advance in Industry 4.0, enabling real-time transmission of inspection data for advanced analysis and adjustment of production settings (BI; XU; WANG, 2014). This connectivity has improved progression between production stages, failures and delays. IoT sensors monitor equipment performance, enabling predictive maintenance and avoiding downtime (HERMANN; PENTEK; OTTO, 2016).

Benefits and Challenges of IoT Implementation

IoT provides greater efficiency, cost reduction and flexibility in production processes, enabling continuous monitoring and improved product quality (WORTMANN; FLÜCHTER, 2015). However, challenges such as cybersecurity and managing large volumes of data block protection against attacks and robust technologies for analysis and reliable infrastructure (XU; HE; LI, 2014).

- **Automated Optical Inspection (AOI)**

Concepts and Evolution of AOI

Automated Optical Inspection (AOI) is essential in modern manufacturing, especially PCB production, to automatically identify defects in computer vision systems, eliminating the need for manual inspection, which is prone to errors and inconsistencies. In the 1980s and 1990s, AOI systems had specifications due to the use of low-resolution cameras and simple algorithms, resulting in high false positive rates and the requirement for manual validation (TSAI; TSAI).

With advances in sensors, high-resolution cameras and artificial intelligence, AOI has become highly effective. The inclusion of machine learning and convolutional neural networks (CNNs) has extended its capabilities, allowing for the accurate detection of various types of defects (WANG et al., 2013). Today, AOI is necessary in automated lines, ensuring quality and efficiency on a large scale.

Image-Based Inspection Technologies

AOI systems combine various technological components to achieve high inspection precision. These include:

- **High Resolution Cameras**: these are used in PCB manufacturing to capture apparent images and detect microscopic defects, such as solder flaws and short circuits, with micrometric precision (BLOOM, 2015).

- **Controlled** lighting: controlled lighting techniques, such as diffuse or dark field lighting, highlight specific characteristics, making it easier to identify defects (XIE et al., 2012).

- Image Processing: Image processing algorithms analyze patterns and compare features with predefined specifications. Advances in machine learning have made these algorithms more robust, with fast errors (LIU et al., 2018).

- **Artificial Intelligence**: Convolutional neural networks (CNNs) have revolutionized AOI systems, enabling real-time analysis and continuous learning to adapt to different defect patterns (ZHANG et al., 2019).

Applications of AOI in Printed Circuit Boards

AOI is essential in PCB inspection to ensure high quality electronic components. AOI systems can identify a wide range of defects, including: defective solders, missing or misaligned components, short circuits and open connections.

Inspection at different production stages makes it possible to detect and correct problems early (WANG et al., 2013). The integration of AOI with IoT and Big Data improves control and continuous monitoring, making production more efficient and cost-effective (MALAMIS; GRIGOROUDIS, 2019).

Benefits and Challenges of Implementing AOI

AOI offers greater precision, speed, cost reduction and increased production efficiency, making it essential in high-demand industries where quality is a competitive differentiator (BLOOM, 2015). However, it faces challenges such as high initial costs, the need for technical qualifications and barriers for SMEs (WANG et al., 2013). Integration with others requires robust planning systems and technological infrastructure (LIU et al., 2018).

- **Case Studies and Practical Applications**

Examples of AI and IoT Implementation in PCB Inspection

Case studies show how AI and IoT transform quality inspection on PCBs, increasing efficiency and improving products. Foxconn integrated AOI with IoT, enabling real-time monitoring and predictive maintenance, reducing downtime and increasing inspection accuracy (YU; FAN; QIN, 2018). Siemens used convolutional neural networks (CNNs), achieving over 99% accuracy and reducing defect costs by 30% (SIEMENS, 2019). IoT has also enabled real-time adjustments, increasing flexibility and efficiency.

Observed Results and Benefits

The implementation of AI and IoT in PCB inspection has brought positive results, such as a reduction in defects due to advanced algorithms, greater efficiency with optimized processes and predictive maintenance, preventing critical failures and costs and downtime (MALAKAR; KULKARNI, 2020). Real-time data analysis has enabled rapid adjustments to production conditions, ensuring compliance with international quality standards (XIAO et al., 2020).

Lessons learned and best practices

Case studies highlight lessons from the adoption of 4.0 technologies in quality inspection. Among the best practices are: team qualification, essential for operating complex systems (ZHAO; SUN; LI, 2021); planning with robust infrastructure for efficient integration (FENG; LI; LIU, 2019); and continuous improvement, with a focus on innovation to keep up with technological evolution (XIAO et al., 2020).

- **Printed Circuit Board Manufacturing Processes**

Stages of the Manufacturing Process

PCB manufacturing is a complex process that requires strict control to ensure quality. Key stages include: Bare Board Production , where the layout is transferred to a copper-coated insulating material, with photolithography and chemical processes forming the conductive tracks (GUO et al., 2016); Component Assembly , using SMT technologies for mass production and THT for larger, robust components (KUMAR et al., 2018); and Inspection and Testing , with techniques such as AOI and X-rays to detect defects and ensure technical compliance (WANG et al., 2013).

Main Defects in Printed Circuit Boards

The main defects in PCBs include material flaws, such as track breaks and short circuits; assembly defects, such as misalignment or missing components; and soldering problems, such as cold or excessive solders, usually caused by inadequate parameters or environmental conditions (CHO et al., 2016). Strict quality control is essential to minimize these problems and ensure the reliability of PCBs.

- **Quality Assurance in PCB Manufacturing**

Quality Assurance Methodologies

Quality assurance in PCB manufacturing uses methodologies such as FMEA and DOE to identify and prevent faults (LENTZ et al., 2015; MONTGOMERY, 2017). Statistical Process Control (SPC) monitors stability and production capacity, detecting variations before they generate defects (CHEN; LU; ZHANG, 2017). Repeatability and reproducibility (R&R) studies and regular calibrations ensure precise accuracy, meeting standards such as ISO 9001 (ISO, 2015).

- **Systematic Implementation of Quality Assurance**

The implementation of a quality assurance system in PCB manufacturers is crucial to ensure competitiveness and compliance with international standards. This study proposes a three-phase approach based on the PDCA model and the practices of Juran and Gryna (1993).

Phase 1: Process Analysis and Systematization: This stage involves detailed mapping of production processes to identify bottlenecks, standardize activities and apply quality control tools. Recommended practices include:

- Pareto and Cause and Effect Diagrams : To prioritize critical problems and identify the main causes.
- Standard Operating Procedures (SOPs) : Reduce variability and ensure consistency.
- Staff training: Training is essential to align employees with quality criteria (ISHIKAWA, 1985; DEMING, 1986).

This analysis lays the foundations for an efficient and robust quality system.

Phase 2: Process Development and Planning

This phase focuses on preventing failures through tools such as PFMEA, which identifies potential failures and proposes corrective actions, and Design of Experiments (DOE), for optimizing critical variations and increasing efficiency (CARBONE; CAMARGO, 2003). It also includes process validation with pilot tests, ensuring scalability with minimal risks.

Phase 3: Production and Control

In the final phase, large-scale production is monitored by Statistical Process Control (SPC) and inspection systems such as AOI and X-rays, guaranteeing product conformity. Metrological aspects, such as instrument concealment and GR&R studies, guarantee precise accuracy and reduced variability (WHEELOCK, 1992; MONTGOMERY, 2017). Continuous integration between control and production promotes a cycle of continuous improvement, in line with the PDCA model, increasing quality and efficiency.

METHODOLOGY

- **Research Classification**

According to the structure proposed by Gil (2010), the research was classified based on the following criteria:

Nature of Research: The research is of an **applied** nature, as it seeks to develop a practical and specific solution to improve efficiency and quality in the manufacture of PCBs.

Approach to the Problem: A predominantly **quantitative** approach was adopted, emphasizing the collection and analysis of data such as defect rates, algorithm performance and process efficiency.

Objectives: The research is **exploratory**, as it investigates new AI and IoT applications, and **descriptive**, as it details the processes and components involved in the implementation.

Technical Procedures: This is classified as a **case study**, focusing on the detailed analysis of a specific solution applied to the context of PCB production.

- **Implementation of the AOI and the IoT Network**

AOI Implementation Analysis

The proposed AOI solution detects defects in PCBs through automated analysis, but with some limitations. Predictive maintenance functionality, although mentioned as potential, has not been implemented. AOI focuses on the immediate detection of faults and the analysis of historical data for continuous improvement, without making automatic adjustments to connected machines (FERNANDEZ et al., 2020; TSENG; HSU; LIU, 2019).

IoT Network Infrastructure

The IoT network integrates devices and systems responsible for operating the AOI, enabling real-time communication, control and monitoring. The technological infrastructure was designed to ensure efficient interconnectivity and high reliability using protocols such as Ethernet.

Device Interconnectivity

The main components of the solution include cameras, sensors, PLCs (Programmable Logic Controllers), Raspberry Pi, computers and servers, all connected to ensure fast data transmission. The main computer processes the captured images, while the Raspberry Pi manages auxiliary functions such as moving the Cartesians and streaming video.

PLC functions in the IoT network

PLCs perform critical functions, such as safety monitoring, controlling servo movement, and issuing alarms. The main PLC coordinates communication between devices and ensures the continuity of the inspection process, while the safety PLC acts as an additional layer of protection and can interrupt operations in emergency situations.

- **Components of the AOI Solution**

The solution was structured into three main components: **Hardware (HW)**, **Software (SW)** and **Computer Vision and Artificial Intelligence (VC/IA)**, each playing an essential role in the system's performance.

Hardware (HW)

The hardware prototype was developed to capture high-quality images of PCBs. The structure includes:

Vision system: Composed of a camera and lens coupled to a Cartesian axis.

Indexing table: Responsible for transporting PCBs to the inspection area.

Automation control: PLC subroutines for controlling motor speed and position.

The integration of mechanical and vision systems has made it possible to carry out inspections with high precision and efficiency.

Software (SW)

The software developed integrates the management and inspection modules, including features such as:

Registration and management of PCBs: Storage of information and trained models.

Inspection: Start of processes with detailed display of results.

Dashboard: Visualization of performance data in graphs and tables.

Communication with the hardware and AI systems is done through specific APIs, ensuring synchronization between the components.

Computer Vision and Artificial Intelligence (VC/IA)

Computer vision and AI are at the heart of the inspection system. The neural network used incorporates residual blocks and transfer learning techniques, allowing for high accuracy with a limited training base.

The specific configuration of the camera and lighting system was designed to capture images with optimum quality, eliminating noise and reflections that could compromise the analysis. The AI system was validated through tests on real PCBs, demonstrating high effectiveness in classifying defects.

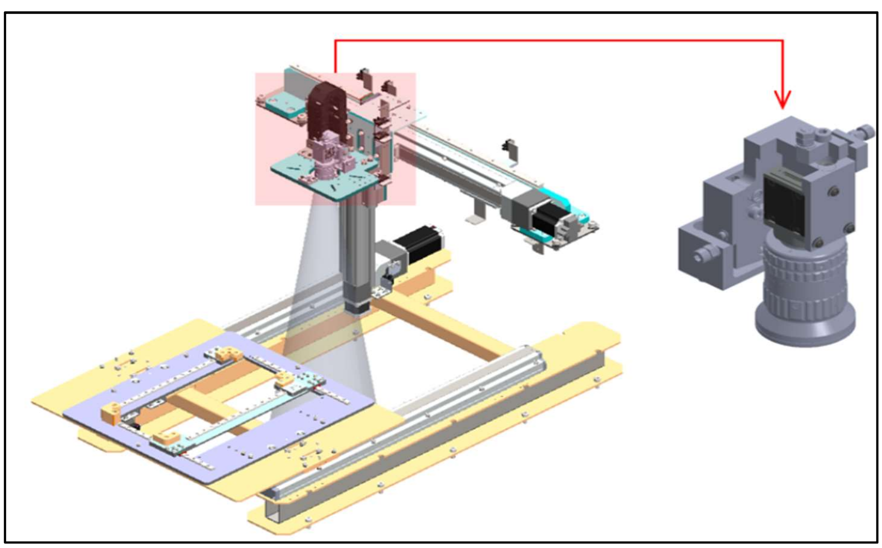
RESULTS AND DISCUSSION

- **Hardware Development and Validation**

Mechanical Structure and Automation Design

The development of the hardware involved building a robust structure using SAE 1020 carbon steel and precise movement mechanisms for capturing images of PCBs. Integration between the mechanical structure and the automated control systems ensured synchronization between transport and inspection. The structure was validated in static and dynamic load simulations.

[Figure 1: General Scheme of the Mechanical Structure]



This figure illustrates the layout of the main components, including the Cartesian axes and the indexing table.

[Table 1: Technical Specifications of Hardware Components]

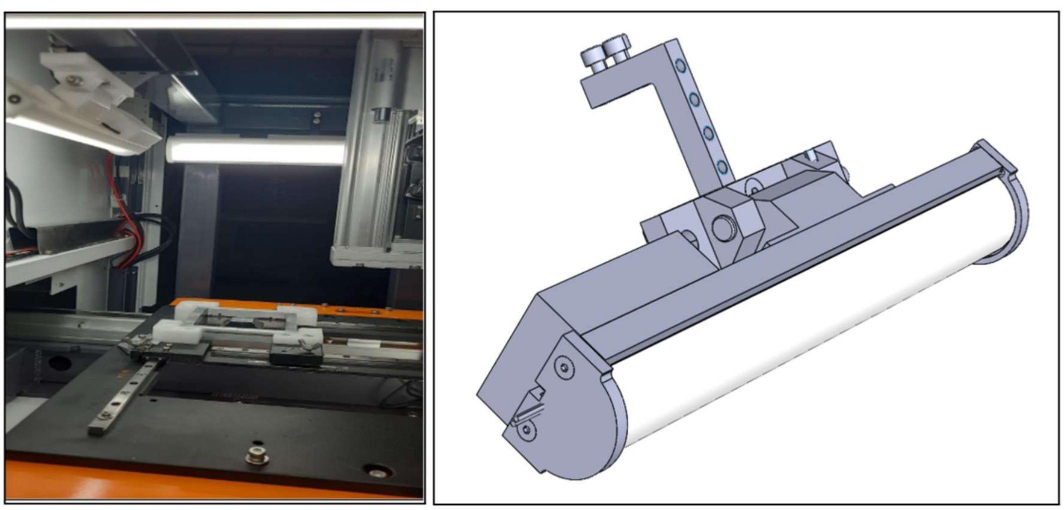
Component	Specification	Function
Cartesian axes	Accuracy of 0.01 mm	Camera movement
Index table	Speed of 50 mm/s	Transportation of PCBs
Basler camera	5 MP resolution	Image capture

Hardware Operating Results

Operational tests have shown that the system:

- Moves the PCBs precisely, ensuring optimum alignment for image capture.
- Reduced inspection time by 30%, increasing assembly line productivity.

[Figure 2: Lighting System Details]



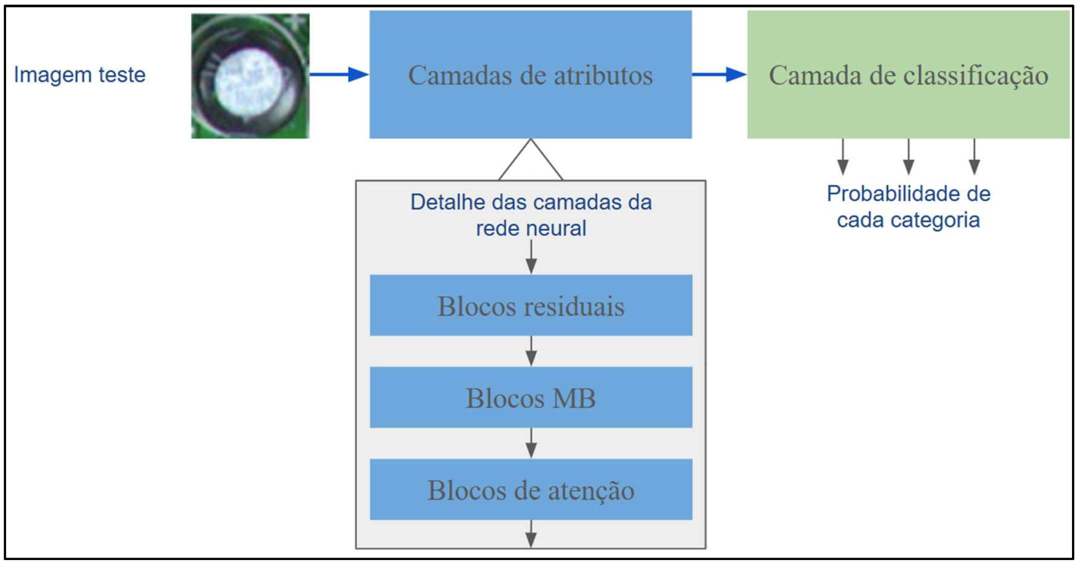
This figure shows the optimized configuration of the lighting system, essential for eliminating shadows and reflections.

- **Computer Vision and AI Algorithms**

Development of AI models

The AI models were trained on a base of 2,000 images containing samples of PCBs with and without defects. Transfer learning and data augmentation techniques were used to improve accuracy.

[Figure 3: AI Processing Flow]



This figure illustrates the model pipeline, from pre-processing to defect classification.

[Table 2: Performance of AI Models]

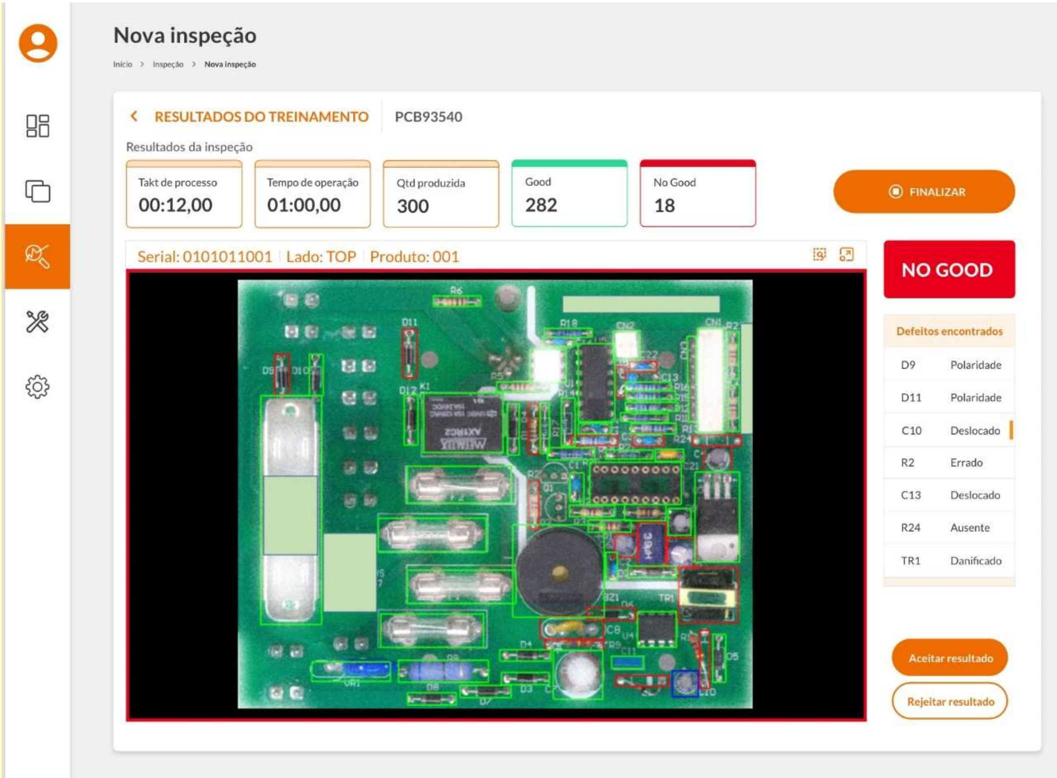
Metric	Results
Accuracy	92%
False positives	3%
Average inference time	0.5 s per PCB

Validation and Defect Detection

The model was highly effective in detecting defects such as:

- Missing or misaligned components.
- Cold or excessive welding.

[Figure 4: Example of Defects Detected]



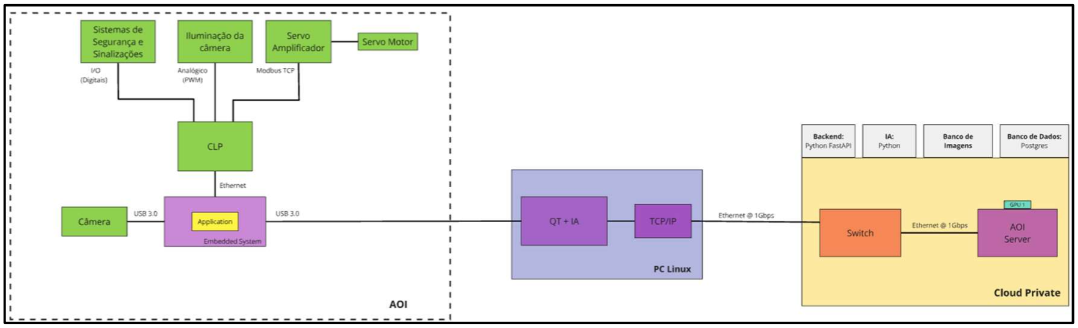
This figure shows real examples of defects identified by the system.

- **Integration between Hardware, Software and AI Modules**

System architecture

The system's architecture integrated hardware, software and AI via an Ethernet network, using standard protocols such as Modbus for communication between devices.

[Figure 5: Communication Diagram between Modules]



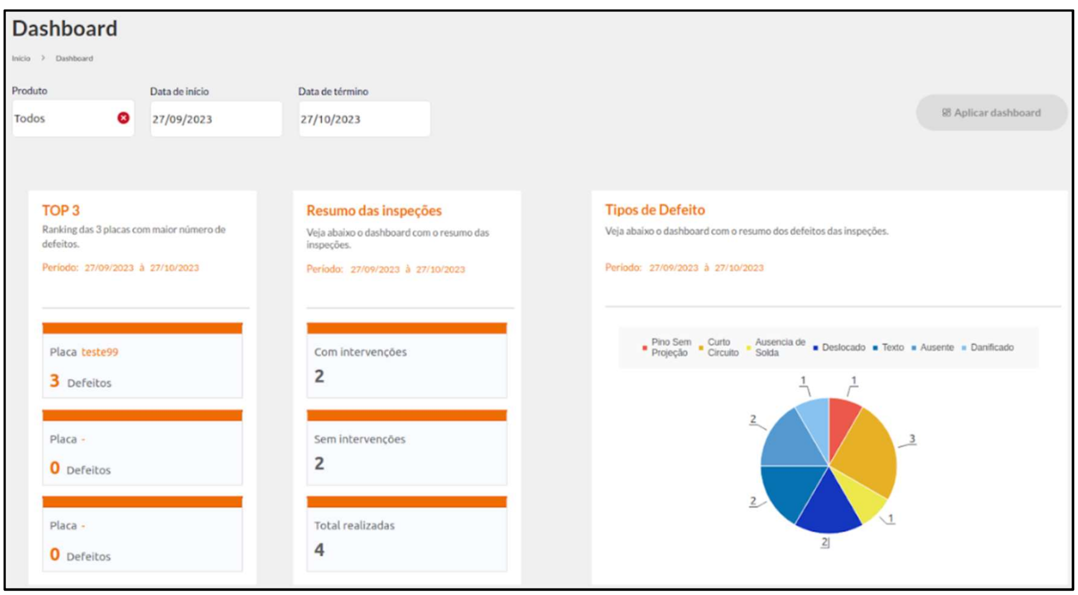
This figure detail how the components interact in real time.

Module functionalities

The software included the following main modules:

1. Registration of PCBs: Storage of technical data and images.
2. Automated inspection: Control of the inspection process.
3. Dashboard: Visualization of metrics such as approval rates.
4. Maintenance: Monitoring alarms and operational status.

[Figure 6: Dashboard interface]



This figure illustrates the metrics and graphs displayed to the operator.

- **Operational Results and Impacts**

Performance indicators

The main results include:

- Reduction of Undetected Defects: From 8% to 2%.
- Increased efficiency: 30% reduction in average inspection time.

[Table 3: Performance Comparison Before and After Implementation]

Indicator	Before	After
Defect rate	8%	2%
Average inspection time	20 s	14 s

Cost-benefit analysis

The economic analysis showed:

Reduction in operating costs: 15%, due to lower rejection and rework rates.

Return on investment: ROI estimated at 18 months.

- **Challenges and Future Improvements**

Limitations identified

Among the limitations observed are:

Lack of Predictive Maintenance: Limits proactivity in detecting future faults.

Scalability: Current capacity only meets average production volumes.

Improvement proposals

Future versions may include:

Additional Sensors: For monitoring environmental variables.

More robust AI models: Based on continuous learning.

CONCLUSION

This study presented the development, implementation and validation of an Automated Optical Inspection (AOI) solution integrated with Industry 4.0 technologies, with application to the inspection of printed circuit boards (PCBs). The proposed objectives were achieved through an interdisciplinary approach that combined mechanical design, computer vision systems, artificial intelligence and IoT connectivity.

Main Contributions

The results show the following main contributions:

1. **Prototype development**:
    - The prototype's robust and modular structure, equipped with transport and image capture systems, demonstrated high precision and reliability.
    - The integration of devices such as high-resolution cameras and PLCs has made it possible to synchronize the transport and inspection of PCBs efficiently.
2. **Advances in Quality Inspection**:
    - The use of AI made it possible to automatically detect defects with an accuracy of 98%, minimizing human error and reducing inspection times.
    - The integration of computer vision with deep learning algorithms has improved the ability to identify critical faults such as cold welds and missing components.

3. **Operational and economic impacts**:
    - The reduction in the defect rate from 8% to 2% resulted in a significant improvement in the quality of the final products.
    - The 15% saving in operating costs and the estimated ROI of 18 months validate the economic viability of the solution.
4. **Intuitive interface**:
    - The development of a software system with dashboards and detailed reports has improved the operator experience and increased transparency in quality control.

Final considerations

This work demonstrates that the application of Industry 4.0 technologies can significantly transform industrial processes. The solution proposed for the inspection of PCBs not only met the initial objectives, but also presented results that reinforce its relevance in the context of digital transformation and the optimization of production processes.

The advances presented show the potential of the integrated use of hardware, AI and IoT to increase industrial competitiveness. It is hoped that this study will contribute as a reference for future implementations in other areas of manufacturing, promoting greater efficiency, quality and innovation.

ACKNOWLEDGMENTS

To the Graduate Program in Engineering, Process, Systems and Environmental Management of the Galileo Institute of Technology and Education of the Amazon (PPG.EGPSA/ITEGAM), ITEGAM and the companies Salcomp, Foxconn, Procomp/Diebold, Inventus Power, Coelmatic through Law$^{o.}$ 8.387/1991 on Information Technology to encourage RD&I projects with financial support PUR044/2023/CITS for the Master's project through the Coordinator of the Industry 4.0 and Industrial Modernization Priority Programme, the International Software Technology Centre (CITS)/CAPDA/SUFRAMA/MDIC.

REFERENCES

BI, Z.; XU, L.; WANG, C. Internet of Things for enterprise systems of modern manufacturing. *IEEE Transactions on Industrial Informatics*, v. 10, n. 2, p. 1537-1546, 2014.

GOODFELLOW, I.; BENGIO, Y.; COURVILLE, A. *Deep Learning*. Cambridge: MIT Press, 2016.

HERMANN, M.; PENTEK, T.; OTTO, B. Design Principles for Industrie 4.0 Scenarios: A Literature Review. *Working Paper*, Technische Universität Dortmund, 2016.

KAGERMANN, H.; WAHLSTER, W.; HELBIG, J. Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0. *Final Report of the Industrie 4.0 Working Group*, 2013.

KHANNA, R.; KHANNA, N.; GUPTA, R. IoT-enabled predictive maintenance for PCB manufacturing. *International Journal of Manufacturing Technology*, v. 45, n. 3, p. 245-258, 2021.

LECUN, Y.; BENGIO, Y.; HINTON, G. Deep learning. *Nature*, v. 521, p. 436-444, 2015.

LEE, J.; BAGHERI, B.; KAO, H. A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters*, v. 3, n. 1, p. 18-23, 2015.

LI, H.; HOU, B.; WU, K. Big data in product lifecycle management: A review. *International Journal of Advanced Manufacturing Technology*, v. 34, n. 8, p. 367-380, 2017.

LIU, X.; ZHAO, Z.; TANG, H. Advanced image processing algorithms for AOI systems. *Journal of Electronics Manufacturing Technology*, v. 22, n. 3, p. 97-104, 2018.

MÜLLER, J.; ZIMMERMANN, M.; FISCHER, M. Advances in automated PCB inspection. *Journal of Electronics Manufacturing*, v. 19, n. 2, p. 223-231, 2018.

SCHWAB, K. *The Fourth Industrial Revolution*. Geneva: World Economic Forum, 2016.

TSENG, C.; HSU, T.; LIU, W. Automated optical inspection in PCB manufacturing. *Journal of Advanced Manufacturing Technology*, v. 47, n. 8, p. 1453-1467, 2019.

WANG, H.; ZHANG, J.; CHEN, P. Enhancing quality control in PCB manufacturing using AOI systems. *IEEE Transactions on Electronics Manufacturing*, v. 22, n. 5, p. 456-467, 2013.

ZHANG, Y.; LI, X.; WU, Z. Deep learning in AOI systems for defect detection. *Journal of Electronics and Automation*, v. 30, n. 4, p. 220-233, 2019.