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APPLICATION OF ARTIFICIAL INTELLIGENCE AND IOT TECHNOLOGIES IN THE MODERNIZATION OF PRINTED CIRCUIT BOARD INSPECTION: A STUDY IN THE INDUSTRIAL POLE OF MANAUS

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Karen Kettelen Souza Soares[1], Gil Eduardo Guimarães[2], Nelson Marinelli Filho[3], Fabricio Carlos Schmidt[4] and Geraldo Nunes Correa[5]

ABSTRACT

The digital transformation driven by Industry 4.0 has fostered the integration of technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) to revolutionize industrial processes. This study presents the development of an innovative Automated Optical Inspection (AOI) solution, which combines deep learning algorithms, IoT, and cyber-physical systems to identify and classify defects in printed circuit boards (PCBs). The methodology covered the design of dedicated hardware, specialized software, and the creation of an interactive dashboard for real-time visualization of inspection data. The results demonstrated significant advances in process efficiency and accuracy, as well as a notable reduction in failure rates. This work reinforces the potential of adopting Industry 4.0

[1] Production Engineer
Student of the Professional Master's Degree in Engineering, Process Management, Systems and Environmental at the Galileo Institute of Technology and Education of the Amazon (PPG. EGPSA/ITEGAM) – AM – BRAZIL
E-mail: karen.kettelen@gmail.com
ORCID: https://orcid.org/0009-0001-8761-2506
[2] D. Sc.
PhD in Materials Science and Engineering
Professor of the Professional Master's Degree in Engineering, Process Management, Systems and Environmental at the Galileo Institute of Technology and Education of the Amazon (PPG. EGPSA/ITEGAM) – AM – BRAZIL
E-mail: gil.guimaraes@itegam.org.br
ORCID: https://orcid.org/0000-0003-2800-4620
[3] D. Sc.
Dr. in Mechanical Engineering
Professor of the Professional Master's Degree in Engineering, Process Management, Systems and Environmental at the Galileo Institute of Technology and Education of the Amazon (PPG. EGPSA/ITEGAM) – AM – BRAZIL
E-mail: nelson.marinelli@itegam.org.br
ORCID: https://orcid.org/0009-0005-4362-0132
[4] D. Sc.
Dr. in Production Engineering
Professor of the Production Engineering Course at the Regional University of the Northwest of RS (UNIJUI) – RS – BRAZIL
E-mail: fabricios@bruning.com.br
ORCID: https://orcid.org/0000-0001-5279-7072
[5] D. Sc.
Dr. in Mechanical Engineering
Professor of the Information Systems Course at the State University of Minas Gerais (UEMG) - MG - BRAZIL
Email: geraldo.correa@uemg.br
ORCID: https://orcid.org/0000-0001-5477-6953

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technologies for the modernization of the Brazilian electronics industry, especially in the Manaus Industrial Pole, highlighting competitive benefits and ways to overcome technological challenges in the sector.

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

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INTRODUCTION

The Industrial Revolution, in its different phases, has played a fundamental role in the transformation of 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 scenario (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 the use of some digital technology, most are still in the early stages of this transformation, which reinforces the urgency of investments in digital infrastructure and technical training (GILCHRIST, 2016).

Printed circuit board (PCB) manufacturing is a flagship industrial area that can largely benefit 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 performed 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 paper presents the development of an automated optical inspection (AOI) solution that uses AI and IoT to detect and classify defects in PCBs. In addition, it is proposed to implement an interactive dashboard for real-time analysis of the data generated during the inspection process. The goal 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 Pole.

THEORETICAL FRAMEWORK

INDUSTRY 4.0: CONCEPTS AND EVOLUTION

History and Definitions

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

Historically, Industry 4.0 has followed three major industrial revolutions. The **First Industrial Revolution**, in the eighteenth century, introduced mechanization with the use of steam engines. The **Second Revolution**, at the end of the nineteenth century, brought electrification and the concept of mass production. The **Third Revolution**, which began in the second half of the twentieth 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).

Key Technologies and Impacts on Manufacturing

Industry 4.0 is based on a set of core technologies that profoundly transform manufacturing. Among these technologies are:

- **Internet of Things (IoT):** Facilitates connectivity between devices and systems, allowing real-time monitoring and data integration throughout the production chain.
- **Artificial Intelligence (AI):** Provides advanced analytics and process automation through algorithms that simulate human capabilities, such as learning and decision-making.
- **Big Data**: Provides infrastructure for the storage and processing of 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).

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These technologies make production lines more flexible. IoT enables predictive maintenance, with failure savings, 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 cybersecurity in connected environments and the need to skill the workforce to operate complex systems (SCHWAB, 2016).

Challenges and Opportunities in Implementation

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 still deal 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 key to Industry 4.0 innovations, simulating human capabilities such as learning and decision-making. Advances such as deep learning enable convolutional neural networks (CNNs) for image and language analysis (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 accuracy (RUSSELL; NORVIG, 2021).

Applications of AI 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 in large volumes (ZHANG et al., 2021). Machine learning techniques train AI systems to identify defects with high accuracy, utilizing computer vision

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and image processing. In PCB manufacturing, AI detects microscopic flaws, ensuring greater quality control (LI et al., 2018). In addition, it allows for real-time inspections, 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 the detection of industrial defects, 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 (H.E. et al., 2016). Integrated with IoT, CNNs enable real-time analysis, optimizing predictive maintenance and productive performance (ZHANG et al., 2019).

INTERNET OF THINGS (IOT) AND CONNECTIVITY IN INDUSTRY 4.0

IoT: Industrial Definition and Applications

The Internet of Things (IoT) connects physical devices to digital networks, enabling real-time communication and data collection, 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). In addition, it improves quality control and production efficiency by collecting detailed data at all stages (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 the real-time transmission of inspection data for advanced analysis and adjustment of production settings (BI; XU; WANG, 2014). This connectivity has improved the progression between production steps, failures, and delays. IoT sensors monitor equipment performance, enabling predictive maintenance and avoiding downtime (HERMANN; PENTEK; OTTO, 2016).

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Benefits and Challenges of IoT Implementation

IoT provides greater efficiency, cost reduction and flexibility in production processes, allowing continuous monitoring and improvement in product quality (WORTMANN; FLÜCHTER, 2015). However, challenges such as cybersecurity and managing large volumes of data block protection against attacks and robust technologies for analytics 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 in 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 manual validation requirement (TSAI; TSAI; TSAI).

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

Image-Based Inspection Technologies

AOI systems combine several technological components to achieve high inspection accuracy. Among them, the following stand out:

- **High-Resolution Cameras**: are used in the manufacture of PCBs to capture apparent images and detect microscopic defects, such as solder flaws and short circuits, with micrometric accuracy (BLOOM, 2015).
- **Controlled Lighting**: Controlled lighting techniques, such as diffuse or darkfield lighting, highlight specific features, making it easier to identify defects (XIE et al., 2012).
- **Image Processing**: Image processing algorithms analyze patterns and compare features to pre-defined specifications. Advances in machine learning have led to these algorithms being more robust, with rapid errors (LIU et al., 2018).

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

Applications of AOI in Printed Circuit Boards

AOI is essential in inspecting PCBs to ensure high quality in electronic components. AOI systems can identify a wide range of defects, including: Faulty welds, Missing or misaligned components, Short circuits, and Open connections.

Inspection at different production stages allows for early detection and correction of problems (WANG et al., 2013). The integration of AOI with IoT and Big Data enhances continuous control and monitoring, making production more efficient and cost-effective (MALAMIS; GRIGOROUDIS, 2019).

Benefits and Challenges of AOI Implementation

AOI offers greater precision, speed, cost reduction and increased production efficiency, being essential in high-demand industries, where quality is a competitive advantage (BLOOM, 2015). However, facing challenges such as high initial costs, the need for technical qualification and barriers for SMEs (WANG et al., 2013). Integration with others requires planning systems and robust 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, decreasing downtime and increasing inspection accuracy (YU; FAN; QIN, 2018). Siemens, on the other hand, used convolutional neural networks (CNNs), achieving more than 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 reduced defects due to advanced algorithms, increased efficiency with optimized

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processes, and predictive maintenance, preventing critical failures and costs and downtime (MALAKAR; KULKARNI, 2020). Real-time data analysis allowed for quick adjustments to production conditions, ensuring compliance with international quality standards (XIAO et al., 2020).

Lessons Learned and Best Practices

Case studies highlight lessons from adopting 4.0 technologies in quality inspection. Among the best practices are: team qualification, essential to operate complex systems (ZHAO; SUN; LI, 2021); planning with robust infrastructure for efficient integration (FENG; READ; 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

Manufacturing Process Steps

PCB manufacturing is a complex process that requires strict control to ensure quality. Among the main stages are: Production of the Bare Plate, 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 and 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).

Major Defects in Printed Circuit Boards

Major defects in PCBs include material flaws such as track breaks and short circuits; defects in assembly, such as misalignments or missing components; and welding problems, such as cold or over-welds, often caused by improper parameters or environmental conditions (CHO et al., 2016). Strict quality control is essential to minimize these issues 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 failures (LENTZ et al., 2015; MONTGOMERY, 2017). Statistical

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Process Control (SPC) monitors stability and production capacity, detecting variations before generating defects (CHEN; LU; ZHANG, 2017). Repeatability and Reproducibility (GR&R) studies and regular calibrations ensure accurate accuracy, meeting standards such as ISO 9001 (ISO, 2015).

Systematic for the Implementation of Quality Assurance

Deploying 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: Analysis and Systematization of Processes

This stage involves the detailed mapping of production processes to identify bottlenecks, standardize activities, and apply quality control tools. Best practices include:

- Pareto Diagram and Cause and Effect: To prioritize critical issues and identify root causes.
- Standard Operating Procedures (SOPs): Reduce variability and ensure consistency.
- Team Training: Training is essential to align employees with quality criteria (ISHIKAWA, 1985; DEMING, 1986).

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

Phase 2: Process Development and Planning

This phase focuses on failure prevention through tools such as PFMEA, which identifies potential failures and proposes corrective actions, and Design of Experiments (DOE), to optimize critical variations and increase efficiency (CARBONE; CAMARGO, 2003; It also includes process validation with pilot trials, ensuring scalability with minimal risk

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, ensuring product compliance. Metrological aspects, such as instrument concealment and GR&R studies, ensure accurate accuracy and reduced variability (WHEELOCK, 1992; MONTGOMERY, 2017). The

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continuous integration between control and production promotes a cycle of continuous improvement, aligned with the PDCA model, raising 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**: Research is applied in nature, as it seeks to develop a practical and specific solution to improve efficiency and quality in PCB manufacturing.
- **Problem Approach**: 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 applications of AI and IoT, and **descriptive**, as it details the processes and components involved in the implementation.
- **Technical Procedures**: It is classified as a **case study**, centered on the detailed analysis of a specific solution applied to the context of PCB production.

IMPLEMENTATION OF AOI AND IOT NETWORK

AOI Implementation Analysis

The proposed AOI solution detects defects in PCBs through automated analysis, but with some limitations. The predictive maintenance functionality, although mentioned as potential, was not implemented. AOI focuses on immediate fault detection and analysis of historical data for continuous improvement, without performing 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 the operation of AOI, allowing real-time communication, control, and monitoring. The technological infrastructure is designed to ensure efficient interconnectivity and high reliability through protocols such as Ethernet.

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Interconnectivity of Devices

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 performs the processing of the captured images, while the Raspberry Pi manages auxiliary functions, such as moving the Cartesians and streaming video.

Functions of PLCs in the IoT Network

PLCs perform critical functions such as safety monitoring, servo motion control, and alarm output. 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, being able to interrupt operations in emergency situations.

AOI Solution Components

The solution was structured into three main components: **Hardware (HW), Software (SW),** and **Computer Vision and Artificial Intelligence (VC/AI),** 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 framework includes:

- **Vision system**: Composed of camera and lens coupled to a Cartesian axis.
- **Indexing table**: Responsible for transporting PCBs to the inspection area.
- **Automation control**: Subroutines in the PLC to control the speed and position of the motors.

The integration of mechanical and vision systems allowed inspections to be carried out 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**: Initiation 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 components.

Computer Vision and Artificial Intelligence (VC/AI)

Computer Vision and AI are the cores 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 camera and lighting system configuration is designed to capture images with optimal quality, eliminating noise and reflections that could compromise analysis. The AI system was validated through tests with real PCBs, demonstrating high effectiveness in defect classification.

RESULTS AND DISCUSSION

HARDWARE DEVELOPMENT AND VALIDATION

Mechanical Structure and Automation Design

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

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[Figure 1: General Scheme of the Mechanical Structure]

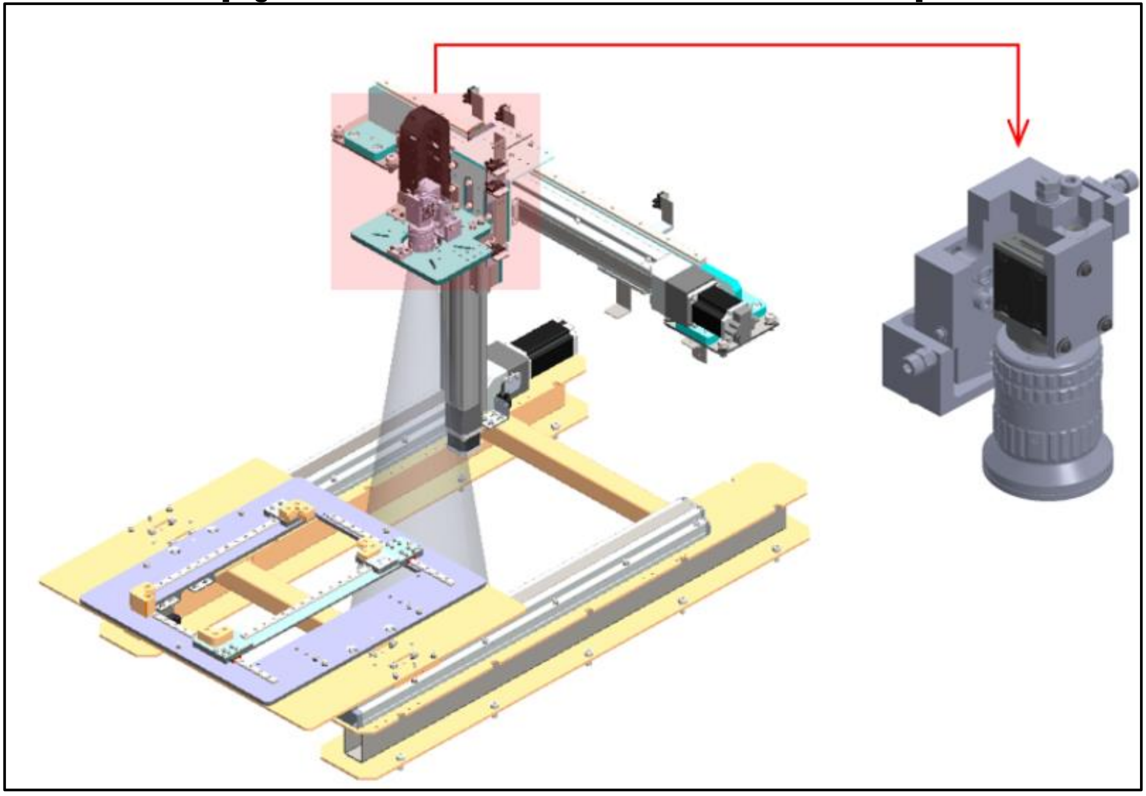

Figure 01 illustrates the arrangement of the main components, including the Cartesian axes and the indexing table.

[Table 1: Technical Specifications of Hardware Components]

Component	Specification	Function
Cartesian axes	Accuracy of 0.01 mm	Camera movement
Indexing table	Speed 50 mm/s	PCB Transport
Câmera Basler	5 MP resolution	Image Capture

Hardware Operating Results

Operational tests have shown that the system:

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

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[Figure 2: Lighting System Details]

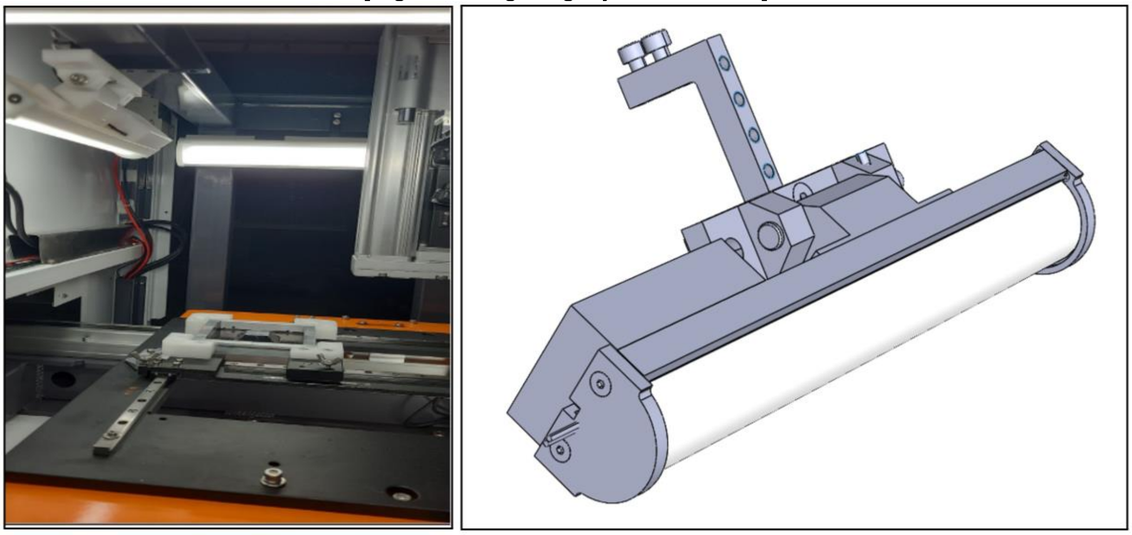

Figure 02 shows the optimized configuration of the lighting system, which is essential for eliminating shadows and reflections.

Computer Vision and AI Algorithms

Development of AI Models

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

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[Table 2: Performance of AI Models]

Metric	Result
Accuracy	92%
False-positives	3%
Mean time to inference	0.5 s per PCB

[Figure 3: AI Processing **Flow]**

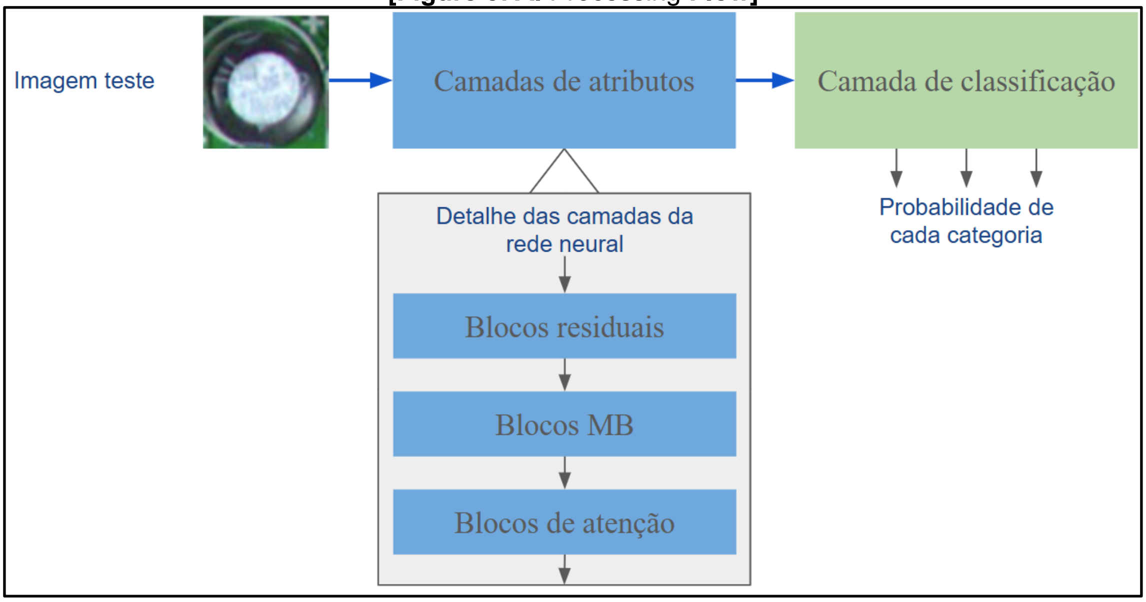

Figure 03 illustrates the model pipeline, from pre-processing to defect classification.

Validation and Defect Detection

The model showed high efficacy in detecting defects, such as:

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

Figure 04 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 through an Ethernet network, utilizing standard protocols such as Modbus for communication between devices.

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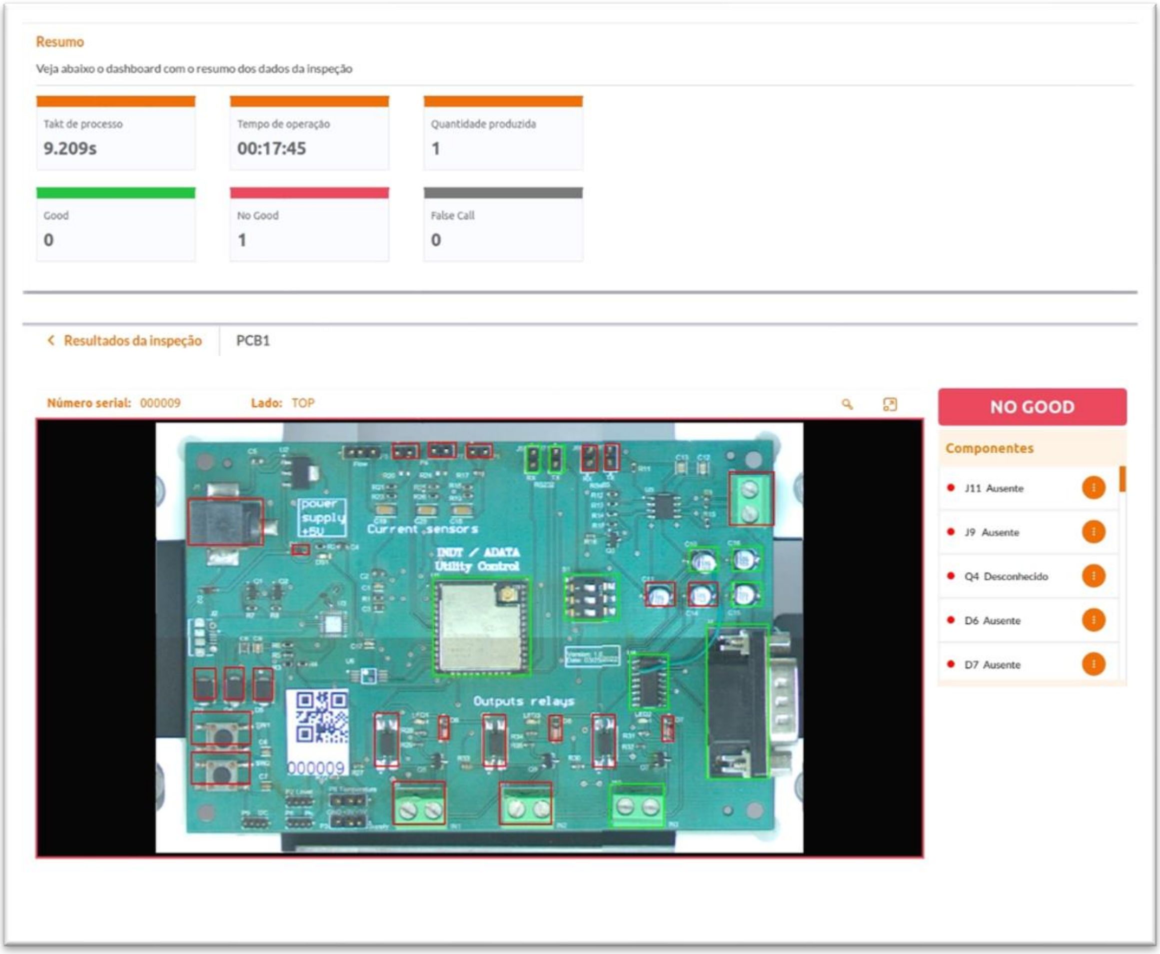
[Figure 4: Example of Defects Detected]



[Figure 5: Communication Diagram between Modules]

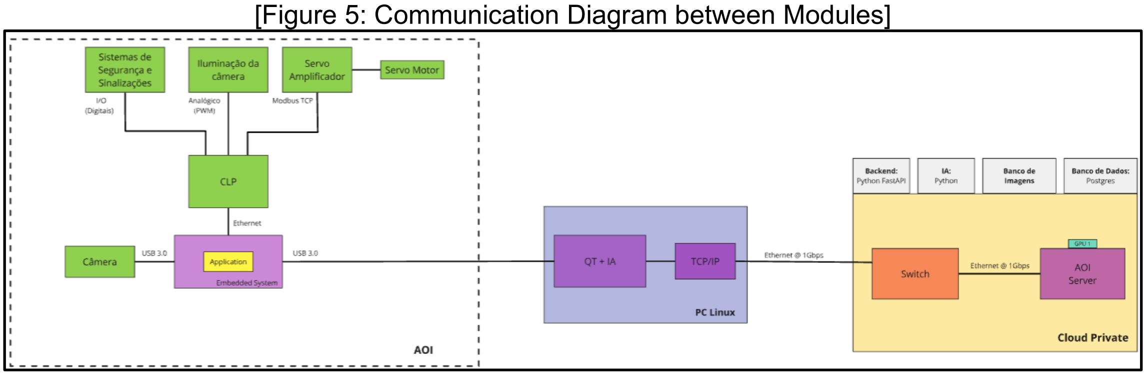


Figure 05 details how the components interact in real time.

Functionalities of two Modules

The software included the following core modules:

1. PCB Registration: Storage of technical data and images.
2. Automated Inspection: Control of the inspection process.

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3. Dashboard: Visualization of metrics, such as approval rates.
4. Maintenance: Monitoring of alarms and operational status.

[Figure 6: Dashboard Interface]

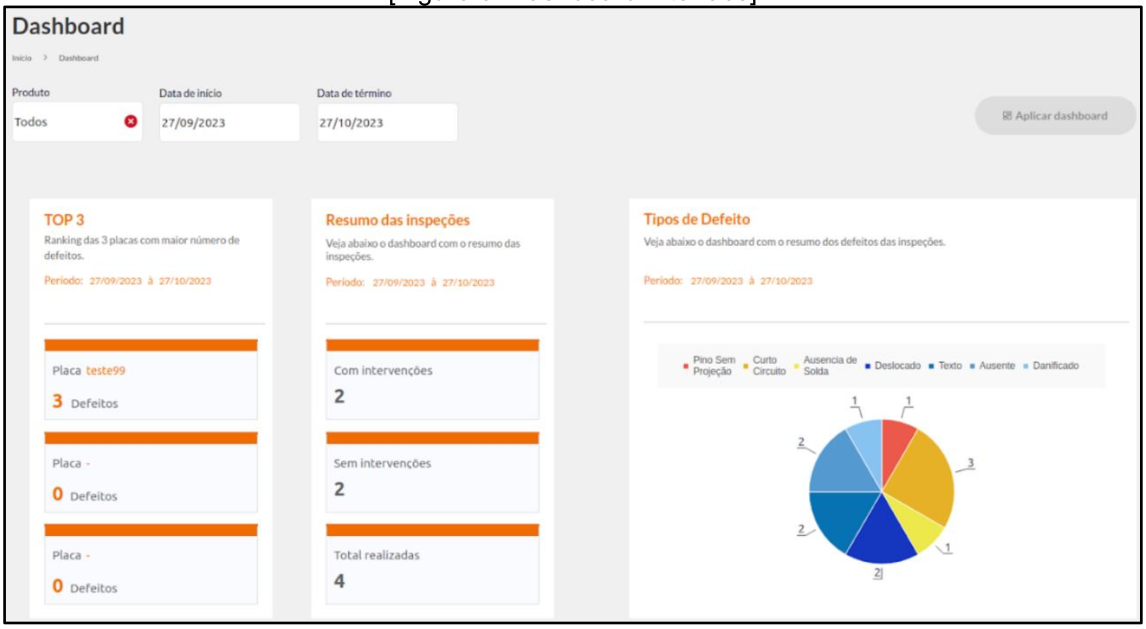

Figure 06 illustrates the metrics and graphs displayed to the operator.

Operating Results and Impacts

Performance Indicators

Key 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 of operating costs: 15%, due to the lower rate of rejection and rework.
- Return on investment: Estimated ROI within 18 months.

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Future Challenges and Improvements

Identified Limitations

Among the limitations observed are:

- Lack of Predictive Maintenance: Limits proactivity in detecting future failures.
- Scalability: The current capacity only serves average production volumes.

Proposals for Improvements

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 in 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 obtained show the following main contributions:

1. **Prototype Development**:
   - The robust and modular structure of the prototype, equipped with transport and image capture systems, demonstrated high accuracy and reliability.
   - The integration of devices, such as high-resolution cameras and PLCs, allowed to synchronize the transport and inspection of PCBs efficiently.
2. **Advances in Quality Inspection**:
   - The use of AI has enabled automatic defect detection 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 flaws, such as cold welds and missing components.
3. **Operational and Economic Impacts**:
   - The reduction of the defect rate from 8% to 2% resulted in a significant improvement in the quality of the final products.

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- The 15% savings in operational costs and the estimated 18-month ROI validate the economic viability of the solution.

4. **Intuitive Interface**:
   - The development of a software system with detailed dashboards and reports 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 proposed solution for PCB inspection not only met the initial objectives, but also presented results that reinforce its relevance in the context of digital transformation and optimization of production processes.

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

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