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| **RESEARCH ARTICLE**

A Deep Learning-Based Cyber-Physical Approach for Visual Inspection of Defects in Pad Printing

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| **ABSTRACT**

Industrial quality inspection processes based on manual visual analysis are prone to human error, fatigue, low repeatability, and high operational variability, especially in high-throughput manufacturing environments. This work presents a Cyber-Physical Framework for Intelligent Visual Inspection, an intelligent computer vision system developed for the automated inspection of logos applied via pad printing on air conditioner condenser cabinets. The proposed architecture integrates deep learning techniques, including YOLOv8-based detection, Region of Interest (ROI) extraction, RGB colorimetric analysis, dimensional validation, and the generation of synthetic images using Generative Adversarial Networks (GANs). The system was designed with real-world industry constraints in mind, such as lighting variations, positioning deviations, mechanical vibrations, and takt time limitations. Experiments were conducted using real and synthetic datasets acquired under controlled industrial conditions. The results demonstrated high robustness in defect detection and good operational repeatability, highlighting the feasibility of integrating the solution into industrial environments aligned with Industry 4.0 concepts. In addition, the study discusses the integration of mechanical design, automation systems, and artificial intelligence to ensure operational stability and reliability in real production lines.

| **KEYWORDS**

Computer Vision; Deep Learning; Industrial Inspection; YOLOv8; GANs; Industry 4.0; Pad Printing; Quality Control.

| **ARTICLE INFORMATION**

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1. Introduction

The visual inspection of logos applied via pad printing is a critical step in quality control during the manufacturing of air conditioner condenser cabinets. Defects such as misalignment, filling defects, color variations, and dimensional inconsistencies can compromise the product's appearance and result in non-conformities. With the advancement of Industry 4.0, computer vision and deep learning techniques have been increasingly employed to automate this process, enhancing the reliability, traceability, and repeatability of industrial inspections [1], [2], [3].

In high-productivity industrial environments, this inspection is still often performed manually, with operators responsible for visually assessing the conformity of the applied logos. Although it is an operationally simple procedure, manual inspection is subject to the subjectivity of human assessment, visual fatigue, variability among inspectors, and the difficulty of maintaining repeatability throughout continuous production cycles [3], [4].

As an alternative to these limitations, computer vision systems based on deep learning have been widely used for the automatic detection of defects in industrial environments. Convolutional neural networks have demonstrated a high capacity for extracting visual features and identifying complex patterns in images, contributing to increased accuracy, consistency, and reliability in automated inspection processes [5], [6], [7].

In this context, the integration of computer vision, artificial intelligence, and cyber-physical systems has enabled the development of solutions capable of performing image acquisition, automated conformance analysis, and real-time monitoring, aligning quality control processes with the principles of Industry 4.0 [2], [8].

Currently, visual inspection in industrial environments is predominantly performed manually, with operators identifying surface defects on electrical cabinets, as illustrated in Figure 1(a). This approach is susceptible to human error and becomes inefficient in high-throughput manufacturing settings. Figure 1(b) presents the proposed automated inspection framework, which employs advanced deep learning techniques, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs), to improve defect detection accuracy and operational efficiency [9].

Figure 1 – Conventional visual inspection process and proposed architecture for the automated inspection of air-conditioning condenser cabinets: a) manual visual inspection; b) proposed architecture for automated quality control.

Source: Conecthus (2025).

In this context, industrial automation has evolved from an approach based primarily on the mechanization of tasks to intelligent systems capable of interpreting data, learning patterns, and supporting decision-making on an ongoing basis. The integration of artificial intelligence and manufacturing has enabled significant advances on various fronts, such as predictive maintenance, process monitoring, and quality control, contributing to a reduction in operational failures and an increase in the reliability of production systems [8].

Among these applications, automated visual inspection based on computer vision and deep learning stands out, as it has been establishing itself as an effective solution for identifying defects in complex industrial environments. In production processes with high quality requirements, traditional inspection methods still face significant limitations, especially when they rely on human evaluation, which is subject to perceptual variations, fatigue, and low consistency over time [10].

Despite technological advances, manual visual inspection is still widely used in various industrial sectors, particularly in processes that require detailed aesthetic evaluation, such as pad printing on equipment cabinets. Although operationally simple, this inspection method has inherent limitations related to operator subjectivity, variability between inspections, and the difficulty of maintaining consistent standards in continuous production environments [3]. These factors make the process susceptible to undetected defects, especially under conditions of high production demand.

The application of artificial intelligence and computer vision techniques has established itself as a promising alternative for overcoming these limitations. In recent years, advances in deep learning have enabled the development of systems capable of analyzing large volumes of visual data with high precision, significantly reducing the reliance on human inspection. In particular, Convolutional Neural Networks (CNNs) have excelled at automatically extracting relevant features from industrial images, demonstrating superior performance in defect detection and classification tasks [5], [6].

Despite this progress, there are still significant gaps in the literature regarding the reliability and applicability of these systems in real industrial environments. Most of the proposed approaches focus on the isolated use of CNNs, without considering the dynamic nature of production processes or the temporal variability associated with the occurrence of defects. Furthermore, there is a lack of integration between different deep learning architectures, such as Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), and cyber-physical systems, which limits the generalization and adaptability of these solutions in complex industrial scenarios [7], [11].

Another important point is that many solutions are still validated exclusively in controlled environments or public databases, without effective integration with actual production lines. This limitation reduces their practical applicability and hinders their scalability to real-world industrial contexts, where factors such as visual noise, lighting variations, and data inconsistencies are constant [12].

Given this scenario, this study proposes an artificial intelligence-based solution for the automated visual inspection of the pad printing process on air conditioning condenser cabinets. The system was designed to replace manual inspection with a computational approach capable of operating in real time, with greater precision, consistency, and reliability.

The proposed architecture integrates various deep learning techniques, combining Convolutional Neural Networks (CNNs) for spatial image analysis, Recurrent Neural Networks (RNNs/LSTMs) for modeling temporal patterns, and Generative Adversarial Networks (GANs) for generating synthetic data and expanding the training dataset. This integrated approach enhances the system's robustness against variations typical of industrial environments, such as lighting, visual noise, and defect diversity.

In addition to algorithmic development, the study includes the implementation of a functional prototype integrated into the production line, enabling validation of the system under real industrial operating conditions. This stage allows for real-time performance evaluation, as well as the automatic generation of quality metrics, such as detection accuracy and defect identification rate.

As a scientific and technological contribution, the project advanced the state of the art by proposing an integrated deep learning approach applied to industrial visual inspection, in line with the principles of Industry 4.0. The solution is expected to contribute to increased production efficiency, reduced inspection errors, lower operating costs, and enhanced industrial competitiveness, in addition to establishing a scalable foundation for future applications in smart manufacturing systems.

Visual inspection is essential for ensuring the aesthetic quality of industrial products. In air-conditioning condenser cabinets, defects in logo pad printing, such as misalignment, incomplete filling, and color variation, can compromise the product's visual appearance and perceived quality. When performed manually, this inspection process is susceptible to operator fatigue and subjective judgment. Recent studies have demonstrated that convolutional neural networks (CNNs) can improve the accuracy, consistency, and repeatability of defect detection in industrial applications [13], [15].

Automated logo inspection presents specific challenges, as defects can be subtle and affected by lighting, reflections, surface deformations, and variations in part positioning. Although conventional image processing techniques can support this process, deep learning models are better able to recognize complex patterns under variable conditions. Studies such as those by Yundong and Cheng [16] and Damacharla et al. [17] underscore the importance of computer vision for detecting surface defects in manufacturing processes. Another challenge lies in the limited availability of images of defective parts, since specific nonconformities may occur infrequently in industrial settings. According to Jin and Chen [18], the small amount of labeled data limits the performance of defect detection models. To address this problem, Song et al. [19], Gao et al. [20], and Guo et al. [21] suggest that Generative Adversarial Networks (GANs) can generate representative synthetic samples, thereby expanding the training dataset and improving the identification of visual defects.

Given this scenario, this study proposes and experimentally validates a cyber-physical approach for the automated visual inspection of logos applied via pad printing on air conditioner condenser cabinets. The approach integrates computer vision, deep learning, and industrial automation techniques into an architecture capable of performing image acquisition, automatic region of interest (ROI) detection, dimensional and colorimetric analysis, and conformance classification in a production environment [7], [8], [22].

The proposed architecture employs YOLOv8-based detection models for the automatic localization of logos and Generative Adversarial Networks (GANs) to expand the training dataset by generating synthetic images representative of defects observed in the industrial process [19], [20], [21], [23]. Additionally, the approach involves the integration of mechanical, electrical, and computational subsystems, aiming to ensure controlled image acquisition conditions, operational stability, and high repeatability of the inspection process.

The experimental validation was conducted using images obtained in an industrial setting and artificially generated synthetic data, allowing for an evaluation of the proposed approach's ability to identify and classify nonconformities associated with pad printing. As its main contribution, the study presents an integrated cyber-physical architecture for automated visual inspection, aligned with the principles of smart manufacturing, providing experimental evidence of its applicability in industrial quality control processes and contributing to the implementation of automated inspection strategies in production environments compatible with Industry 4.0 concepts.

2. Methodology

2.1 System Architecture

This system will be developed as an integrated cyber-physical architecture consisting of: an image capture module; a pad printing system; a mechanical positioning system; an AI-based inspection pipeline; and electrical and automation infrastructure.

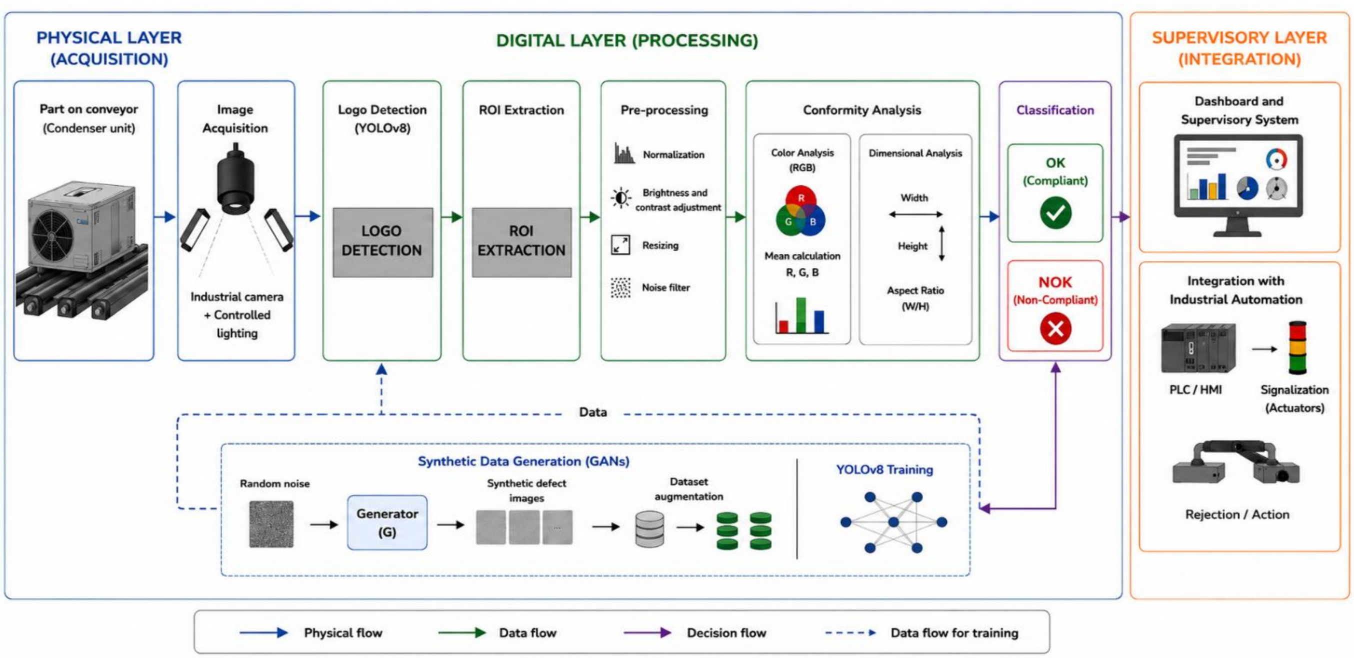
The system's operational workflow consists of: image capture; logo detection; ROI extraction; feature processing; dimensional validation; colorimetric analysis; and part classification.

The proposed architecture will be designed as an integrated cyber-physical system for the automated visual inspection of logos applied via pad printing. The framework combines image acquisition subsystems, deep learning-based processing, compliance analysis, and integration with industrial automation devices.

As shown in Figure 2, the operational workflow begins with image capture by an industrial camera installed in the inspection cell. The acquired images are processed by a YOLOv8 model responsible for automatically locating the logos and defining Regions of Interest (ROIs). The ROIs are then subjected to preprocessing and analysis steps, including dimensional validation, RGB colorimetric evaluation, and identification of nonconformities.

The results produced by the inspection module are used to classify parts as conforming (OK) or nonconforming (NOK), enabling the generation of operational indicators and integration with the automated cell's supervisory system. This structure enables communication between the system's physical and computational components, a fundamental characteristic of cyber-physical systems applied to smart manufacturing [8], [24].

Figure 2 – General architecture of the Cyber-Physical Framework for Intelligent Visual Inspection (FCIVI), highlighting the image acquisition, deep learning-based processing, compliance analysis, and industrial automation system integration modules.



Source: Conecthus (2025).

2.2 Image Acquisition

The images will be acquired as part of the project, which aims to develop a solution based on computer vision and deep learning for the automated visual inspection of logos applied via pad printing on air conditioner condenser cabinets. To obtain the experimental data, an inspection cell developed specifically to validate the proposed approach will be used, enabling standardized image capture under controlled conditions.

The capture system will consist of a GigE Vision industrial camera, model Basler ACA2440-35GC, with a resolution of 2448 × 2048 pixels (5 MP), equipped with a 12-mm lens and positioned approximately 300 mm from the inspection area.

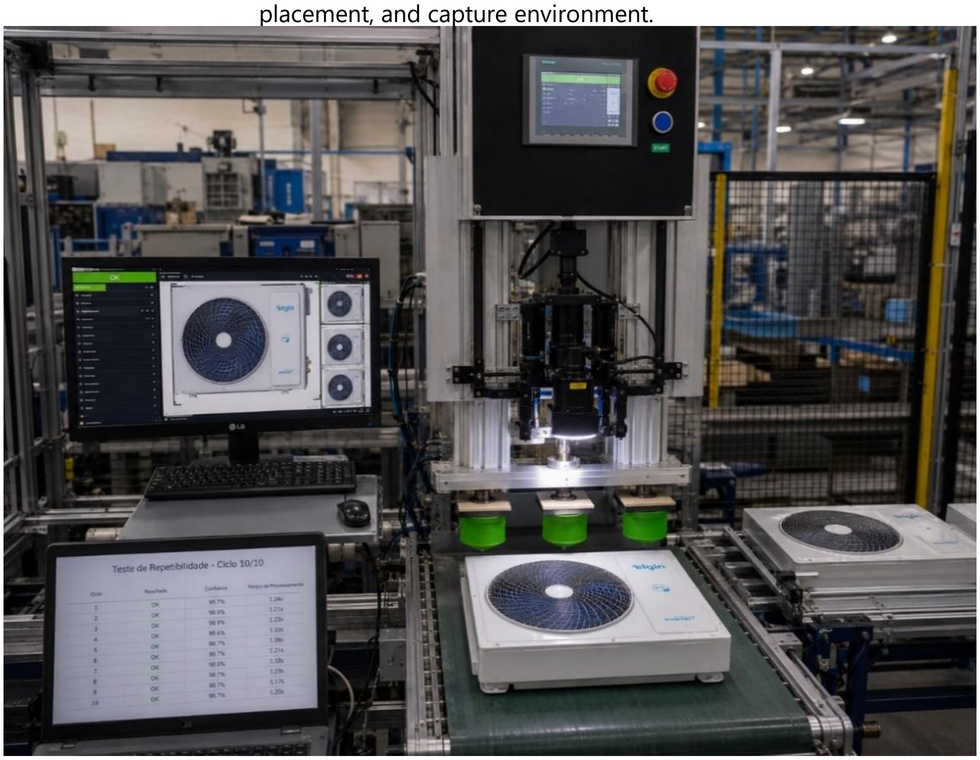
Image acquisition will be performed under diffuse white LED lighting, designed to minimize interference caused by shadows, reflections, and variations in brightness that could compromise image quality and the performance of the detection algorithms. The parts were positioned in a clamping device developed to ensure repeatability during the capture process and uniformity in the framing of the logos.

The acquired images represent different pad printing conditions observed in an industrial setting, including both conforming and non-conforming samples. Among the defects considered are filling failures, misalignments, dimensional variations, and color inconsistencies. These samples were used to build the database employed in the training, validation, and testing stages of the deep learning models used in the proposed solution.

During the project’s development, a database containing at least 5,000 annotated images was planned, enabling the creation of a representative dataset for training the computer vision models. In addition to the real images obtained during the experiments, synthetic images generated by Generative Adversarial Networks (GANs) were used; this strategy was employed to increase data diversity and enhance the generalization ability of the artificial intelligence models [23].

The acquisition strategy was designed to replicate conditions found in real-world industrial environments, taking into account challenges such as variations in lighting, visual noise, and a variety of print patterns. The goal was to ensure that the data used would be suitable for evaluating the applicability of the proposed approach in smart manufacturing and automated visual inspection scenarios, as shown in Figure 3.

Figure 3. Image acquisition system for automated visual inspection, showing the industrial camera, lighting, fixture, logo placement, and capture environment.



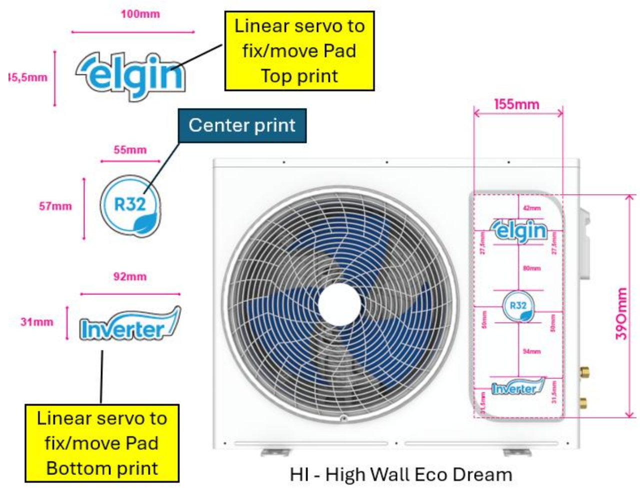
Source: Conecthus (2025).

2.3 Preprocessing Based on Region of Interest (ROI)

After the image acquisition stage, a preprocessing procedure based on the Region of Interest (ROI) will be performed, with the goal of focusing the computational analysis exclusively on the area corresponding to the pad-printed logo. This strategy reduces the influence of irrelevant information present in the condenser housing, such as metallic surfaces, textures, reflections, and structural elements that do not contribute to the inspection process.

Automatic ROI identification will be performed using the YOLOv8 model, which locates the logo in the captured image, as shown in Figure 4.

Figura 4. Especificação geométrica das logomarcas e delimitação das regiões de inspeção utilizadas na localização automática por YOLOv8.



Source: Conecthus (2025).

The detected region is represented by a bounding box defined by the coordinates:

$$B = (x_1, y_1, x_2, y_2) \quad (1)$$

where x_1 and y_1 represent the coordinates of the upper-left corner of the detected region, while x_2 and y_2 correspond to the coordinates of the lower-right corner. From these coordinates, the width (w) and height (h) of the ROI can be obtained using Equations (2) and (3):

$$w = x_2 - x_1 \quad (2)$$
$$h = y_2 - y_1 \quad (3)$$

Thus, the ROI will be defined by the set of pixels within the range $[x_1, x_2] \times [y_1, y_2]$, corresponding exclusively to the area of the logo identified by the detector. Extracting this region reduces the dimensionality of the analyzed data, increases computational efficiency, and directs the inspection algorithms toward the elements that are actually relevant to the decision-making process [25], [26].

After ROI extraction, preprocessing steps will be applied to standardize the images, including resizing to 224 × 224 pixels, normalizing pixel values, and adjustments related to the visual quality of the analyzed region. These procedures aim to reduce variations resulting from capture conditions and provide more consistent data for the deep learning algorithms employed in the system. The use of regions of interest is widely adopted in industrial computer vision applications, as it increases the accuracy of the analysis by restricting processing to the critical areas of the inspection.

In the context of this work, the strategy will help improve the efficiency of the processing workflow and increase the reliability of the subsequent stages of dimensional analysis, colorimetric evaluation, and conformity classification of printed logos.

An ROI-based strategy will be adopted to reduce interference from the background of the part and increase the system's robustness.

The preprocessing steps included: resizing; illumination normalization; brightness correction; contrast adjustment; and class balancing.

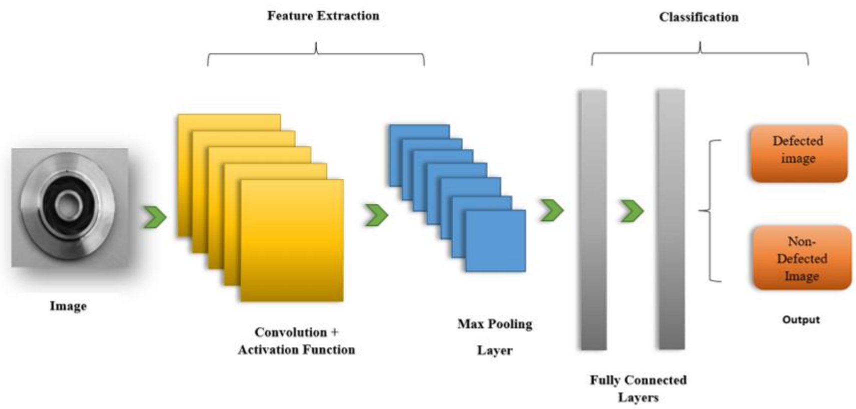
The images were standardized to a resolution of 224×224 pixels for compatibility with CNN architectures.

Processing Module: The application of CNNs to identify visual patterns and defects is illustrated in Figure 5. The loss function for classification will be based on the cross-entropy equation described as follows:

$$L = -\frac{1}{N}\sum_{I=1}^{N}[Y_I \log(y_i) + (1 - Y_I)\log(1 - y_i) \tag{4}$$

Where Y_I is the true label and y_i is the probability predicted by the model.

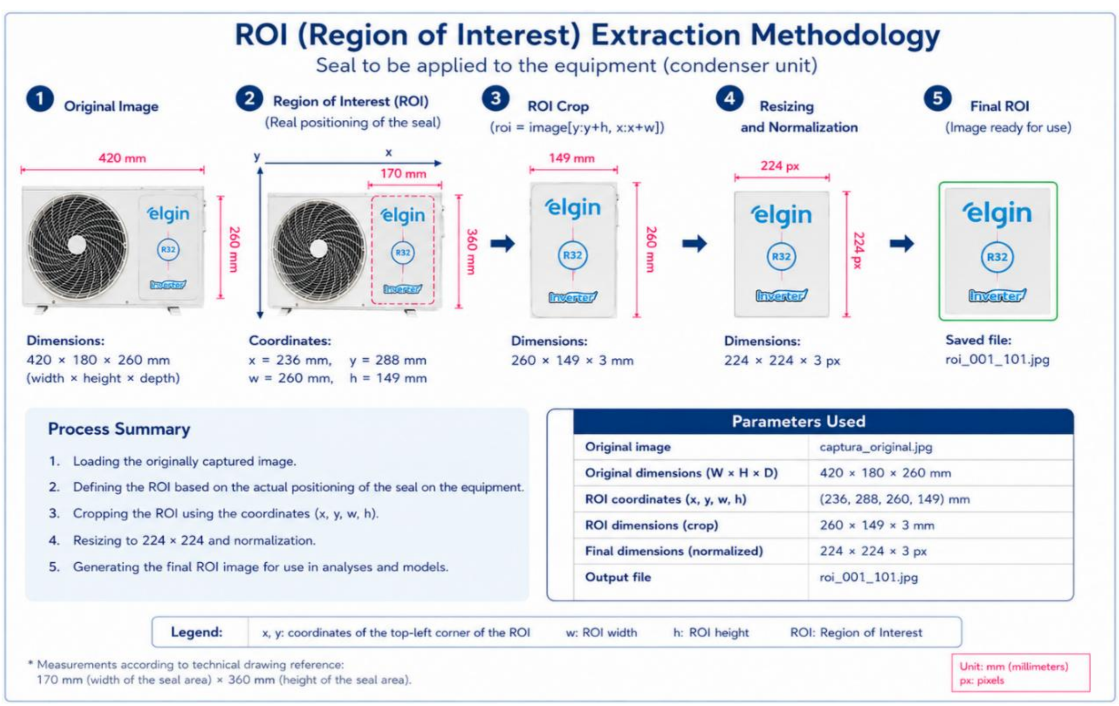
Figure 5 – CNN architecture model



Source: Reproduced from Ref. [9].

First, the complete visual inspection pipeline will be validated. It is structured into sequential steps: image capture, spatial detection of the logo, definition of the ROI as shown in Figure 6, feature extraction, and final classification of the part.

Figure 6 - ROI boundary applied to the logo, allowing the analysis of deep learning models to focus on the critical inspection area.



Source: Conecthus (2025).

2.4 Deep Learning Model

The YOLOv8 model was used for the automatic detection of logos on condenser cabinets; it was responsible for the spatial localization of the elements of interest and for extracting the coordinates of the region of interest (ROI), represented by B = (x_1, y_1, x_2, y_2). Based on these coordinates, the subsequent steps of dimensional analysis, colorimetric (RGB) validation (an abbreviation for the additive color system consisting of the hues Red, Green, and Blue), and compliance classification were performed.

The experiments were conducted using the YOLOv8n (Ultralytics 8.x) version, due to its balance between computational performance and inference speed for real-time industrial applications. Training was performed over 20 epochs, with a batch size of 32 images, an initial learning rate of 0.001, and the Adam optimizer. The images were resized to 224 × 224 pixels and subjected to the normalization and preprocessing steps described above.

For object detection, a confidence threshold of 0.50 and an Intersection over Union (IoU) threshold of 0.50 were adopted. The stopping criterion was either reaching the maximum number of epochs or the stabilization of the validation loss function without significant performance gains. Training and inference were performed on a computing environment consisting of an Intel Core Ultra 7 laptop with 32 GB of RAM and a development workstation based on an Apple MacBook Pro with an M1 Pro chip, in accordance with the infrastructure provided by the project. The parameters were defined experimentally to maximize the model's generalization ability and minimize the risk of overfitting to the available dataset.

2.5 Generating Synthetic Data with Generative Adversarial Networks (GANs)

With the aim of reducing class imbalance and increasing the diversity of the dataset, a Generative Adversarial Network (GAN) was used to generate synthetic images that accurately represent the defects observed in the pad printing process. The architecture consisted of two neural networks trained in an adversarial manner: a generator, responsible for synthesizing new images from random noise vectors, and a discriminator, tasked with distinguishing real images from the synthetic images produced by the generator.

Synthetic Data Generation Module: Use of GANs to create defect samples and balance the dataset. The GAN's discriminator and generator were optimized iteratively by minimizing the cost function:

$$\underset{G}{min}\,\underset{D}{max}\ V\,(D, G) = \mathbb{E}_{x \sim Pdata(x)[\log\left(1 - D(G(z))\right)]} \qquad (5)$$

Where D(x) is the probability that x is real and G(Z) is the image generated from the noise z

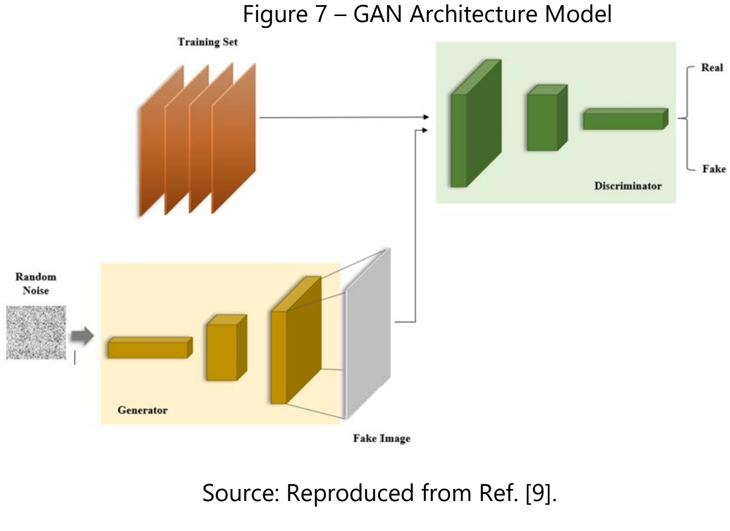
The GAN was trained using real images collected during the data acquisition phase.

After generation, the synthetic images underwent a technical validation procedure consisting of specialized visual inspection and analysis of compliance with actual manufacturing standards. Only samples considered representative of the actual process behavior were included in the final dataset.

The use of GANs helped balance the classes and increase the diversity of the dataset, reducing the scarcity of examples of specific defects. Consequently, the final dataset now includes a greater variety of visual patterns, which benefits the training of the computer vision models used in this study.

Figure 7 shows the methodological workflow adopted for the generation, validation, and incorporation of synthetic images into the training dataset.

Figure 7 – GAN Architecture Model



Source: Reproduced from Ref. [9].

2.6 Mechanical Integration and Automation

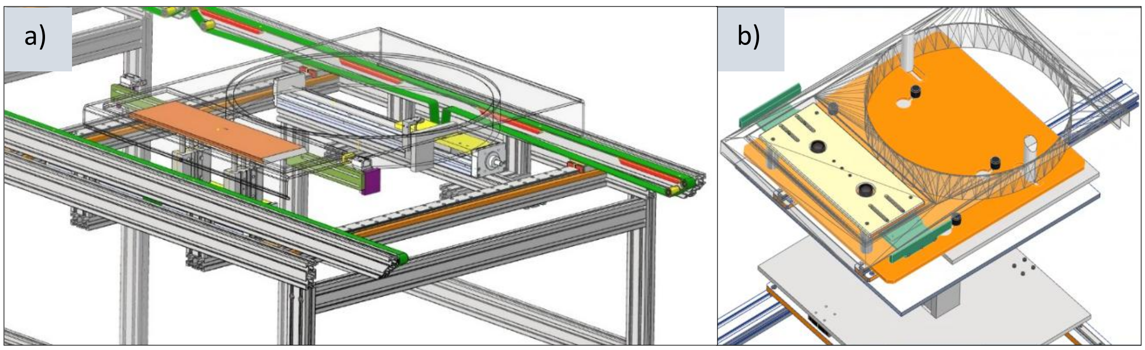
The mechanical design of the system was carried out in a CAD (Computer-Aided Design) environment using Autodesk Inventor software. This stage enabled the three-dimensional modeling of components, the analysis of geometric interferences, and the validation of the integration between the mechanical, electrical, and automation subsystems prior to prototype manufacturing.

The developed structure incorporated conveyor belts, servomotors, pneumatic cylinders, fixtures, electrical panels, and industrial automation modules. The positioning of these components was defined to ensure synchronization between the movement of the part and the image acquisition process by the computer vision system.

During the mechanical design phase, aspects related to the positioning and stability of the metal lids along the inspection line were taken into account. To this end, fixtures and guidance mechanisms were incorporated to minimize displacement, vibrations, and misalignment during image capture. Additionally, dimensional tolerances and the possible effects of geometric deformations in the parts were evaluated to ensure standardized inspection conditions.

As shown in Figure 8, the analyses performed in a CAD environment made it possible to verify the geometric alignment of the components, the operating space of the actuators, the integration between sensors and motion mechanisms, as well as the structural stability of the assembly. These procedures were adopted to ensure repeatability in the image capture conditions and uniformity in the positioning of the parts during the experimental tests.

Figure 7 – GAN Architecture Model



Source: Conecthus (2025).

The integration of mechanical, automation, and computer vision systems was a key step in the methodology, as it established the operational conditions necessary for the consistent acquisition of the images used in the subsequent stages of processing and automated inspection.

3. Results and Discussion

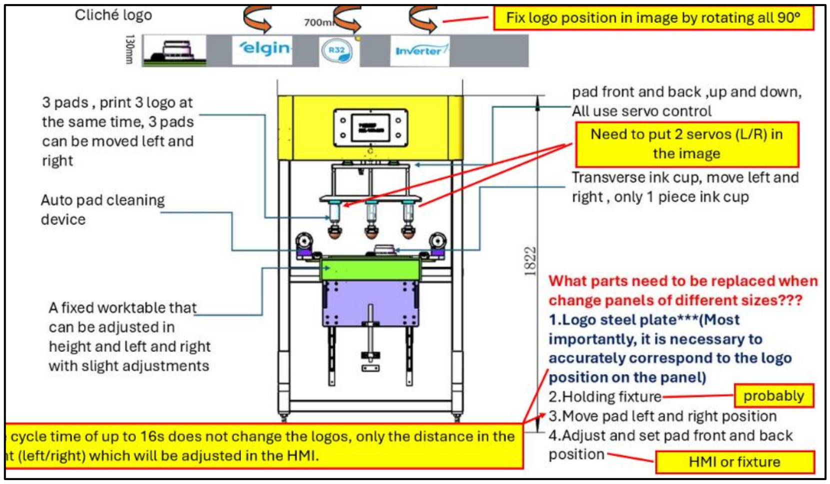
The results obtained in this study were organized into five complementary experimental stages, designed to evaluate the performance of the proposed approach from different perspectives. Initially, the visual inspection pipeline was validated to verify the system's ability to seamlessly perform the stages of image acquisition, logo detection, region of interest (ROI) extraction, and compliance analysis. Next, an evaluation of the deep learning model used for automatic logo detection was conducted, considering performance metrics associated with the process of identifying and locating elements of interest.

Subsequently, experiments were carried out to analyze the system's repeatability, with the aim of verifying the consistency of the results obtained in successive inspections conducted under controlled conditions. Next, an integration test of the cyber-physical framework was performed to evaluate communication between the capture, processing, and supervision modules. Finally, an operational evaluation of the proposed solution was conducted to verify its applicability in scenarios representative of the industrial environment for automated visual inspection.

The adopted structure allows for the analysis not only of the individual performance of the algorithms used, but also of the system's behavior as an integrated intelligent visual inspection solution, aligned with the principles of Industry 4.0 and smart manufacturing.

Figure 9 shows a schematic configuration of the proposed pad printing solution, highlighting the system's main components, including printing plates, printing cups, servomotors, and workpiece positioning fixtures. The operational model includes the simultaneous application of multiple logos, as well as the necessary movements along the longitudinal and transverse axes for the correct positioning of the part during the printing process. Clamping and positioning systems are essential in automated industrial environments, as they ensure stability, dimensional accuracy, and operational repeatability during manufacturing processes [27].

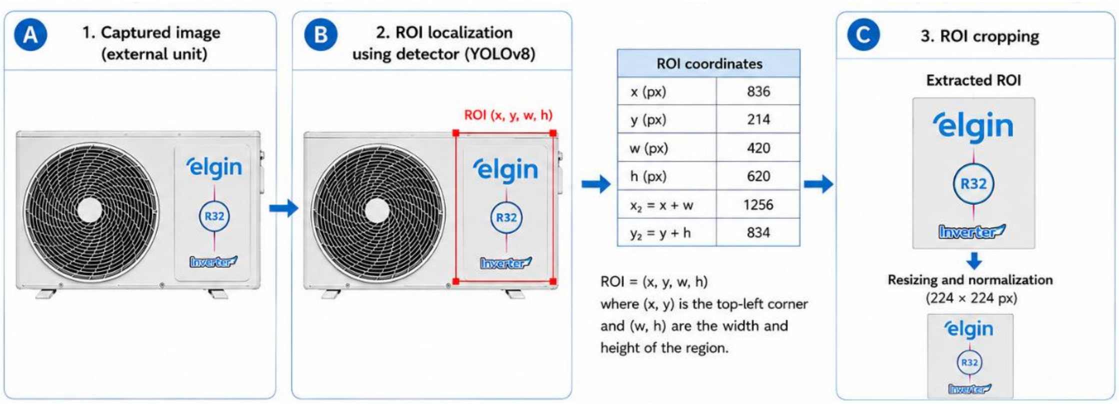
Figure 9 - Schematic diagram of pad printing.



Source: Conecthus (2025).

In Figure 10, defining the ROI allows for standardization of logo framing, ensuring greater repeatability in preprocessing and greater robustness of the inspection system. Controlling the coordinates and dimensions of the ROI helps ensure that the computer vision model processes only relevant information that aligns with the expected standard [28].

Figure 10 – Methodological workflow for defining the ROI during image preprocessing.



Source: Conecthus (2025).

The YOLOv8 model was used to detect logos and dynamically identify the coordinates of the Regions of Interest (ROIs), as represented by Equation (6), consisting of the corner points of the bounding box (x_1, y_1, x_2, y_2). And insert the following below:

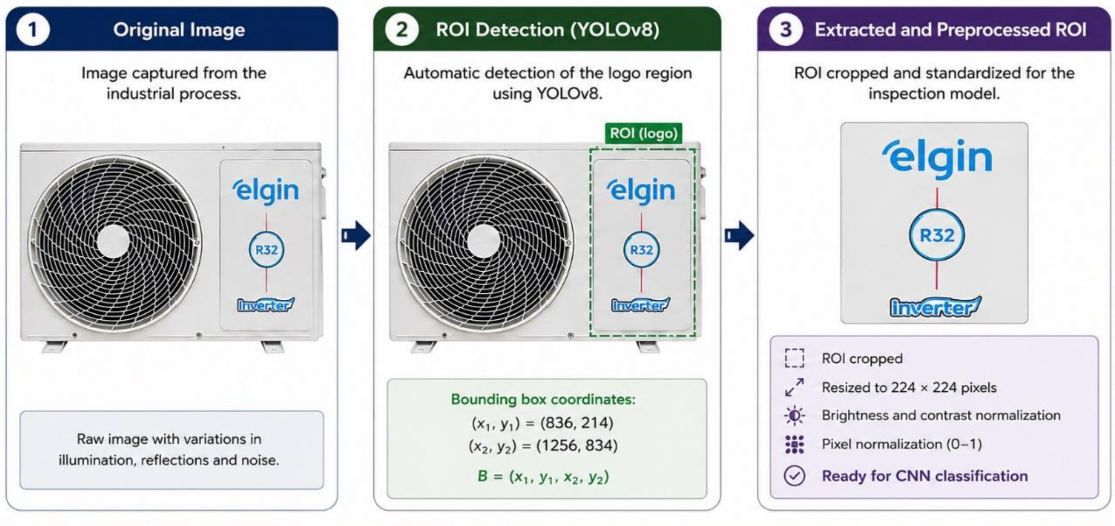
$$(x_1, y_1, x_2, y_2) \qquad (6)$$

Or, to put it more technically: where x1 and y1 represent the coordinates of the upper-left corner, while x2 and y2 correspond to the lower-right corner of the detected region.

The use of the ROI proved essential for restricting the analysis to the critical area of the logo, reducing the influence of noise, surface reflections, and irrelevant elements of the part. Furthermore, standardizing the framing contributed to greater repeatability in preprocessing and greater stability in the inferences made by deep learning models—factors considered essential in industrial visual inspection systems based on computer vision [28], [29].

During dataset preparation, the images underwent a structured curation and technical labeling process, being classified into conforming (OK) and non-conforming (NOK) categories, including subclasses associated with different types of visual defects, as shown in Figure 11 (a).

Figure 11 - a) Methodological workflow adopted for preparing the dataset. (1) Curation and labeling of real images into inspection classes; (2) preprocessing and standardization of the images; and (3) expansion of the dataset using synthetic samples generated by GANs, followed by technical validation and incorporation into the final training set.



Source: Conecthus (2025).

Preprocessing included operations such as lighting normalization, brightness and contrast correction, resizing, and class balancing using OpenCV libraries in Python. The images were standardized to a resolution of 224×224 pixels, aiming to strike a balance between computational cost and the preservation of features relevant to deep learning models. According to Ma et al. [30], preprocessing and dimensional standardization steps are essential for increasing the stability, performance, and generalization ability of convolutional networks applied to industrial visual inspection. Furthermore, Shorten and Khoshgoftaar [31] highlight that data normalization and balancing techniques directly contribute to the improvement of deep learning models.

Concurrently, GANs were employed for controlled dataset expansion. The generated synthetic images reproduced visual defects consistent with those observed in industrial settings, including contrast variations, partial printing defects, surface imperfections, and filling inconsistencies, as demonstrated in the source code snippet shown in Figure 6(b). The use of GANs to generate synthetic defects has proven effective in industrial settings with limited sample availability, contributing to an increase in the scope of the evaluated scenario and the generalization ability of automated inspection models [21].

Figure 12 - a) Practical tests of the pad printing process with simultaneous pad operation on the prototype, used to validate print quality and define the logos. b) Result of applying the logos to the part during initial testing of the pad printing system.

Source: Conecthus (2025).

After visual and technical validation, only the samples deemed to reflect the actual process behavior were included in the final dataset. The use of GANs significantly contributed to increasing the diversity of the dataset, reducing class imbalance, and improving the generalization ability of visual inspection models, as observed in industrial applications of automated defect detection [19], [20].

Functional tests were conducted using real images obtained in an industrial setting and previously validated synthetic images, as shown in Figure 12.

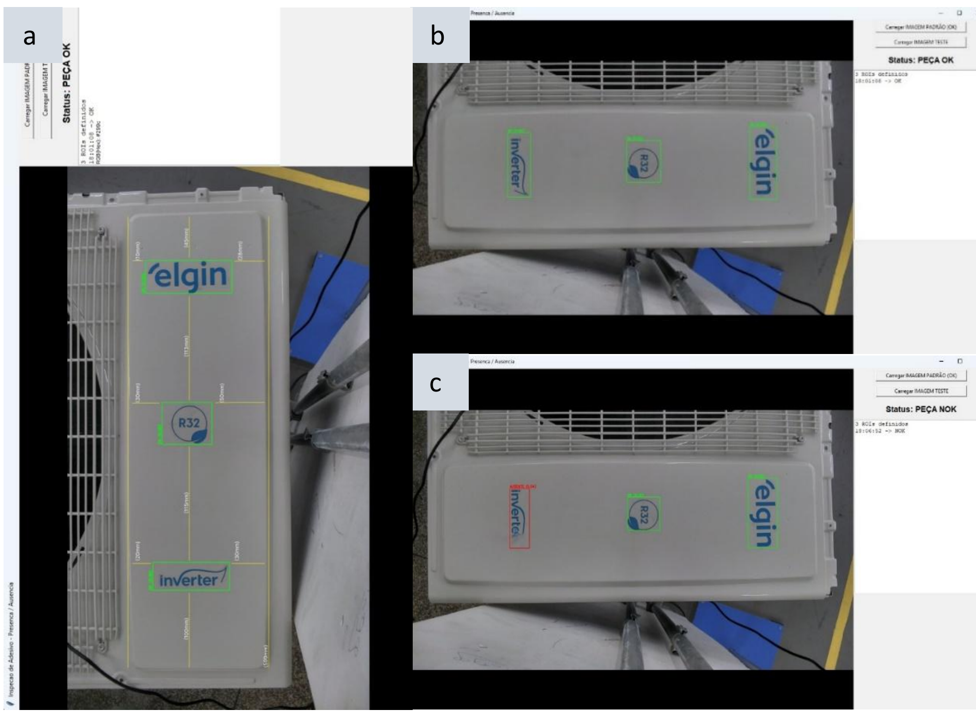
Given that the pad printing module was still in the development phase, the logos used in the experiments were applied manually using adhesive labels, visually simulating the conditions expected for the final process.

The experimental results suggest that the proposed approach has the potential to distinguish between conforming and non-conforming parts under conditions involving minor variations in positioning, application pressure, and the visual uniformity of the logos.

The inspection mechanisms made it possible to identify positioning and filling defects, as well as dimensional and colorimetric inconsistencies. Dimensional analysis combined with RGB validation contributed to greater robustness and reliability in the classification process, since the combination of geometric and colorimetric features increases the accuracy and efficiency of automated visual inspection systems [26], [30].

Experimental validations demonstrated the correct functioning of the compliance (OK) and non-compliance (NOK) states, as observed in the inference tests conducted during the functional validation stage, as shown in Figure 13.

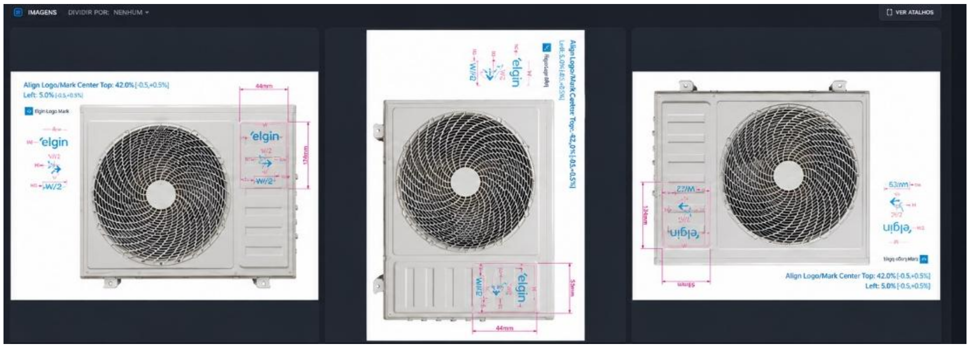
Figure 13 - a) Detection of logos using ROIs and dimensional measurements as a reference for validating the inspection system. b) Validation of a conforming part (OK) with correct logo detection by the computer vision system. c) Identification of a nonconforming part (NOK) by the inspection system, indicating a failure in logo detection or positioning.



Source: Conecthus (2025).

With regard to the learning process, an initial test dataset was structured containing representative images of the 27,000 Btu/h capacity model with the logos applied, covering different positioning and orientation conditions of the part. As shown in Figure 9, variations in rotation and positioning (0°, 90°, and 180°) were used to increase the model's robustness in the face of real-world variations in the production process.

Figure 14 - Structure of the dataset used to train the computer vision model, containing variations in the positioning and orientation of the parts.

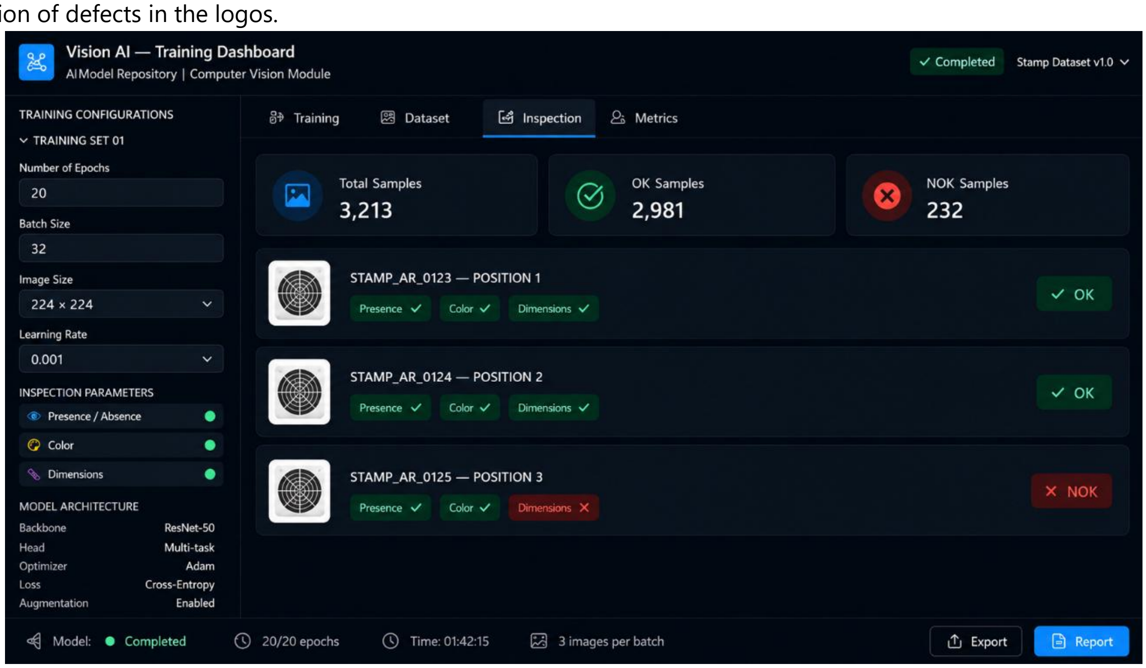


Source: Conecthus (2025).

The inspection was performed simultaneously on the three logos present on the part, allowing for the individual identification of nonconformities. As illustrated in Figure 15, the system demonstrated the ability to correctly detect failure scenarios, specifically highlighting the logo with an inconsistency, thereby demonstrating its effectiveness in distinguishing between valid and invalid conditions.

Recent studies show that deep learning-based visual inspection systems are highly capable of locating and classifying defects in automated industrial environments, contributing to greater accuracy and traceability in quality control [26], [30].

Figure 15 - Results from the visual inspection system, showing the classification of parts as OK and NOK and the individual identification of defects in the logos.



Source: Conecthus (2025).

In addition, a front-end was developed to visualize and track the process, enabling intuitive interaction with the system. The implemented dashboard allowed for visualization of the dataset, monitoring of training, analysis of performance metrics, and review of inspection results, consolidating the information in a structured and accessible manner.

According to Garcia et al. [32], real-time monitoring and visualization systems are essential for operational support, performance analysis, and efficient integration between smart manufacturing platforms and industrial operators. Furthermore, Hoffmann and Reich [33] highlight that visual interfaces in automated inspection systems aid in the interpretability of models and the management of industrial quality information.

As part of the development of the supervisory system, the production monitoring dashboard designed for computer vision-based inspection enabled the consolidation and visualization of key process indicators in real time.

Figure 16 - Monitoring dashboard for the computer vision inspection system, showing production metrics, classification results (OK/NOK), and operational alerts.

Source: Conecthus (2025).

As shown in Figure 16, the dashboard displays metrics relevant to the operation, such as total processed volume, the number of approved and rejected parts, and the system error rate. Additionally, visualizing the production flow over time allows for monitoring the line's operational behavior and identifying performance variations-key characteristics of smart industrial systems based on real-time monitoring and data analysis [29], [34].

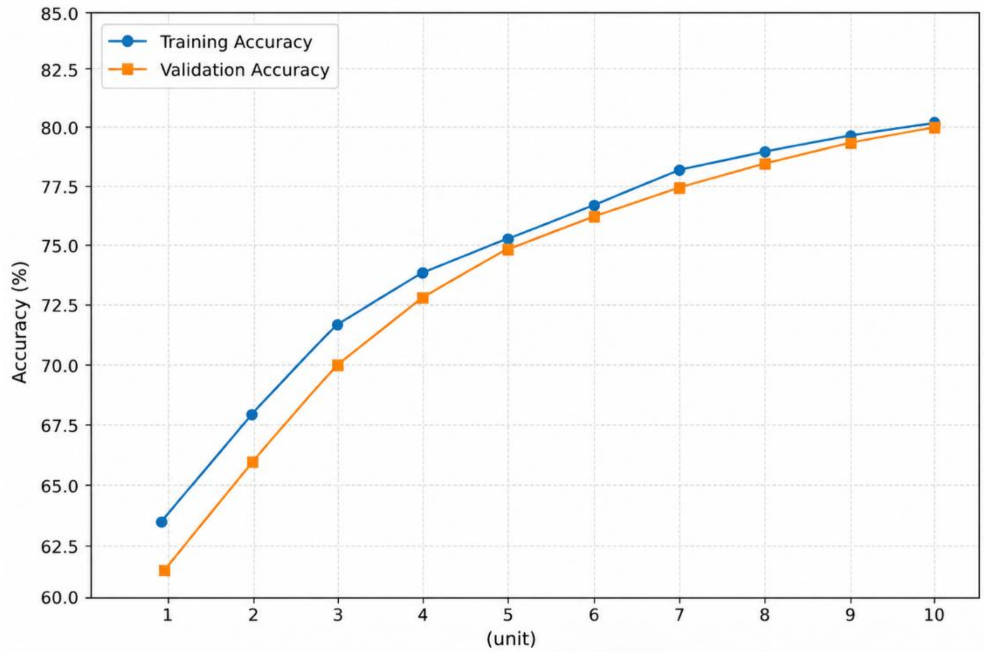
Operational repeatability tests were also conducted, in which the system was subjected to multiple inspection cycles using equivalent samples. The results demonstrated low variability between consecutive runs, stability of the inferences, and consistency in classifications over time, indicating potential for application in continuous industrial environments. According to Susto et al. [35], operational stability and the repeatability of inferences are fundamental factors for ensuring reliability and robustness in intelligent systems applied to industrial monitoring and inspection.

As shown in Figure 17, the training results demonstrated a gradual improvement in accuracy, as well as a consistent reduction in the loss function, indicating that the model was able to learn patterns relevant to the inspection task.

Figure 17 - Performance metrics for the computer vision model during training, showing the improvement in accuracy and the reduction in the loss function.

Source: Conecthus (2025).

Figure 18 – Model performance on the accuracy curve (Training vs. Validation).



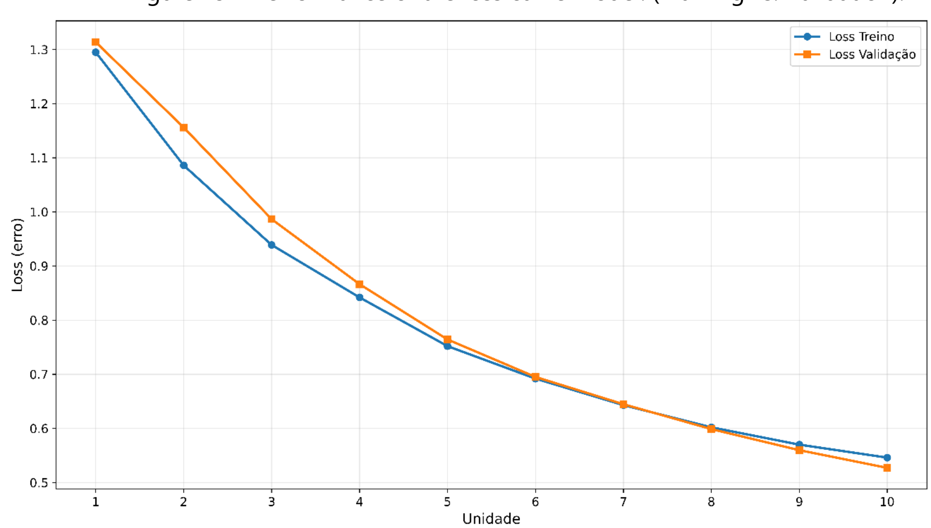
Source: Conecthus (2025).

The graph shown in Figure 18 illustrates the evolution of the model's accuracy over the ten training epochs. A gradual increase is observed in both training accuracy and validation accuracy, indicating consistent learning by the neural network during the optimization process.

Training accuracy increased from 63.31% in the first epoch to 80.34% in the tenth epoch, while validation accuracy rose from 61.42% to 80.21% over the same period. The closeness between the values obtained in the training and validation sets demonstrates stable model behavior and suggests adequate generalization ability for data not used during training.

Furthermore, the absence of significant differences between the curves indicates that the model shows no significant signs of overfitting, a phenomenon characterized by excessive learning from the training data at the expense of the ability to recognize new patterns.

Figure 19 – Performance of the loss curve model. (Training vs. Validation).



Source: Conecthus (2025).

Figure 19, shown above, illustrates the evolution of the loss function during model training and validation. The loss function is a metric used to quantify the error in the predictions made by the neural network. The lower the value of this metric, the better the model's performance tends to be.

A continuous reduction in loss values is observed across the ten units analyzed. In the training set, the loss decreased from 1.295 to 0.546. In the validation set, it decreased from 1.314 to 0.527.

This behavior indicates adequate convergence of the learning algorithm, demonstrating that the model was able to progressively adjust its internal parameters to minimize classification errors.

The closeness between the training and validation curves reinforces the stability of the training process and demonstrates that the model maintains similar performance when applied to data not used during the training phase.

Although the initial dataset is small, the results obtained in this stage are considered satisfactory for preliminary validation of the proposed approach. The analyses indicated preliminary compatibility with the takt time requirements established for the production system, demonstrating potential for application in industrial environments with real-time processing and automated inspection based on computer vision and deep learning [15], [29]. Translated with DeepL.com (free version).

According to Damacharla et al. [17], small surface deformations and variations in positioning can compromise the performance of computer vision algorithms applied to the automatic detection of defects on metal surfaces. In this context, the presented studies on clamping and positioning demonstrated the need to implement criteria for structural rigidity, positioning control, and mechanical repeatability, ensuring greater stability during image capture and greater reliability of the inferences made by the system.

Finally, the consolidation of the physical prototype made it possible to validate the compatibility between the mechanical, electrical, pneumatic, and computational subsystems, demonstrating a high degree of alignment between the three-dimensional design developed in CAD and the physical implementation of the automated cell. The results obtained demonstrate that the integrated approach combining artificial intelligence, industrial automation, and mechanical engineering holds great potential for application in smart industrial systems aligned with the principles of Industry 4.0

4. Conclusion

This study presented the development of a cyber-physical framework for intelligent visual inspection, based on computer vision and deep learning techniques, for the automated analysis of logos applied to air conditioner condenser cabinets.

The results indicate that the proposed architecture was able to identify patterns associated with compliance (OK) and non-compliance (NOK) in the analyzed logos, demonstrating potential for application in automated visual inspection activities. The use of the YOLOv8 model in conjunction with region of interest (ROI) extraction techniques, dimensional analysis, and color feature validation made it possible to structure a consistent inspection workflow for the evaluated scenarios.

Additionally, the use of data augmentation and balancing techniques contributed to the construction of more representative training datasets, enhancing the learning process of the developed models. The experimental results also indicated promising performance in terms of operational repeatability and the potential for future integration into industrial environments.

In terms of the system's physical integration, the prototype developed made it possible to evaluate aspects related to the mechanical structure, the electronic components, and the synchronization between the computational and inspection modules, providing initial evidence of the feasibility of implementing the proposed concept.

However, the results presented should be analyzed in light of the study's limitations. Part of the experiments was conducted using adhesive bonding as a strategy to simulate the pad printing process, which may not fully represent all the variations encountered under real production conditions. Therefore, future studies should include expanding the sample set, validation in a continuous industrial environment, and evaluation of the system using exclusively parts produced by the final process.

Thus, it is concluded that the proposed solution showed promising preliminary results for application in automated visual inspection, providing a foundation for future research aimed at improving the system's reliability and technological maturity in real industrial settings.

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References

[1] Kagermann, H.; Wahlster, W.; Helbig, J. Recommendations for implementing the strategic initiative INDUSTRIE 4.0. Frankfurt: German National Academy of Science and Engineering, 2013.

[2] Liao, Y. et al. Past, present and future of Industry 4.0: a systematic literature review and research agenda proposal. International Journal of Production Research, v. 55, n. 12, p. 3609-3629, 2017.

[3] Santos, R. M. et al. Automated visual inspection in manufacturing processes: challenges and applications in Industry 4.0. Journal of Manufacturing Systems, v. 58, p. 294-302, 2021.

[4] Malhotra, R.; Jain, A. Human factors in visual inspection systems and quality control in manufacturing industries. International Journal of Advanced Manufacturing Technology, v. 103, p. 3567-3579, 2019.

[5] Lecun, Y.; Bengio, Y.; Hinton, G. Deep learning. Nature, v. 521, p. 436-444, 2015.

[6] Ren, S. et al. Deep learning-based defect detection in industrial manufacturing: a survey. IEEE Transactions on Instrumentation and Measurement, v. 70, p. 1-22, 2021.

[7] Chen, L. et al. A survey on deep learning for visual inspection in manufacturing. IEEE Access, v. 9, p. 105321-105340, 2021.

[8] Lee, J.; Bagheri, B.; Kao, H. A. A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. Manufacturing Letters, v. 3, p. 18-23, 2015.

[9] Kumbhar, A.; Chougule, A.; Lokhande, P.; Navaghane, S.; Burud, A.; Nimbalkar, S. DeepInspect: an AI-powered defect detection for manufacturing industries. arXiv preprint, 2023.

[10] Deng, L.; Yu, D. Deep learning: methods and applications. Foundations and Trends in Signal Processing, v. 7, n. 3-4, p. 197-387, 2014.

[11] Albeldán, J., et al. (2022). Deep learning in industrial inspection systems: limitations and opportunities. Expert Systems with Applications, 200, 117–134.

[12] Lee, J.; Kao, H. A.; Yang, S. Service innovation and smart analytics for Industry 4.0 and big data environment. Procedia CIRP, v. 16, p. 3-8, 2014.

[13] Da Silva, L. A. et al. Métodos espaço-temporais baseados em aprendizagem profunda para detecção de defeitos: um caso de estudo de aplicação industrial. Applied Sciences, v. 11, n. 22, p. 10861, 2021. DOI: 10.3390/app112210861.

[14] Arikan, S.; Varanasi, K.; Stricker, D. Surface defect classification in real-time using convolutional neural networks. arXiv preprint arXiv:1904.04671, 2019.

[15] Nguyen, T. P.; Choi, S.; Park, S. J.; Park, S. H.; Yoon, J. Inspecting method for defective casting products with convolutional neural network (CNN). International Journal of Precision Engineering and Manufacturing-Green Technology, v. 8, n. 2, p. 583-594, 2021.

[16] Yundong, L.; Cheng, Z. Automated vision system for fabric defect inspection using Gabor filters and PCNN. SpringerPlus, v. 5, p. 765-777, 2016.

[17] Damacharla, P.; Rao, A.; Ringenberg, J.; Javaid, A. Y. TLU-net: a deep learning approach for automatic steel surface defect detection. In: INTERNATIONAL CONFERENCE ON APPLIED ARTIFICIAL INTELLIGENCE (ICAPAI), 2021. Proceedings [...]. Piscataway: IEEE, 2021. p. 1-6.

[18] JIN, Q.; CHEN, L. A survey of surface defect detection of industrial products based on a small number of labeled data. arXiv preprint arXiv:2203.05733, 2022.

[19] Song, S.; Chang, K.; Yun, K.; Jun, C.; Baek, J. G. Defect synthesis using latent mapping adversarial network for automated visual inspection. Electronics, v. 11, n. 17, p. 2763, 2022.

[20] Gao, H. et al. A deep convolutional generative adversarial networks-based method for defect detection in small sample industrial parts images. Applied Sciences, v. 12, n. 13, p. 6569, 2022.

[21] Guo, Y. et al. Using ISU-GAN for unsupervised small sample defect detection. Scientific Reports, v. 12, n. 1, p. 11604, 2022.

[22] Liu, Y. et al. Artificial intelligence and computer vision in smart manufacturing: applications, challenges and future trends. Journal of Manufacturing Systems, v. 68, p. 412-428, 2023.

[23] Goodfellow, I. et al. Generative adversarial nets. In: ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS. Proceedings [...]. [S. l.: s. n.], 2014.

[24] Lee, J. et al. Industrial artificial intelligence for Industry 4.0-based manufacturing systems. Manufacturing Letters, v. 18, p. 20-23, 2018.

[25] G. Jocher, A. Chaurasia, and J. Qiu, Ultralytics YOLOv8, 2023. [Online]. Available: https://github.com/ultralytics/ultralytics. Accessed: Jun. 17, 2026.

[26] Li, J., Wu, J., & Shao, Y. (2024). FSNB-YOLOV8: Improvement of object detection model for surface defects inspection in online industrial systems. Applied Sciences, 14(17), 7913..

[27] Fiedler, F. et al. Jigs and fixtures in production: a systematic literature review. Journal of Manufacturing Systems, v. 72, p. 373-405, 2024.

[28] Szeliski, R. Computer vision: algorithms and applications. 2. ed. Cham: Springer, 2022. Disponível em: https://szeliski.org/Book/. Acesso em: 26 maio 2026.

[29] Lupi, F.; Biancalana, M.; Rossi, A. et al. A framework for flexible and reconfigurable vision inspection systems. The International Journal of Advanced Manufacturing Technology, v. 129, p. 871-897, 2023. Disponível em: https://link.springer.com/article/10.1007/s00170-023-12175-6. Acesso em: 27 maio 2026.

[30] Ma, Y.; Yin, J.; Huang, F. et al. Surface defect inspection of industrial products with object detection deep networks: a systematic review. Artificial Intelligence Review, v. 57, p. 333, 2024. Disponível em: https://link.springer.com/article/10.1007/s10462-024-10956-3. Acesso em: 27 maio 2026.

[31] Shorten, C.; Khoshgoftaar, T. M. A survey on image data augmentation for deep learning. Journal of Big Data, v. 6, n. 60, 2019. Disponível em: https://journalofbigdata.springeropen.com/articles/10.1186/s40537-019-0197-0. Acesso em: 27 maio 2026.

[32] Garcia, A.; Oregui, X.; FRANCO, J. et al. Time series manufacturing data edge monitoring and visualization to support industrial maintenance teams. SN Computer Science, v. 5, n. 131, 2024. Disponível em: https://link.springer.com/article/10.1007/s42979-023-02442-4. Acesso em: 27 maio 2026.

[33] Hoffmann, R.; Reich, C. A systematic literature review on artificial intelligence and explainable artificial intelligence for visual quality assurance in manufacturing. Electronics, v. 12, n. 22, p. 4572, 2023. Disponível em: https://www.mdpi.com/2079-9292/12/22/4572. Acesso em: 27 maio 2026.

[34] Lee, J., Davari, H., Singh, J., & Pandhare, V. (2018). Industrial Artificial Intelligence for Industry 4.0-based Manufacturing Systems. Manufacturing Letters, 18, 20–23. https://doi.org/10.1016/j.mfglet.2018.09.002.

[35] Susto, G. A., et al. (2015). *Machine learning for predictive maintenance: A multiple classifier approach*. IEEE Transactions on Industrial Informatics, 11(3), 812–820.