# Applicative Framework for End-to-End AOI Implementation

2022-03-17


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# Overview

## 1.1 Introduction

Timely and accurate detection of defects helps industries to apply quality control strategies to maintain a competitive edge. The target is to achieve 100% qualified products while reducing internal scraps. Among the techniques used to assess the product quality, optical inspection approach for defect detection is one of the most common procedures used in industry. Optical inspection techniques can be performed by human inspectors (manual optical inspection) or automatically by using sensors and image processors. This last technique takes the name of Automatic Optical Inspection (AOI).

In the competition between manual and automatic approaches, inspection speed and accuracy play a determinant role and the gap between the two is becoming much more difficult to fill. Indeed, the fast and increasing development of technology has pushed the success of AOI over manual inspection. The most advanced systems are capable of identifying a variety of surface defects such as nodules, missing components, scratches and stains as well as tiny defective deviations, (with low intensity and contrast) that are difficult to detect with the naked eye. Moreover, according to M.-J.-J. Wang and C.-L. Huang[1], human vision inspection performance gets worse with repetitive routine jobs due to fatigue.

## 1.2 State of Art

Three key elements drive Automatic Optical Inspection processes: the image capturing system, composed mainly by a camera and its controlling software, one or more light sources and the running application for image analysis.

The former may present many variants depending on the complexity of quality control to carry out: it may involve single or multiple cameras to provide a better 2D imaging or even a 3D capture.

Mainly, the vision systems allow two different acquisition types (from now on, one single camera is taken as reference):

- Streaming video: the camera takes a streaming video and extracts frames from it. The image processing is performed on the captured frame. This approach is not highly accurate in terms of image quality but guarantees very high speed.
- Still image capturing: the system is placed relatively close to the object to be inspected and takes a picture by reacting to an external or internal input.

[1] M.-J.-J. Wang and C.-L. Huang, ‘‘Evaluating the eye fatigue problem in wafer inspection,’’ IEEE Trans. Semicond. Manuf.

In general, the key elements and the acquisition type described so far are selected based on use case, in order to build an architecture which guarantees a good balance between accuracy and speed.

The accuracy of the output can be improved also by studying the most appropriate illumination system. It is fairly common for the surface of the components analyzed to be enlightened by several lighting sources which are carefully chosen according to the refraction material characteristics and the type of defects to spot. By selecting the correct light type and making it diffuse homogeneously it is possible to amplify defects thus reducing the processing effort.

Built-in solutions are available in the market today, but despite optimized integration of all the components, they come at a remarkably high cost. Single architecture is calibrated and delivered to handle a specific check; however it is difficult to scale the same system to different use cases due to its rigidity. This is why companies often opt for traditional methods such as manual inspection over AOI.

The scientific community is increasing their focus on Automatic Optical Inspection studies in the last 5 years (Figure 2-1). Most of the published articles since 2016 include manufacturing-related use cases emphasizing the image analysis methods over the architectures themselves.

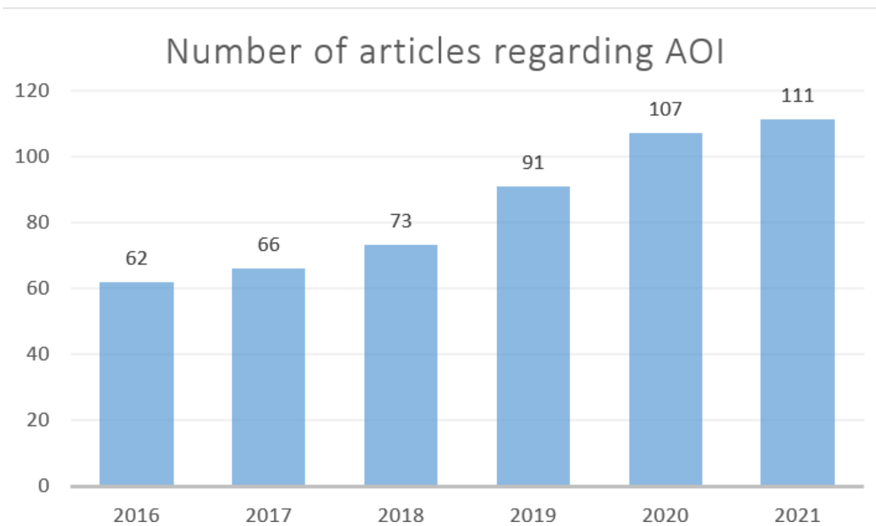


Figure 2-1: Number of articles published on Scopus platform. Research strategy with keywords: “Automatic Optical Inspection”.

The following chapters illustrate a complete framework for an AOI system including hardware and software architectural paradigms for a from-scratch-implementation of a complete Automatic Optical Inspection system, and it will prove its scalability illustrating two different use cases.

## 1.3 PURPOSE

The aim of this paper is to illustrate a concrete implementation of an Automatic Optical Inspection system from scratch, describing a proposed architecture from both hardware and software point of view, and how it has been applied to real manufacturing processes.

## 1.4 SCOPE

This study aims at providing a scalable solution for autonomously implementing an Automatic Optical Inspection system on existing processes. It is not intended to provide focus on AI algorithms used for AOI.

## 1.5 STRUCTURE

This article consists of three chapters:

- Chapter 2 – *Proposed solution overview.* An illustration of hardware and software architecture design,
- Chapter 3 – *Use cases.* The proposed solution implemented on two different existing assembly lines,
- Chapter 4 – *Conclusion.*

## 1.6 AUDIENCE

This document addresses leaders aiming at increasing digital know-how in their companies, to show how an emerging technology can be deployed with limited costs and effort without relying on external suppliers.

## 1.7 USE

This document can be intended as a concrete guide to assemble and integrate an AOI system to existing processes.

# 2 PROPOSED SOLUTION OVERVIEW

The following chapters thoroughly illustrated the solution architectural paradigms for both hardware and software infrastructures.

## 2.1 HARDWARE

The hardware architecture of the structure consists of:

- A high-definition GigE camera to capture images[2],
- A lighting source to spread the illumination across the products to analyze,
- Sensors to detect the presence of the components on the control position,
- 8 Channel Digital Input module to manage incoming electrical signals, mastered by means of appropriate Python libraries[3],
- 8 Channel Digital Output module to manage outgoing electrical signals, mastered by means of appropriate Python libraries,
- A dedicated PC where the master coordinator, consisting of a Python application, is hosted into a Docker container,
- A lighting device to notify the overall analysis feedback,
- IoT Gateway to exchange information with the physical process.

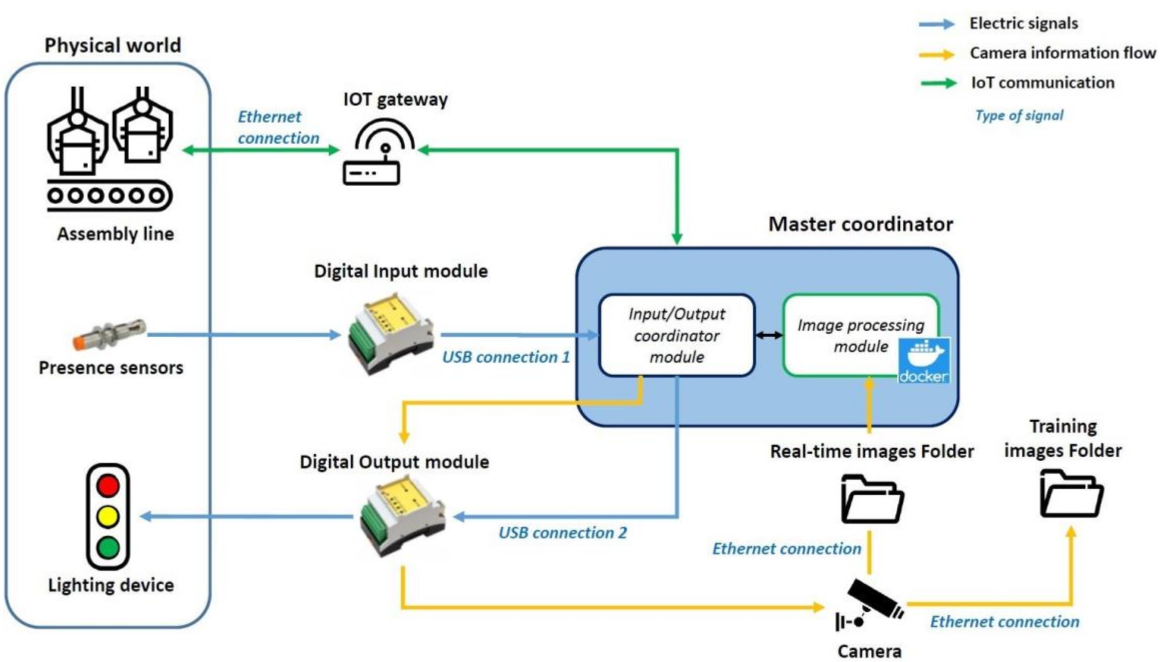


Figure 2-1: Hardware blueprint of the designed solution.

[2] Visionlink Triton DataSheet, *https://visionlink.it/wp-content/uploads/2021/06/index-2532.pdf*
[3] LucidControl Product Series, User Manual (2.0), *https://www.lucid-control.com/wp-content/uploads/2013/04/User-Manual-LucidControl.pdf*

Communication between all the components is enabled by traditional USB and Ethernet connections. In addition, they share information by means of the electrical signals, managed through I/O modules, sent and interpreted by the Master Coordinator.

Information exchange between PLC and AOI systems, instead, is performed through IoT Gateway.

The Master coordinator represents the pillar of the entire architecture, managing the overall logic of the AOI structure. It is composed by two main modules, each of them controlling a different step of the flow:

1. Input/Output coordinator: it receives and sends electrical signals from and to external devices (e.g. sensor/RFID reader detecting the presence of a new object to be inspected, camera to start acquisition of a new frame, traffic lights for a visual feedback communicating the outcome of the control back to the operators).

```
# Import Functionality of Digital Output Module
from lucidIo.LucidControlDO4 import LucidControlDO4
# Import Functionality of Digital Input Module
from lucidIo.LucidControlDI4 import LucidControlDI4
# Import Value Type for reading an writing of digital states
from lucidIo.Values import ValueDI1
# Import LucidControl return values
from lucidIo import IoReturn

# Set communication with Input module through the right USB port
di4 = LucidControlDI4('input USB port name')
# Set communication with Output module through the right USB port
do4 = LucidControlDO4('input USB port name')
# Get the input boolean variable of the set input channel
input_value = di4.getIo('input channel number', ValueDI1())
# Initialize an output signal variable that can be sent through the I/O module channel
output = ValueDI1()
# Set the output signal value to true or false
 output.setValue('True or False')
# Send the output signal to the set output channel
do4.setIo('output channel number', output)
```

Figure 2-2: Libraries and Python commands used to manage input and output signals through the Digital I/O modules.

In addition, through the IoT Gateway, the Input/Output coordinator retrieves information about parameters or requirements to be considered during the analysis and it communicates the outcome of the visual check to the PLC.

2. Image Processing module: it contains the AOI algorithm, selected for the specific task to be addressed.

### 2.2 SOFTWARE

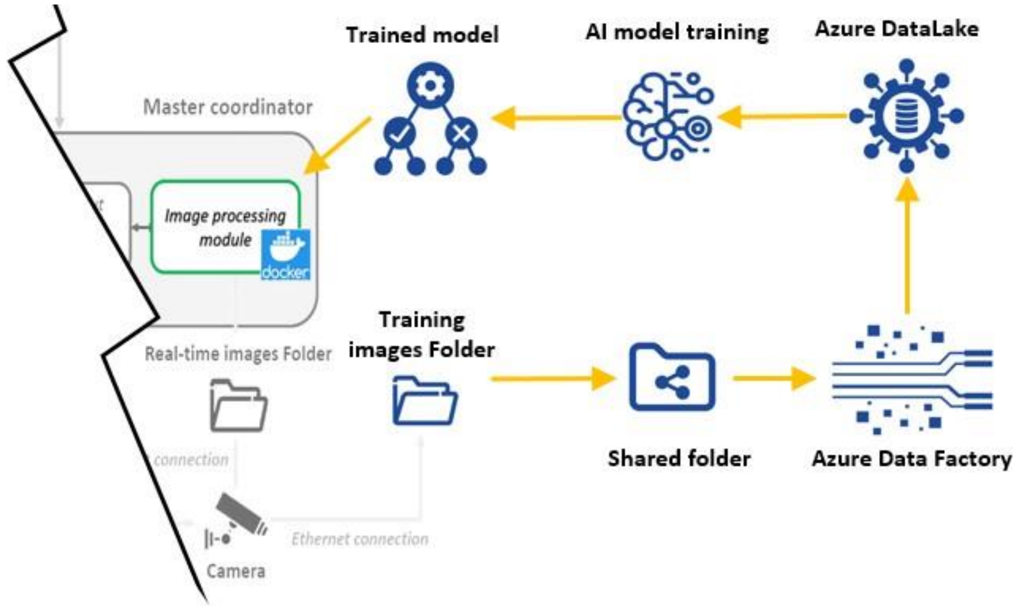


Figure 2-3: Software topology blueprint of the designed solution.

A considerable number of images are needed to develop the AI models. Frames are retrieved directly from the physical process through the installed camera and first saved in a dedicated pc local folder, then, once properly renamed, duplicated into a shared folder.

At constant intervals of time, the shared folder is analyzed, and new contents are transferred into Azure Data Lake, a cloud data warehouse service suitable for unstructured data, where they are stored in different locations based on the metadata embedded in their names (id, timestamp, information from PLC).

The pipeline used for moving data across different data sources is based on Azure Data Factory cloud service. This workflow allows for keeping track of images from different applications and makes them easily available for processing, AI model parametrization and training.

The new trained model is then imported in the main application which runs as a service in a dedicated container managed with Docker platform and located in the dedicated pc: in this way it performs continuously the analysis on the real process.

# 3 USE CASES

### 3.1 AOI FOR MATERIAL MIXING PREVENTION

Add Main Chapter A Section

To maximize competitiveness on the market, often manufacturing companies opt for the adoption of highly flexible and automated multi-product lines, and standardized products designed to generate components to be as similar as possible. At the same time maintaining the diversity in terms of both performance and application of the final products. This approach creates risks in material handling due to the similarity of certain components, such an approach enables a series of advantages. Namely, it minimizes the number of component validations and necessary stocks per product type. This section examines a case study of an AOI system installed on a vacuum pump production line to distinguish potential mixes between rotor sub-assemblies due to human error.

The rotor is the main component of the pump whose rotary motion is activated by special belts, or by directly keying it to the camshaft or to the rear of the alternator. Being a component that acts as an interface with the external environment, the rotor is generally difficult to standardize since its design is influenced by specific needs and applications of each customer. In particular, the case study aims at intercepting the positioning of an incorrect rotor in the very early stages of the process before its assembly in the pump to eliminate scrap and reduce waste.

Three different types of products are assembled on the line, each requiring a different type of rotor. These rotors differ from each other in geometry or material. However, since these differences are sometimes minimal, it was necessary to distinguish them by means of small circles present on the metal coupling and highlighted in red in Figure 3-1.

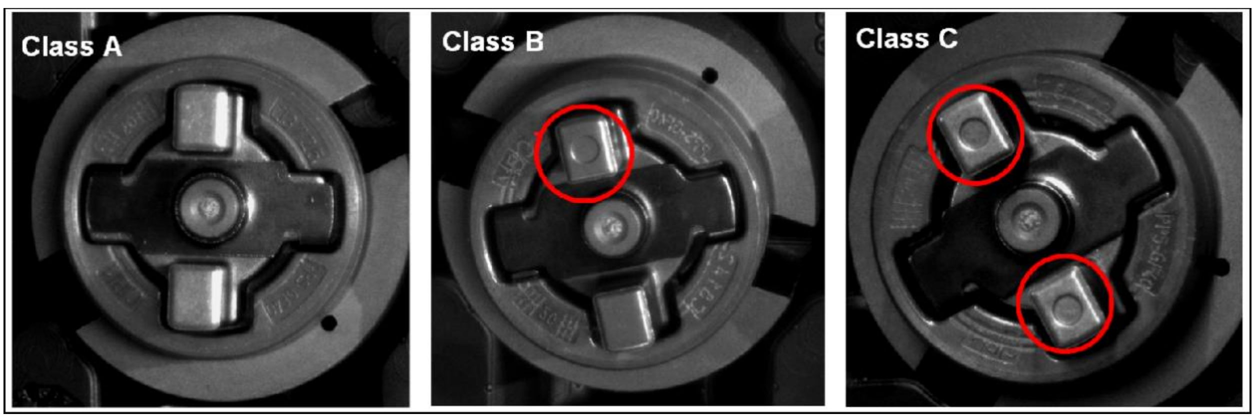


Figure 3-1: Rotor subgroup of class A, B and C (from left to right).

To address the identification of misplaced rotors, an Automatic Optical Inspection (AOI) system is implemented in a standalone material procurement facility and integrated with the production line (see Figure 3-2).

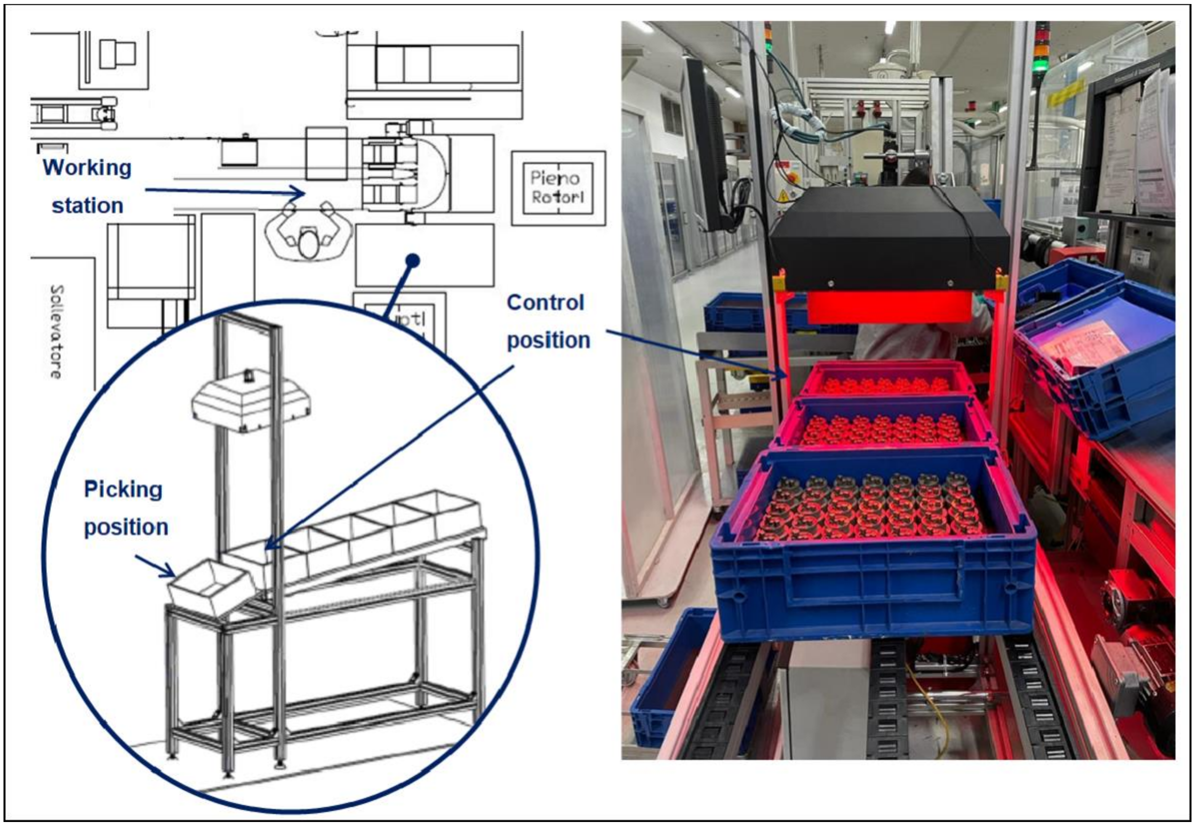


Figure 3-2: AOI device installed on the assembly line. A graphical representation of the line layout (left) with specific focus on the standalone structure (bottom left) and a real image of the vision system (right).

On the shop floor, dedicated operators move material from the supermarket to the assembly line. Rotors are neatly placed inside boxes and arranged on a gravity roller conveyor. The vision system analyzes the first box, which is then moved to the picking position if no misplacement is detected. To avoid interference between the operator and the field of view of the AOI camera, the detection system is placed above the box prior to the one in use.

When a new rotor box arrives at the control position, a dedicated sensor, connected to the digital input module and monitored through the Input/Output coordinator, sends a signal to start a new cycle. More in detail, the sensor detecting the presence of the box sets the Boolean variable of the dedicated Input module channel from 0, indicating absence, to 1, standing for presence.

The Input/Output module operates on a simple difference between the previous and the current state of the sensor: a non-negative result means that no new box has arrived, while a negative value states for a new box to be analyzed. When it occurs, the Input/Output coordinator sends a signal to the camera through the output module, triggering the acquisition of a new frame that is saved in a dedicated pc local folder. At this stage, the Image Processing module analyzes the image in two steps:

1. **Identification of rotors inside the picture.** The used algorithm first recognizes the location of each rotor through unsupervised semantic segmentation based on pixels clustering. Pixels are singularly classified and then grouped through a convolutional neural network, trained by minimizing a loss function which takes into account both pixel value and their spatial arrangement. The idea relies on the fact that pixels with similar values and spatially close belong to the same object. The rotor class is identified, and the output consists of the coordinates of each rotor location, which are used for their extraction from the original image.

2. **Recognition of the rotor typology.** A second algorithm spots the smaller circles identifying the different classes. Each rotor detected in the previous step is isolated and processed singularly through the Hough Circle Transform method, parametrized to spot the circumferences on the rotor metal coupling and, as a consequence, the correspondent class.

The outcome of the AI algorithm is compared to the recipe set on the PLC, thus verifying if all rotors inside the box belong to the right class. Finally, a visual outcome of the control is displayed on the PC monitor by overlaying red marks on the original image at the positions where the misplaced rotors are detected.

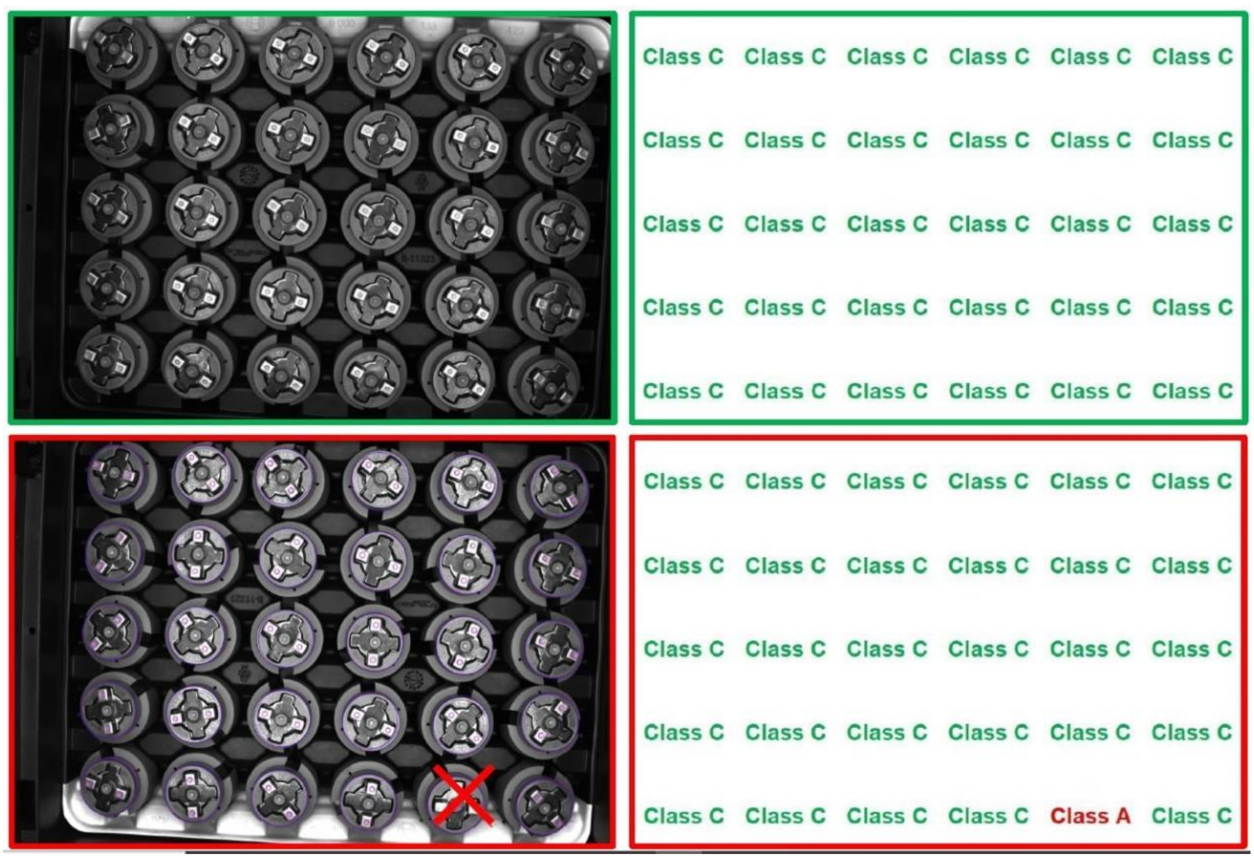


Figure 3-3: Final processed image (left images) shown on screen after the AI algorithm analysis is performed during production of Class C, indicating wrong rotor type belonging to class A with a red cross.

This approach prevents the assembly of a wrong component in the final product and thus reduces waste.

## 3.2 AOI FOR POROSITY DETECTION

The designed system has been implemented in a gear pump assembly line to detect porosity on the outer surface of the housing. The housing is manufactured using die-casting technology and subsequently performs a surface heat treatment that makes it black in color.

Porosity is the most common casting defect. If not detected during the assembly process, when the pump operates at full speed porosity can lead to fluid leakage and reduced performance.

Before implementation, line operators used to perform this check visually. However, visual check is commonly considered as not reliable[4].

That is why the company decided to integrate the designed system in the existing line, exploiting its non-invasive nature: the final station, the one designated for the visual check, already featured a camera for DMC reading. It has been equipped with a new camera for image recording and a presence sensor, in order to replicate the design in Figure 2-1.

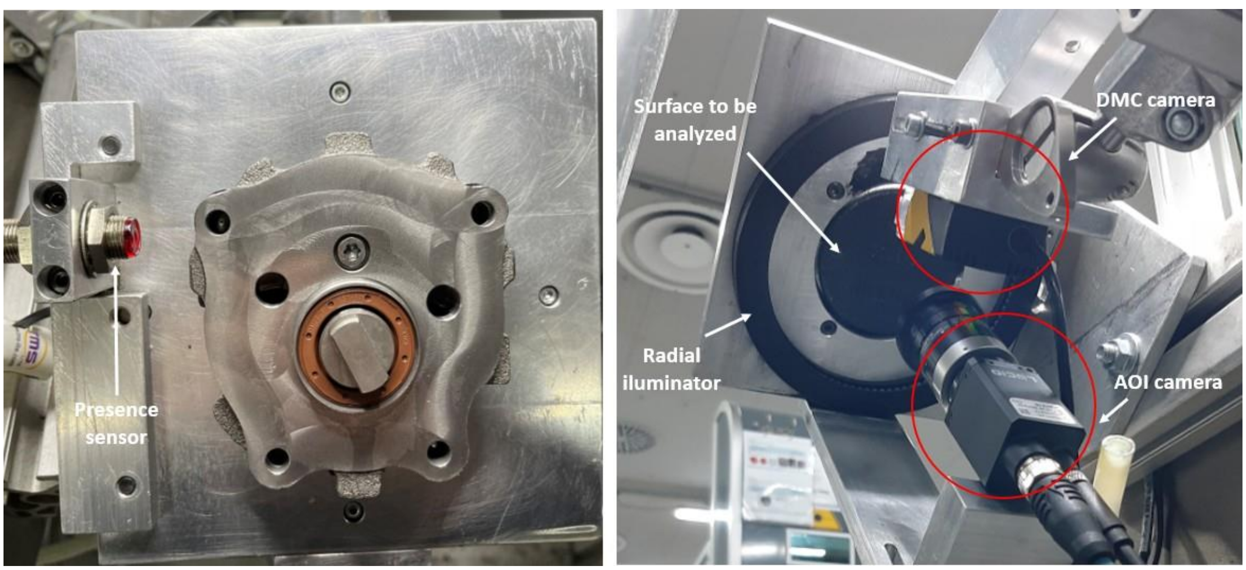


Figure 3-4: Top (left image) and bottom view (right image) of the designed solution applied to porosity detection use case. On the left, the gear pump is positioned by the operator on the control position, where the sensor detects its presence. On the right, the camera and the illumination system.

[4] M.-J.-J. Wang and C.-L. Huang, ''Evaluating the eye fatigue problem in wafer inspection,'' IEEE Trans. Semicond. Manuf

Two main criticalities were encountered:

1. **Integration of the new system with the DMC camera already implemented.** The co-existence of DMC reading, and porosity check has been guaranteed tuning the timing of the Input/Output coordinator in order not to hinder the DMC reading, that is performed as soon as a new component is detected: the Input/Output coordinator, instead, is set to wait few seconds from the presence sensor signal reception before triggering the AOI light source ignition, in order to not affect the DMC camera proper work. As already stated, the proposed system allows full control and adaptability.

2. **Making the defect visible.** After heat treatment, cast iron appears very dark. As a result, the capability of a proper illumination system to highlight the defect plays a significant role. The chosen illuminator provides circular radial lighting, so that the hidden surface appears bright in color while missing material/cavities stand out as black, since light is not reflected.

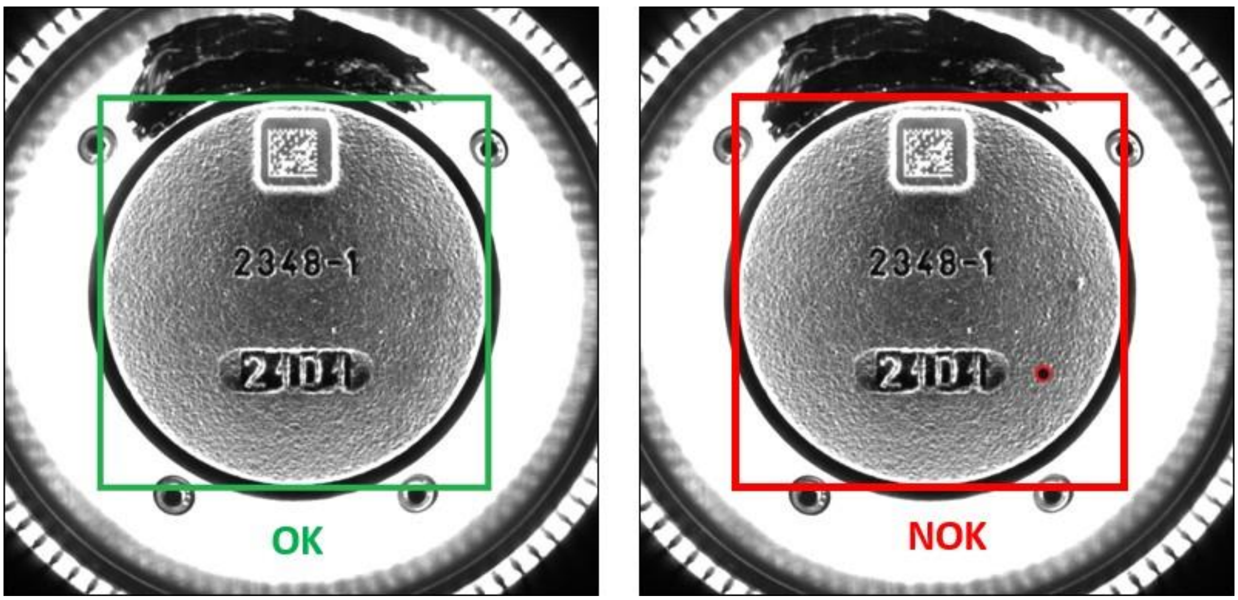


Figure 3-5: Example of OK (left) and NOK (right) parts analyzed through the proposed AOI system spotting the presence of a porous cavity on the defective part.

The part of the system customized specifically for the described application is the AI image-processing module. Again, the algorithm is composed by two different steps:

- **Component isolation.** The surface to be inspected is limited to the outer part of the pump. Given the circular shape of the pump, isolation is achieved through the Hough Circle Transform algorithm. As mentioned, the algorithm finds any circumference with a radius included in a pre-defined range, which is set in advance as a hyperparameter. Then, it returns the coordinates in terms of radius, x-center and y-center.

- **Porosity detection.** Since radial light is not reflected by concavities, the defects are well visible and much darker than the general surface. In a grey-scale image, the darker the visual color the lower the correspondent pixel value. Thus, the algorithm computes the average of the pixel values inside the isolated circumference and compares it to a defined threshold to discriminate between good and bad parts (Figure 3-5).

The threshold is set in advance by means of elemental statistical analysis: 250 images of good components have been collected and pixel average values computed for each image. The threshold is set by averaging once again all the results obtained and decreasing the result by a factor equal to three times the standard deviation of the original population.

## 4 CONCLUSION

In this study, after assessing a lack of information in literature regarding concrete implementations of end-to-end AOI systems, the authors described a framework easily able to be adapted to existing manufacturing processes and requiring limited investments. Its technical feasibility, as well as its scalability, were demonstrated through two different use cases, where the proposed solution was integrated into existing vacuum and oil pumps assembly lines in a non-invasive manner.

Adaptability and easy implementation were the main advantages achieved.

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## 6 ACKNOWLEDGEMENTS

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