Recognition system based on artificial vision using OpenCV for discarding and detecting ceramics with defects

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ABSTRACT

Early detection of defects through preventive maintenance is important in industry to avoid economic losses, as in the case of ceramic tile manufacturing, where manual inspection allows defective parts to advance in production, causing delays. The research review shows that computer vision enables the automation of object detection, classification, and elimination tasks in industrial processes, using solutions based on Python, OpenCV, and MATLAB. For this reason, the design of a computer vision recognition system with OpenCV is proposed, which allows automatic discarding of ceramics with defects using an algorithm for detecting ceramics with a camera and Arduino-based hardware, comparing the captured images with a standard image on a conveyor belt. The machine vision system was integrated with a camera connected to a computer running OpenCV, achieving effective automatic detection with a threshold of 25% difference from the standard part. This percentage was calculated by comparing the grayscale pixel values with a reference image. The system calculates the proportion of pixels that exceed the similarity threshold. The conclusion is that the developed system contributes to production, highlighting the possibility of future industrial integration.

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1. INTRODUCTION

Industrial equipment maintenance, related to early fault detection, involves monitoring equipment performance to identify problems before they become costly failures through visual inspections, sensor data analysis, and preventive maintenance. Furthermore, fault detection enables maintenance planning [1], reduces downtime, and improves equipment reliability [2], [3]. In the case of interruptions in the ceramic manufacturing process due to defects, the personnel usually do not detect these because a manual inspection method is used, which depends on the operator's vision. As a result, defective pieces go unnoticed and continue in the production process [4], which causes delays in production goals [5], [6]. Furthermore, the persistence of these defective parts in the process generates additional losses, as they accumulate value. However, when they are identified as defective at the end of the process, they are rejected, generating economic losses for the company and delays in the production of product batches [7], [8].

The reviewed research works focus on the application of technology based on artificial vision and its potential to detect, classify, track or discard objects in industrial processes that use conveyor belts, allowing computers to interpret the parameters that characterize their environment, in areas where discarding is done manually [9], [10]. Furthermore, it is also mentioned that not detecting defective products has a significant impact on ceramic industry, making it necessary to review image processing techniques, identifying several methods from traditional image processing techniques to complex neural networks [11], [12]. In the context of artificial vision techniques, the literature review indicates that there are training and validation methods for classifiers [13] for image detection using services such as custom vision [13], [14], which is applied in the identification of various moving and static objects. On the other hand, designs of an artificial vision device for the visualization and monitoring of objects on a conveyor belt were found [15], [16], in some cases, integrating a 2D BOA-INS smart camera [17].

Other research describes the use of conventional computers where biometric facial recognition is performed, identifying images of human faces for recognition [18], [19]. In addition, technologies such as OpenCV in Python are also integrated for face recognition in sports [20], [21]. On the other hand, other works describe the use of the MATLAB software tool with artificial vision and object recognition mechanisms applying neural network training [22].

Another relevant aspect found in the literature is the applications of artificial vision to recognize abnormal postures [23], [24]. They also allow to detect skin alterations such as melanoma through image analysis using deep learning with convolutional neural networks [25]. In addition, artificial vision technologies allow to identify animal species such as cattle [26], [27]. In conclusion, the literature review indicates the need to develop technology through artificial vision to identify various anomalous pattern elements and it can be applied to various industrial sectors to automate manual tasks.

Therefore, the need arises to reduce interruptions in the ceramic tile manufacturing process due to defects, raising the following research question: how to implement an identification system to discard ceramic tiles with defects using artificial vision? To answer this question, the main objective is to design a computer vision recognition system using Python and OpenCV to eliminate defective ceramics on the production line. To do so, the system architecture must be determined, the system hardware implemented, and the recognition algorithm developed.

Regarding the project's contribution, from a research perspective, it describes the implementation of a method for applying a computer vision-based algorithm to detect defective ceramics found in the final production stage. Furthermore, the system contributes to improving product quality and production times, which impacts ceramic production and greater process efficiency. Operators will also benefit, as they will use a ceramic recognition and discard system that will support the process.

2. PROPOSED SYSTEM

The design of a system to identify defective tiles is proposed, using a camera and Arduino hardware to send and receive signals, capture images, and activate outputs. Defection is based on comparing the captured images with a standard image, as shown in Figure 1. The first stage is the artificial vision process, which obtains images of the current ceramic products and compares them with the standard image to determine whether the piece is accepted or rejected. In the next phase, the electronic control stage is designed, which is responsible for controlling the start and stop of the conveyor belt and the discard actuator. Finally, it is necessary to integrate the mechanical structure, which consists of the conveyor belt, camera support, and electronic components.

2.1. System architecture

The system architecture integrates image processing tools using the Python language. Considering the requirements of the machine vision components [28], the webcam (with full HD 1080p video resolution at 30 fps, up to 15 megapixels, autofocus, and USB 2.0 connectivity), a programming language with image processing libraries and an active community (OpenCV) and computer vision software were selected. For the control electronics, the Arduino UNO hardware, IR-1000 infrared sensors, NPN transistors, a conveyor belt with a 12 VDC electric motor drive and S90 actuators with pulse-width modulation (PWM) control are used (Figure 1).

The development of the defective ceramic disposal system consists of three main parts: machine vision, control electronics, and mechanical structure. The first part includes elements such as the camera, lighting, and a computer for image processing. The second part includes the controller, sensors, transistors, and LEDs that indicate operating status. The third part is the mechanical structure, which supports all the components, including the conveyor belt, motor, camera, sensors, and controller (Figure 2).

2.2. Artificial vision stage

Machine vision processing involves acquiring images, performing preprocessing to improve their quality, and then detecting features. Segmentation and recognition algorithms are then applied using OpenCV. Finally, postprocessing is performed to visualize and analyze the results to decide whether the part should be discarded (Figure 3).

During the comparison process with a reference image, the percentage of error between the standard part and the part being analyzed is determined. The current image is displayed with a box in the center and the percentage of difference. If the difference exceeds a threshold of 25%, a signal is sent to the controller hardware, but if the difference is less than 45%, a deactivation signal is sent.

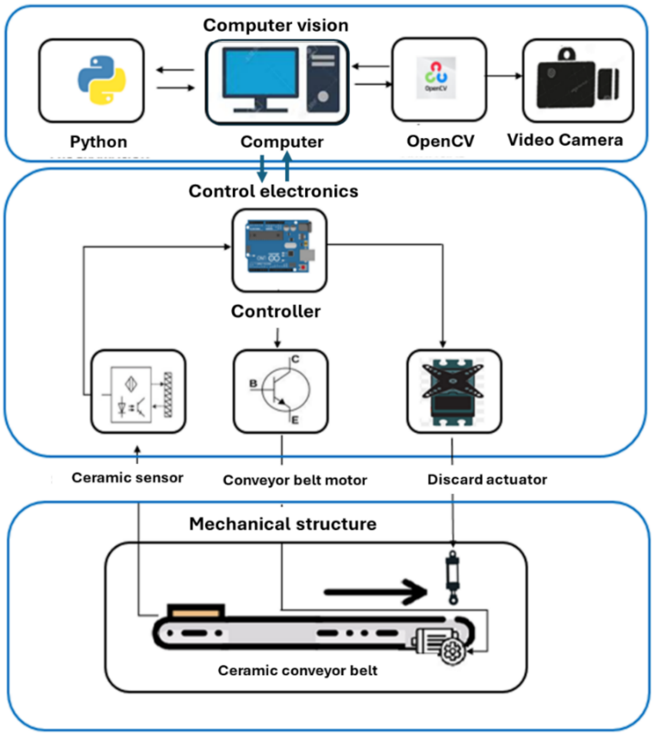

Figure 1. Diagram of the machine vision recognition system

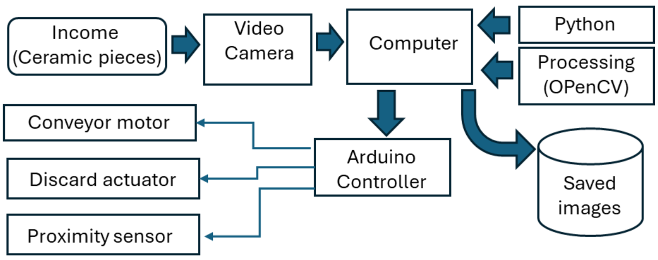

Figure 2. Architecture of the computer vision recognition system

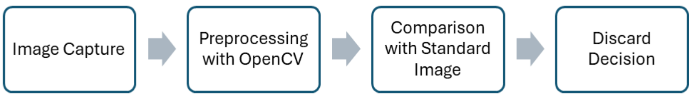

Figure 3. Machine vision design diagram

2.3. Control electronics

The main control element is the Arduino Uno development board, which uses a 5V DC source to activate the discard motor and power the ceramic piece sensor. It also controls the operating mode selector, configured to work with the Arduino's internal resistance. Additionally, it manages the connection of a green LED indicating the detection mode and an LED for detecting a defective piece (Figure 4).

The diagram shown in Figure 5 shows the firmware flowchart for Arduino, where when a part is detected, the conveyor belt is stopped and an image is captured, considering the following: if the system is in calibration mode, the image of a standard part is captured; if it is in auto-detection mode, the image of the current part is captured. Subsequently, the conveyor belt is restarted. Depending on the mode and the condition of the part, a discard motor is activated if necessary.

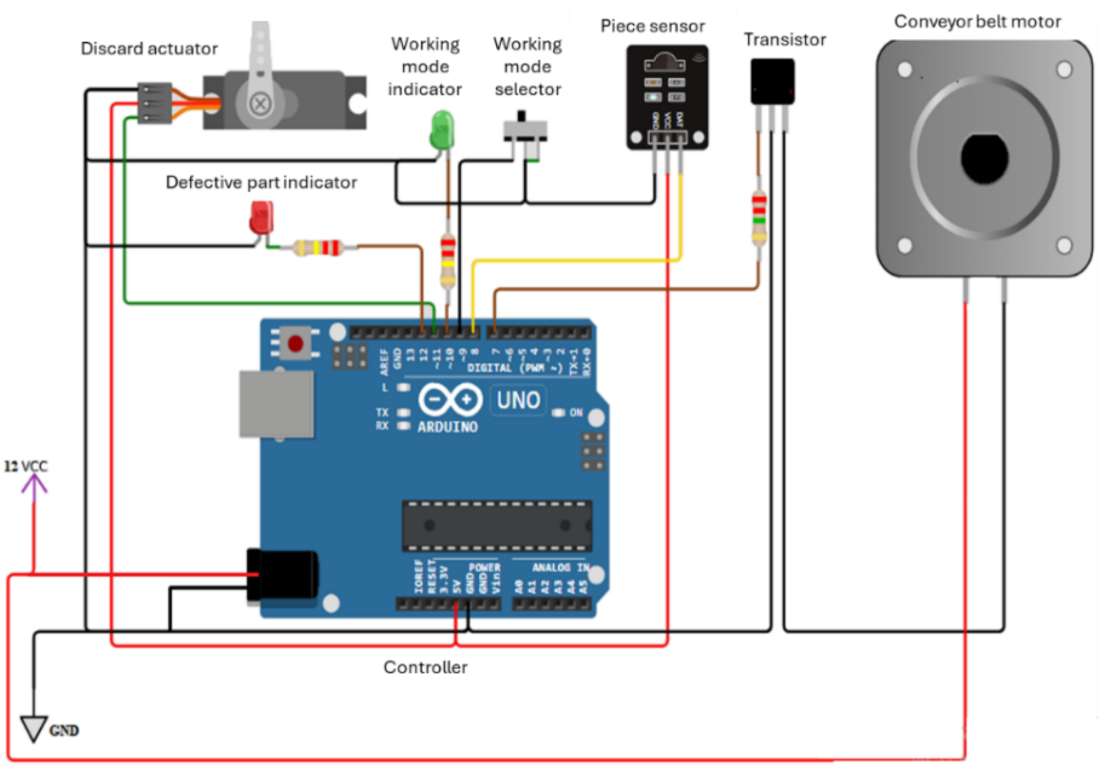

Figure 4. Control electronics diagram

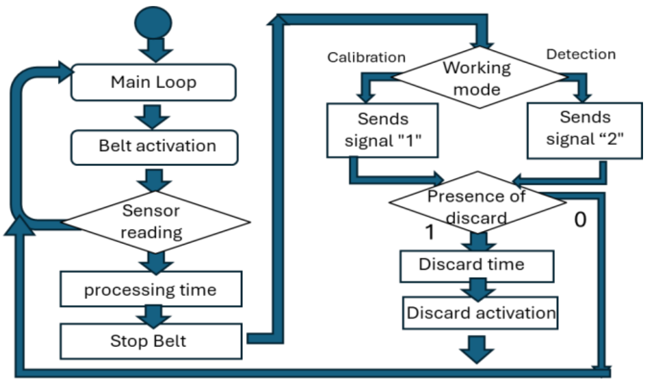

Figure 5. Firmware flowchart

2.4. Mechanical structure

The mechanical structure includes, first, an adjustable camera mount, positioned to capture images of the moving tiles. A second mount is used for the sensor, ensuring its alignment with the piece detection area and is also designed to accommodate the conveyor belt. The mechanical structure contains several components, the most important of which is the conveyor belt mounted on a support (Figure 6). The arrangement and organization of these elements ensure continuous operation, optimizing the detection of ceramic tile defects.

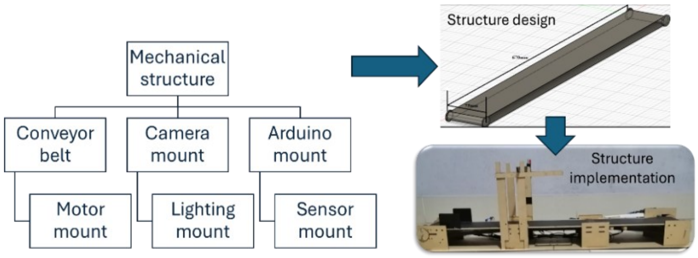

Figure 6. Mechanical structure and conveyor belt

3. RESULTS AND DISCUSSION

3.1. Machine vision system hardware

To capture images, the camera is mounted on a stand, allowing manual focus adjustment. This camera is also connected to a computer where the algorithm script is run in Python and the OpenCV library. Images are stored in different folders ("errors" folder for ceramics with defects, and "pattern_capture" folder for pattern images) (Figure 7). The use of a webcam is suitable in low-cost machine vision systems for defect detection activities, because its integration with image processing allows for quality control, as demonstrated in another research [3], [12].

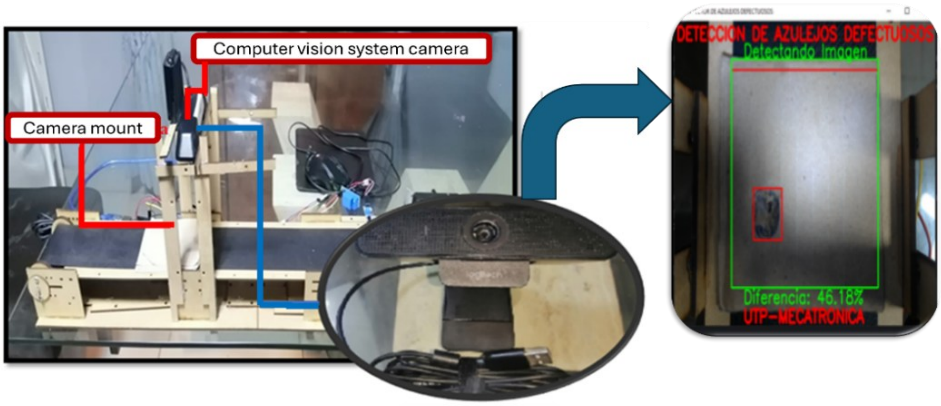

Figure 7. Webcam mounted on the mechanical structure for detection

3.2. Control electronics and mechanical structure

The use of NPN transistors, instead of mechanical relays for motor activation, is suitable considering the response time in systems using conveyor belts, as described in similar works [16], [17]. This activation test was performed in an evaluation environment (Figure 8), evaluating the servomotor at different speeds and position angles. Adequate results were obtained by controlling the activation time using PWM.

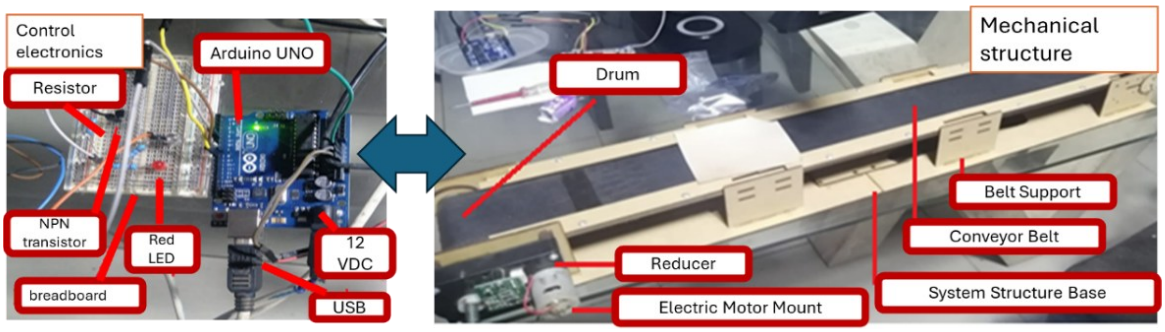

Figure 8. Electronic components integrated into the conveyor belt

3.3. System integration

The machine vision recognition system was properly integrated with the components described in the development section, along with the discard system and LED lights for image capture illumination. In addition, guides on the conveyor belt were used to ensure proper positioning of the parts (Figure 9). The tests performed consisted of entering half of the input parts with defects and the other half as correct. These parts were compared with an image of the standard part. In addition, a threshold of 25% difference (error) with respect to the standard part was calibrated to determine the part as defective and discard it.

This type of threshold-based pixel comparison has been used in flaw detection systems, where empirical calibration allows for balancing false positives and false negatives according to the application requirements [4], [6]. This case shows some detection cases by observing reference part, the part with errors, and then the parts with detected defects. Indicating their percentage difference, performing the efficient detection process (Figure 10).

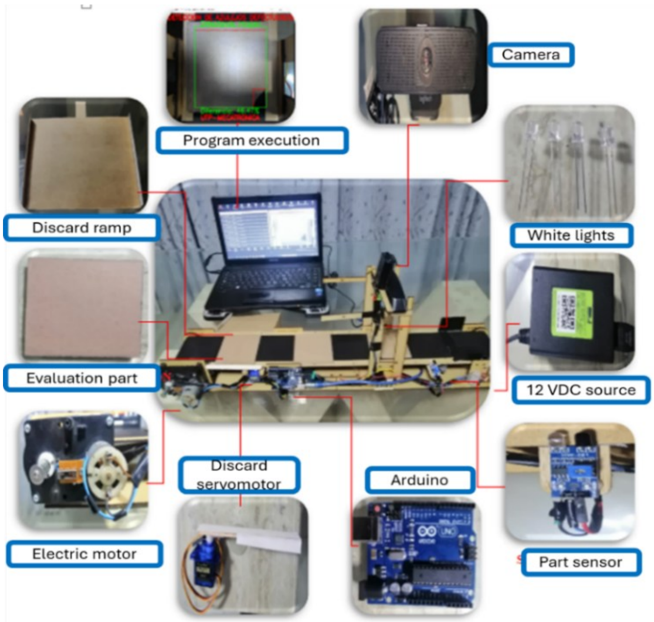

Figure 9. Components integrated into the recognition system

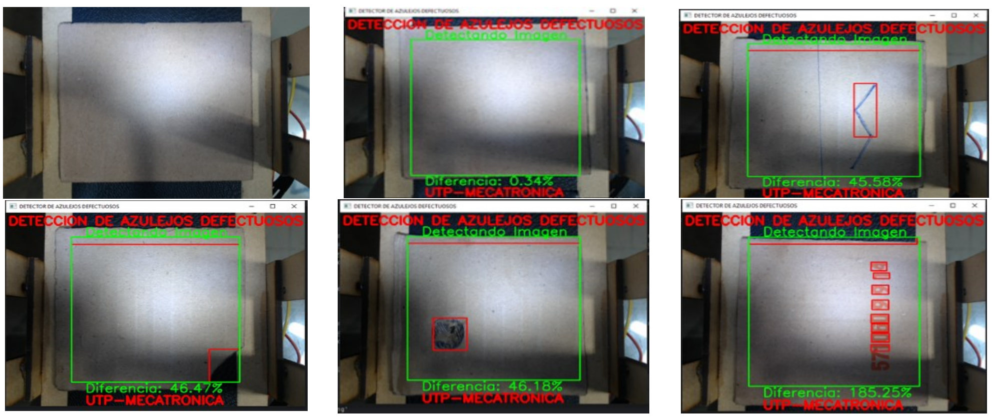

Figure 10. Detection of defective parts

4. CONCLUSION

The integrated system successfully removes defective ceramics in industries using image processing tools such as OpenCV and Python. Furthermore, it has been successfully determined that the system architecture, which integrates hardware and software components, works efficiently to meet the objectives.

Furthermore, the selected elements, such as cameras, lighting, processors, and software, were appropriately selected for the detection of defective ceramics. Each phase was appropriately designed following the machine vision hardware and application development methodology, demonstrating its replicability. To ensure its long-term operation, it is important to train personnel in its use and maintenance. To calculate the absolute pixel-by-pixel difference between the captured image and a stored reference, the proportion of pixels exceeding the similarity threshold is determined. When this error exceeds 25%, the system automatically classifies the part as defective and activates the rejection mechanism. As a future improvement, a monitoring system can be implemented to evaluate system performance. In parallel, it is necessary to research and adopt emerging technologies in the field of machine vision to improve system efficiency.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Ricardo Yauri		✓			✓	✓			✓	✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [RY], upon reasonable request.

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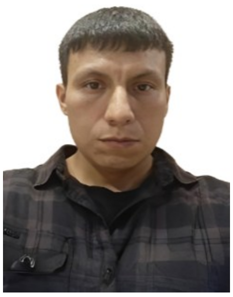

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