Sorting Line Assisted by A Robotic Manipulator and Artificial Vision with Active Safety

María F. Mogro [1], Fausto A. Jácome [2*], Guillermo M. Cruz [3], Jonathan R. Zurita [4]
[1, 2, 3, 4] Universidad de las Fuerzas Armadas ESPE, Sangolquí, Ecuador
Email: [1] mfmogro@espe.edu.ec, [2] fajacome1@espe.edu.ec, [3] gmcruz@espe.edu.ec, [4] jrzurita1@espe.edu.ec
*Corresponding Author

Abstract—**This article presents the design, implementation and evaluation of an object classification and manipulation system in industrial environments by integrating artificial vision and a MELFA RV-2SDB robotic manipulator. The central problem lies in the need to achieve rapid and accurate classification of objects for palletizing, while ensuring the safety of operators. To address this challenge, a machine vision system based on Logitech C920 HD Pro cameras and force and torque sensors was used on the robotic manipulator. The methodology focused on the use of object and person detection algorithms, as well as direct and inverse kinematics to calculate adaptive movements of the manipulator. The experiments covered evaluation of the system's accuracy and efficiency under various lighting and environmental conditions, as well as testing people detection and geometric shape classification. The results indicated that the system allowed precise and efficient manipulation, adapting in real time to the position and characteristics of the detected objects. The conclusions highlighted the effectiveness of the system in improving productivity and safety in collaborative industrial environments, highlighting the importance of integrating cutting-edge technologies to address automation challenges in the industry.**

Keywords—Artificial Vision; MELFA RV-2SDB Robotic Manipulator; Object Classification; Active Safety, Inverse Kinematics.

I. INTRODUCTION

Manual object sorting in industry faces significant challenges in terms of efficiency and accuracy [1], [2]. Manual processes are inherently limited by the human ability to handle large volumes of products consistently and without errors [3], [4]. This limitation results in higher costs, longer production times, and variable product quality. The urgent need for effective and accurate automation solutions becomes evident in this context [5], [6], [7].

Numerous studies and success stories support the idea that automation has revolutionized entire industries, improving efficiency, reducing costs and raising product quality [8]. For example, in the automotive industry, the introduction of automation systems on the assembly line has enabled faster and more consistent production of vehicles [9], [10], [11], [12], while, in logistics, automated sorting and storage systems have greatly streamlined the management of inventory [13], [14], [15], [16].

Sorting objects presents specific challenges, such as the variability of shapes, sizes and materials, as well as the need to handle constantly changing products [17], [18]. Robotics offers a more effective solution than manual processes by addressing these challenges with precision and speed [19], [20], [21], [22]. The ability of robots to perform repetitive tasks with high precision makes them ideal for object classification in industrial environments [23], [24].

Computer vision and sensors play a crucial role in object classification by providing accurate information about the location, shape and characteristics of products [25], [26], [27]. While there are clear advantages to using these technologies, such as the ability to work in variable environments and speed in identifying objects, there are also potential limitations, such as the need for adequate lighting and dependence on the quality of the images captured [28], [29], [30], [31].

The article proposes a comprehensive solution that addresses these challenges by designing and implementing a sorting line [32], [33], assisted by the MELFA RV-2SDB robotic manipulator through mathematical modeling of the robotic manipulator to establish placement trajectories and proper positioning of objects, based on the references given by a computer vision algorithm using OpenCV (open-source computer vision) software [34], [35], [36]. Highlighting unique features such as reconfigurable trajectories, autonomous configuration capability and the integration of an active safety system, image capture is performed using a Logitech C920 HD Pro webcam.

The MELFA RV-2SDB robotic manipulator, as indicated in Figure 1, is distinguished by its precision and versatility, making it the ideal choice for demanding sorting tasks [37], [38], [39], [40]. Its ability to dynamically adapt to different products and work environments contributes significantly to the overall effectiveness of the proposed classification system [41], [42], [43].

II. MATERIALS AND METHODS

A. Robot Manipulator

The MELFA RV-2SDB robotic manipulator was specifically selected for implementation on the automated sorting line due to its unique features and capabilities that made it suitable for this application [43], [44]. This manipulator is recognized for its high speed and multifunctionality with six degrees of freedom (DOF) as seen in Fig. 1, allowing optimal performance in industrial environments where fast and precise manipulation of objects is required. Additionally, its compact design and ability to operate with a maximum load of 3 kg and cycle times of 0.6

seconds make it ideal for handling objects of varying size and weight on the sorting line [45], [46], [47], [48].

One of the main reasons for choosing the MELFA RV-2SDB robotic manipulator was its ability to integrate with machine vision systems and force and torque sensors, allowing for smooth and safe interaction with the work environment [49], [50], [51], [52]. This was critical for the implementation of the automated sorting line, where accurate object detection and the ability to avoid collisions with the environment and operators were required.

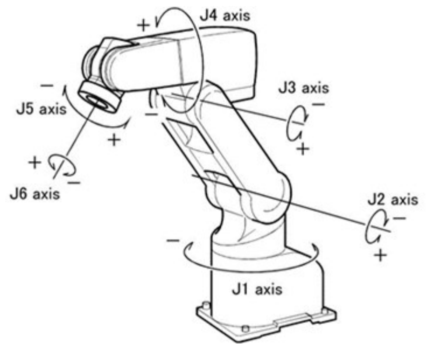

Fig. 1. Mitsubishi MELFA RV-2SDB

B. *Mathematical Model*

The mathematical model of the MELFA RV-2SDB robotic arm is composed of the direct and inverse kinematics (IK) [44], [53]. The direct mathematical model is used to calculate the axis positions from the end point coordinates, and the inverse mathematical model is used to calculate the end point coordinates from the axis positions [54]. The robot has 6 degrees of freedom (DOF) and 6 links (n), which means that it has 6 kinematic pairs of revolution of J_i one degree of freedom as indicated in equation (1). The mathematical model of the robotic arm is important to establish placement trajectories and proper positioning of objects, based on the references given by the artificial vision algorithm [55], [56], [57], [58].

$$DOF = 6(n-1) - 5J_1 - 4J_2 - 3J_3 - 2J_4 - J_5 \tag{1}$$

The direct mathematical model of the robot is based on the Denavit-Hartenberg model, which is a model used to describe the kinematics of articulated robots [59]. This model plays an important role in the kinematics of the robotic arm by enabling precise trajectory planning and positioning of objects on the automated sorting line. It also provides a systematic description of the geometry and kinematics of the robot, facilitating the conversion between coordinate systems and allowing efficient programming of movements [60].

In this model, the extent to which the last link of the arm will reach is determined from the movement of each joint based on the geometry of the robotic arm indicated in Fig. 2. Thus, the parameters (θ) angle of rotation along the "z" axis, (d) distance along the "z" axis, (a) distance along the "x" axis and (α) angle of rotation along the "x" axis are defined; the magnitudes of the parameters obtained are shown in Table I.

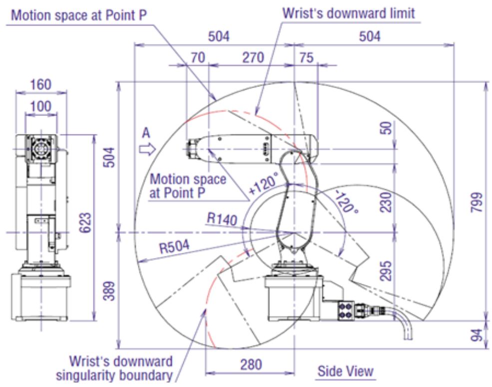

Fig. 2. Geometry of the MELFA RV-2SDB robotic arm

TABLE I. DENAVIT - HARTENBERG PARAMETER MAGNITUDES

J	$\theta[°]$	$d[mm]$	$a[mm]$	$\alpha[°]$
1	θ_1	295	0	90
2	$\theta_2 + 90$	0	230	0
3	$\theta_3 - 90$	0	0	-90
4	θ_4	270	0	90
5	θ_5	0	0	-90
6	θ_6	70	0	0

Then the homogeneous transformation matrices $[A_i^{i-1}]$ are calculated for each joint as indicated in equation (2), considering that simple θ_2 and θ_3 are used, and at the end the 90° values are subtracted. The final homogeneous transformation matrix is obtained through equation (3); subsequently the origin point $[P_0]$ is related to the end point $[P]$ through equation (4), and finally equation (5) is obtained.

$$[A_i^{i-1}] = \begin{bmatrix} cos\,\theta_i & -cos\,\alpha_i\,sin\,\theta_i & sin\,\alpha_i\,sin\,\theta_i & a_i\,cos\,\theta_i \\ sin\,\theta_i & cos\,\alpha_i\,cos\,\theta_i & -sin\,\alpha_i\,cos\,\theta_i & a_i\,sin\,\theta_i \\ 0 & sin\,\alpha_i & cos\,\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

$$[A_6^0] = [A_1^0][A_2^1][A_3^2][A_4^3][A_5^4][A_6^5] \tag{3}$$

$$[P] = [A_6^0][P_0] \rightarrow \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} = [A_6^0] \begin{bmatrix} X_0 \\ Y_0 \\ Z_0 \\ 1 \end{bmatrix} \rightarrow \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} = [A_6^0] \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \tag{4}$$

$$[A_6^0] = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0.99 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5}$$

Within the inverse kinematics model, the iterative Newton-Raphson method plays a fundamental role in determining the joint movements necessary for precise positioning of the robotic manipulator [61], [62]. This approach allows the robot's joints to be calculated efficiently, ensuring effective and accurate operation of the automated classification system.

The Newton-Raphson iterative method is used to find the solution of a system of nonlinear equations. This model determines the value that the joints must move to reach a point required by the application or user [63], [64]. The solutions to the IK problem consist of finding the values that the joint coordinates of the robot must adopt $[q]$ according to equation (6), so that its end is oriented and positioned according to a certain configuration. Solving this problem may lead to multiple solutions, there may be no solution, or it may lead to singularities.

$$[q] = [q_1, q_2, \ldots, q_n] \tag{6}$$

The methods used to solve IK were the Geometric Method, which is suitable for few DOFs and is based on finding sufficient geometric relationships in which the final coordinates of the robot and its joint coordinates will intervene. In addition, Kinematic Decoupling was used, which is used in robots with 6 DOF [65], [66], and consists of the separation of orientation and position, given a desired final position and orientation, the position of the robot's wrist is established by calculating the values (q_1, q_2, q_3) and considered (q_4, q_5, q_6) independently.

C. Implementation of Automated Sorting Line Subsystems

In the operational stages, first the acquisition and processing of images was considered to obtain their characteristics, then the communication between the image processing software and the IK calculation software was established, and finally the positioning coordinates for the control of the robotic arm, resulting in autonomous control of the robotic arm by sending coordinates. The first subsystem is the hardware, where it was verified that all physical elements can be controlled. As identified in Fig. 3, there are the cameras, robotic arm controller, conveyor belt and computer. The second subsystem is the software, in Fig. 4 you can see the flow of information from the acquisition of the image, then passing through the communication interface through the controller, until reaching the execution of the movement. The following paragraphs detail what is indicated in more depth.

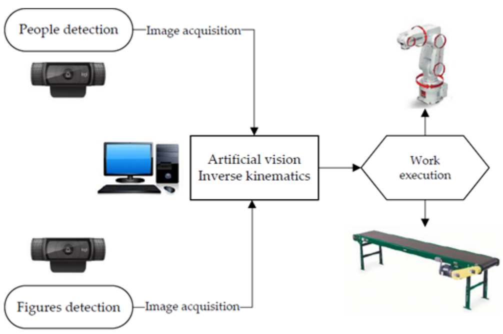

Fig. 3. Connection of physical components

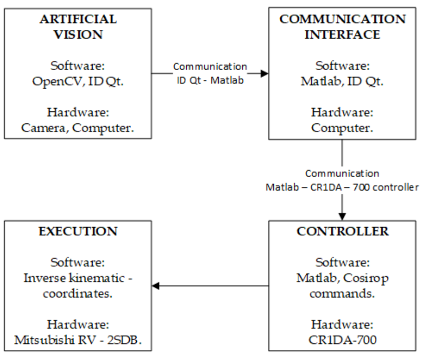

Fig. 4. Stages and flow of system information

1) Artificial Vision Algorithm: In the classification and selection system of parts on the classification line, two Logitech C920 HD Pro cameras were used to acquire images of the moving parts [67], [68]. The first camera was used to identify the pieces by their geometric shape, while the second was used to detect people within the robot's work area. Images were processed in real time to send control commands to the robotic arm and were acquired at a resolution of 1920×1080 pixels. The size of the image allowed us to determine the position of the moving parts in the "x" and "y" axes within a predefined workspace, as seen in Fig. 5, where the different geometric figures are identified.

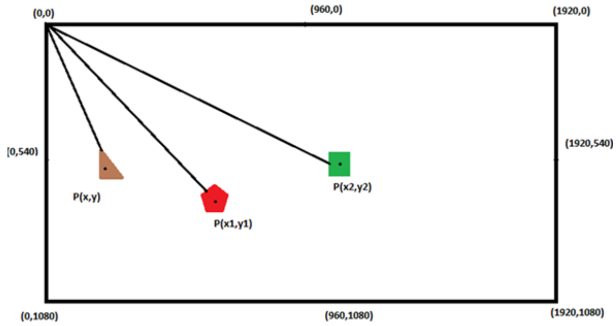

Fig. 5. Position of the pieces within the workspace

The center point of the pieces in Fig. 5 were determined based on the acquired image and served as a reference for the robotic arm, which moved towards the center point of the piece to pick it up. The part sorting and selection system used a methodology called visual servo, which controls the joint movements of the robotic arm to position and pick up parts on a conveyor belt.

The importance of the artificial vision algorithm lies in its ability to improve the overall functioning of the system by allowing automated manipulation of parts with high precision and speed. By identifying parts and their position quickly and accurately, the algorithm optimizes the performance of the robotic manipulator by ensuring it can perform sorting tasks efficiently and without errors. This results in greater productivity and quality in industrial sorting operations, as the system can process a greater volume of parts in less time and with greater precision, leading to a significant improvement in the efficiency of the sorting process.

2) ID Qt (OpenCV) – Matlab Interaction: This interaction was used in the part sorting and selection system to send the coordinates necessary for the correct positioning of the robotic arm. ID Qt is a software development oriented framework that contains a compilation of libraries with pre-built functions for different processes [67], [69], [70], [71]. In this case, the libraries "QTcpSocket" were used for local communication through sockets, "QTcpServer" to establish the TCP/IP communication protocol, "QHostAddress" to open the communication ports and "QString" to transform all data into a character string that could be sent correctly. This allowed fluid and efficient communication between the different components of the system, facilitating the coordination and control of the robotic arm for classification tasks. OpenCV provided the necessary tools for image processing and object detection, while Matlab was responsible for the configuration and manipulation of the CR1DA-700 driver [72], [73], [74], [75].

3) Matlab - CR1DA 700 Controller Interaction: This interaction was used to configure and manipulate the robot in the part sorting and selection system. The controller of the robotic arm has an Ethernet communication port that was used to send positioning coordinates to the robot so that it could follow the controller's commands [76], [77]. In order for the robot to recognize the commands sent from the computer, a sequence called the Point-to-Point Interface (PPI) protocol was followed [75]. To establish communication between the Matlab software and the controller, certain parameters were defined, such as the IP address of the robotic arm, port, and computer address [78]. The IP address of the computer only changes the last digit, which can be a value between 0 and 255. Communication between the robot controller and the mathematical calculation software was carried out through the TCP/IP protocol using the "tcpip" command. specific to Matlab, which allows sending commands to the robotic arm controller. Once the IP address and port were configured, the communication was opened with the "fopen(variable)" command and the port and communication were closed with the "fclose(variable)" command.

III. TEST AND RESULTS

A. Determination of the Useful Area of the Cameras

Accurately determining the usable area of the cameras is essential to ensure efficient operation and accurate detection in the sorting process. By delimiting the useful area of the cameras, image capture capacity is optimized, ensuring that only regions relevant to the classification task are processed. To process the information received from a two-dimensional space (2D image), Logitech C920 HD Pro video cameras were used, which require a high use of computational resources, causing a minimum delay in the video, which does not affect most of the processing.

1) Useful Area - Parts Sorting Camera: To determine the useful detection area of the camera, the distance (H) from the central axis to one of the ends of the conveyor belt was measured, which was 0.425 m. Once the data was obtained, the focal length was calculated to define the height at which the camera should be placed. This was located in the center of the conveyor belt, at a height of 0.81 m, in order to obtain a wide field of view of the belt's trajectory and, above all, correct detection of the geometric figures. Considering the reach of the robotic arm and adequate manipulation of the pieces, a lateral distance of 0.275 m was established, this being the “x” axis. For the “y” axis, the distance of the width of the conveyor belt was determined, which was 0.11 m; Thus, a useful rectangular detection area of 0.0605 m^2 was established as seen in Fig. 6. It is crucial to highlight the importance of evaluating the geometric figure classifier algorithm, especially in terms of its accuracy to correctly identify different shapes in the conveyer belt. This precision contributes significantly to the effective functioning of the robotic arm in the precise manipulation of objects, thus ensuring an optimal and efficient sorting process [79], [80].

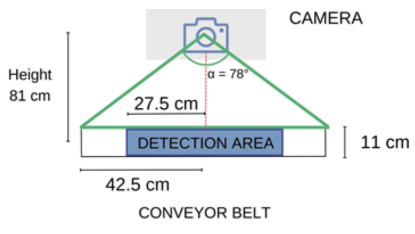

Fig. 6. Useful area - parts sorting camera

2) Useful Area - Active Safety Camera: To detect people entering the work area of the robotic arm, a static camera located at a considerable distance was used so that the image obtained covered the safety zone of the people. The measurements shown in Fig. 7 were obtained, where people are detected from 3 m measured from the center of the camera, and from that distance there is 1 m for detection. As with the previous camera, a viewing area is obtained, where a useful detection area of 2.77 m2 is determined. It is crucial to highlight the importance of evaluating the active security camera, especially in terms of its accuracy in identifying people, highlighting how this accuracy contributes to the effective functioning of the robotic arm in manipulating objects.

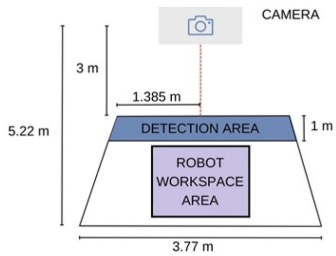

Fig. 7. Useful area - active safety camera.

3) Evaluation of the People Detection Algorithm: To demonstrate person detection for active safety using a camera, different distances were taken from the camera to the person. The data showed that at a distance of less than 3 m, the detection of people is 25%. In the range of 3 to 4 m, the percentage of correct detections of people was 90%. Finally, in the range of 4 to 5 m, detection was 50%. In the 3 to 4 m range, most detections were correct. In the remaining two ranges, the detection was erroneous at the highest percentage. In the case of the range less than 3 m, the shape of the people could not be defined because they were too close. In the range of 4 to 5 m, the work area was very close and the silhouette was often distorted by the equipment. Overall, the person detection algorithm works well. However, it is important to note that performance may vary depending on the distance between the camera and the person, as well as the location of the person in the work area.

Evaluating the positioning of the robotic arm on the pieces is essential to guarantee efficient palletizing. Accurate robotic arm placement not only improves productivity, but also reduces the risk of part damage and increases safety in the work environment. Furthermore, a 90% effectiveness rate for the active safety system indicates strong performance in detecting people, suggesting high reliability in preventing accidents and injuries in the work area. Compared with previous work [81], [82], [83], this study provides a significant improvement in person detection accuracy, demonstrating advances in the security and performance of the automated selection and classification system.

4) Evaluation of the Geometric Figures Classifier Algorithm: For the classification of geometric figures, three types were considered: squares, triangles and pentagons indicated in Fig. 8. To evaluate the triangle classifier, figures of different shapes and positions were placed on the conveyor belt. The algorithm had to draw only the shape of the triangular figure. To verify the proper detection of triangles within the detection area, a series of tests were performed. Table II shows a sample of 10 tests, in which between 5 and 7 pieces of different shapes were placed. The tests were performed to verify that the algorithm is able to discriminate only triangular pieces and each with its respective coordinate (X, Y) for the positioning of the robotic arm. From a set of 62 pieces of different shapes containing 17 triangular shapes, the same could be detected properly since the classification of 100% of the pieces with their respective coordinates was achieved.

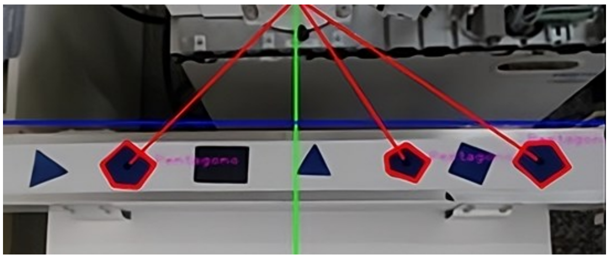

Fig. 8. Types of geometric figures

TABLE II. TRIANGLE DETECTION

No.	Total pieces conveyor belt	Triangles conveyor belt	Triangles detected	Coordinates (X, Y)
1	7	2	2	(-2.65, -315)
2	7	2	2	(-40, -297)
3	5	1	1	(80, -311)
4	7	2	2	(0, -324)
5	5	2	2	(-105, -315)
6	7	1	1	(197, -306)
7	5	2	2	(-167, -315)
8	7	2	2	(-40, -297)
9	7	2	2	(106, -309)
10	7	1	1	(-105, -315)
Total	62	17	17	

The evaluation of the square sorter was carried out by placing figures of different shapes and positions on the conveyor belt. The algorithm had to draw only the shape of the square figure. The adequate detection of squares within the area of the conveyor belt was verified by performing tests similar to Table II. Given 51 pieces of different shapes (squares, triangles and pentagons) of which 17 figures were square, these could be detected consistently. correctly, since the total of square figures were detected without problem, resulting in 100%. Finally, in the pentagon classifier it was verified that, out of a total of 60 pieces of different shapes, which contained 23 pentagons, the total number of pentagons could be defined with the classifier algorithm, resulting in a 100% detection rate. In general, the geometric figures classifier algorithm had a good performance. It was possible to detect 100% of the triangular, square and pentagonal figures, with their respective coordinates as seen in Table III.

5) *Positioning of the Robotic Arm on the Pieces:* Once the geometric pieces (square, triangle and pentagon) and their respective coordinates (X, Y) were identified, they were sent to the robot controller so that it could position itself on each piece to pick it up. The positioning of the robotic arm on the pieces was carried out taking into account that priority is given to the geometric figures most likely to go out of the detection range with respect to the "x" axis of the conveyor belt, where (+) is the indicator for correct compensation and (-) for incorrect compensation in Table IV.

TABLE III. X COORDINATE COMPENSATION - TRIANGLES

No.	Triangles		
	60 [mm]	70 [mm]	80 [mm]
1	+	+	-
2	-	+	-
3	+	+	-
4	-	+	-
5	-	+	-
6	-	+	-
7	-	+	-
8	-	+	-
9	-	+	-
10	-	+	-
Total	10	10	10
%	20	100	0

TABLE IV. X COORDINATE COMPENSATION - TRIANGLES

No.	Triangles		
	60 [mm]	70 [mm]	80 [mm]
1	+	+	-
2	-	+	-
3	+	+	-
4	-	+	-
5	-	+	-
6	-	+	-
7	-	+	-
8	-	+	-
9	-	+	-
10	-	+	-
Total	10	10	10
%	20	100	0

6) *X Coordinate Compensation:* When determining the correct positioning of the robotic arm, it is crucial to calculate the displacement in the "x" axis. This is because the conveyor belt is in motion during the process, which causes a change in the X coordinate. By analyzing data such as those presented in Table V, where the indicator (+) denotes a correct offset and (-) an incorrect offset, it is observed that the appropriate offset value for the X-axis of the triangles is 70 mm, and for the other figures the same value is obtained. This allows the robotic arm to be positioned correctly on the part while the conveyor belt is moving. X-coordinate compensation is essential to ensure accurate positioning of the robotic arm, regardless of the speed or direction of the conveyor belt. This compensation contributes significantly to the overall accuracy of the sorting system, ensuring that the robotic arm can perform sorting operations with maximum accuracy and efficiency, even under dynamic conditions.

TABLE V. COMPENSATION OF X COORDINATE

No. of test	Triangle (mm)			Square (mm)		
	60	70	80	60	70	80
1	+	+	-	-	+	-
2	-	+	-	-	+	-
3	+	+	-	-	+	-
4	-	+	-	-	+	-
5	-	+	-	-	+	-
6	-	+	-	-	+	-
7	-	+	-	-	+	-
8	-	+	-	-	+	-
9	-	+	-	-	+	-
10	-	+	-	-	+	-
Total	10	10	10	10	10	10
Adequate	2	10	0	0	10	0
Non-adequate	8	0	10	10	0	10
%	20	100	0	0	100	0

7) Distance Between Pieces: Regardless of the size and shape that the geometric pieces may have, an adequate distance was established between them to avoid possible collisions with the gripper of the robotic arm during the positioning, picking and palletizing process. In Table VI, different values of distances are indicated, marking with a (+) those magnitudes that are considered appropriate and with a (-) those that are not. The data indicates that, from 3 cm onwards, the distance is sufficient to avoid collisions between the pieces or with the gripper. It is crucial to highlight that the distance between pieces plays a fundamental role in the efficiency and safety of the sorting process. A detailed analysis of these distances ensures smooth and incident-free operation of the robotic arm, minimizing the risk of damage to parts or the system itself. The proper configuration of these distances contributes significantly to the precise and effective operation of the sorting system, ensuring that the robotic arm can manipulate the parts safely and efficiently, without compromising the quality of the process.

TABLE VI. ADEQUATE DISTANCE BETWEEN PIECES

No.	Distance		
	2 [cm]	3 [cm]	4 [cm]
1	-	+	+
2	+	+	+
3	+	+	+
4	-	+	+
5	-	+	+
6	-	+	+
7	-	+	+
8	+	-	+
9	-	+	+
10	-	+	+
Total	10	10	10
%	30	90	100

8) Fully System Test: Before implementing the complete system, the efficiency of the algorithms for classifying geometric pieces and detecting people was evaluated, obtaining very favorable results for both algorithms. Once the complete system was developed, through the execution of several classification iterations, it was determined that environmental conditions, such as lighting, can affect the complete percentage of efficiency of the system. However, when the classification system was implemented in well-controlled facilities, the accuracy and performance of the human recognition algorithm only decreased by 7%, since these effects can be reduced in these spaces. Therefore, once an operator is detected within the safety zone of the robotic arm, the running process stops completely to ensure the safety of the operator, until the safety zone is clear again.

On the other hand, the geometric part classification and palletizing system assisted by a robotic arm is a safe and efficient solution that can help companies improve their productivity. With the integration of software tools such as Matlab and hardware resources such as the control unit of the robotic manipulator and the manipulator itself, the reliability and efficiency of the positioning and coordinate compensation of the object to be manipulated were evaluated. Furthermore, by executing the algorithms, the variables immersed in the process can be manipulated, such as the speed of the conveyor belt to compensate for the inverse kinematics of the manipulator.

However, the adaptation and reconfiguration of trajectories of classification systems are usually in real time, although they will be restricted by the transmission speed of the camera interface and the processing speed of the computer. After system testing, it was determined that the efficiency of the active safety system has good reliability; if the environmental factors do not change severely during the process, an efficiency of 90% can be achieved depending on the iterations carried out, as shown in the figure. Table VII.

TABLE VII. SYSTEM TESTING ITERATIONS

No. of iteration	Test with operator	Test without operator
1	+	-
2	+	-
3	+	-
4	+	-
5	-	-
6	+	-
7	+	+
8	-	-
9	+	-
10	+	+
11	+	-
12	+	-
13	+	-
14	+	-
15	+	-
16	+	-
17	+	-
18	+	+
19	+	-
20	+	-
Detected	18	3
Non-Detected	2	17
%	90	15

During the tests, it was possible to implement an active security system that detects operators while the classification process is developing. This system, together with the process of detecting geometric figures and transmitting the position and orientation during the movement of the conveyor belt for the positioning of the robotic manipulator, reached a level of efficiency and reliability of 90%.

IV. CONCLUSIONS

The present study demonstrates the feasibility and effectiveness of an automated object classification and selection system assisted by a robotic manipulator and artificial vision. Challenges inherent to manual sorting processes were addressed, such as limitations in accuracy and speed, as well as variability in product quality and associated high costs.

The integration of a MELFA RV-2SDB robotic manipulator with an OpenCV-based machine vision algorithm enabled an efficient and accurate classification system. The mathematical model of the manipulator enabled the precise calculation of trajectories and the correct arrangement of objects, while the computer vision algorithm allowed the rapid and accurate identification of moving objects on the conveyor belt.

The evaluation of the effectiveness of the system revealed a high detection and classification rate of geometric objects, with 100% results in the detection of triangular, square and pentagonal figures. Likewise, an efficiency of 90% was achieved in detecting people in the manipulator's work area, demonstrating solid performance in accident prevention.

Coordinate compensation and proper setting of distances between objects contributed significantly to the accuracy and safety of the classification process. The successful implementation of an active safety system ensured the immediate stopping of the process if the presence of operators in the work area was detected, guaranteeing their safety.

Altogether, the proposed system offers an efficient and safe solution to improve productivity in industrial sorting operations. The integration of software tools such as Matlab and hardware resources such as the robotic manipulator and its control unit proved to be crucial for the reliability and efficiency of the system. Although potential limitations in real-time adaptation and reconfiguration of sorting trajectories were identified, the overall efficiency and reliability of the system is at a high level, with a potential efficiency of 90% under controlled conditions.

In addition to the achievements made, advanced image processing and machine learning techniques can be explored to further improve the accuracy and efficiency of the machine vision system. Additional research could focus on detecting and classifying more complex objects and adapting the system to more challenging industrial environments.

REFERENCES

[1] A. Dzedzickis, J. Subačiūtė-Žemaitienė, E. Šutinys, U. Samukaitė-Bubnienė, and V. Bučinskas, "Advanced Applications of Industrial Robotics: New Trends and Possibilities," *Applied Sciences*, vol. 12, no. 1, p. 135, Dec. 2021, doi: 10.3390/APP12010135.

[2] J. Chen, Y. Fu, W. Lu, and Y. Pan, "Augmented reality-enabled human-robot collaboration to balance construction waste sorting efficiency and occupational safety and health," *J. Environ. Manage.*, vol. 348, p. 119341, Dec. 2023, doi: 10.1016/J.JENVMAN.2023.119341.

[3] F. Tao, Q. Qi, A. Liu, and A. Kusiak, "Data-driven smart manufacturing," *J. Manuf. Syst.*, vol. 48, pp. 157–169, Jul. 2018, doi: 10.1016/J.JMSY.2018.01.006.

[4] S. Barris and C. Button, "A review of vision-based motion analysis in sport," *Sports Medicine*, vol. 38, no. 12, pp. 1025–1043, Oct. 2008, doi: 10.2165/00007256-200838120-00006/METRICS.

[5] K. K. H. Ng, C. H. Chen, C. K. M. Lee, J. (Roger) Jiao, and Z. X. Yang, "A systematic literature review on intelligent automation: Aligning concepts from theory, practice, and future perspectives," *Advanced Engineering Informatics*, vol. 47, p. 101246, Jan. 2021, doi: 10.1016/J.AEI.2021.101246.

[6] B. M. Muir, "Trust in automation: Part I. Theoretical issues in the study of trust and human intervention in automated systems," *Ergonomics*, vol. 37, no. 11, pp. 1905–1922, 1994, doi: 10.1080/00140139408964957.

[7] E. Hofmann and M. Rüsch, "Industry 4.0 and the current status as well as future prospects on logistics," *Comput. Ind.*, vol. 89, pp. 23–34, Aug. 2017, doi: 10.1016/J.COMPIND.2017.04.002.

[8] R. Pozzi, T. Rossi, and R. Secchi, "Industry 4.0 technologies: critical success factors for implementation and improvements in manufacturing companies," *Production Planning & Control*, vol. 34, no. 2, pp. 139–158, 2023, doi: 10.1080/09537287.2021.1891481.

[9] I. El Makrini *et al.*, "Working with Walt: How a Cobot Was Developed and Inserted on an Auto Assembly Line," *IEEE Robot Autom. Mag.*, vol. 25, no. 2, pp. 51–58, Jun. 2018, doi: 10.1109/MRA.2018.2815947.

[10] P. Dias, F. J. G. Silva, R. D. S. G. Campilho, L. P. Ferreira, and T. Santos, "Analysis and Improvement of an Assembly Line in the Automotive Industry," *Procedia Manuf.*, vol. 38, pp. 1444–1452, Jan. 2019, doi: 10.1016/J.PROMFG.2020.01.143.

[11] H. ElMaraghy, L. Monostori, G. Schuh, and W. ElMaraghy, "Evolution and future of manufacturing systems," *CIRP Annals*, vol. 70, no. 2, pp. 635–658, Jan. 2021, doi: 10.1016/J.CIRP.2021.05.008.

[12] I. P. Vlachos, R. M. Pascazzi, G. Zobolas, P. Repoussis, and M. Giannakis, "Lean manufacturing systems in the area of Industry 4.0: a lean automation plan of AGVs/IoT integration," *Production Planning & Control*, vol. 34, no. 4, pp. 345–358, 2023, doi: 10.1080/09537287.2021.1917720.

[13] P. M. Reyes, J. K. Visich, and P. Jaska, "Managing the Dynamics of New Technologies in the Global Supply Chain," in *IEEE Engineering Management Review*, vol. 48, no. 1, pp. 156-162, 2020, doi: 10.1109/EMR.2020.2968889.

[14] B. Ferreira and J. Reis, "A Systematic Literature Review on the Application of Automation in Logistics," *Logistics*, vol. 7, no. 4, p. 80, Nov. 2023, doi: 10.3390/LOGISTICS7040080.

[15] D. Perkumienė, K. Ratautaitė, and R. Pranskūnienė, "Innovative Solutions and Challenges for the Improvement of Storage Processes," *Sustainability*, vol. 14, no. 17, p. 10616, Aug. 2022, doi: 10.3390/SU141710616.

[16] O. F. Odeyinka, O. G. Omoegun, O. F. Odeyinka, and O. G. Omoegun. *Warehouse Operations: An Examination of Traditional and Automated Approaches in Supply Chain Management*. Operations Management - Recent Advances and New Perspectives, 2023.

[17] S. Paneru and I. Jeelani, "Computer vision applications in construction: Current state, opportunities & challenges," *Autom. Constr.*, vol. 132, p. 103940, Dec. 2021, doi: 10.1016/J.AUTCON.2021.103940.

[18] P. Papcun and J. Jadlovský, "Optimizing industry robot for maximum speed with high accuracy," *Procedia Eng.*, vol. 48, pp. 533–542, 2012, doi: 10.1016/J.PROENG.2012.09.550.

[19] C. Yang, S. Liu, H. Su, L. Zhang, Q. Xia, and Y. Chen, "Review of underwater adsorptive-operating robots: Design and application," *Ocean Engineering*, vol. 294, p. 116794, Feb. 2024, doi: 10.1016/J.OCEANENG.2024.116794.

[20] A. Perdana, W. E. Lee, and C. Mui Kim, "Prototyping and implementing Robotic Process Automation in accounting firms: Benefits, challenges and opportunities to audit automation," *International Journal of Accounting Information Systems*, vol. 51, p. 100641, Dec. 2023, doi: 10.1016/J.ACCINF.2023.100641.

[21] Z. Luo, W. Cheng, T. Zhao, and N. Xiang, "Intelligent sensory systems toward soft robotics," *Appl. Mater. Today*, vol. 37, p. 102122, Apr. 2024, doi: 10.1016/J.APMT.2024.102122.

[22] S. Y. Nof. *Springer handbook of automation*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2009, doi: 10.1007/978-3-030-96729-1.

[23] A. Billard and D. Kragic, "Trends and challenges in robot manipulation," *Science*, vol. 364, no. 6446, Jun. 2019.

[24] M. Rinaldi, M. Caterino, and M. Fera, "Sustainability of Human-Robot cooperative configurations: Findings from a case study," *Comput. Ind. Eng.*, vol. 182, p. 109383, Aug. 2023, doi: 10.1016/J.CIE.2023.109383.

[25] Z. Ren, F. Fang, N. Yan, and Y. Wu, "State of the Art in Defect Detection Based on Machine Vision," *International Journal of Precision Engineering and Manufacturing-Green Technology 2021*, vol. 9, no. 2, pp. 661–691, May 2021, doi: 10.1007/S40684-021-00343-6.

[26] T. Benbarrad, M. Salhaoui, S. B. Kenitar, and M. Arioua, "Intelligent Machine Vision Model for Defective Product Inspection Based on Machine Learning," *Journal of Sensor and Actuator Networks*, vol. 10, no. 1, p. 7, Jan. 2021, doi: 10.3390/JSAN10010007.

[27] X. Wang and Z. Zhu, "Context understanding in computer vision: A survey," *Computer Vision and Image Understanding*, vol. 229, p. 103646, Mar. 2023, doi: 10.1016/J.CVIU.2023.103646.

[28] A. Ettalibi, A. Elouadi, and A. Mansour, "AI and Computer Vision-based Real-time Quality Control: A Review of Industrial Applications," *Procedia Comput. Sci.*, vol. 231, pp. 212–220, Jan. 2024, doi: 10.1016/J.PROCS.2023.12.195.

[29] E. S. Kim, Y. Oh, and G. W. Yun, "Sociotechnical challenges to the technological accuracy of computer vision: The new materialism perspective," *Technol. Soc.*, vol. 75, p. 102388, Nov. 2023, doi: 10.1016/J.TECHSOC.2023.102388.

[30] Z. Wei, J. Calautit, S. Wei, and P. W. Tien, "Real-time clothing insulation level classification based on model transfer learning and computer vision for PMV-based heating system optimization through piecewise linearization," *Build Environ.*, p. 111277, Feb. 2024, doi: 10.1016/J.BUILDENV.2024.111277.

[31] S. Nawoya *et al.*, “Computer vision and deep learning in insects for food and feed production: A review,” *Comput. Electron. Agric.*, vol. 216, p. 108503, Jan. 2024, doi: 10.1016/J.COMPAG.2023.108503.

[32] G. Alnowaini, A. Alttal, and A. Alhaj, "Design and simulation robotic arm with computer vision for inspection process," *2021 International Conference of Technology, Science and Administration (ICTSA)*, pp. 1-6, 2021, doi: 10.1109/ICTSA52017.2021.9406541.

[33] S. M. Hussein and Y. I. Mohammed, “Modeling and Simulation of Industrial SCARA Robot Arm,” *International Journal of Engineering and Advanced Technology (IJEAT)*, pp. 2249–8958, 2015.

[34] S. Gollapudi. *Learn computer vision using OpenCV*. Apress, 2019.

[35] S. Taheri, A. Vedienbaum, A. Nicolau, N. Hu, and M. R. Haghighat, “OpenCV.js: Computer vision processing for the openWeb platform,” *Proceedings of the 9th ACM Multimedia Systems Conference, MMSys 2018*, pp. 478–483, Jun. 2018, doi: 10.1145/3204949.3208126.

[36] D. A. Bastidas, L. F. Recalde, P. N. Constante, V. H. Andaluz, D. E. Gallegos, and J. Varela-Aldás, “Non Immersive Virtual Laboratory Applied to Robotics Arms,” *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 13343, pp. 898–906, 2022, doi: 10.1007/978-3-031-08530-7_76.

[37] B. Araujo, J. Araujo, R. Silva, and D. Regis, “Machine vision for industrial robotic manipulator using raspberry Pi,” *2018 13th IEEE International Conference on Industry Applications, INDUSCON 2018 - Proceedings*, pp. 894–901, Jul. 2018, doi: 10.1109/INDUSCON.2018.8627203.

[38] M. Abdelaal, “A Study of Robot Control Programing for an Industrial Robotic Arm,” *ACCS/PEIT 2019 - 2019 6th International Conference on Advanced Control Circuits and Systems and 2019 5th International Conference on New Paradigms in Electronics and Information Technology*, pp. 23–28, Nov. 2019, doi: 10.1109/ACCS-PEIT48329.2019.9062878.

[39] O. I. Borisov *et al.*, “Human-free robotic automation of industrial operations,” *IECON Proceedings (Industrial Electronics Conference)*, pp. 6867–6872, Dec. 2016, doi: 10.1109/IECON.2016.7793922.

[40] O. I. Borisov *et al.*, “Case study on human-free water heaters production for industry 4.0,” *Proceedings - 2018 IEEE Industrial Cyber-Physical Systems*, pp. 369–374, Jun. 2018, doi: 10.1109/ICPHYS.2018.8387686.

[41] A. Maria Zanchettin, I. Dieter Uckelmann, and F. Ahmed, “Automation of an RFID measurement chamber with a robotic manipulator,” *POLITesi*, 2023.

[42] B. G. F. Araujo. *Sistema de visão de máquina para detecção e localização automática de peças utilizando raspberry pi*. MS thesis. 2019.

[43] E. Mujčić, S. Lonić, and M. Muminović, “Programming and Experimental Analysis of MELFA RV-2SDB Robot,” *Lecture Notes in Networks and Systems*, vol. 28, pp. 810–818, 2018, doi: 10.1007/978-3-319-71321-2_70.

[44] P. Papcun and J. Jadlovský, “Mathematical Model of Robot Melfa RV-2SDB,” *Advances in Intelligent Systems and Computing*, vol. 316, pp. 145–154, 2015, doi: 10.1007/978-3-319-10783-7_16.

[45] P. Papcun and J. Jadlovský, “Optimizing Industry Robot for Maximum Speed with High Accuracy,” *Procedia Eng*, vol. 48, pp. 533–542, Jan. 2012, doi: 10.1016/J.PROENG.2012.09.550.

[46] Q. Wu, M. Li, X. Qi, Y. Hu, B. Li, and J. Zhang, “Coordinated control of a dual-arm robot for surgical instrument sorting tasks,” *Rob Auton Syst*, vol. 112, pp. 1–12, Feb. 2019, doi: 10.1016/J.ROBOT.2018.10.007.

[47] R. Basu and S. Padage, “Development of 5 DOF Robot Arm -Gripper for sorting and investigating RTM Concepts,” *Mater Today Proc*, vol. 4, no. 2, pp. 1634–1643, Jan. 2017, doi: 10.1016/J.MATPR.2017.02.002.

[48] X. Zhang *et al.*, “Design and operation of a deep-learning-based fresh tea-leaf sorting robot,” *Comput Electron Agric*, vol. 206, p. 107664, Mar. 2023, doi: 10.1016/J.COMPAG.2023.107664.

[49] E. Mujčić, S. Lonić, and M. Muminović, “Programming and Experimental Analysis of MELFA RV-2SDB Robot,” *Lecture Notes in Networks and Systems*, vol. 28, pp. 810–818, 2018, doi: 10.1007/978-3-319-71321-2_70/COVER.

[50] A. Issa, M. O. A. Aqel, A. Tubail, Y. Alkayyali, A. Alay, and M. Ferwana, “Vision assisted SCARA manipulator design and control using arduino and LabVIEW,” *Proceedings - 2017 International Conference on Promising Electronic Technologies, ICPET 2017*, pp. 54–59, Nov. 2017, doi: 10.1109/ICPET.2017.16.

[51] V. Kumar, Q. Wang, W. Minghua, S. Rizwan, S. M. Shaikh, and X. Liu, “Computer vision based object grasping 6DoF robotic arm using picamera,” *Proceedings - 2018 4th International Conference on Control, Automation and Robotics, ICCAR 2018*, pp. 111–115, Jun. 2018, doi: 10.1109/ICCAR.2018.8384653.

[52] R. Reddy and S. R. Nagaraja, “Integration of robotic arm with vision system,” *2014 IEEE International Conference on Computational Intelligence and Computing Research, IEEE ICCIC 2014*, pp. 373–378, 2015, doi: 10.1109/ICCIC.2014.7238302.

[53] O. Hock and J. Sedo, “Inverse kinematics using transposition method for robotic arm,” *12th International Conference ELEKTRO 2018, 2018 ELEKTRO Conference Proceedings*, pp. 1–5, Jun. 2018, doi: 10.1109/ELEKTRO.2018.8398366.

[54] A. Loungthongkam and C. Raksiri, “A Development of Mathematical Model for Predictive of the Standard Uncertainty of Robot Arm,” *2020 IEEE 7th International Conference on Industrial Engineering and Applications, ICIEA 2020*, pp. 281–286, Apr. 2020, doi: 10.1109/ICIEA49774.2020.9101979.

[55] Y. Dai, C. Xiang, Y. Zhang, Y. Jiang, W. Qu, and Q. Zhang, “A Review of Spatial Robotic Arm Trajectory Planning,” *Aerospace 2022, Vol. 9, Page 361*, vol. 9, no. 7, p. 361, Jul. 2022, doi: 10.3390/AEROSPACE9070361.

[56] M. Intisar, M. Monirujjaman Khan, M. Rezaul Islam, and M. Masud, “Computer Vision Based Robotic Arm Controlled Using Interactive GUI,” 2021, doi: 10.32604/iasc.2021.015482.

[57] X. Hou and S.-K. Tsui, “A mathematical model for control of flexible robot arms,” *Systems modelling and optimization*, pp. 391–398, Mar. 2022, doi: 10.1201/9780203737422-51.

[58] P. Sooraksa and G. Chen, “Mathematical modeling and fuzzy control of a flexible-link robot arm,” *Math Comput Model*, vol. 27, no. 6, pp. 73–93, 1998, doi: 10.1016/S0895-7177(98)00030-2.

[59] T. Punnoose Valayil, V. Selladurai, and N. Rajam Ramaswamy, “KINEMATIC MODELING OF A SERIAL ROBOT USING DENAVIT-HARTENBERG METHOD IN MATLAB,” 2018, Accessed: Feb. 11, 2024. [Online]. Available: www.tagajournal.com

[60] K. S. Gaeid, A. F. Nashee, I. A. Ahmed, and M. H. Dekheel, “Robot control and kinematic analysis with 6DoF manipulator using direct kinematic method,” *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 1, pp. 70–78, Feb. 2021, doi: 10.11591/EEI.V10I1.2482.

[61] Z. Liao, G. Jiang, F. Zhao, X. Mei, and Y. Yue, “A novel solution of inverse kinematic for 6R robot manipulator with offset joint based on screw theory,” *Int J Adv Robot Syst*, vol. 17, no. 3, May 2020, doi: 10.1177/1729881420925645/ASSET/IMAGES/LARGE/10.1177_1729881420925645-FIG10.JPEG.

[62] T. S. Lee and E. A. Alandoli, “A critical review of modelling methods for flexible and rigid link manipulators,” *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, vol. 42, no. 10, pp. 1–14, Oct. 2020, doi: 10.1007/S40430-020-02602-0/METRICS.

[63] D. Wang and Z. Zhang, “High-efficiency nonlinear dynamic analysis for joint interfaces with Newton–Raphson iteration process,” *Nonlinear Dyn*, vol. 100, no. 1, pp. 543–559, Mar. 2020, doi: 10.1007/S11071-020-05522-9/FIGURES/15.

[64] A. Torres-Hernandez and F. Brambila-Paz, “Fractional Newton-Raphson Method and Some Variants for the Solution of Non-linear Systems,” *Applied Mathematics and Sciences An International Journal (MathSJ)*, vol. 7, no. 1, pp. 13–27, Aug. 2019, doi: 10.5121/mathsj.2020.7102.

[65] M. Heydarzadeh, N. Karbasizadeh, M. Tale Masouleh, and A. Kalhor, “Experimental kinematic identification and position control of a 3-DOF decoupled parallel robot,” *https://doi.org/10.1177/0954406218775906*, vol. 233, no. 5, pp. 1841–1855, May 2018, doi: 10.1177/0954406218775906.

[66] R. Dou *et al.*, “Inverse kinematics for a 7-DOF humanoid robotic arm with joint limit and end pose coupling,” *Mech Mach Theory*, vol. 169, p. 104637, Mar. 2022, doi: 10.1016/J.MECHMACHTHEORY.2021.104637.

[67] Y. Miao, J. Y. Jeon, and G. Park, “An image processing-based crack detection technique for pressed panel products,” *J Manuf Syst*, vol. 57, pp. 287–297, Oct. 2020, doi: 10.1016/J.JMSY.2020.10.004.

[68] M. Meenu, C. Kurade, B. C. Neelapu, S. Kalra, H. S. Ramaswamy, and Y. Yu, “A concise review on food quality assessment using digital image processing,” *Trends Food Sci Technol*, vol. 118, pp. 106–124, Dec. 2021, doi: 10.1016/J.TIFS.2021.09.014.

[69] Nursalim, C. S. Octiva, S. Sri Wahyuningsih, M. Lukman Hakim, and N. Hasti, “Application of The Speed-Up Robust Features Method To Identify Signature Image Patterns On Single Board Computer,” *Jurnal Sistim Informasi dan Teknologi*, pp. 14–18, Oct. 2023, doi: 10.60083/JSISFOTEK.V5I4.312.

[70] S. Sankaraiah and R. S. Deepthi, "Highly optimized OpenCV based cell phone," *2011 IEEE Conference on Sustainable Utilization Development in Engineering and Technology, STUDENT 2011*, pp. 47–52, 2011, doi: 10.1109/STUDENT.2011.6089323.

[71] R. S. Deepthi and S. Sankaraiah, "Implementation of mobile platform using Qt and OpenCV for image processing applications," 2011 IEEE Conference on Open Systems, ICOS 2011, pp. 284–289, 2011, doi: 10.1109/ICOS.2011.6079235.

[72] G. A. Odesanmi, Q. Wang, and J. Mai, "Skill learning framework for human–robot interaction and manipulation tasks," Robot Comput Integr Manuf, vol. 79, p. 102444, Feb. 2023, doi: 10.1016/J.RCIM.2022.102444.

[73] R. Szczepanski, K. Erwinski, M. Tejer, A. Bereit, and T. Tarczewski, "Optimal scheduling for palletizing task using robotic arm and artificial bee colony algorithm," Eng Appl Artif Intell, vol. 113, p. 104976, Aug. 2022, doi: 10.1016/J.ENGAPPAI.2022.104976.

[74] G. D'Ago et al., "Modelling and identification methods for simulation of cable-suspended dual-arm robotic systems," Rob Auton Syst, p. 104643, Feb. 2024, doi: 10.1016/J.ROBOT.2024.104643.

[75] Y. Cheng, C. Su, and H. Li, "Design of power monitoring system for 33MW DC submerged arc furnace based on PLC," 2021 3rd International Conference on Intelligent Control, Measurement and *Signal Processing and Intelligent Oil Field, ICMSP 2021*, pp. 403–407, Jul. 2021, doi: 10.1109/ICMSP53480.2021.9513331.

[76] E. Decky *et al.*, "Pick and place robot automation module for learning industrial motion, web server GUI, and vision sensor using Kalman filter," *AIP Conf Proc*, vol. 2710, no. 1, p. 050016, Feb. 2024, doi: 10.1063/5.0145128.

[77] A. M. Jazeel, "Theme Emerging Technologies for Industrial Sustenance Symposium Chair Editorial Board", Accessed: Feb. 11, 2024. [Online]. Available: https://www.researchgate.net/publication/332190133

[78] R. Badarinath and V. Prabhu, "Integration and evaluation of robotic fused filament fabrication system," *Addit Manuf*, vol. 41, p. 101951, May 2021, doi: 10.1016/J.ADDMA.2021.101951.

[79] Y. Murase, M. Hidaka, and R. Yoshida, "Self-driven gel conveyer: Autonomous transportation by peristaltic motion of self-oscillating gel," *Sens Actuators B Chem*, vol. 149, no. 1, pp. 272–283, Aug. 2010, doi: 10.1016/J.SNB.2010.06.017.

[80] M. Andrejiova, A. Grincova, and D. Marasova, "Monitoring dynamic loading of conveyer belts by measuring local peak impact forces," *Measurement*, vol. 158, p. 107690, Jul. 2020, doi: 10.1016/J.MEASUREMENT.2020.107690.

[81] I. Q. Habeeb, "Image Processing Based Ambient Context-Aware People Detection and Counting," 2018, doi: 10.18178/ijmlc.2018.8.3.698.

[82] A. Brunetti, D. Buongiorno, G. F. Trotta, and V. Bevilacqua, "Computer vision and deep learning techniques for pedestrian detection and tracking: A survey," *Neurocomputing*, vol. 300, pp. 17–33, Jul. 2018, doi: 10.1016/J.NEUCOM.2018.01.092.

[83] R. K. Tripathi, A. S. Jalal, and S. C. Agrawal, "Suspicious human activity recognition: a review," *Artif Intell Rev*, vol. 50, no. 2, pp. 283–339, Aug. 2018, doi: 10.1007/S10462-017-9545-7/METRICS.