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A Robotic Arm Prototype for Automated Packaging of Chocolates with Artificial Intelligence

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Abstract*– This paper details the development of an advanced robotic arm designed to package chocolates efficiently in a small-scale process. The arm features a Prismatic-Revolute-Revolute configuration and is equipped with a Universal Vacuum Grip to handle chocolates precisely. Its construction utilizes PLA 3D printed parts for the mechanical structure and flexible TPU belts to ensure optimal movement control. Electronically, the system is powered by NEMA 17 motors, controlled by an Arduino board and a CNC interface for precision motor management. The programming, conducted in Python, integrates artificial intelligence through computer vision techniques to enhance the accuracy and adaptability of the packaging process. A graphical user interface was developed, allowing intuitive control and sequence management of the robotic arm's operations. The incorporation of artificial intelligence enabled the robotic arm to identify successfully and sort chocolates of varying types, greatly enhancing packaging efficiency. The results demonstrate the arm's capability to consistently place chocolates in trays, thereby augmenting productivity, reducing human error, and maintaining packaging quality. This project underscores the significance and potential of integrating automation and artificial intelligence in the food packaging industry.

Keywords*-- Prismatic-Revolute-Revolute Robot, Universal Vacuum Grip, Artificial intelligence, Process Automation, Computer Vision.

I. INTRODUCTION

Automated food packaging has become an essential component in the food industry, driven by its ability to enhance operational efficiency, precision, safety, adaptability in production processes, and error reduction [1].

A key innovation in this domain is the development of a Universal Vacuum Grip (UVG) prototype, inspired by researches such as that in [2], [3]. The UVG, equipped with a mini pump and balloon, offers a versatile and secure solution for handling products like chocolates, adapting to various shapes and sizes. The design process incorporated detailed considerations, such as vacuum cup selection, pressure requirements, and holding force calculations, as outlined in [3]. Additionally, insights from FESTO [4] provided a deeper understanding of vacuum technology principles, ensuring the prototype's functionality aligns with practical demands. This integration of theoretical and practical knowledge underscores UVG's potential for broader applications in food packaging.

The need for advanced grippers to manage soft, irregularly shaped foods, addressing challenges like material deformation, irregular surfaces, and hygiene requirements, has been underscored in [5]. Gripping technologies, including pinch, vacuum-based, and multi-fingered designs, minimize damage and contamination while ensuring effective force transfer. Designs prioritize cleanability and use materials like stainless steel and polymers [5].

Grippers are categorized by their degrees of freedom (DOF): fully constrained (DOF equals the number of actuators), underactuated (DOF exceeds the number of actuators), and deformable (shape-adaptive). Actuation mechanisms include linear/rotary actuators, cables, pneumatics, and elastomers, while gripping styles, i.e., parallel, cylindrical, and spherical, depend on object shape. Materials like silicone and rubber offer elasticity but pose manufacturing complexities. Sensor integration improves safety, while their absence increases the risk of damage. Fully constrained grippers suit high-force tasks, whereas underactuated and deformable designs excel with irregular objects. The passive-flexible mechanism with rigid links and gecko-inspired surfaces balances flexibility and strength and is ideal for unpredictable environments [6].

Soft robotic grippers for agricultural and food products have advanced in adaptability and safety for fragile objects, yet challenges persist in matching human dexterity in flexibility, precision, and adaptability. Progress includes fluidic and mechanical actuators, sensor integration for enhanced intelligence, and closed-loop control systems to manage uncertainties, i.e., varying object sizes, shapes, and stiffness. Inspired by nature (e.g., tentacles, fingers, suction systems), gripper designs range from single-actuator to multi-actuator configurations. Actuation principles, such as pneumatic, vacuum, adhesion, and tendon-driven systems, have unique strengths and limitations. The combination of actuators, sensors, and advanced control algorithms enables the flexibility, stability, and adaptability necessary for agricultural and food handling applications [7].

Robotics for manipulation and packaging highlight efficiency and adaptability through mobile robots and UVGs, which employ selection algorithms to handle diverse object shapes. In particular, a dual-arm mobile robot with UVG can navigate slopes <2/100, grasp objects weighing 100-400 g, and adjust the vacuum pressure between -80 and -1.3 kPa. The UVG employs a flexible elastomeric membrane and granular jamming for irregular surfaces; however, challenges persist in dynamic environments and variable lighting. The Prismatic-Revolute-Revolute (PRR) robotic arm prototype for chocolate packaging, using a UVG with a balloon and sea salt, achieves high success rates but faces degradation after repeated operations due to UVG deformation and misalignment. Combining dual-arm robots, UVGs, and AI-driven object recognition offers a robust solution, as asserted in [8].

Integrating robotic arms with computer vision is advancing automation by enhancing efficiency and precision in object classification. For instance, a 3-DOF robotic arm using You Only Look Once (YOLO) v5 in [9] achieves 87% accuracy in color-based object classification and supports automatic and remote operation. This work highlights how robotics, computer vision, and AI drive automation across industries, improving productivity and reducing errors.

Automating processes using robotic arms is gaining traction across sectors, with color sensors enhancing efficiency and precision. While this study focuses on chocolate packaging using a PRR robotic arm and YOLO-based computer vision, the one in [10], demonstrate real-time color detection using a low-cost Pixy2 camera and robotic arm, achieving over 75% accuracy in pick-and-place tasks. Unlike YOLO's complex algorithms, Pixy2 employs hue-based color filtering, enabling real-time detection of six colors. Notably, their prototype cost around $200, compared to commercial systems priced at $1,680, showcasing the affordability and practicality of integrating color detection into robotic automation for industrial and everyday applications.

In [11], the PixyCMU camera is utilized for color detection (80% accuracy) and OpenCV for shape and size recognition (100% accuracy), employing an Arduino Mega and MG996R servomotors for a cost-effective robotic arm system. Unlike AI-based approaches, their contour-based method detects geometric shapes and evaluates object size, demonstrating the viability of traditional image processing. This research complements the present work, highlighting the diversity of cost-effective technologies for object classification in industrial automation and offering practical insights into integrating hardware and image processing for efficient object recognition.

A study on the TCS3200 sensor for real-time color classification [12] achieved 95% accuracy in bright light and 91% in low-light conditions. Using a K-Nearest Neighbor algorithm, the sensor enables color detection at 5 cm, offering a simpler alternative to complex models like YOLO. The work integrates the Internet of Things (IoT) for object counting and employs DC servo motors for robotic arm movement ranging from 0° to 180°; pointing also expands existing knowledge, demonstrating the role of color detection and IoT in industrial automation.

The authors of [13] propose a method for detecting robotic arm positions using blue squares on key joints, with a color detection algorithm on a Spartan-6 Field-Programmable Gate Array (FPGA) and VmodCAM camera. The system constructs a skeletal representation by connecting detected squares, offering a more straightforward, cost-effective alternative to traditional sensor-based methods, in which FPGA processing enhances real-time accuracy. This research contributes to the advancement of robotic vision systems by presenting a scalable and efficient solution for automation.

Traditional image processing techniques, including RGB-to-HSV conversion and the Douglas-Peucker algorithm, were employed in [14] for real-time object detection and classification. Their system uses a webcam, median filtering for noise reduction, and HSV-based color masks with contour detection to identify shapes like squares and triangles. Integrated with a robotic arm controlled by an Atmega328 microcontroller, the study highlights the effectiveness of geometry-based methods in automated sorting, offering a practical alternative to deep neural networks and extending insights into traditional image processing applications in automation.

A cost-effective system using an ultrasonic sensor for object detection and a TCS230 sensor for color identification (red, green, blue) was proposed in [15]. Their robotic arm, controlled by an ATMEGA328P microcontroller and DC servomotors, achieves 360-degree movement for precise object placement.

On another site, work like that in [16] presents a 6-DOF robotic arm with proximity and color detection controlled by an Arduino Mega microcontroller. This arm integrates object detection, distance measurement, and color identification. This combination of low-cost microcontroller technology with advanced sensing offers a versatile and cost-effective solution.

The authors in [17] developed a 5-DOF robotic arm with computer vision for color-based object recognition, obstacle detection, and precise object manipulation. Forward kinematics is modeled using the Denavit-Hartenberg algorithm, while inverse kinematics is solved with a modified flower pollination algorithm (MFPA). The system prioritizes safety, offering practical solutions for industrial automation and human-robot collaboration.

A control system for pre-harvest fruit cultivation introduced in [18] uses aerial robotics and YOLOv8-based computer vision. This system achieves 78.95% efficiency and employs drones for image acquisition and a web interface for data management.

A soft gripper for the KUKA KR-16 robot was designed and simulated in [19], utilizing the Fin-Ray effect and 3D-printed thermoplastic polyurethane (TPU) for flexibility. A piezoresistive sensor enables adaptive gripping of diverse objects, with tensile tests identifying optimal printing parameters. This research advances soft robotics.

On the other hand, a prototype for automated strawberry harvesting in hydroponic systems was developed in [20], combining a robotic arm with computer vision for ripeness detection. Using SolidWorks, Raspberry Pi for image processing, and Arduino Mega for control, the system achieved 98.5% efficiency in size detection but required 51 seconds per strawberry, indicating room for optimization. This research highlights the potential of robotics and computer vision to advance precision agriculture and hydroponic farming.

The authors in [21] engineered a computer vision system for classifying Tommy Atkins mangos, utilizing open-source tools like Python for K-means segmentation, PHP for the GUI, and Arduino for hardware-software communication. Tested at Frutalandia S.A., the system demonstrates the feasibility of automating mango classification, offering an innovative solution to enhance efficiency in Ecuador's agro-industrial sector through computer vision integration.

The robotic arm prototype in [22] includes a computer vision system for packaging color classification, aiming to automate and improve accuracy in the process. The system uses a USB camera and conveyor belt to integrate LabVIEW for image processing, Arduino for control, and SQL Server for data storage. While the prototype demonstrates effectiveness in classification, sensitivity varies with lighting, suggesting the need for further testing and higher-resolution cameras to enhance performance.

Automated food packaging using Delta Parallel Robots for high-speed pick-and-place operations is explored in [23], emphasizing precision, speed, and hygiene. A two-fingered gripper minimizes product damage, while image processing techniques (Edge Detection, Hough Transform) via OpenCV enable object localization. Achieving an 82% success rate, the research demonstrates the feasibility of integrating visual perception into robotic systems, offering scalable solutions for food and pharmaceutical industries.

Robots in manufacturing enhance precision, but they are limitedly used in the food industry for pick-and-place and meat processing. The review in [24] explores recent advancements in robotics, including sensors, end-effectors, and technologies for food tasks and gastronomy, highlighting the need for further research.

As detailed in [25], Industry 4.0 technologies (i.e., machine vision, machine learning, robotics) are applied for automated chocolate chip cookie inspection. The system achieved 95% training accuracy, 90% testing accuracy, and 98% effectiveness in defect removal. Using artificial neural networks for classification and a robotic arm for sorting improves food quality control and reduces defective products.

Chocolats Halba, a Coop-owned chocolate producer, automated the labor-intensive task of loading a 30-year-old hollow-body spinning machine using ABB robots. Implemented by Marti Systeme AG, the solution proposed in [26] improved efficiency and working conditions by automating mold filling with liquid chocolate in a cold environment, showcasing successful robotics applications in the food industry.

The work in [27] examines the cam-linkage mechanism in the push device of a chocolate packaging machine, addressing vibration issues at high speeds. Using equivalent component substitution and D'Alembert’s principle, dynamic equations are derived and simulated with MATLAB/Simulink.

BOLÇI Bolu Chocolate integrated Omron robots into its packaging. The deployment of Omron’s Quattro robot, supported by Pack-Xpert software, increased production capacity by 40%, reduced labor by 20%, and ensured hygienic, high-quality handling of delicate chocolates. This project marks a significant step toward Industry 4.0 compliance, aligning with BOLÇI’s vision of a smart factory [28].

KUKA robots at Josef Zotter, an Austrian chocolate manufacturer, enhance productivity and precision in its bean-to-bar production [29]. The space-saving KUKA KR AGILUS robots handle liquid chocolate, filling molds with accuracy and reducing space requirements compared to traditional systems. Zotter also hired employees to support the robotic system, demonstrating the potential of robotics to augment skilled labor in artisanal production.

The “Chocomatic,” developed by Roose Automation, is an automated chocolate dispenser used at Roose’s Chocolate World in Bruges, Belgium. As stated in [30], they utilize a 5-axis robolink robotic arm for efficiency. Customers select chocolates via a tablet or smartphone while the robot autonomously prepares and packages the selection. This system reduces operational costs and enhances customer experience.

The ACMA Robotic Distribution systems have transformed the packaging and distribution of delicate chocolate *pralines* by providing precision, consistency, and flexibility, reducing downtime, and improving operational agility. Authors in [31] explained that those systems are equipped with advanced sensors and a user-friendly HMI, enhancing operational agility and efficiency in the confectionery industry.

According to [32], Additive Manufacturing (AM) offers innovative solutions for robotic automation in the food sector. AM enables the creation of flexible, FDA-approved pneumatic actuators and grippers with deformable structures, reducing damage to food and simplifying design. Despite challenges like deformation and dust accumulation, AM provides a promising approach to developing lightweight, adaptable, and efficient food-handling robotic systems.

II. Design

A. *Understanding the Needs*

Developing a PRR robotic arm with AI-enhanced object detection for chocolate packaging addresses critical needs in the confectionery industry, where traditional manual methods often fall short. Precision and consistency are vital to maintaining the product's integrity and aesthetic appeal in the chocolate packaging domain. Although manual packaging is a traditional method, it is prone to errors and inefficiencies, leading to inconsistent product placement, increased waste, and potential damage to delicate chocolates.

This project comes from the need for a more efficient production process. With the growing demand for chocolates, a faster and more consistent packaging method is essential to meet market requirements.

In addition, this project was built on a previously developed system framework. This study integrates artificial intelligence to expand automation capabilities [33].

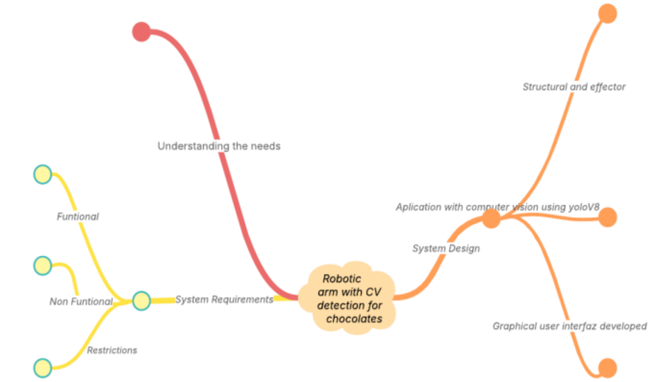

Fig. 1 Proposal Methodology.

B. System Requirements

In order to fulfill the objectives, the following system requirements were established, as can be seen in Fig. 1:

1. *Functional Requirements:*
   - The system should be able to manipulate the chocolates without damaging them.
   - The system should be able to classify chocolates into two categories: white and gold.
   - The system should be able to move the chocolates from the classification area to the packaging area.
2. *Non-Functional Requirements:*
   - The interface should allow the user to control the system manually or automatically.
   - The classification time should not exceed five minutes per cycle.
   - The system should be able to organize the chocolates in different configurations.
   - The working area should be 36 x 20 cm^2.
3. *Restrictions:*
   - System hardware, like NEMA17 stepper motors and Arduino boards, should be highly available.

C. System Design - Structural and End-Effector Design

A PRR configuration was chosen for the robotic arm to ensure the system can work within the working area.

Regarding the connection system, steel rods and an endless screw for link one was incorporated, which is a prismatic joint. These elements allow for smooth and precise linear movement, guaranteeing the correct performance of the robotic arm in its grip and displacement functions. The final prototype can be seen in Fig. 2 [33].

TPU [34] was chosen to manufacture the timing belts. Timing belts with specific measurements were needed, and they were not available on the market. Printing these belts in TPU resulted in a more precise and efficient assembly of the robot because they were customized according to needs.

PLA (Polylactic Acid) [35] was used instead of more rigid materials for parts not subject to significant loads or stress. PLA offers good rigidity for most applications, and its printing is more accessible in terms of cost and availability.

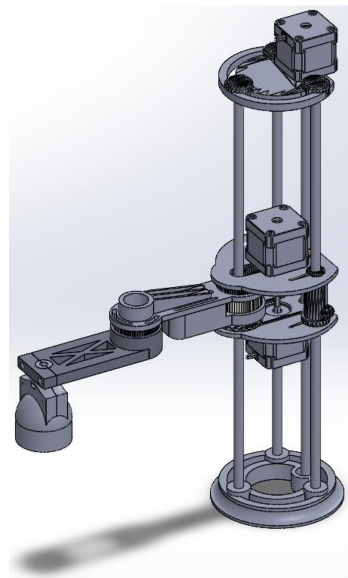

Fig. 2 Robot Arm CAD Model Assembly.

However, it is important to note that the pieces were carefully designed to ensure their resistance and functionality. The structural design from the previous work in [33] is retained.

D. System Implementation

The system is comprised of three distinct codes. The first is an Arduino code responsible for orchestrating the movements of the stepper motors and managing the 5V relay module, which controls the vacuum pump. This code forms the backbone of the robotic arm's mechanical operations.

The second piece of code is a Python-based user interface. This interactive platform allows users to directly control and manipulate the robotic arm's movements, providing an intuitive and user-friendly experience for operation and management.

The third and final code, developed in Python, focuses on object detection. It utilizes YOLOv8's advanced capabilities and loads and implements a pre-trained model.

Its primary function is to accurately detect and classify the two types of chocolates in a real-time scenario. This cutting-edge machine learning technology integration is crucial for the robotic arm's precision and efficiency in identifying and handling chocolates.

1. Arduino Code: The program processes serial commands from the user interface and converts this information into motions that drive the robot hardware. It requires users to enter three integers that define the robot's target position using angle or linear axis measurements.

When receiving these input values from the serial connection, the Arduino generates a suitable output scale for every stepper motor between 0 and 50. After processing the instructions, the Arduino system instructs each motor to move to the intended location.

The Arduino relay control function accepts commands from the Python interface to activate the relay into a HIGH state when the "Relay On" command is received. Users engage the "'Relay Off" button to transition the relay state to LOW.

The Arduino code enables robot calibration through its built-in functions for axes and gripper movement. The code sets all axes to their home positions at the start-up system and turns the pump off before executing any other instructions.

The calibration process is necessary because it ensures the accurate execution of all commands from this setup procedure. The Arduino code enables verification of received commands by implementing critical logic confirming their feasibility and safety for robot execution. The logical structure supports the robot system's operational safety and integrity throughout operations. Fig. 3 displays the robotic arm behavior.

2. User Interface: The robotic arm system user interface emerged from using the Tkinter library, which generated an easy-to-use graphical control system [36]. The interface has manual control sliders, which users can employ to modify both rotational and single linear Z joints.

It contains buttons that permit storing positions, releasing pre-configured sequences, and handling gripper functions. Operators can maintain efficient system monitoring through this user interface, which presents a configuration list box and a status label for easy control.

The interface gives users control of the vacuum pump through its built-in relay component. The automatic mode within this system enables the operation of pre-programmed positions in an automatic loop cycle to simplify repetitive work tasks. Users can quickly start the automated packaging process through the interface after implementing its object detection algorithm. The interface uses three buttons to serve two configuration settings to instruct chocolate sorting according to preference patterns and one-stop control.

Users must utilize the stop button to end object detection functions after completing tasks or to access non-detection features of the graphical user interface.

The detailed interface design methodology improves user engagement and simplifies the process for better efficiency. The graphical user interface presents its design through the illustration in Fig. 4.

The code enables serial connection with the Arduino board by using the features of the PyArduino library. This library provides expertise in bidirectional data management, transferring Python code commands to the Arduino board, and sending Arduino platform data back to the Python environment.

The Arduino receives Python code commands through serial communication to perform direction changes and activate or inhibit vacuum pump operations based on command parameters.

The effective communication mechanism between Python code and the Arduino board makes correctly controlling robot movements and operations possible. Fig. 3 illustrates the flowchart showing the user interface behavior.

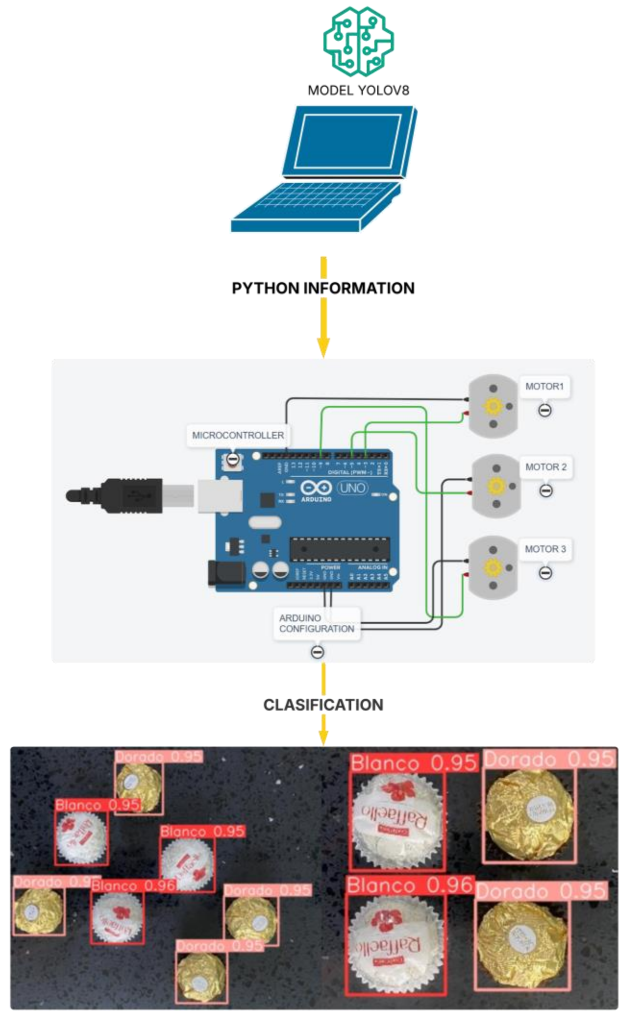

Fig. 3 Complete Used System.

E. Computer Vision Model

1. Dataset: Developing a specialized dataset facilitated the successful integration of artificial intelligence into the chocolate packaging robotic arm. A total of 1,920 images were meticulously collected for training, validation, and testing of the object detection model. This dataset was strategically divided into 1,680 training images (88%), 160 validation images (8%), and 80 test images (4%), thereby creating a robust foundation for extensive model training.

The dataset categorization included two classes: "Gold" for Ferrero Rocher chocolates, recognized by their signature golden wrappers, and "White" for Raffaello chocolates, characterized by their white, coconut-dusted appearances. This classification was essential for the YOLO model's precise differentiation between these two types of chocolate.

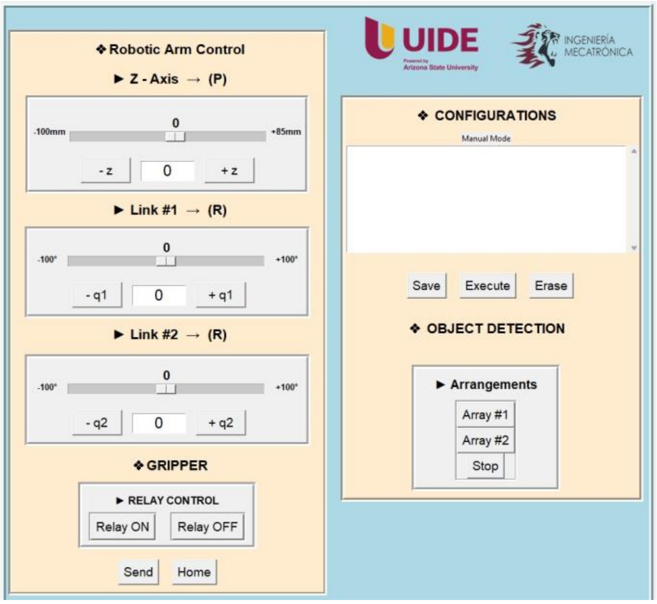

Fig. 4 Graphical User Interface developed.

High-quality images for the dataset were captured using an iPhone 11, featuring a camera resolution of 12MP and an aspect ratio of 4:3. To maintain consistency and enhance the model's performance, each image was uniformly resized to 640x640 pixels. This standardization of image dimensions was pivotal for ensuring practical training input.

The image annotation process was efficiently conducted using Roboflow, a proficient tool for marking chocolate types and their respective positions within each image.

Various techniques were implemented to augment the training dataset’s diversity, including rotations, shearing, and adjustments in brightness, noise, blur, and exposure. Table I shows that these augmentations were designed to simulate different environmental conditions, thus equipping the model for effective performance under various lighting and orientation scenarios encountered during the packaging process.

TABLE I
IMAGE AUGMENTATION PARAMETERS

Augmentation Type	Range/Description
90° Rotate	Clockwise, Counter-Clockwise, Upside Down
Rotation	Between -15° and +15°
Shear	±15° Horizontal, ±15° Vertical
Brightness	Between -30% and +30%
Exposure	Between -25% and +25%
Blur	Up to 2.5px
Noise	Up to 5% of pixels

Limiting training to 50 epochs demonstrated an optimal balance, allowing the model to learn critical features while mitigating the risk of overfitting. Consequently, this approach has yielded a highly accurate and generalizable model well-suited for meeting the dynamic demands of the chocolate packaging process.

2. Object Detection: A primary feature of this project is the integration of real-time object detection, accomplished through a pre-trained YOLOv8 model. This model is fundamental to a sophisticated computer vision system identifying and classifying chocolates in real-time. The system employs a camera to continuously capture images of the operational area, which the YOLO model subsequently analyzes to recognize and categorize the chocolates into two specific classes: “White” and “Gold.”

The YOLO model, particularly in its eighth iteration, constitutes the foundation of the object detection framework. Renowned for its rapid processing capabilities, it is exceptionally equipped to meet the dynamic requirements of the chocolate packaging industry. The model operates by scrutinizing each image, detecting chocolates, and determining their precise locations via bounding box coordinates. These coordinates are crucial for guiding the robotic arm to the accurate pickup and placement locations.

Effective communication between the object detection system and the robotic arm is vital. The system transmits essential information regarding the chocolates, including type and position, to the robotic arm's control system. The arm then aligns its movements according to the user-selected configuration and the identified type of chocolate, thereby ensuring precise placement within the designated tray compartments. This cycle persists until all chocolates have been sorted or the operation is manually terminated.

The amalgamation of advanced computer vision and artificial intelligence enhances the capabilities of the robotic arm, transforming it into an intelligent system capable of autonomous decision-making. The YOLOv8 model, integral to this system, has been meticulously trained to differentiate between various types of chocolates, accommodating a range of shapes and sizes and adapting to diverse configurations.

Incorporating artificial intelligence and computer vision allows the robotic arm to transcend its role as a mere mechanical tool, evolving into an adaptable, intelligent entity essential for the variable nature of chocolate packaging. The AI system continuously learns and adapts, improving its detection accuracy and ensuring a reliable packaging process.

Addressing the challenge of maintaining consistent detection accuracy under varying lighting conditions and chocolate orientations was a critical aspect of this project. The YOLO model was fine-tuned to address this challenge and explicitly optimized for chocolate detection. Additionally, size filters were implemented to minimize false positives, such as incorrect identification of base elements as chocolates. This meticulous optimization ensures the robustness and reliability of the system across various operational scenarios.

A computer vision system based on the YOLOv8 model was implemented to automatically detect and classify Ferrero Rocher (golden) and Raffaello (white) chocolates. YOLOv8 is a modern convolutional neural network (CNN) architecture specialized in real-time object detection tasks [37]. This model was trained using a custom dataset, which included images captured with an iPhone 11, labeled through the Roboflow platform, and subsequently trained on Google Colab using hardware accelerators, i.e., Tensor Processing Unit, available through Colab Pro.

The YOLOv8 model was implemented using the official Ultralytics library in Python [37], which allows for direct integration of the trained model without requiring additional complex configurations. The model was loaded from a *.pt* file corresponding to the training performed and used to carry out real-time inferences on the video stream from the camera.

Additionally, the Supervision library [38] was incorporated to facilitate the visualization of detections through bounding box annotations with customized labels and representative color scales for each type of chocolate. This tool also enabled the establishment of filters and conditions, such as validating the size of detected objects to ensure that only valid chocolates within the expected range were processed.

The system achieved an accuracy of 99.4% and a recall of 98.6%, resulting in robust performance during the practical execution of the robotic arm. The model successfully identified the type and the approximate position of each chocolate in the image, enabling their subsequent handling by the automated mechanical arm.

III. RESULTS

The initial training phase was executed on Google Colab, requiring approximately 3 hours and 45 minutes. However, upgrading to Colab Pro and utilizing advanced GPUs significantly reduced the training, with 50 epochs, which took approx. 32 minutes. Table II briefly describes its results. Training beyond 50 epochs resulted in overfitting, which occurs when a model performs exceptionally well on training data but fails to generalize effectively to new data. Also, the corresponding Confusion Matrix of the Training stage is depicted in Fig. 5.

The evaluation phase of the project encompassed two primary testing modalities to validate the object detection algorithm's efficacy.

Initial assessments utilized static images of chocolates from the validation dataset, which the model had not encountered during its training phase (illustrated in Fig. 6).

These controlled tests were critical for gauging the model's precision in a stable environment. The algorithm consistently demonstrated confidence levels above 0.95, indicating robust recognition and classification capabilities.

Live testing conditions introduced real-time analysis, where the model's responsiveness to chocolates presented in the operational environment was gauged.

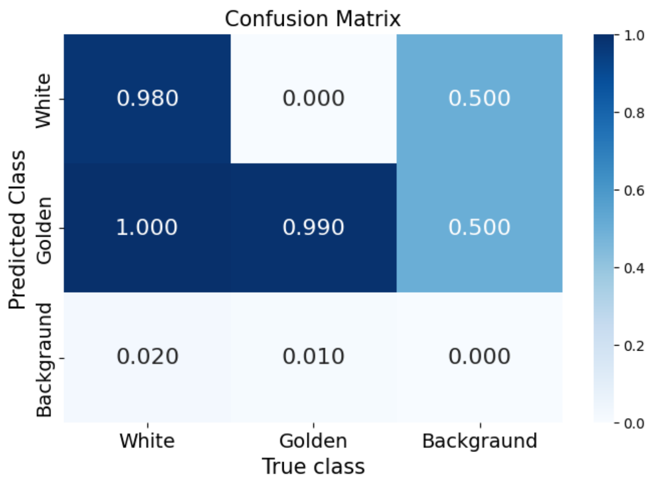

Fig. 5 Training Stage Confusion Matrix.

Despite a marginal decline in confidence scores, with an average of around 0.84 (depicted in Fig. 7), the model showed its potential for real-world applications, affirming its practical applicability and resilience against the complexities inherent in live scenarios.

TABLE II
RESULTS OF TRAINING FOR THE COMPUTER VISION MODEL

Class	Images	Instances	Precision	Recall	mAP50	mAP50-95
All	160	518	0.993	0.986	0.99	0.957
White Chocolate	160	256	0.990	0.984	0.988	0.954
Gold Chocolate	160	262	0.996	0.989	0.992	0.959

In-depth analysis was conducted through 20 practical tests, bifurcated into controlled and variable lighting conditions.

Under constant white light illumination, the algorithm's performance was impeccable, executing flawless identification and placement of chocolates, as detailed in Table III. This outcome emphasizes the significance of stable lighting for optimal system performance.

Conversely, the variable lighting tests, where light sources fluctuated and originated from natural settings such as doors or windows, presented more challenging conditions.

Fig. 6 Testing Stage Images.

Fig. 7 Real Time View Testing.

These tests, the results of which are presented in Table IV, indicated a decrease in detection and placement precision, although the algorithm still maintained a commendable level of accuracy.

TABLE III
RESULTS UNDER CONTROLLED LIGHTING CONDITIONS

# Tests	Total Time		Correct Detect		Correct Place	
	Array #1	Array #2	Array #1	Array #2	Array #1	Array #2
1	3:00	3:02	4	4	4	4
2	2:58	2:59	4	4	4	4
3	2:59	3:03	4	4	4	4
4	3:01	2:59	4	4	4	4
5	3:02	2:58	4	4	4	4
6	3:00	3:01	4	4	4	4
7	2:59	3:00	4	4	4	4
8	2:58	3:02	4	4	4	4
9	3:00	3:01	4	4	4	4
10	3:01	2:59	4	4	4	4
Average	**2.83 min**	**2.84 min**	**4**	**4**	**4**	**4**

When the “Array 1” button is pressed, the corresponding chocolate arrangement is depicted in Fig. 8. Similarly, pressing the “Array 2” button reveals the arrangement for this selection in Fig. 9.

TABLE IV
RESULTS UNDER VARIABLE LIGHT CONDITIONS

# Tests	Total Time		Correct Detect		Correct Place	
	Array #1	Array #2	Array #1	Array #2	Array #1	Array #2
1	3:02	2:58	3	3	3	3
2	2:59	2:59	4	3	4	3
3	2:58	3:03	3	2	3	2
4	3:01	3:01	3	3	3	3
5	3:02	3:00	4	3	4	3
6	3:00	2:58	2	4	2	4
7	2:59	3:01	3	3	3	3
8	3:00	3:00	4	3	4	3
9	3:00	3:01	4	4	4	4
10	3:01	2:59	3	3	3	3
Average	**2.88 min**	**2.85 min**	**3.3**	**3.1**	**3.3**	**3.1**

The operational efficiency of the end effector, a UVG, was also scrutinized. The UVG, utilizing a balloon and salt configuration to adapt to the shape of the chocolates, exhibited a decline in performance after the eighth consecutive pickup. It failed to secure chocolates 9 and 10 as the balloon could no longer maintain the requisite grip shape (refer to Table V).

To remediate this, a dual-pump system has been proposed. The secondary pump will not only aid in releasing chocolates but will also reconstitute the balloon's shape, ensuring consistent grip quality and extending the UVG's operational longevity.

Fig. 8 Array 1.

The trials offer a comprehensive view of the prototype's robustness, revealing insights into environmental impacts on system performance and paving the way for enhancements.

Key recommendations include maintaining controlled lighting conditions and strategically positioning the camera to preempt detection issues. Addressing these factors can optimize the system's functionality, improving reliability and efficiency.

TABLE V
END EFFECTOR PERFORMANCE TEST RESULTS

# Chocolates	Picked Up Successfully	Failed to Pick Up
Chocolate #1	✓	
Chocolate #2	✓	
Chocolate #3	✓	
Chocolate #4	✓	
Chocolate #5	✓	
Chocolate #6	✓	
Chocolate #7	✓	
Chocolate #8	✓	
Chocolate #9		X
Chocolate #10		X

To better assess the performance of the robotic arm system, a reference baseline was established using a traditional manual chocolate packaging process. An operator manually conducted ten packaging cycles without any automated assistance, with an average time of approximately 4.5 minutes per cycle and a misplacement rate of around 12%.

Fig. 9 Array 2.

In comparison, the robotic system consistently completed each packaging configuration in approximately 2.85 minutes under controlled lighting, with no errors reported in the placement of chocolates. This comparison highlights the system's ability to significantly improve speed and precision, reinforcing its suitability for real-world applications in small-scale food packaging.

IV. Conclusions

The project's testing and results reveal a compelling picture of advancements in automated food packaging, particularly through the integration of artificial intelligence and a robust mechanical system.

The object detection algorithm stands out with its remarkable ability to differentiate between two types of chocolates, achieving an impressive precision rate of 99.4% and a recall rate of 98.6%. Even in real-time scenarios, the algorithm performs commendably, with confidence levels oscillating between 0.8 and 0.9, demonstrating its adaptability across various configurations. Notably, the average time to complete a configuration is approximately 2.84 minutes, showcasing the system's efficiency. However, the algorithm's effectiveness is sensitive to fluctuating lighting conditions, underscoring the importance of environmental control in AI-driven systems. This sensitivity highlights the crucial role of precise camera calibration and adjustment before initiating the configuration process, a step essential for minimizing detection errors and ensuring accurate chocolate labeling.

The UVG, used as the end effector, initially exhibited high effectiveness, adeptly picking up the first eight chocolates. This success illustrated its capacity to mold to the object's shape and maintain a secure grip. However, the performance waned after the eighth cycle, with the UVG struggling to lift chocolates nine and ten, attributed to the balloon losing its adaptive shape. This observation underscores the UVG's need for periodic recalibration to sustain its gripping efficiency. To combat this limitation, a secondary air pump has been proposed. This pump would re-inflate the balloon after each cycle, thus restoring its shape for consistent operation. The anticipated result is a continuous, reliable operation of the UVG, theoretically enabling limitless cycles without performance degradation.

The project has made significant strides in merging AI with robotic technology for complex tasks like chocolate packaging. The empirical evidence gathered from the system's performance in various settings supports the broader application potential in different production environments. Integrating AI and robotics in manufacturing heralds a promising future characterized by enhanced operational efficiency, reliability, and quality assurance.

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