Design of a Smart Sorting Cobot Cell as an Experiential Learning Tool in Robotics and Mechatronics

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Abstract

This paper presents the design, construction, and programming of a smart collaborative robot (cobot) cell as an experiential learning tool in robotics and mechatronics coursework. The senior design project embraces this trend by developing a pick-and-sort system that integrates smart cameras with a robotic arm. The goal is to provide engineering and technology students with a hands-on learning platform that combines intelligent vision capabilities with robotic control. The system supports robotics and mechatronics coursework, offering students practical experience with modern automation technologies. Key components include the IFM machine vision 2-D camera, 3-D camera, and the UFactory Lite 6 robotic arm. The 2-D camera identifies object types based on shape and size, while the 3-D camera determines object coordinates in 3D space. The robot uses this data to pick and sort objects into designated pallet zones. An additional component includes a model conveyor belt for object transport. The entire system is integrated using Python. The 2-D camera communicates via TCP/IP, the 3-D camera interfaces through the ifm3dpy API, and the robotic arm is controlled using the xArm SDK. This project delivers a fully functional smart sorting system, providing students with a valuable opportunity to explore and analyze the integration of smart technology, machine vision, and robotics in an applied setting.

1. Introduction

This paper discusses an educational effort that incorporates smart sorting design concept for a smart collaborative robot (cobot) cell a senior design project at Drexel University. In the field of Robotics, new and developing technologies are created with the goal of implementing smart technology with robotic systems to create smarter and efficient robots for different applications defined by the user. In the manufacturing industry, robotics are integrated into daily manufacturing tasks by companies who seek to design and develop the most efficient manufacturing process and maximize profits. We will examine how a smart robot can be implemented into a manufacturing task called palletizing.

Palletization is a manufacturing process defined as "a logistical process that involves placing goods on top of a pallet to secure and consolidate the load and ease its handling during transportation, storage, handling, and distribution." In industry, palletization prepares products for storage, shipping, and occurs towards the end of the manufacturing process. Smart robots can contribute to the palletization process by having robots which can perform the palletization tasks without constant employee supervision or intervention. Typically, these palletizing robots would require a time-consuming process called "jogging." Jogging is defined as "manually moving a robot using a teach pendant to determine coordinates for programming points, it allows precise programming for teaching tasks or aligning robots with workpieces." Therefore, robots combined with smart technology capabilities would improve the palletization process by not requiring "manual jogging" and adapting the program for each individual object produced through the manufacturing assembly line [1-3].

This project aims to design, build, and test a smart sorting cobot cell as an experiential learning tool in Robotics and Mechatronics [4]. The design feasibility for the educational automated cobot work cell is based upon how well it can deliver for the project requirements, objectives, and goals. This led to determining both the 3D printer and cobot that have the functionality and performance that would produce successful integration into the work cell. Education in palletizing, robotics and smart technology are crucial for future engineers. The smart technology involved in this project helps students understand how smart technology is used and can aid the industry [5-7]. As the field of smart technology is ever growing and becoming much more commercialized it is crucial for students to understand the basics and how it can be used in something like palletizing. In order to demonstrate these aspects a learning module has been created to guide students on the processes of this project and all applications being used such as palletizing, robotics and smart technology. Students are able to use the module to demonstrate the project and practice its different intricacies such as testing with different objects or seeing the machine vision in action. Through detailed guides, manuals, and video demonstrations, key information will be provided to make sure faculty and students understand the operation of a work cell while ensuring safety. In section 2, the design and architecture is discussed. In section 3, the experiments and results are presented. Economic analysis is shown in section 4, which is followed by student project assessment and evaluation in section 5 and conclusion in section 6.

2. System Design Approach

2.1. Design Approach

Palletizing is the manufacturing process at the end of the assembly line and it's important for future engineers to understand and be able to troubleshoot any problems they encounter. Manufacturing is present in most industries and it's important for engineers to know its general practices. The robotics aspect impacts the lives of the operators involved in the assembly lines. A methodological approach was used to testing and designing. A robot simulation was created identical to how the actual system would operate as seen in Figure 1. This simulation was completed through a software known as RoboDK, which is a software for simulation and offline programming which means that the robot programs can be created, simulated, and generated offline for a specific robot arm and robot controller.

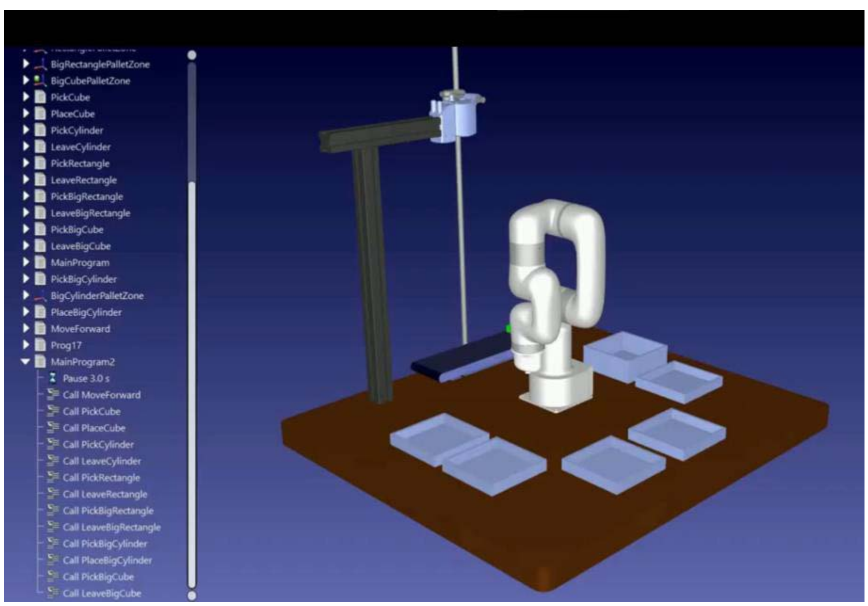


Figure 1. RoboDK Simulation Screenshot

Some features of the software include selecting files to load, 3-D navigation of the interface, a robot library with over 1000+ robot options to select from, library categories to split the robot sections for ease of searchability, and reference frames for location definition of items in respect to another item with a given location. To select the uFactory Lite 6 robot for simulation, the user should open the RoboDK software and follow the following steps: 1. File, 2. Open Robot Library (Online web browser), 3. Brand, 4. Select uFactory, 5. Select uFactory Lite 6 (from 6 listed options), and 6. Click Open, then return to the RoboDK Software.

After completing these steps, the user will load in a previously created SolidWorks assembly into the RoboDK interface and define reference frame positional coordinates to all the components with respect to the robot's position and orientation. Next, the user will add both an approach and retract program which will create a new program that will enable the robot to safely approach and retract to the parts in the simulation. After this is completed, the simulation is ready to run, verify, and generate the results.

2.2. System Architecture

The final design was created and is precisely scaled to match the physical work cell as shown in Figure 2. At the center of the design is the UFactory robot, which serves as both the focal point of the system and the origin of the digital coordinate plane. The robot is equipped with a vacuum gripper at its end-effector. Surrounding the robot are designated pallet zones for test objects retrieved from the conveyor belt. There are six distinct zones, each assigned to a specific object based on its shape and geometry.

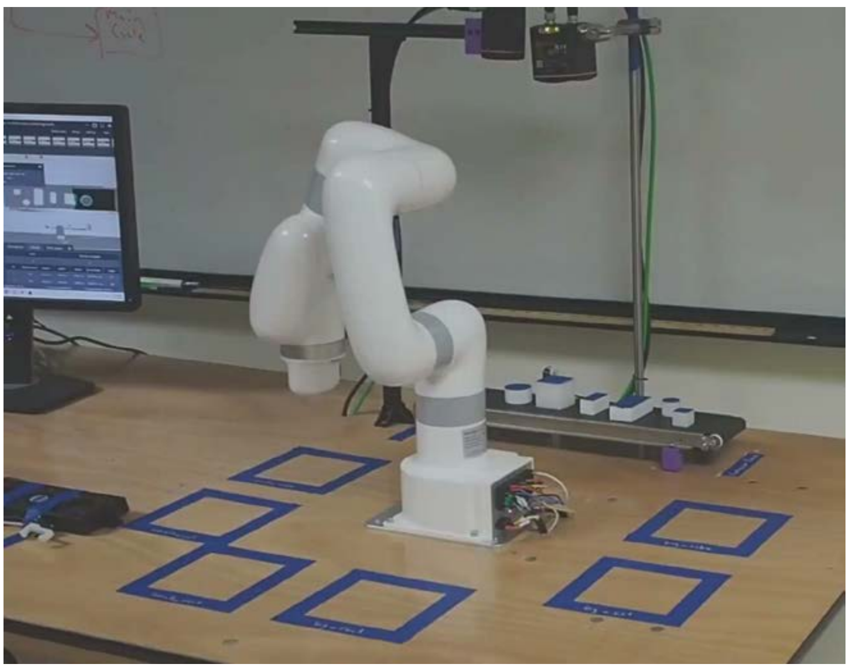


Figure 2. Physical Model of Robotic Arm System

The electrical system's flow is illustrated in Figure 3, with the complete wiring diagram provided in Figure 4. Essentially, all key components, including the conveyor belt, O2D and O3D, and photoelectric sensors, are wired to the robot's I/O ports, while the cameras connect to the computer via Ethernet [8-9]. The robot's I/O ports serve as the central hub, facilitating communication between major components, while the cameras transmit data to the computer for processing through Ethernet. To meet power requirements, two separate power supplies were necessary. The O3D requires at least 2.4 Amps, whereas the O2D only requires 0.9 Amps. The DN1030 power supply (rated at 1.3 Amps) was carried over from the previous project and is already wired to multiple components, including the O2D, conveyor belt, and photoelectric sensor. To avoid disrupting this setup, we opted to use a separate DN4013 power supply (rated at 10 Amps) for the O3D. While consolidating everything into a single power supply may be possible, it is not part of our current plans.

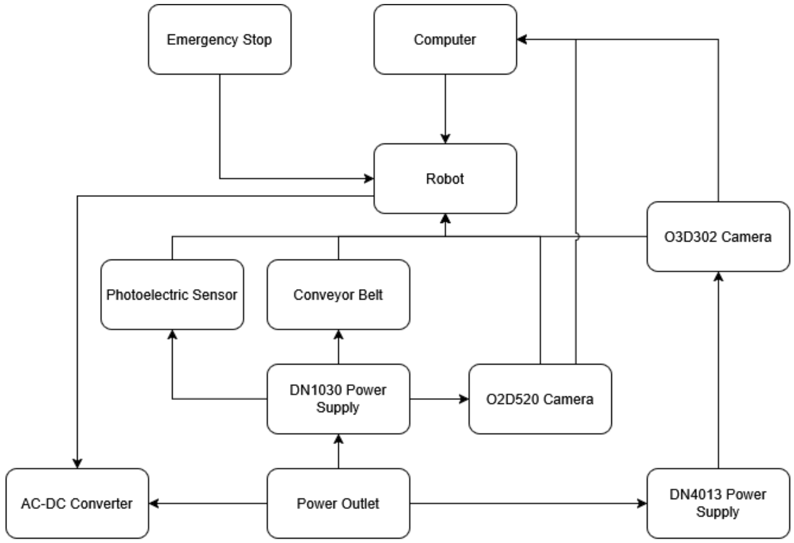


Figure 3. Wiring Diagram Flowchart

To visualize our workflow, we created a flowchart that outlines each step in the process, as shown in Figure 4 below. The starting three sequences are to place objects onto the conveyor belt, starting the main program and then the robot moving to home position. Once all of this is completed the program enters the main loop.

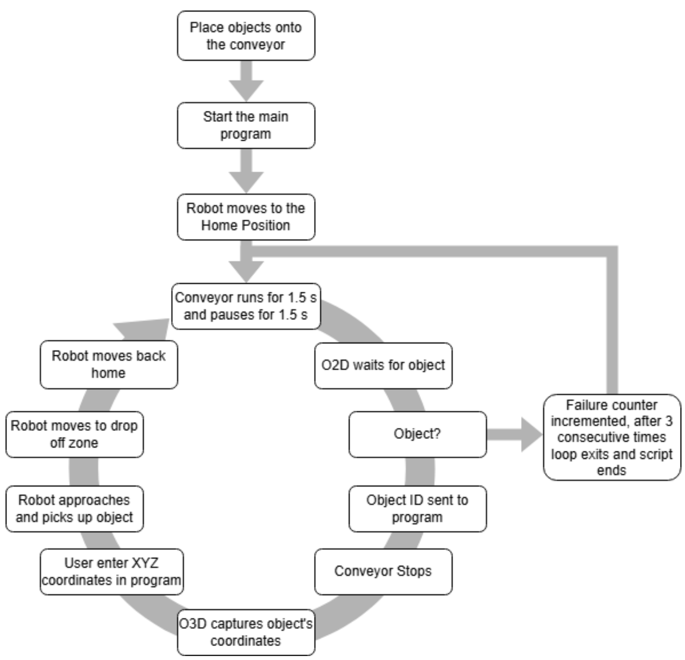


Figure 4. System Program Logic Flowchart

3. Experimental Setup and Results

For our project we decided that contour analysis would best fit our needs. This function works by the camera comparing the light and dark pixels it sees and creates an outline between the contrast as seen in Figure 5 below. Models were created for each object to be picked up and then allowed for the O2D to send a TRUE value for whenever one object fit any of the models best when passed through the sensor. This value is then sent to a selection function which either sends a string ID to the PCIC output via TCP/IP if the model is TRUE and then nothing if it is FALSE (ie, when a small cube is passed through the sensor the PCIC would output "small_cube"). Figure 6 shows a table of each string ID corresponding to each object. We have also implemented an exit feature such that if the O2D does not detect an object after its' wait step then it will increment a failure counter. After the failure counter reaches a total of three attempts the program will exit the loop and end the script. The counter is reset every time an object is detected.

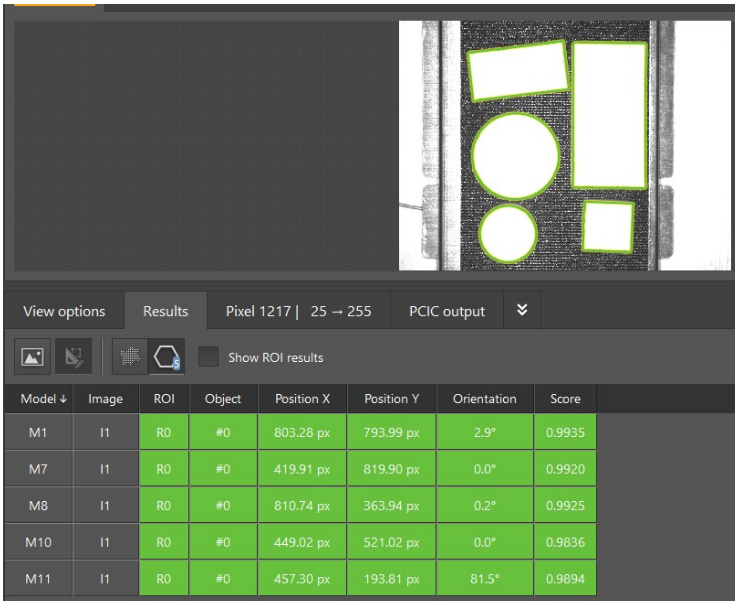


Figure 5. IFM O2D recognition grid

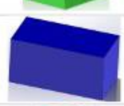
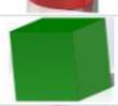
String ID (O2D)	Picture	CAD Model
small_cube		
small_rect		
small_cyl		
big_cube		
big_cyl		
big_rect		

Figure 6. Object ID's and 3D-Printed and CAD Models

All the wiring and other connections are safely set up under the platform for safety and presentation. Based on the limits provided by ISO standard 15066 guidelines, a protection cage that could be easily set up and taken down would be a cheap viable option to satisfy safety requirements. The primary functions of the O3D are configured through IFM's proprietary software, IFM Vision Assistant, which enables users to adjust camera settings, view the generated point cloud, and access object XYZ coordinates. To ensure accurate coordinate mapping, the O3D was calibrated to align with the robot's coordinate system. This was achieved by placing reference markers at key points within the robot's working zone. The robot was then jogged to each marker position, and its corresponding coordinates were entered into Vision Assistant. This calibration enabled both the robot and the O3D to operate within a unified coordinate system. Notably, the O3D output coordinates in meters, while the robot operates in millimeters—this unit discrepancy was accounted for during integration. With this configuration, users can manually extract XYZ coordinates from Vision Assistant, input them into the main Python program, and have the robot accurately approach objects centered over the top surface of the object.

For the best palletizing results in our system, the IFM O3D (03D303) utilizes Tof capabilities. Tof, which stands for Time of Flight, incorporates a sensor which projects a field of view using pixelations and records positional coordinates of objects inside the field of view by measuring the amount of time it takes for pixels to be disturbed by light reflecting off of the object. In this case, the objects will be each part on the conveyor belt. The shorter the time for each pixel, the closer the object and vice versa. Each pixel should have slightly different times due to marginal position differences throughout the body of the object. This then allows for a point cloud 3D space to be generated based on the pixels of the set reference zone of the camera. An example of the point cloud can be seen in Figure 7.

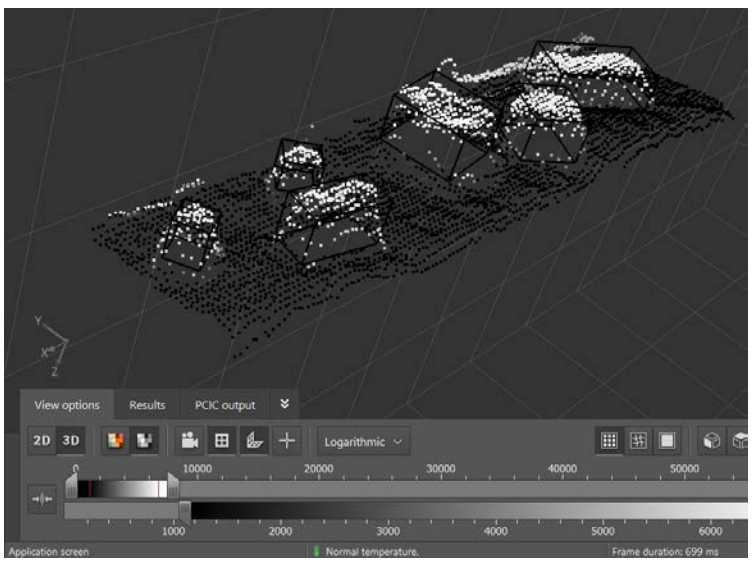


Figure 7. O3D point cloud space

The initial step of this loop is the conveyor belt moving and then stopping for 1.5 seconds each. Then the O2D waits for an object for it to detect, if it sees an object, the loop continues with the Object ID being sent to the program. The object ID is taken from the PCIC output from the vision assistant via TCP/IP. This is done by O2D's unique IP and the open PCIC port being referenced as set earlier. Each object ID is set to a preset XYZ coordinate and roll, pitch and yaw angle of [-180°, 0°, 0°] respectively. Then the conveyor belt stops and the O3D captures the object's coordinates. From here, the program will prompt the user to manually enter the XYZ position of the object from the vision assistant and the robot will then approach there and pick up that object. The robot will move the object to the drop zone, lower and drop it off and then back to home position. This is the completion of one loop. We have also implemented an exit feature such that if the O2D does not detect an object after its' wait step then it will increment a failure counter. After the failure counter reaches a total of three attempts the program will exit the loop and end the script.

The counter is reset every time an object is detected.

4. Economic Analysis

As this project enters its third year, many of the essential components for our system have already been acquired. The key components of this project include the UFactory robot arm and the IFM O2D and O3D. The UFactory robot arm, along with its accessories and UFactory Studio software for interfacing, was already provided. The O2D was installed in a previous iteration of the system, while the O3D, along with its accessories, was generously provided by IFM. In addition to hardware, various software tools are utilized for this project, including Google Workspace, Draw.io, PyCharm, and SolidWorks, the latter of which is provided by Drexel University. The estimated cost for newly purchased components as tabulated in Appendix F is $2,564, while the value of existing equipment totals $6,080, bringing the overall project cost to $8,643.

5. Student Project Assessment and Evaluation

Student performance was evaluated longitudinally across the three-quarter senior design sequence using both oral presentations and written technical reports in Fall, Winter, and Spring. Each term included a formal oral presentation assessed by faculty and industry evaluators, along with a comprehensive written report documenting project progress and technical development. The ten Performance Evaluation Indicators (PEIs) used in the assessment include: (1) Problem Definition and Need Analysis, (2) Project Planning and Management, (3) Design Process and Creativity, (4) Technical Approach and Engineering Methods, (5) Engineering System Modeling and Analysis, (6) Implementation and Testing, (7) Experimentation and Data Interpretation, (8) Teamwork and Communication, (9) Professional and Ethical Responsibility, and (10) Lifelong Learning and Contemporary Issues.

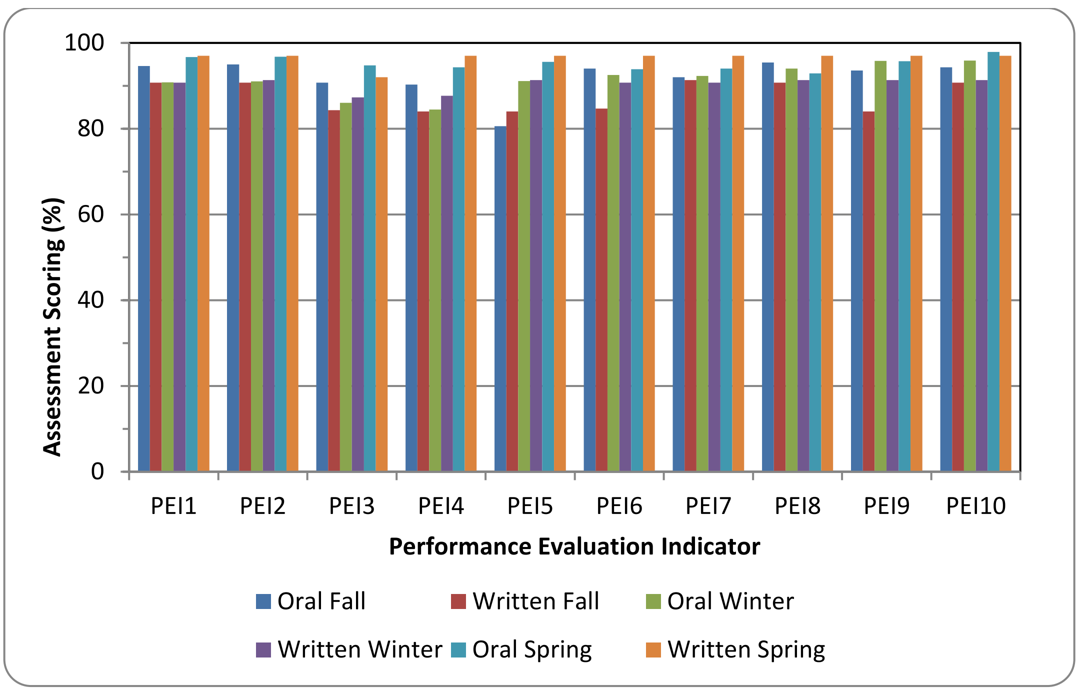


Figure 8. The Team's oral and written assessment from Fall 24 to Spring 25

Figure 8 further demonstrates consistent improvement across all PEIs for both oral and written components. Oral assessment scores increased from the low–mid 90% range in Fall to the mid–high 90% range by Spring, while written report scores showed more pronounced gains, particularly in later-stage PEIs related to system integration, testing, and professional communication (PEI5–PEI10). Notably, Spring written scores approach or exceed 97% across multiple indicators, reflecting substantial improvement in technical documentation quality and clarity.

These trends highlight the effectiveness of the iterative assessment structure embedded within the capstone sequence. Early-stage evaluations indicate relatively lower performance in areas such as system modeling (PEI5) and experimentation (PEI7), where students are still developing structured approaches to analysis and validation. However, by Winter and especially Spring, significant gains are evident, with improvements of approximately 5–10 percentage points in these higher-order competencies. The convergence of oral and written scores in the Spring term further suggests that students not only developed stronger technical solutions but also improved their ability to communicate and justify those solutions effectively. Overall, Figure 8 reinforces that the combination of repeated oral presentations and written deliverables drives continuous improvement, enabling students to progress from conceptual understanding to validated, professionally communicated engineering solutions.

6. Conclusion

This project successfully developed an experiential learning platform via the integration between the two IFM vision systems with the Ufactory Robot for semi-automatic object detection and sorting. By utilizing the IFM O2D for object identification and the O3D for spatial positioning, the system accurately recognized and located objects on a conveyor. The Ufactory robot with a vacuum gripper efficiently performed pick-and-place tasks based on real time input. The system was integrated using python allowing seamless communication between the components. The work will provide a solid foundation for future improvements, including complete O3D integration for automatic object sorting, expanded object recognition capabilities and constant object feeding flow.

7. Acknowledgement

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