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A Modular Multi-Agent Architecture for Order Fulfillment in Industry 5.0

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Abstract: This article presents the design and validation of an automated packaging agent built on a modular multi-agent architecture that integrates generative AI, computer vision, robotics, and simulation. In response to spoken user commands, specialized agents (planning, production, packaging, inventory, and quality control) collaboratively identify target items, plan order fulfillment, execute packaging actions, and verify outcomes. The system is validated in a simulated industrial environment implemented in CoppeliaSim, with a web-based control layer for service integration and orchestration. A large language model (LLM) converts verbal instructions into structured task plans, while OpenCV-based perception is complemented by a custom YOLOv11 detector trained on automatically labeled data generated with the Segment Anything Model (SAM). Experimental results in simulation demonstrate reliable end-to-end autonomy, including conveyor control, box selection, pick-and-place execution, and vision-based quality checks. The agent completes a full packaging cycle in ~6 minutes and achieves near-perfect object identification accuracy in the evaluated simulated scenarios. Remaining challenges include improving grasp reliability for physical deployment and reducing inter-platform latency. Overall, the proposed approach illustrates the potential of combining AI, robotics, and simulation to build resilient, adaptable industrial agents aligned with Industry 5.0 requirements.

Keywords: artificial intelligence; Industry 5.0; intelligent agents; pick-and-place; computer vision; robotic packaging.

面向工业 5.0 的智能订单履行环境智能代理

摘要： 本文提出了一种基于模块化多智能体架构的智能自动包装智能体设计与验证方案，该方案融合了生成式人工智能、计算机视觉、机器人技术及仿真技术。基于用户语音指令，智能体（规划器、生产器、包装器、产品器和质量器）协同工作以实现物体的识别、处理、存储与验证。为实现仿真验证，采用 CoppeliaSim 构建虚拟环境，运用 Streamlit 与 FastAPI 实现网页界面及服务集成，以 n8n 作为多智能体流程编排器，并借助 GPT-4/5 长文本模型解析用户语音指令。OpenCV 用于物体检测与分类，通过自动图像标注模型 SAM 生成的数据训练定制 YOLOv11 模型，实现模拟场景中精准的物体识别。智能代理架构支持用户通过语音指令发起订单准备请求，执行以下操作：规划每批次发货并确认用户需求、控制传送带、选择包装箱、执行抓取放置流程，并通过图像分析验证包装质量。测试表明，该智能代理在物体检测与分类方面具有极高精度，能够自主执行整个流程，每个包装周期耗时约六分钟，物体识别准确率接近 100%。但仍存在挑战，例如需提升物理抓取精度及平台间延迟问题。总体而言，该项目展现了融合人工智能、机器人技术与仿真技术的潜力，可开发出适应不同生产场景的弹性智能工业代理，为应对工业 5.0 挑战提供了强有力的解决方案。

关键词：人工智能，工业 5.0，智能代理，拣选，计算机视觉

1. Introduction

The development of Industry 5.0 has been accompanied by the growing availability and maturity of artificial intelligence (AI) services offered by technology providers [1]. Through human–machine interaction and data-driven workforce management, AI is already shaping and is expected to continue shaping modern manufacturing systems [2]. Accordingly, intelligent agents have been developed and applied in diverse industrial contexts, including energy management [4], decision support [5], mass production [6], port logistics for berth allocation [7], intelligent transport systems [8], and food-packaging technologies [9].

The demonstrated effectiveness of intelligent agents has stimulated the adoption of multi-agent systems (MAS) in industrial settings, in which specialized agents coordinate across different stages of the production chain [9] as well as service logistics [10]. MAS have been applied to assembly-line optimization [12], cooperative decision-making [13], Internet of Things (IoT)-enabled solutions [14], coordinated motion planning [15], and other production-related tasks [16]. Recent advances in large language models (LLMs) have further expanded MAS capabilities by enabling more flexible natural-language interfaces and higher-level task decomposition [16].

Prior studies indicate that Industry 4.0 has transformed human–machine interaction by enabling language-based communication, which supports next-generation smart manufacturing [18] and the integration of intelligent agents with LLMs across multiple application domains [19–21]. In addition, AI-based workflows [22] and orchestration tools such as n8n [23] facilitate the integration of multi-agent pipelines that combine AI algorithms, virtual environments, and natural language processing. Virtual environments are also widely used to develop digital twins [24, 25], thereby enabling systematic evaluation of robotic systems and agent-based automation in production contexts.

Building on this state of the art, this study aims to design and evaluate an intelligent agent for product selection and dispatch using a virtual simulation environment. The proposed approach combines workflow-based agent orchestration (n8n) with a simulated packaging-line setting to support operator interaction in packaging and supply-chain scenarios. The resulting system integrates robotics, computer vision, and generative AI into a unified automated pipeline. The main contribution is a simulation-validated multi-agent solution under CoppeliaSim that supports product and packaging selection based on size, leveraging LLM-enabled coordination and decision-making.

2. Methodology

To support Industry 5.0 order-fulfillment workflows and reduce lead time from customer request to automated packaging, we employ a modular multi-agent architecture and workflow-orchestration tools to integrate databases, natural-language processing components, and supporting services. This design enables rapid reconfiguration and iterative system upgrades.

The primary objective is to enable a robotic manipulator to identify items to be packed (colored cubes), select an appropriate shipping box based on item size, and verify correct execution of the end-to-end workflow. In addition, the system logs key outcomes in a results table to ensure traceability and support historical analysis. The workflow is initiated via spoken natural-language commands. The proposed multi-agent architecture autonomously plans, executes, validates, and reports each dispatch operation. System development and validation integrate (i) robotics for object manipulation, (ii) computer vision for detection and classification using vision sensors, and (iii) generative AI components embedded in the agent roles along the production chain.

The system is operated through a conversational interface that allows users to specify, by voice, which products should be packaged. It then plans, executes, and verifies the process from start to finish. The implementation stack includes OpenCV-based image processing and a YOLOv11 detector, physics-based simulation in CoppeliaSim, workflow orchestration with n8n, service middleware implemented with FastAPI, and a Streamlit-based user interface. These components are integrated into a single workflow that interprets user requests, manipulates objects in simulation, and validates dispatch completion. Fig. 1 illustrates the virtual work environment.

Packaging automation is implemented by integrating the following components:

1. Web interface (Streamlit): enables user interaction via voice commands and displays system feedback.
2. Simulation environment (CoppeliaSim): provides physics-based simulation of the robot arm, sensors, cameras, object interactions, and secondary equipment (e.g., conveyor belts), and supports control via internal scripts or external APIs (e.g., Python).
3. Workflow orchestration (n8n + FastAPI): triggers and coordinates subprocesses, issues requests to endpoints that control the simulated environment, and manages execution state.
4. Large language model (e.g., GPT-4/GPT-5): interprets spoken instructions, supports task planning and validation logic, and generates natural-language responses.

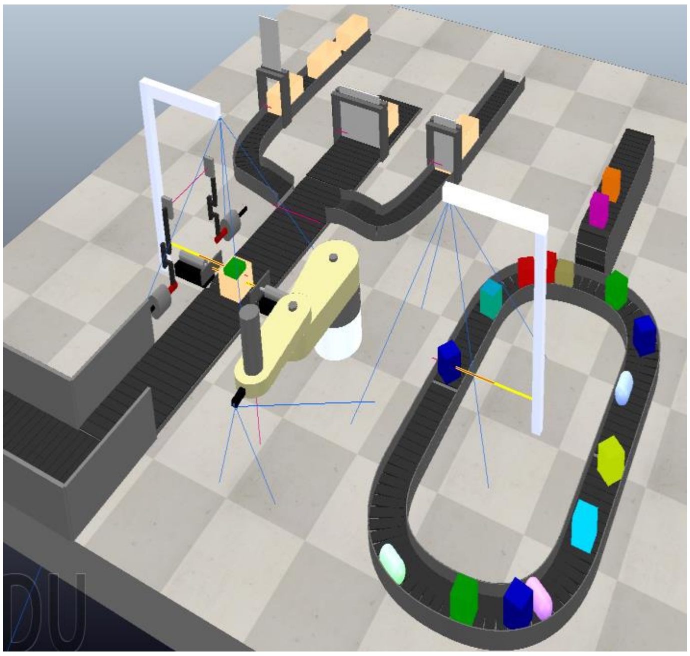


Figure 1. Virtual work environment (developed by the authors)

The simulation environment (Fig. 1) comprises three functional zones:

1. Object collection zone: items are placed on a conveyor belt controlled by a proximity sensor that stops motion when an object is detected. An overhead camera captures images processed with OpenCV to extract contours and estimate centroids for grasp planning; object identity is confirmed using YOLOv11.
2. Storage zone: packaging boxes are staged on a second conveyor equipped with a presence sensor and an overhead camera. The vision module estimates pixel coordinates of placed items and identifies available placement regions for subsequent items.
3. Manipulator: performs pick-and-place actions. Motion is controlled in CoppeliaSim through predefined routines triggered via FastAPI requests.

Fig. 2 presents the planned scene layout; side planes are visually offset from the true camera-support profiles to avoid occluding the view and saturating the rendering.

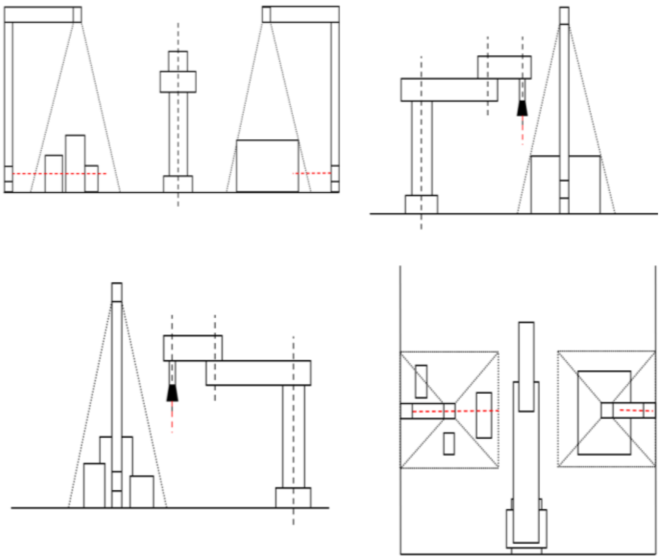


Figure 2. Scene set up for the process (developed by the authors)

2.1. Definition and training of the vision model

One of the most important stages of the system is achieving reliable detection and localization of objects on the scene. Among the deep learning algorithms that solve this task with a high degree of performance are YOLO networks. Although pre-trained architectures are available, YOLOv11 must be customized for the objects of interest, creating a custom dataset adapted to the project context. Fifty images per object type were taken directly from the virtual cameras in the CoppeliaSim environment, ensuring variations in position, orientation, and background (see Figure 3).

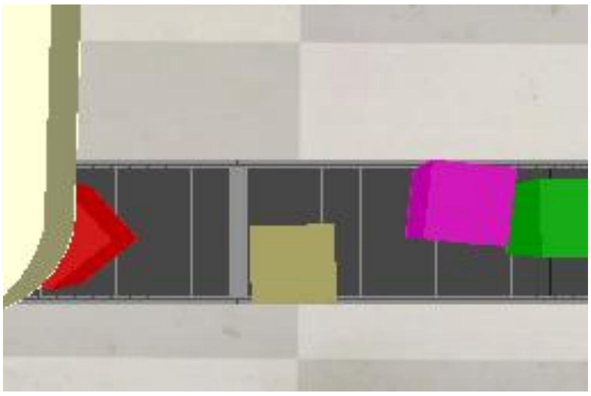


Figure 3. Example capture for the YOLO network database (Source: developed by the authors)

Once the objects were labeled using bounding boxes, the YOLOv11 network was trained for 100 epochs, dividing the dataset into 70% for training and 30% for validation. During testing, a progressive decrease in the loss function was observed for both training and validation, while the precision and recall metrics stabilized at values close to 1.0, as seen in Figure 4, indicating near-perfect detection.

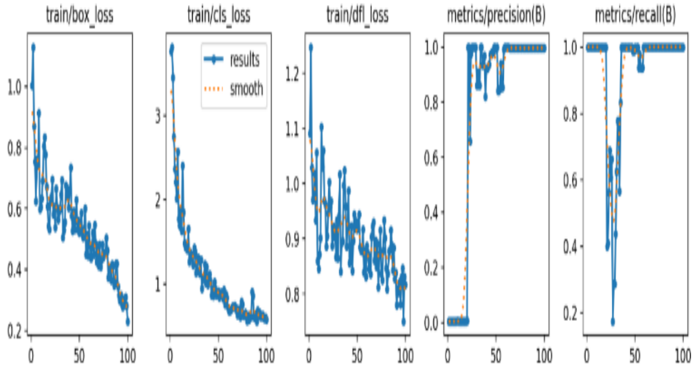


Figure 4. Training curves (Source: developed by the authors)

In addition, a confusion matrix was generated with the validation set, showing 100% classification with no evidence of overfitting (see Figure 5), since the images contained no external noise and the context was fully controlled. In this case, it was important to identify the object and its location within the visual area, excluding the background, so only one class is evident.

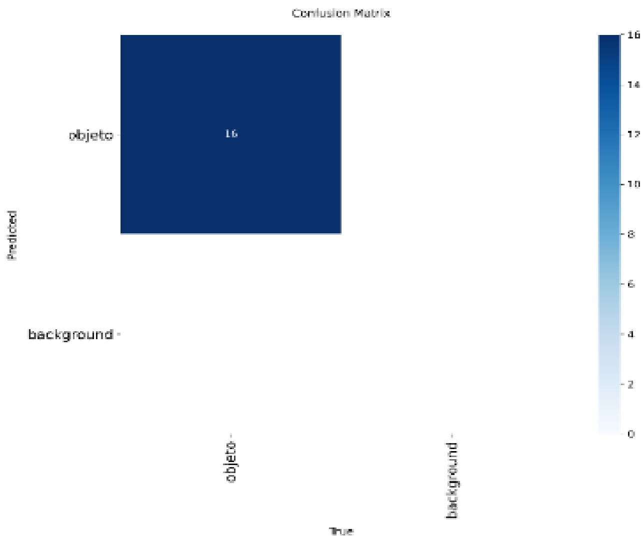


Figure 5. Confusion matrix (developed by the authors)

The resulting model was able to detect and locate objects in the CoppeliaSim scene with high accuracy and stability, avoiding identification errors. Figure 6 shows images of examples of the model trained to detect objects in the scene, based on the first object to be evaluated for being grabbed or continuing the conveyor belt.

Figure 6. Identification and location of the online object to be classified (Source: developed by the authors)

2.2. General system architecture

The automation system was designed using a multi-agent architecture to divide responsibilities and allow for flow scalability. Each of the system's five agents has a well-defined role within the process and is interrelated, as shown in the red box in Figure 7. Figure 7 illustrates the complete automation workflow process.

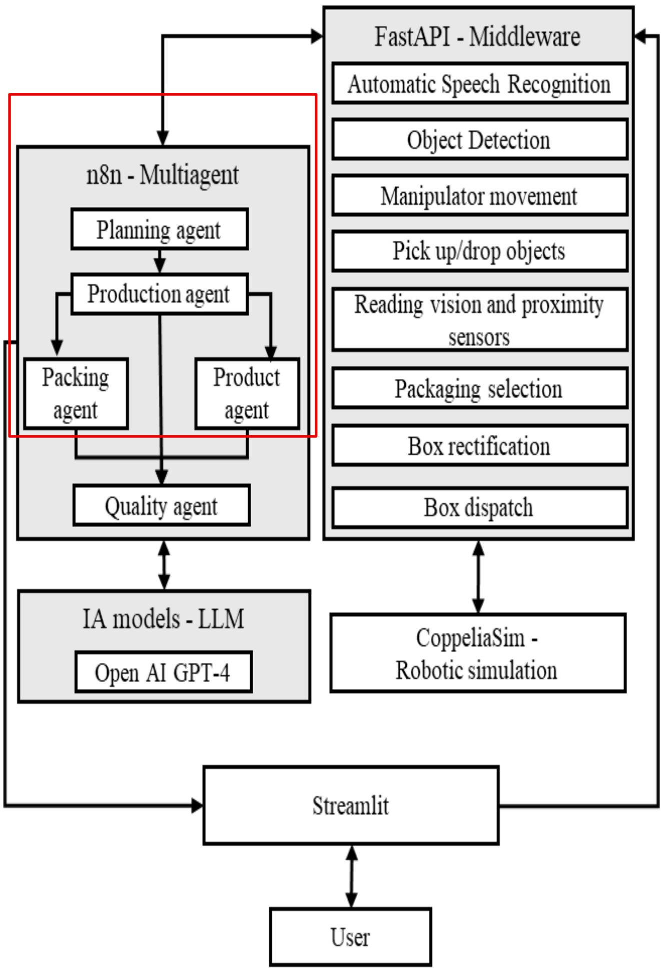


Figure 7. General system architecture (developed by the authors)

Table 1 shows the actions of each agent within the multi-agent architecture, which allows for dividing responsibilities and generating scalability of the workflow in n8n, which acts as the brain orchestrating the entire process.

Table 1. Roles of agents (Source: developed by the authors)

Agent	Roles
Planner	Maintains the conversation with the user, identifies the products to be packed, calculates the required boxes, and creates the dispatch plan.
Production	Converts the plan into an ordered task list, defines how many iterations to execute (one per object), and controls the overall flow.
Packaging	Manages the conveyor belts, selects the box type, and activates its positioning.
Products	Physically picks up the items with the manipulator, validates that they are the correct ones, and places them in the box.
Quality	Analyzes the final images of the packed boxes to determine if the process was correct or if there were errors.

2.3. Workflow by Agent

The following workflows are presented: the general system, the pick and pack, the production orchestrator, and the object processing.

2.3.1. Picking and Packing Agent Flow

This flow receives the user's command via Webhook and uses GPT-4 as a LLM to understand which products to operate and in what quantities, query product and box tables, and assemble lists with packing orders and box types (see Figure 8). It also returns the plan to the user for confirmation, and if confirmed, calls the "Production Orchestrator" with the lists of objects and boxes.

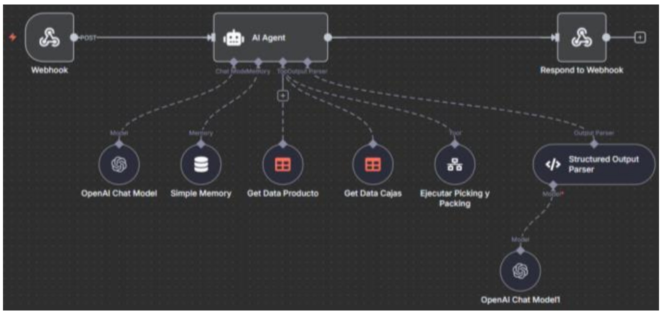


Figure 8. Picking and Packing Agent Flow in n8n (developed by the authors)

2.3.2. Production Orchestrator Flow

This workflow transforms lists into JSON grouped by box. Where it defines the number of iterations, each iteration involves picking and placing an object. For each object, it activates the Packing Agent, which selects the appropriate box from the line. It then activates the Product Agent, which invokes the Process Object function in the Coppelia interface. This process checks whether the box is filled when it is complete and triggers the dispatch_box routine to prepare the next one. Once all the objects are processed, it calls the Quality Agent to analyze the box images and validate the process.

2.3.3. Object Processing Flow – Coppelia

This flow receives the object to be processed from the Orchestrator. It uses a prompt to validate whether the object picked up is correct and takes actions in the simulated environment in sequence. It begins with the pick_up_object routine, where the robot grabs an object. The YOLO network validates with an image whether it is the correct one; if so, it places it in the box (routines such as move, correct box, drop object, move to home);

if not, it drops the incorrect object and repeats.

Figure 9 shows the interconnection between the agents operating at a high level, from the user's request to the execution of each task. The Planner agent creates the packing plan with boxes and objects in the production agent, controlling the execution from start to finish. The agent decides how many times the pick → place cycle is repeated and supervises the activation of both the packaging and product agents in parallel.

The packing agent maintains the flow of boxes on the conveyors. Each time a shipment is completed, the box is sent, and a new one is selected. The Product agent performs the physical part, picking items one by one until they meet the lists. Finally, the Quality agent checks that the packaging matches the plan. If errors are detected, they return an objective diagnosis with an accurate percentage.

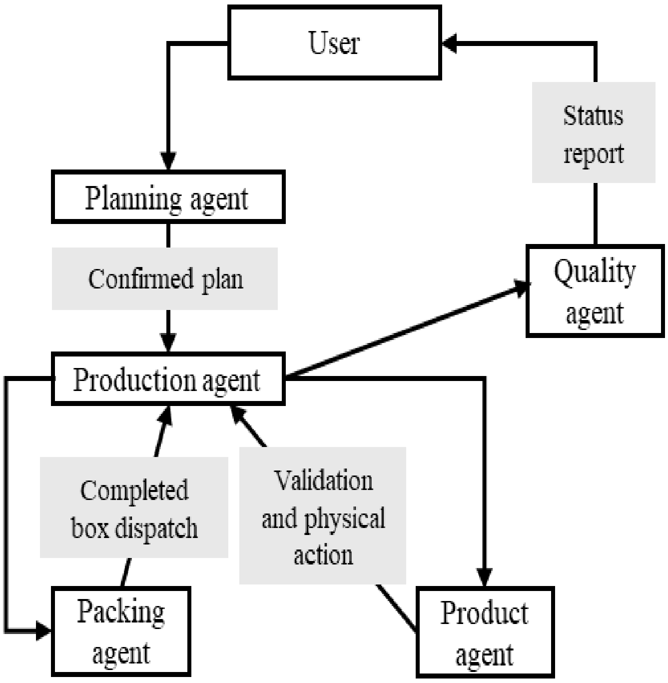


Figure 9. High-level interaction between agents (developed by the authors)

2.4. Routines implemented

Routines are the basis of all operational logic in a packaging automation system. They are defined as functional blocks that can be executed, repeated, or combined to build more complex sequences. Table 2 lists the main routines and their purpose.

Table 2. Execution routines implemented (Source: developed by the authors)

Routine	Agent that executes	Process timing	Purpose
Box type selector	Packaging Agent	Before dispatch	Activate the belt and bring the correct box.
Pick object	Product Agent	Each iteration	Detect and grab an object from the belt.
Drop wrong object	Product Agent	If validation fails	Drop the object incorrectly.
Box rectifier	Product Agent	Before releasing the object	Align the box correctly.
Drop object	Product Agent	After validation	Drop the object into the selected box.
Move object to home	Product Agent	End of cycle	Return the manipulator to the home position.
Dispatch box	Packaging Agent	Box full	Send the box to the output area.
Dispatch images	Quality Agent	End of process	Analyze images of the boxes and validate.

Table 3 lists the tasks executed by the multi-agent system, generally describing the actions performed during each process.

Table 3. Task sequence (Source: developed by the authors)

Task	Role	Tools
Understanding Requirements	Understand the user's request and define the quantity and which objects will be considered.	- Analysis
Validating and Collecting Objects	Based on an object to be processed, execute the routine to retrieve the corresponding objects and perform the necessary validations.	-Detect object -Move manipulator -Detect object position -Validate manipulator positioning -Read end effector distance sensor -Activate suction cup -Move end effector
Storing Objects	Based on a retrieved object and a box, define the location to store the object.	-Detect box -Detect objects inside the box -Set storage position -Move manipulator -Calculate drop position -Move manipulator -Move end effector -Disable suction cup -Move end effector

3. Results and validation

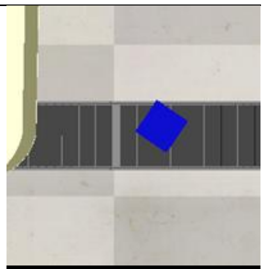
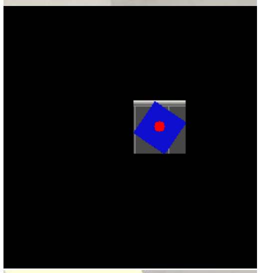
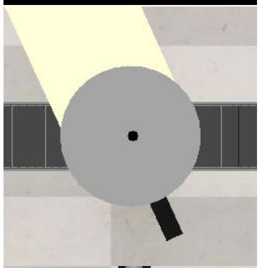
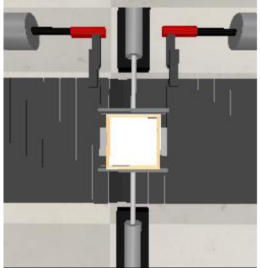
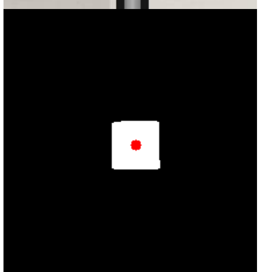
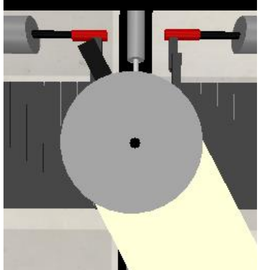
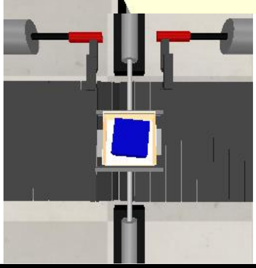
The development is displayed through a window in a web browser with which the user interacts, at which time the CoppeliaSimen environment opens. Figure 10 illustrates an initial user interaction. This occurs by pressing the microphone icon in the yellow box, which demonstrates audio capture through the variation of the audible signal and the recording time. The captured audio then appears in text as initial user validation. In this case, since the environment and the LLM model are configured in Spanish, a question input was used: "What can you do?" To which the model responds, "My role is to identify products you wish to pack, define the most appropriate type of box, and the storage order, if necessary. To begin, please indicate the products you wish to pack and the quantity of each. This way, I can guide you step by step in planning your picking and packing."

Figure 10. Voice interaction and virtual execution environment (Source: developed by the authors)

From this point on, the agent is informed of the type of object to be packed, for example, a red box, and the size, for example, 10x0x10. Tests were performed for box identification, object validation, and visual quality control, demonstrating a practically autonomous process from planning to final validation. Inaccuracies were detected when picking up or releasing objects because the grip does not always occur from the geometric center of the object, resulting in grip instability and occasionally resulting in the grip being released. This effect, from the simulation environment, did not allow for adjustment by grip strength, which in real environments could solve the problem.

Overall, the system demonstrated stable coordination and robust execution, successfully integrating the various AI, vision, and simulation modules, with each stage of the process illustrated in Table 4. The table graphically illustrates the processes of picking up, releasing, and validating the object to be stored for shipment.

Table 4. Process validation (Source: developed by the authors)

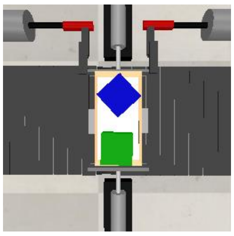
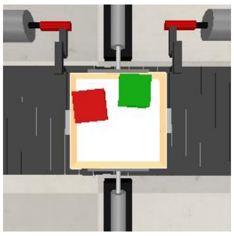
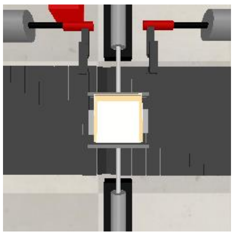
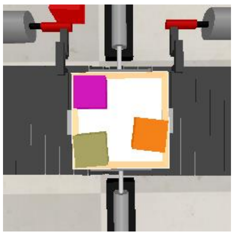
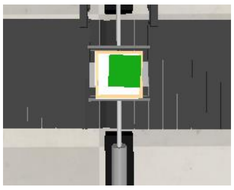
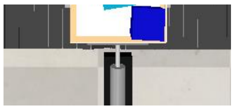
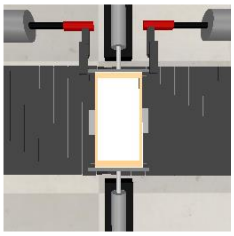
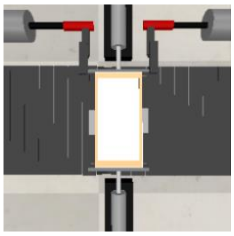
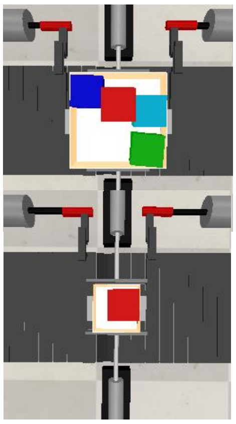
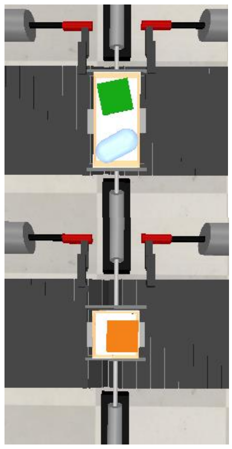
Process	Detail	Reference image
Pick object	Object Detection	
	Object Classification	
	Object Capture	
Drop object	Box Detection	
	Box Sorting	
	Object Drop	
Validate object	Parse stored object	

In several cases, asynchronous communication between services generated small delays or temporary blockages, especially when running simultaneous tasks such as image processing, AI validation, and updating the simulated environment. To mitigate this, a unified executable was developed that keeps all modules running in parallel, controlling the sequential initialization of each component and reducing latency in interprocess communication.

Ten complete dispatch tests were run to calculate the accuracy percentages in item selection (83.33 %) and box packing (54.56 %), varying the number of products and box type; the results are presented in Table 5. The tests are designed to request the shipment of different quantities of products, which are also of different types.

At a general level, a major challenge was interconnection between platforms, as the project combines different environments and technologies (n8n, FastAPI, CoppeliaSim, Streamlit, and LLM models).

Table 5. Dispatch tests (Source: developed by the authors)

#	Products	Box Types	Shipping Image
1	- 1 blue cube - 1 green cube	Type_2	
2	- 1 blue cube - 1 green cube - 1 red cube	Type_3	
3	- 1 red cube	Type_1	
4	- 1 fuchsia cube - 1 green cube - 1 orange cube - 1 blue cube	Type_3	
5	- 1 green cube	Type_1	
6	- 1 green cube - 2 blue cubes	Type_3	
7	- 2 red cubes	Type_2	
8	- 1 red cube - 1 fuchsia cube	Type_2	
9	- 1 green cube - 2 blue cubes - 2 red cubes	Type 3 Type 1	
10	- 1 fuchsia cube - 1 green cube - 1 orange cube	Type 2 Type 1	

4. Discussion

Regarding the hardware environment, the project was run on a computer with the following specifications:

- Processor: Intel® Core™ i7-8550U CPU @ 1.80GHz (4 cores / 8 threads)
- RAM: 24 GB
- Storage: PNY CS900 1TB SSD
- Dedicated graphics: NVIDIA GeForce MX150 2GB
- Integrated graphics: Intel® UHD Graphics 620

The hardware enabled acceptable performance in most tests. No limitation was evident in the GPU (only 2 GB of VRAM) on the inference speed of the

YOLOv11 model. However, the low-power processor (U series) slightly increased execution times when running multiple processes simultaneously (simulation and orchestration).

Despite these limitations, the system managed to maintain average execution times of around 6 minutes per complete dispatch, which includes the planning, acquisition, validation, and storage of all required objects. These results are considered satisfactory considering the complexity of the workflow and the coordination between the different agents.

Another challenge identified was occasional failures in CoppeliaSim's physics, mainly during the grabbing and releasing routines, where the physics engine did not always respond deterministically to collisions or small object displacements. These incidents required adjusting the refresh rate and collision parameters to prevent abnormal behavior, such as objects passing through the gripper or slipping inside the box.

The process automation trends encompassed by Industry 5.0 are geared towards human-machine interaction through natural language processing, where the design presented, in which the user speaks with the multi-agent system to request an order, demonstrates the technological integration that facilitates the customer-industry approach, aimed at optimizing processes by reducing response times or service hours restrictions.

5. Conclusion

A novel multi-agent model based on computer vision was established to integrate the user's requirement with the dispatch process directly, supported by a database of products in stock, where the virtual environment allowed the validation of the functionality of the direct client-agent interaction, through natural language processing.

The integration of robotics and generative artificial intelligence demonstrated the potential for automating industrial packaging processes with minimal human intervention. The use of modular routines and a multi-agent architecture enabled the system to behave like a real production environment, capable of planning, executing, and validating each task autonomously. The project's evolution, from basic object manipulation to an orchestrated workflow with automatic quality validation, demonstrates the potential of combining simulation, AI, and vision for smart manufacturing tasks. However, improvements in physical manipulation precision are still needed, optimizing end-effector grip and position calculations.

Future work includes establishing operating conditions under real-world conditions, for example, identification under variations in ambient light, and validating the packaging of polymorphic objects.

Declarations

Author Contributions

Conceptualization, formal analysis and writing—review and editing Jiménez-Moreno R. and Espitia-Cubillos A.; methodology, validation, and investigation Jiménez-Moreno R.; supervision, project administration, funding acquisition, and data curation Espitia-Cubillos A.; Software, writing—original draft preparation and visualization Pulido Aponte M. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committe of the Universidad Militar Nueva Granada (project INV-ING-4150, date of approval: 27/01/2025).

Conflicts of Interest

The author declares that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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