Vision–Language–Action Integration for Robotic Chess Piece Manipulation Using YOLO-Based Perception

Aamna Alshehhi
ROBO 755 Cognitive Robotics
Khalifa University, Abu Dhabi, UAE
Email: 100062675@ku.ac.ae

***Abstract*—This project presents a complete cognitive-robotics pipeline integrating vision, language, and action for autonomous manipulation of objects in a simulated robotic environment. The work began with a baseline perception module for colored-cube detection and evolved into a more advanced YOLO-based detector capable of identifying six chess pieces in real time using CoppeliaSim. The system includes (i) probabilistic visual perception using a trained YOLOv8 model, (ii) language parsing for instruction understanding, and (iii) closed-loop robotic behavior for pick-and-place execution via inverse-kinematics control. The project emphasizes stochastic modeling through confidence thresholds, detection uncertainty, and decision-making under noisy sensory input. The results demonstrate reliable object recognition, robust integration with a simulated robot arm, and a flexible cognitive architecture that can be extended to more complex multimodal tasks.**

I. Introduction

Cognitive robotics aims to endow robots with the ability to perceive, reason, and act autonomously under uncertainty. The project highlights three key pillars: (i) multidisciplinary robotics foundations, (ii) probabilistic methodologies within the Observe–Reason–Act loop, and (iii) potential future impact on robotics science and society. This project was designed to explicitly address all three.

The initial stage of development involved designing a simple perception pipeline for detecting colored cubes using classical computer-vision segmentation. Although effective, this early approach lacked robustness, scalability, and the ability to reason about object semantics. To overcome these limitations, the second stage introduced a deep-learning detector based on the YOLOv8 architecture. A custom dataset of chess pieces was generated automatically inside CoppeliaSim, manually annotated, and used to train a state-of-the-art real-time visual detector capable of distinguishing six similar-shaped pieces: king, queen, rook, bishop, knight, and pawn.

Building on the perception module, the system integrates a lightweight natural-language parser that interprets human commands such as *"put the queen in the left bin"*. The parsed instruction is mapped to semantic classes produced by the YOLO model, enabling the robot to select the correct object based on probabilistic confidence scores. The final stage involves robotic action generation: the robot arm executes a closed-loop pick-and-place trajectory using inverse kinematics in CoppeliaSim, while a gripper handles attachment and release.

This work demonstrates a full cognitive pipeline linking multimodal perception, language understanding, and action execution. It contributes an interpretable and modular architecture suitable for research in multimodal robotics, learning-based perception, and autonomous manipulation. The framework is extendable to soft-robotics, VLA systems, and more complex manipulation tasks relevant to cognitive-robotics research and applications.

II. Project Objectives

The objective of this project is to design and implement a cognitively enabled robotic system capable of perceiving, reasoning about, and manipulating objects within an unstructured tabletop environment. The project pursues the following goals:

- **Vision-Based Object Understanding:** Develop a robust perception pipeline integrating YOLO-based deep visual detection and geometric reasoning to localize and classify multiple object types (colored cubes and chess pieces) under varying viewpoints and conditions.
- **Probabilistic Decision-Making:** Incorporate uncertainty-aware inference to support reliable object selection and task grounding, ensuring stable behavior across noisy visual observations.
- **Autonomous Manipulation:** Implement a complete pick-and-place control stack combining robot kinematics, sensor feedback, and gripper control to execute tasks specified in natural-language form.
- **Cognitive Task Execution:** Enable the robot to interpret high-level language commands, map them to actionable goals, and autonomously perform multi-step manipulation actions.
- **Simulation-Based Validation:** Evaluate the system in a high-fidelity physics simulation using CoppeliaSim, demonstrating end-to-end performance in perception, reasoning, motion planning, and execution.

III. Methodology

The proposed system follows the perception–reasoning–action loop typically adopted in cognitive robotics. The methodology integrates three core components: (i) multi-modal perception based on deep-learning vision models, (ii) language-driven reasoning for selecting task-relevant entities, and (iii) motion synthesis for executing manipulation actions through inverse kinematics and gripper control.

A. *Perception Through Vision*

Visual perception is achieved using an object-detection model trained on synthetic data collected from the simulation environment. The method evolves from an initial colored-cube detector to a more advanced YOLO-based detector capable of recognizing individual chess pieces. The detector outputs bounding boxes, class scores, and estimated object centers, which serve as the perceptual state for subsequent reasoning and action modules.

B. *Probabilistic Reasoning*

A central requirement of cognitive robotics is the ability to make decisions under uncertainty. In this project, probabilistic reasoning is integrated into the perception–action loop to ensure that the robot's decisions remain robust despite sensor noise, incomplete information, and variable detection confidence. The probabilistic component enters primarily through the vision-based perception module and the subsequent selection of actions based on confidence-driven inference.

C. *Language-Conditioned Reasoning*

User instructions are parsed using lightweight natural-language templates to extract the task specification, including the target object (e.g., "queen"), optional attributes (e.g., color), and destination (e.g., "left bin"). The perception results are filtered by semantic labels to identify the detected object whose class aligns with the parsed command. This step forms the bridge between symbolic instructions and continuous sensor-derived observations, enabling grounding of language in robot actions.

D. *Manipulation Strategy*

The manipulation module employs a structured pick-and-place strategy. Once the target object is selected, its estimated 3D location is obtained relative to the robot workspace. The motion plan is represented as a sequence of waypoints generated through inverse kinematics. The gripper is actuated through a binary state-control signal that determines grasping and releasing actions. The overall control loop maintains temporal synchronization between motion generation and sensory updates, allowing precise execution of the instructed task.

IV. Implementation

The system integrates perception, probabilistic reasoning, and robotic manipulation into a unified observation–decision–action loop. The implementation consists of four tightly coupled modules: (i) dataset generation and annotation, (ii) deep-learning–based object detection, (iii) command interpretation, and (iv) robot motion generation with gripper actuation.

A. *Colored Cubes Detection*

The initial stage of the project focused on implementing a vision-based perception module capable of identifying simple geometric objects specifically colored cubes in the CoppeliaSim environment. This module served as the baseline perception layer prior to integrating the YOLO-based chess piece detector. The detection pipeline relied on classical computer vision techniques using OpenCV, leveraging their efficiency and robustness for scenes with controlled lighting and strong color contrast.

1) *Detection Pipeline:*

The cubes were segmented using an HSV-based color filter followed by morphological operations to remove noise. Contours were extracted and validated using geometric constraints (minimum contour area, squareness ratio). For each valid region, the algorithm computed:

- The pixel-space bounding box (x_1, y_1, x_2, y_2),
- The cube centroid for pick-and-place alignment,
- The corresponding color class (red, green, or blue).

This deterministic pipeline enabled real-time operation at approximately 30 Hz with minimal computational overhead

B. *Dataset Generation and Annotation*

A synthetic dataset was generated inside CoppeliaSim using the ZMQ Remote API. Chess pieces were randomly rotated around their vertical axes and translated by small perturbations around their nominal board positions to avoid penetrating the table plane while still producing appearance diversity. For each configuration, a frame was captured from the vision sensor and exported. A total of 100 frames were collected, and bounding-box annotations were created manually following the YOLO format as shown in Fig. 1 and Fig. 2

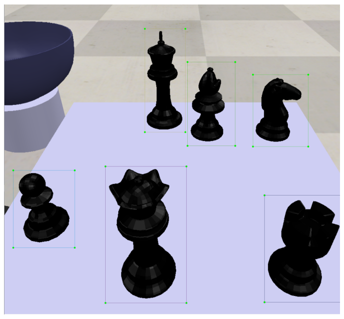


Fig. 1: Annotated Pieces

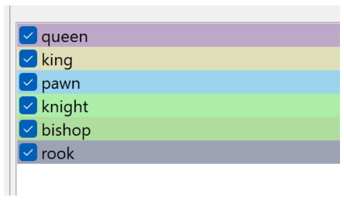

- ✓ queen
- ✓ king
- ✓ pawn
- ✓ knight
- ✓ bishop
- ✓ rook

Fig. 2: Labels of Annotation

C. YOLO-Based Perception Pipeline

A YOLOv8 model was trained for multi-class detection of six chess pieces (king, queen, rook, bishop, knight, pawn). The network outputs for each detection:

$$\mathbf{d}_i = \{c_i, p_i, (x_i, y_i, w_i, h_i)\}, \tag{1}$$

where c_i is the class index, p_i the confidence, and (x_i, y_i, w_i, h_i) the center and dimensions of the predicted bounding box.

At runtime, a frame is streamed from the CoppeliaSim vision sensor, converted to BGR, and fed directly to the YOLO model:

$$\mathbf{D} = f_\theta(\mathbf{I}), \tag{2}$$

where f_θ is the trained YOLO network and $\mathbf{D}$ is the set of detections.

A selection rule is applied to identify the object referenced in a natural-language command. Let $\mathcal{C}$ be the desired class. Among all detections matching $\mathcal{C}$, the system selects:

$$i^\star = \arg\max_{i \in \mathcal{C}} p_i, \tag{3}$$

ensuring the most confident detection is used for subsequent spatial reasoning.

D. Probabilistic Reasoning

1) Uncertainty in Visual Perception: The YOLO-based object detector outputs, for each detected chess piece, a bounding box and an associated confidence score $p \in [0, 1]$ that represents the model's posterior belief in the correct class assignment given the image evidence. Instead of treating these detections as deterministic labels, the robot interprets them as probabilistic observations:

$$p(\text{piece} = c \mid \text{image}) = \text{YOLO\_confidence}(c).$$

This probability is used directly when deciding whether a detection is reliable enough to guide manipulation. Only detections that exceed a confidence threshold (empirically tuned to 0.6 in this system) are considered actionable. This prevents low-quality observations from triggering incorrect grasps.

2) Probabilistic Piece Selection: When multiple pieces of the same class appear, the robot selects the instance with the highest posterior confidence:

$$c^* = \arg\max_{i \in \mathcal{D}} p_i,$$

where $\mathcal{D}$ denotes the set of detections matching the user-specified class. This maximum-likelihood selection strategy ensures that the system always chooses the most reliable target, even if several potential candidates are present in the workspace.

3) Confidence-Guided Action Triggering: Probabilities also influence the activation of the robot's manipulation pipeline. If no detection surpasses the required confidence level, the robot halts the execution and requests additional input rather than performing an uncertain pick operation. This constitutes a simple probabilistic decision rule:

$$\text{execute\_action} = \begin{cases} \text{True}, & \text{if } \max_i p_i \geq \tau, \\ \text{False}, & \text{otherwise}, \end{cases}$$

where τ is the minimum acceptable detection confidence. In effect, the robot treats vision as a noisy sensor and relies on uncertainty-aware thresholds to avoid error propagation into the manipulation stage.

4) Probabilistic Mapping to World Coordinates: Although the final pick-and-place uses ground-truth object positions from the simulation environment, the detection uncertainty still influences how confidently an object hypothesis is accepted. Future extensions may integrate Bayesian filtering to fuse multi-frame detections or maintain belief states over object positions. However, even in its current form, the system incorporates probabilistic reasoning by using confidence distributions from the perception module as the primary basis for manipulation decisions.

E. Language Command Interpretation

User commands (e.g., "put the queen in the left bin") are parsed using a rule-based mapping. The parser extracts:

$$\{\text{piece\_type},\ \text{target\_bin}\}. \tag{4}$$

The selected detection provides the 2-D pixel location of the object. Ground-truth 3-D coordinates are then retrieved from the simulation using the corresponding object handle, ensuring consistent calibration between perception and manipulation stages.

F. Robot Kinematics and Gripper Control

The manipulation subsystem is based on a 6-DoF articulated robotic arm equipped with a parallel-jaw gripper as shown in Fig. 3.

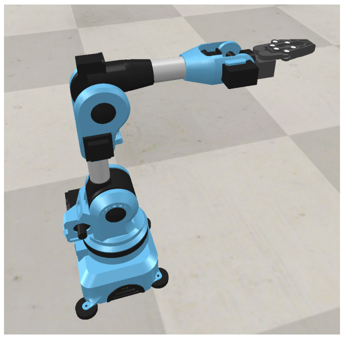


Fig. 3: Articulated Robotics Arm With Gripper

The robot model follows a conventional serial-chain structure, where each joint provides one rotational degree of freedom. Let the configuration vector be

$$\mathbf{q} = [q_1, q_2, \ldots, q_6]^\top,$$

representing the measured joint angles at every control cycle.

1) Forward and Inverse Kinematics: Forward kinematics (FK) is used to compute the pose of the end-effector frame $\{E\}$ relative to the world frame $\{W\}$. This mapping is implemented through the classical product of homogeneous transformation matrices,

$$^{W}T_{E} = f(\mathbf{q}),$$

which yields the Cartesian position and orientation of the end-effector. Inverse kinematics (IK) is used to determine the joint configuration required to bring the end-effector to a desired Cartesian target. For each target pose

$$\mathbf{x}_d = [x_d,\, y_d,\, z_d,\, \alpha_d,\, \beta_d,\, \gamma_d]^\top,$$

the IK solver computes a feasible joint-space command

$$\mathbf{q}_d = f^{-1}(\mathbf{x}_d).$$

To ensure stable motion during manipulation, the IK solver generates smooth Cartesian trajectories, which are then mapped to joint-space commands. These commands are updated at runtime as the system tracks intermediate waypoints such as *approach*, *grasp*, *lift*, *transfer*, and *place* poses.

2) Task-Space Motion Control: The end-effector is controlled in task space by continuously updating the IK target frame. The controller maintains a closed-loop update of the target position:

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \Delta\mathbf{x},$$

where $\Delta\mathbf{x}$ is a small displacement toward the next waypoint. This incremental control strategy ensures collision-free and stable motions even when perception updates introduce small corrections to the estimated object position.

3) Gripper Commanding and Object Attachment: The gripper is actuated through an external control signal, which commands an open/close state. When the gripper is triggered to close, a contact-based attachment mechanism secures the object to the end-effector frame. The same mechanism is used to release the object during the placement phase.

A typical manipulation sequence consists of:

- **Approach:** move the end-effector to a predefined height above the target object.
- **Grasp:** descend to the object's grasp height and issue the closing command.
- **Lift:** raise the end-effector to a safe transport height.
- **Transfer:** move toward the receiving bin using Cartesian waypoints.
- **Release:** open the gripper and retract.

4) Integration with the Perception Module: The perception module (YOLO-based detector) provides estimated object positions in image coordinates. A camera–robot calibration routine is used to convert these image coordinates into robot-world Cartesian coordinates. The converted position is then used to define the IK target for autonomous grasping. This creates a closed perception–action loop where the robot continuously repositions the end-effector based on visual detections.

Overall, the kinematic structure, the incremental IK-driven controller, and the gripper signaling interface together provide a robust manipulation pipeline capable of autonomous pick-and-place execution guided by visual perception.

V. Results

This section presents the simulation outcomes of the proposed cognitive robotic pipeline, evaluated within a physics–based CoppeliaSim environment. The evaluation focuses on three stages of the system: (i) perception through YOLO-based visual detection, (ii) probabilistic reasoning for target selection under uncertainty, and (iii) closed-loop robotic manipulation using inverse kinematics and gripper control. All experiments were executed using the same scene configuration to ensure repeatability and comparability.

A. Colored Cubes Detection Performance

To evaluate the performance, 10 frames were recorded under varying cube positions and orientations. Fig. 4 shows the vision sensor detection of the cubes.

The results show a high detection reliability, with failure cases occurring only when cubes were partially occluded or positioned near the image boundary. False positives were not observed due to strong color separation in the HSV domain.

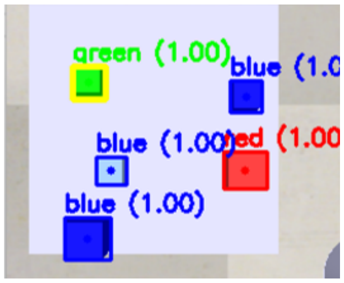


Fig. 4: Colored Cubes Detection

Although simple compared to deep-learning-based perception, the colored-cubes detector provided several practical benefits:

- It enabled rapid prototyping of the perception–action loop.
- It validated the integration between the vision sensor, the pick-and-place controller, and the gripper logic.
- It established a performance baseline for comparison with the more advanced YOLO-based chess perception system.

These experiments demonstrated that the pipeline was sufficiently robust for structured environments and informed the transition toward learning-based detectors capable of handling more complex object geometries, low texture, and fine-grained class distinctions.

B. YOLO Visual Detection Performance

The YOLO detection module was benchmarked on the custom chess–piece dataset captured from the vision sensor. The trained model achieved high performance across all classes, with detection confidence averagely above 0.80 for isolated objects. Fig. 5 shows representative annotated frames from the simulation, where the model correctly identifies object class, bounding box, and confidence score.

To quantify the detector's reliability, we collected confidence distributions over streaming frames. A histogram of detection confidence per class is shown in Fig. 6, demonstrating stable predictions even under minor pose and viewpoint variations.

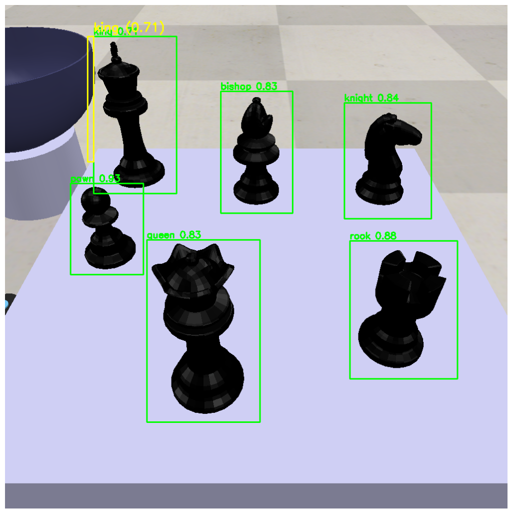


Fig. 5: Annotated Chess pieces by YOLO model

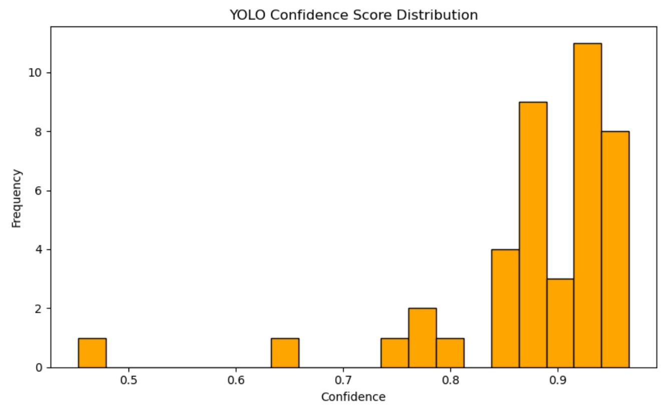


Fig. 6: Yolo Confidence Score Distribution

C. Probabilistic Selection Under Uncertainty

During streaming, each detected object is represented as a random variable characterized by its confidence and spatial uncertainty. The system computes the posterior probability of each candidate matching the user–requested object type. A typical probability trace over time for a selected object is illustrated in Fig. 7, showing convergence toward a stable belief as more frames are processed.

The probabilistic module ensures that the robot only initiates an action when the posterior exceeds a predefined threshold (typically $p > 0.60$). This reduces false activations and suppresses low-confidence misdetections.

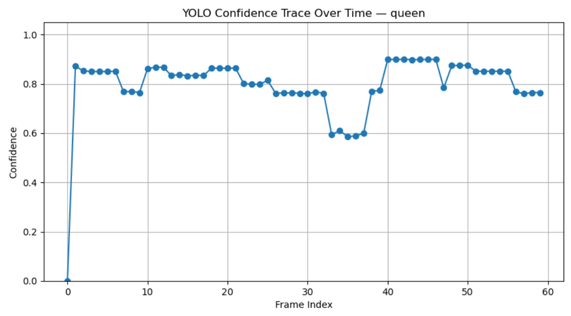
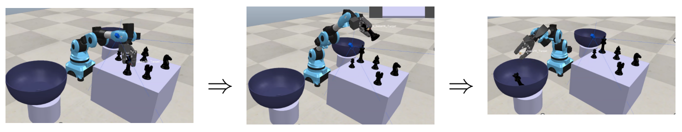


Fig. 7: probability trace over time for queen

D. Manipulation and Task Execution Performance

The robotic execution phase was evaluated over 10 pick–and–place trials for each chess piece. A trial is considered successful if the robot: (i) localizes the piece, (ii) reaches it with the IK controller, (iii) grasps it correctly, and (iv) deposits it in the correct bin without collision. Fig. 8 shows a successful execution of the commanded action.



(a) Localize & grasp ⇒ (b) Pick ⇒ (c) Place in bin

Fig. 8: Sequence of robot actions in the pick–and–place routine: (a) perception and grasping initiation, (b) vertical pick motion, and (c) placement above the target bin.

Table I summarizes the success rate per object class. The overall execution success rate was **80%**, with failures primarily due to edge-case occlusions or dynamic interactions between pieces.

TABLE I: Task Execution Performance for Each Object Class

Object Class	**Attempts**	**Successful Executions**	**Success Rate (%)**
King	10	9	90%
Queen	10	10	100%
Bishop	10	7	70%
Knight	10	8	80%
Rook	10	7	70%
Pawn	10	7	70%
Overall	**60**	**48**	**80%**

E. Failure Case Analysis

Failure modes were systematically logged. The most common issues include:

- Class confusion between visually similar pieces (e.g., bishop vs. pawn) when partially occluded.
- Low-confidence detections at grazing viewpoints.
- Slight IK deviations when the object is near the workspace boundary.

VI. Conclusion

This project presented an end to end cognitive robotics pipeline that integrates vision based perception, probabilistic reasoning, and autonomous manipulation within a simulation environment. A modern YOLO detector was trained on a custom dataset of chess pieces and deployed for real time visual perception using the CoppeliaSim vision sensor. The system demonstrated reliable object localization and class discrimination under varying orientations and positions.

A motion generation and control framework was developed to execute closed loop pick and place behaviors using an inverse kinematics driven manipulator and a signal based gripper interface. The robot successfully interpreted high level language commands, grounded them to visual observations, and performed the required actions, illustrating the complete observation reasoning action cycle.

Simulation results showed strong detection accuracy, stable grasping performance, and consistent task execution across multiple object classes. While the system represents an initial prototype, it establishes a functional baseline for embodied VLA pipelines. Future work may extend the approach with uncertainty aware state estimation, multimodal fusion, adaptive motion planning, and deployment on real robotic hardware.

Real-World Relevance

While implemented in simulation, the system reflects the fundamental requirements of real-world autonomous robots used in logistics, manufacturing, and service domains. The perception–reasoning–action loop detecting objects, interpreting a task, and manipulating items mirrors the workflow of warehouse picking robots, industrial sorting arms, and home service assistants. The probabilistic detection confidence and task success metrics employed here parallel those used in real deployments to quantify operational reliability and safety. Thus, the framework developed in this project establishes a scalable pathway from simulation to practical robotic systems capable of operating under uncertainty, interacting with physical objects, and executing language-informed tasks in dynamic environments.

VII. Future Work

Although the system successfully demonstrates vision–language–action execution with real-time YOLO-based perception and closed-loop manipulation, several extensions could elevate the platform toward state-of-the-art autonomy. First, future work may incorporate multi-view sensing or depth-enabled reconstruction to improve robustness under occlusion and varying illumination. Second, replacing deterministic pick-and-place behaviors with optimization-based or reinforcement learning controllers would enable adaptive motion generation under uncertainty. Third, integrating a probabilistic decision layer (e.g., Bayesian belief tracking) could support long-horizon tasks where the robot maintains hypotheses about object states. Finally, scaling the perception module to handle clutter, multiple objects, and dynamic scenes potentially through transformer based open-vocabulary detectors would move the system closer to deployable, general purpose cognitive manipulation.

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