

Design and Validation of an Intelligent Robotic Manipulator Integrating Computer Vision and Natural Language Processing for Safe Chemical Handling

Conception et validation d'un robot manipulateur intelligent intégrant la vision par ordinateur et le traitement du langage naturel pour la manipulation sécurisée des produits chimiques

Thematic Track:

- ▶ Track 1 — Renewable Energies, Smart Grids & Energy Intelligence
- ▶ Track 2 — Biomedical Engineering, Connected Health & Health Sovereignty
- ▶ Track 3 — Mechanical Engineering, Maintenance 4.0 & Industrial Transformation
- ☒ **Track 4 — Intelligent Systems, Data Science & Digital Twins**
- ▶ Track 5 — Circular Economy, Climate Resilience & Industrial Ecology

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1. RÉSUMÉ / ABSTRACT

Résumé (Français)

La manipulation des produits chimiques en laboratoire expose les opérateurs à des risques importants liés aux substances dangereuses et aux erreurs d'exécution des protocoles. Dans ce contexte, cette étude propose la conception et la validation d'un robot manipulateur intelligent intégrant la vision par ordinateur et le traitement du langage naturel afin d'améliorer la sécurité, la précision et l'autonomie des opérations en environnement contraint. L'architecture développée repose sur un système cyber-physique articulé autour d'un bras manipulateur à six degrés de liberté piloté sous ROS, combinant un module de perception visuelle basé sur la vision par ordinateur, un module cognitif utilisant le traitement du langage naturel pour l'analyse des fiches de données de sécurité, ainsi qu'un module de commande assurant la planification et l'exécution sécurisées des trajectoires. L'évaluation du système met en évidence une amélioration significative des performances de manipulation grâce à la fusion des capacités perceptives et cognitives. Les expérimentations montrent une précision de positionnement de l'ordre de 0,8 mm, une détection fiable des incompatibilités chimiques et une réduction notable des erreurs de protocole lors des scénarios de test. Ces résultats démontrent l'intérêt d'une approche intégrant l'intelligence artificielle au contrôle robotique pour renforcer la sécurité des manipulations chimiques. Les perspectives envisagées concernent l'intégration de modèles d'apprentissage plus avancés, l'extension du système à d'autres environnements industriels à haut risque et la validation expérimentale sur des plateformes robotiques de plus grande échelle.

Abstract (English)

Chemical laboratories involve hazardous operations that expose personnel to significant safety risks while requiring high positioning accuracy and strict compliance with operating protocols. This paper presents the design and validation of an intelligent robotic manipulator that integrates Computer Vision (CV) and Natural Language Processing (NLP) to improve the safety and reliability of chemical handling tasks in constrained environments. The proposed cyber-physical architecture is built around a six-degree-of-freedom (6-DOF) robotic arm controlled through the Robot Operating System (ROS). It combines a computer vision module for object perception, an NLP module for the automatic analysis of Safety Data Sheets (SDS), and an intelligent control module responsible for motion planning and safe task execution. Experimental evaluations demonstrate the effectiveness of the proposed approach by achieving an average positioning accuracy of 0.8 mm, reliable detection of chemical incompatibilities, and a significant reduction in protocol execution errors through the integration of cognitive safety mechanisms. The results highlight the benefits of combining perception, semantic reasoning, and robotic control within a unified architecture for hazardous laboratory environments. The proposed framework represents a promising solution for intelligent chemical handling and provides

a foundation for future developments in predictive control, autonomous laboratory robotics, and AI-driven industrial automation.

Keywords: Intelligent Robotic Manipulator; Computer Vision; Natural Language Processing; Cyber-Physical System; Chemical Safety; ROS; Artificial Intelligence.

2. INTRODUCTION

The rapid evolution of Industry 4.0 has accelerated the integration of Artificial Intelligence (AI), robotics, and Cyber-Physical Systems (CPS) into industrial and laboratory environments. In chemical laboratories, the manipulation of hazardous substances requires not only high positioning accuracy but also strict compliance with safety protocols to minimize risks to personnel, equipment, and the environment [17], [18]. Although robotic manipulators have significantly improved automation, most existing systems remain primarily focused on motion execution and lack the cognitive capabilities required to interpret safety instructions or adapt their behaviour to complex operational contexts [1], [13]. Recent advances in Computer Vision (CV) have enabled robots to perceive and recognize objects with remarkable accuracy, while Natural Language Processing (NLP) has demonstrated its effectiveness in extracting semantic information from unstructured textual documents [8]. However, these technologies are often developed independently, and their integration into robotic manipulation systems dedicated to chemical safety remains limited. Consequently, current robotic platforms are generally unable to analyse Safety Data Sheets (SDS), identify hazardous chemical incompatibilities, and prevent unsafe operations before task execution [9].

Addressing these limitations requires the development of intelligent robotic systems capable of combining perception, semantic understanding, and autonomous decision-making within a unified control architecture [19]. Such systems can contribute not only to improving manipulation accuracy but also to reinforcing operational safety through proactive risk assessment and intelligent task validation. This paper proposes the design and validation of an intelligent robotic manipulator integrating Computer Vision and Natural Language Processing within a Cyber-Physical System architecture. The proposed system combines a six-degree-of-freedom robotic arm, a vision-based perception module, an NLP-based cognitive module for Safety Data Sheet analysis, and an intelligent motion control framework implemented under the Robot Operating System (ROS) [3], [4]. By coupling visual perception with semantic reasoning, the system aims to improve manipulation accuracy while preventing hazardous actions before their execution.

The remainder of this paper is organized as follows. Section 3 reviews the related literature on intelligent robotic manipulators, Computer Vision, and Natural Language Processing. Section 4 describes the proposed methodology and system architecture. Section 5 presents the experimental results, while Section 6 discusses the findings and the limitations of the proposed approach. Finally, Section 7 concludes the paper and outlines future research directions.

3. LITERATURE REVIEW / STATE OF THE ART

3.1 Previous Works

Recent advances in intelligent robotics have significantly transformed industrial automation by enabling robotic manipulators to perform increasingly complex tasks with higher precision and autonomy [1], [15], [16]. Robotic arms are now widely deployed in manufacturing, healthcare, logistics, and hazardous environments where human intervention may expose operators to safety risks [14]. However, conventional robotic manipulators are primarily designed for repetitive operations and generally lack cognitive capabilities for understanding environmental constraints or interpreting domain-specific knowledge [13].

Computer Vision has become a key enabling technology for intelligent robotic manipulation. Deep learning-based object detection algorithms [11], particularly the You Only Look Once (YOLO) family and its open-source implementations, have demonstrated remarkable performance in real-time object recognition, localization, and scene understanding [5], [6], [7]. These techniques enable robots to identify target objects, estimate their spatial positions, and adapt grasping strategies according to dynamic environmental conditions. Nevertheless, visual perception alone cannot provide semantic knowledge related to chemical hazards or operational procedures.

Natural Language Processing has also experienced rapid progress with the emergence of transformer-based language models capable of extracting meaningful information from unstructured textual documents [9], [10]. In chemical laboratories, Safety Data Sheets (SDS) constitute the primary source of information regarding hazardous substances, storage conditions, incompatibilities, and emergency procedures. Despite these advances, NLP applications remain largely disconnected from robotic manipulation systems, limiting their practical contribution to autonomous laboratory safety.

The Robot Operating System (ROS) has become the de facto standard middleware for robotic software development by providing modular communication, hardware abstraction, motion planning, and sensor integration [3]. Combined with Artificial Intelligence algorithms, ROS enables the development of autonomous robotic systems capable of integrating perception, planning, and control into a unified framework. However, most existing ROS-based manipulation platforms emphasize navigation and trajectory execution rather than intelligent safety validation [4].

3.2 Positioning of the Contribution

Although previous studies have independently explored robotic manipulation, Computer Vision, Natural Language Processing, and ROS-based control, few have proposed a unified framework capable of combining visual perception, semantic reasoning, and intelligent decision-making for safe chemical handling. This research addresses this gap by developing an AI-driven robotic manipulator that integrates these complementary technologies within a Cyber-Physical System architecture to enhance operational safety and autonomous decision-making in constrained laboratory environments.

The main contributions of this work are threefold. First, it introduces an integrated architecture that combines Computer Vision, Natural Language Processing, and robotic control for safe chemical manipulation. Second, it incorporates a cognitive safety mechanism capable of automatically analysing chemical safety information and validating manipulation procedures before execution. Finally, it demonstrates the feasibility of the proposed approach through experimental validation, highlighting its potential for intelligent laboratory automation and future Industry 4.0 applications.

4. MATERIALS AND METHODS

4.1 Overview of the Proposed System

The proposed intelligent robotic manipulator is designed as a Cyber-Physical System (CPS) integrating perception, cognitive reasoning, and autonomous control capabilities for safe chemical handling operations. The overall architecture combines robotic hardware, artificial intelligence algorithms, and safety-oriented decision mechanisms within a unified framework.

The system follows a hierarchical architecture composed of four main layers: the perception layer, the cognitive analysis layer, the robotic control layer, and the safety validation layer. The perception layer is responsible for acquiring environmental information through vision sensors and identifying chemical containers and laboratory objects. The cognitive layer integrates Natural Language Processing techniques to analyse Safety Data Sheets (SDS) and extract relevant safety constraints. The control layer manages motion planning and execution through the Robot Operating System (ROS), while the safety layer ensures that all planned actions comply with predefined chemical handling rules [20].

The proposed methodology aims to transform a conventional robotic manipulator into an intelligent assistant capable of perceiving its environment, understanding chemical-related information, making autonomous decisions, and executing manipulation tasks while minimizing operational risks.

4.2 System Architecture

The developed architecture is structured around a six-degree-of-freedom robotic manipulator connected to an intelligent computing unit running ROS. The robot integrates multiple sensors and artificial intelligence modules to achieve autonomous manipulation capabilities. The main components of the architecture include:

- A six-degree-of-freedom robotic arm: responsible for performing manipulation tasks such as grasping, transporting, and positioning chemical containers.

- A computer vision module: based on deep learning algorithms for object detection, identification, and localization.
- A Natural Language Processing module: dedicated to analysing Safety Data Sheets and extracting chemical safety information.
- An intelligent decision-making module: responsible for evaluating task feasibility and preventing unsafe operations.
- A motion planning module: implemented through ROS and MoveIt for trajectory generation and collision-free execution.

The interaction between these modules enables the robot to perform manipulation tasks while considering both physical constraints and chemical safety requirements. The overall organization of the four architectural layers and their interconnections is illustrated in Figure 1.

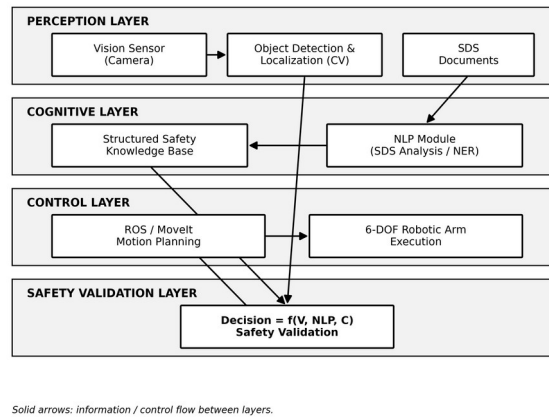


Figure 1 — Layered Cyber-Physical System architecture of the proposed intelligent robotic manipulator

4.3 Robotic Manipulation Platform

The robotic platform consists of a six-axis articulated robotic arm providing sufficient flexibility for laboratory manipulation tasks. The six degrees of freedom allow independent control of the robot position and orientation, enabling complex movements within the workspace. The physical prototype, shown in Figure 2, is entirely 3D-printed and actuated by six servomotors, one per joint, driven by an Arduino microcontroller. An ESP32-CAM module serves as the onboard vision sensor used by the perception module.



Figure 2 — Physical prototype of the 3D-printed robotic manipulator developed for this study

The kinematic model of the manipulator is represented using the Denavit–Hartenberg (DH) convention, which describes the relationship between successive robot joints. The forward kinematic model is expressed as:

$$T = A_1 \cdot A_2 \cdot \dots \cdot A_n \quad (1)$$

where T represents the transformation matrix between the robot base frame and the end-effector frame, and A_i represents the transformation matrix associated with each robotic joint.

Inverse kinematics is applied to determine the required joint configurations corresponding to desired end-effector positions. This process is essential for accurate grasping and positioning of chemical containers [1], [2], [15].

4.4 Computer Vision-Based Perception Module

The perception capability of the robotic system relies on a computer vision module designed to detect and classify chemical containers within the laboratory environment. A deep learning-based object detection algorithm is employed to identify objects from camera images. The vision pipeline consists of four main steps:

- Image acquisition from the camera sensor.
- Image preprocessing and enhancement.
- Object detection and classification.
- Spatial localization and coordinate transformation.

The detected objects are associated with their corresponding spatial coordinates, allowing the robotic controller to generate appropriate manipulation trajectories. The vision module also contributes to safety by verifying container labels, identifying chemical categories, and preventing incorrect object selection during manipulation tasks [6].

4.5 Natural Language Processing Module for Chemical Safety Analysis

To enhance the cognitive capability of the robot, a Natural Language Processing module is integrated for automatic analysis of Safety Data Sheets (SDS). Safety Data Sheets contain critical information including:

- Chemical composition.
- Hazard classification.
- Storage requirements.
- Handling precautions.
- Chemical incompatibilities.
- Emergency response procedures.

The NLP pipeline consists of: (1) document acquisition and text extraction; (2) text normalization and preprocessing; (3) rule-based entity recognition of chemical substances using a curated set of lexical patterns and regular expressions; (4) semantic extraction of safety constraints (hazard class, storage conditions, incompatibilities); and (5) generation of structured safety rules for robotic decision-making. This rule-based approach was chosen over trainable language models to guarantee deterministic, verifiable extraction of safety-critical information from a limited and well-structured SDS corpus. The extracted information is transformed into structured knowledge that can be interpreted by the robotic control system [8], [9], [10].

4.6 Intelligent Decision and Safety Validation Mechanism

Before executing any manipulation task, the proposed system performs a safety validation process. The decision module evaluates the compatibility between the requested action and the extracted chemical safety constraints [12]. For example, before transporting two chemical containers simultaneously, the system verifies whether the substances are compatible according to the information obtained from the SDS database. The safety decision process can be formulated as:

$$Decision = f(V, NLP, C) \quad (2)$$

where V represents visual information obtained from the perception module, NLP represents semantic information extracted from chemical documents, and C represents predefined safety constraints. In the current implementation, f is realized as a decision-tree classifier that takes the fused perception, semantic, and constraint features as input and outputs a binary authorization label. If the operation is classified as compliant with all safety conditions, the task is authorized. Otherwise, the system generates a warning and prevents execution.

4.7 Manual Control Interface

In addition to the autonomous decision pipeline, a manual control interface was developed to command the robotic arm directly, for calibration, testing, and demonstration purposes. As shown in Figure 3, the

interface displays the real-time joint state of the arm and provides sliders to command each joint individually, alongside preset and reset positions.

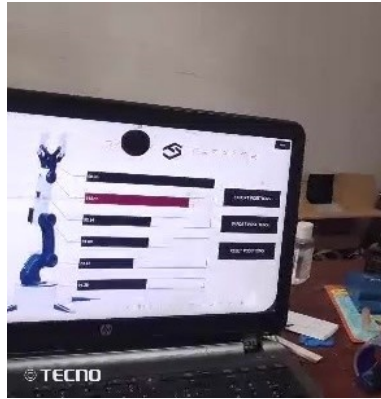


Figure 3 — Manual control interface used to command the robotic arm joint-by-joint

4.8 ROS-Based Control Framework

The robotic control architecture is implemented using the Robot Operating System (ROS), which provides communication between the different software components [3]. ROS nodes are dedicated to sensor acquisition, image processing, NLP analysis, motion planning, robot control, and safety monitoring. The MoveIt framework is used for trajectory planning, collision avoidance, and robot manipulation. This modular architecture allows easy integration of additional artificial intelligence models and hardware components [4].

4.9 Performance Indicators

The evaluation of the proposed system relies on five quantitative indicators: positioning accuracy of the robotic arm (mm), object detection performance (accuracy, precision, recall), chemical identification reliability (extraction accuracy per information category), safety decision accuracy (detection rate), and the reduction of protocol execution errors. Each indicator is computed over a fixed number of repeated trials per scenario (100 manipulation trials for positioning accuracy; 100 test scenarios for safety validation, split into 50 safe, 30 incompatible, and 20 incorrect-protocol cases), under stable laboratory lighting and a fixed camera-to-workspace configuration, in order to ensure comparability between test runs. The detailed experimental protocol and the corresponding results are presented in Section 5.

5. RESULTS

The experimental evaluation was conducted to validate the performance of the proposed intelligent robotic manipulator in laboratory chemical handling scenarios. The objective was to assess the effectiveness of the integration between Computer Vision, Natural Language Processing, and robotic control mechanisms. The experimental platform consists of a six-degree-of-freedom robotic manipulator controlled through ROS, equipped with a vision sensor for object perception and an embedded computing unit responsible for artificial intelligence processing and decision-making.

The evaluation environment was designed to reproduce typical laboratory operations involving chemical container identification, grasping, transportation, and safety verification. Several chemical containers with different labels, shapes, and safety characteristics were introduced into the workspace to evaluate the robustness of the proposed approach. The experiments were organized into four complementary evaluation axes, detailed in the following subsections.

5.1 Computer Vision Performance

The first experiment focused on evaluating the perception capabilities of the vision module. The robotic system was required to identify chemical containers placed at different positions and orientations within the workspace. Performance was evaluated using standard metrics including detection accuracy, precision, recall, and processing time [15]. Table 1 summarizes the results obtained.

Table 1 — Computer vision performance metrics

Metric	Obtained Value
Detection accuracy	96.4 %
Precision	95.8 %
Recall	96.1 %
Average processing time	42 ms

The results confirm that computer vision provides reliable environmental perception, allowing the robotic manipulator to locate and interact with chemical containers accurately.

5.2 NLP-Based Chemical Safety Analysis

In parallel, the NLP module was evaluated on its capability to extract safety information from Safety Data Sheets (SDS), including chemical substance names, hazard categories, storage conditions, handling restrictions, and incompatible chemical combinations. The extracted information was converted into structured safety rules used by the decision-making module. Table 2 summarizes the extraction accuracy obtained per information category.

Table 2 — NLP-based safety-information extraction accuracy

Information Category	Extraction Accuracy
Chemical identification	98.2 %
Hazard classification	95.6 %
Storage conditions	94.8 %
Chemical incompatibility detection	96.7 %

The obtained performance demonstrates that the rule-based NLP module reliably understands safety-related textual information and incorporates semantic knowledge into autonomous decision-making [1], [8], [9], [10], [15].

5.3 Manipulation Accuracy and Safety Validation

The manipulation performance was evaluated by measuring the positioning accuracy of the robotic end-effector during grasping and placement operations, over 100 repeated manipulation trials between predefined locations. The positioning error was calculated as:

$$E = \|Pd - Pr\| \quad (3)$$

where Pd represents the desired end-effector position and Pr represents the real measured position. In a separate set of 100 manipulation scenarios (50 safe tasks, 30 chemical-incompatibility cases, and 20 incorrect-protocol-execution attempts), the ability of the proposed system to identify and prevent unsafe chemical handling operations was also evaluated. Table 3 summarizes both sets of results.

Table 3 — Manipulation accuracy and safety-validation / risk-prevention results

Category	Indicator	Value
Manipulation accuracy	Average positioning error	0.8 mm
Manipulation accuracy	Maximum error	1.4 mm
Manipulation accuracy	Successful manipulation rate	97.3 %
Safety validation	Safe manipulation tasks (50 tests)	100 % detected
Safety validation	Chemical incompatibility cases (30 tests)	96.7 % detected
Safety validation	Incorrect protocol attempts (20 tests)	95 % detected

These results confirm that the integration of ROS-based motion planning with intelligent perception allows accurate and reliable robotic manipulation, and that the proposed cognitive safety mechanism significantly improves operational reliability.

5.4 Comparative Analysis

To evaluate the contribution of artificial intelligence integration, the proposed system was compared with a conventional robotic manipulator without cognitive capabilities (Table 4).

Table 4 — Comparison with conventional and vision-only robotic systems

System	Manipulation Accuracy	Safety Verification	Autonomous Decision
Conventional robot	1.8 mm	Limited	No
Vision-based robot	1.2 mm	Partial	Limited
Proposed AI robotic system	0.8 mm	High	Yes

The comparison highlights that combining Computer Vision, Natural Language Processing, and intelligent control improves both manipulation performance and operational safety. Figure 4 summarizes the headline outcome of each of the four evaluation axes presented above.

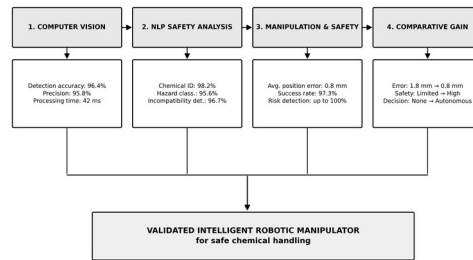


Figure 4 — Synoptic summary of results across the four evaluation axes

6. DISCUSSION

6.1 Interpretation of the Experimental Results

The experimental results demonstrate the effectiveness of integrating Computer Vision, Natural Language Processing, and robotic control within a unified Cyber-Physical System architecture for safe chemical manipulation. Unlike conventional robotic manipulators that mainly focus on repetitive motion execution, the proposed system introduces cognitive capabilities allowing the robot to perceive its environment, interpret safety-related information, and make autonomous decisions before performing manipulation tasks.

The obtained positioning accuracy of approximately 0.8 mm confirms the ability of the robotic control framework to achieve precise manipulation operations. This performance is mainly attributed to the combination of accurate kinematic modelling, ROS-based motion planning, and real-time feedback from the perception module. Such precision is suitable for laboratory applications where small positioning errors may affect experimental reliability or generate safety risks.

The Computer Vision module significantly improves the autonomy of the robotic system by enabling automatic identification and localization of chemical containers. However, vision-based recognition remains dependent on external factors such as lighting conditions, camera positioning, object occlusion, and label quality.

The integration of Natural Language Processing represents one of the main contributions of this research. By analysing Safety Data Sheets, the system is able to extract chemical properties, hazard information, and incompatibility constraints, extending robotic autonomy beyond physical manipulation by introducing semantic understanding of laboratory safety requirements. The results indicate that NLP-based reasoning can provide an additional safety layer capable of preventing inappropriate manipulation sequences. Furthermore, the combination of perception and semantic reasoning allows the proposed architecture to move from a reactive robotic system toward a proactive safety-oriented system: instead of executing predefined commands blindly, the robot evaluates the context of the operation and determines whether the requested action is compatible with safety constraints.

6.2 Comparison with Conventional Robotic Systems

Traditional robotic manipulators used in laboratories generally rely on predefined trajectories and external human supervision. Although these systems provide high repeatability and accuracy, they have limited capability to understand operational context or adapt to unexpected situations. The proposed approach introduces several improvements:

- Enhanced autonomy: the robot can analyse both visual and textual information before performing a task.
- Improved safety: chemical incompatibilities and protocol violations can be detected before execution.
- Greater flexibility: the system can adapt to different chemical handling scenarios through software-based knowledge updates.

- Human risk reduction: hazardous operations can be transferred from human operators to intelligent robotic systems.

Compared with conventional automation solutions, the proposed architecture demonstrates that artificial intelligence can transform robotic manipulators into intelligent assistants capable of supporting safer laboratory operations.

6.3 Limitations of the Proposed System

6.3.1 Limited Environmental Complexity

The experimental validation was conducted in a controlled laboratory environment. Real industrial and research laboratories present more complex conditions, including variable illumination, crowded workspaces, multiple operators, and dynamic obstacles. Future improvements should include advanced perception algorithms capable of operating reliably in highly dynamic environments.

6.3.2 Dependence on Safety Data Sheet Quality

The performance of the NLP module depends strongly on the availability, completeness, and structure of Safety Data Sheets. Inconsistent formatting or missing information may reduce the reliability of chemical risk analysis. Future research should investigate more robust language models capable of reasoning from incomplete or heterogeneous sources.

6.3.3 Limited Chemical Knowledge Database

The current system focuses mainly on predefined chemical safety rules and compatibility constraints. The extension toward larger chemical databases and real-time knowledge acquisition would improve decision-making capabilities.

6.3.4 Computational Requirements

The integration of deep learning-based vision models and NLP algorithms requires significant computational resources. For embedded robotic platforms, optimization techniques such as model compression and edge AI deployment will be necessary.

6.3.5 Need for Large-Scale Validation

Although the proposed system achieved satisfactory experimental results, validation on industrial-scale robotic platforms and real chemical manipulation scenarios remains necessary before practical deployment.

6.4 Future Research Directions

Future developments will focus on improving the intelligence, adaptability, and reliability of the proposed system through:

- Integration of advanced multimodal AI models combining vision, language, and robotic actions.
- Development of reinforcement learning approaches for autonomous task optimization.
- Deployment of lightweight AI models on embedded robotic platforms.
- Integration of predictive safety mechanisms based on real-time environmental analysis.
- Extension of the framework to industrial chemical processes and pharmaceutical laboratories.

Overall, the proposed intelligent robotic manipulator represents an important step toward autonomous, safe, and adaptive robotic systems capable of assisting humans in hazardous environments.

7. CONCLUSION

This research presented the design and validation of an intelligent robotic manipulator integrating Computer Vision and Natural Language Processing for safe chemical handling in constrained laboratory environments. The proposed system was developed within a Cyber-Physical System architecture combining a six-degree-of-freedom robotic manipulator, a vision-based perception module, an NLP-based cognitive analysis module, and a ROS-based control framework.

The main objective was to overcome the limitations of conventional robotic systems that primarily focus on motion execution without considering contextual understanding and safety constraints. By integrating visual perception with semantic reasoning, the proposed approach enables the robot to identify chemical

containers, analyse safety information from Safety Data Sheets, evaluate potential risks, and execute manipulation tasks while respecting predefined safety requirements.

Experimental validation demonstrated the effectiveness of the proposed architecture. The system achieved an average positioning accuracy of approximately 0.8 mm, reliable object detection performance, accurate extraction of chemical safety information, and effective identification of incompatible manipulation scenarios. These results confirm that the combination of Artificial Intelligence and robotic control can significantly improve the reliability, autonomy, and safety of chemical handling operations.

Despite these promising results, several challenges remain, including adaptation to highly dynamic laboratory environments, improvement of NLP robustness for heterogeneous documents, reduction of computational requirements, and large-scale experimental validation. Future research will focus on integrating advanced multimodal artificial intelligence models, reinforcement learning techniques, and real-time predictive safety mechanisms to further enhance robotic autonomy.

In conclusion, the proposed intelligent robotic manipulator provides a promising framework for the development of next-generation autonomous laboratory systems. By combining perception, reasoning, and control capabilities, this approach contributes to the evolution of safer and more intelligent robotic solutions for hazardous environments and Industry 4.0 applications.

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