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Bridging Engineering and Biochemistry: Hands-On Automation Laboratory Modules with an Open-Source Pipetting Robot

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Abstract

Laboratory automation is essential in industrial sectors to improve efficiency, precision, and repeatability. As automation science plays a vital role in applied fields like biochemistry, it is crucial to equip engineering students with the skills to develop and implement these technologies. This study addresses the challenge of bridging hands-on learning with practical applications by integrating computer vision with an open-source OT-One pipetting robot to perform autonomous liquid-handling tasks common in the biochemistry/biomedical field. The system employs a modular framework that combines real-time depth and color imaging with precise robotic control. Students engage in interactive laboratory modules designed to teach automation principles, programming, and biochemical protocols. Experimental results from a pilot study indicate observed improvements in participants' proficiency in automation and biochemistry, with high ratings for module effectiveness and interactivity. These findings demonstrate the system's potential to advance cross-disciplinary education by integrating hands-on learning with cutting-edge laboratory automation. This work highlights the role of open-source tools in creating scalable, cost-effective solutions for interdisciplinary STEM education.

1 Introduction

Laboratory automation has revolutionized modern scientific research, addressing the need for efficiency, precision, and reproducibility. The increasing demand for high-precision experiments, particularly in drug discovery and genomic research, has highlighted the limitations of manual processes, which are time-consuming and prone to error. The global urgency for rapid drug development, exemplified by the COVID-19 pandemic, further underscores the need for automated solutions that streamline workflows, minimize errors, and accelerate scientific discovery [1, 2].

Automated liquid handling systems (ALHS) are a key innovation in addressing these challenges, offering precision and repeatability in tasks such as liquid transfer, sample preparation, and reagent dispensing. In genomics and proteomics, ALHS have significantly improved the accuracy and efficiency of workflows like DNA extraction and PCR setup, reducing human error and increasing throughput [1]. In pharmaceutical research, high-throughput screening (HTS) benefits from systems like the OT-One robot, which automates complex processes to expedite drug discovery [3]. ALHS also play a vital role in chemical synthesis and environmental monitoring, where systems like HeinSight and OpenWorkstation integrate computer vision and modularity to enhance experimental control and customization [4, 5]. These systems have also proven essential in large-scale diagnostic testing and specialized applications like membrane protein crystallization [1, 2].

Despite these industrial advances, a significant gap exists in biochemistry education. Traditional biochemistry lab curricula at four-year programs often rely on manual pipetting training and practices, failing to expose students to the automated instrumentation ubiquitous in modern biomedical companies. Consequently, graduates enter the workforce with limited experience in these critical technologies. While students joining advanced research labs may encounter automation, the general biochemistry student population lacks access to such expensive equipment. This disconnect between academic training and industry practice necessitates affordable, accessible educational tools.

The Opentron OT-One open-source pipetting robot presents a solution to this gap. Its a low-cost, modular education platform that allows for integration into standard biochemistry teaching laboratories, providing students with hands-on automation experience prior to graduation. Furthermore, an OT-One-based curriculum fosters multidisciplinary collaboration, positioning biochemistry students as end-users and engineering students as developers for cross-discipline collaboration to achieve a common pipetting objective. This approach aligns with studies showing that active learning and problem-based approaches significantly improve student engagement and comprehension, bridging the gap between theoretical knowledge and real-world applications [6].

This study employs the OT-One pipetting robot, integrated with an Intel Depth Camera D435i, to automate liquid handling tasks with precision. This method leverages both RGB and depth-sensing capabilities, enabling the system to autonomously identify and interact with laboratory components. Unlike other systems that focus solely on liquid-level monitoring, the implemented system uses computer vision to map pixel coordinates to G-code, allowing for precise, real-time control of pipetting processes [4, 7]. The open-source nature of the OT-One allows for continuous customization, ensuring it can be tailored to specific experimental and educational needs, thus improving upon existing approaches [4].

A series of laboratory curriculum modules on the integration of computer vision and robotics in this educational setup demonstrates a marked improvement in learning efficiency and technical proficiency. By automating liquid handling tasks, the system reduces human intervention while maintaining high accuracy. The use of depth and RGB frame detection ensures precise movements, which are critical for understanding automation principles. This combination enhances the overall learning experience, equipping students with skills relevant to drug discovery, biofabrication, and environmental monitoring [5, 8].

The OT-One pipetting robot incorporating computer vision technologies represents a significant advancement for educational laboratory automation. Its ability to autonomously perform precise liquid handling tasks provides a platform for experiential learning and making it an adaptable tool for interdisciplinary education. By incorporating insights from biochemistry education research [6, 9], this research underscores the importance of automation in advancing both laboratory workflows and interdisciplinary learning.

2 Methods

2.1 Open-Source OT-One Pipetting Robot

The Opentrons OT-One is an open-source, modular pipetting robot designed to automate liquid handling tasks in laboratory settings. It is widely used in applications such as PCR setup, sample preparation, and reagent dispensing, offering precision and repeatability for workflows in genomics, biochemistry, and drug discovery. The OT-One was selected for this educational initiative due to its affordability, open-source nature, and pedagogical accessibility, which are paramount for deployment in typical university settings. Its design allows for extensive customization and integration with other tools, such as computer vision systems, making it a versatile platform for both research and education. The 3-axis gantry system is directed by a Smoothieboard, which serves as the motion control hardware and G-code, the numerical control language used to command the robot's precise spatial movements, such as the X, Y, and Z axes. Key components include a pipette holder for attaching single or multi-channel pipettes and a work deck with customizable plate holders.

2.2 System Architecture for Automation

The OT-One robot control system integrates several components to automate liquid handling tasks. The system architecture, depicted in Fig. 1, illustrates the pipeline from visual input to robotic action. The OT-One robot receives G-code commands that control its stepper motors. The Smoothieboard acts as an intermediary, translating these G-code commands into electrical pulses that move the robot's gantry. A Linux machine serves as the command center, managing real-time data from the image processing pipeline and sending movement instructions to the OT-One via USB serial communication.

The system leverages several key software tools:

- **PyRealSense Depth Camera API:** Handles inputs from the Intel RealSense D435i camera, capturing synchronized RGB and depth frames.
- **OpenCV:** Processes the captured images to detect colors, positions, and objects within the robot's workspace using computer vision techniques.
- **Opentrons API:** Automates pipetting protocols and controls the robot's actions.

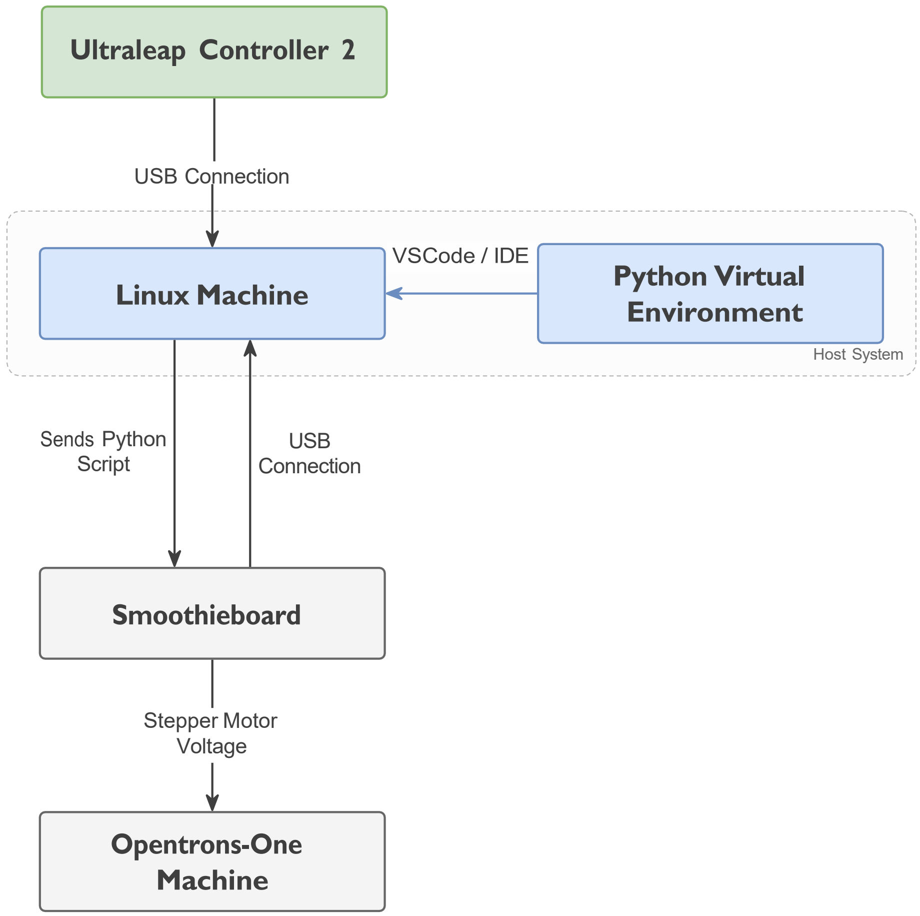

Figure 1: **Hardware and Communication Pipeline.** The system integrates external sensory input (Ultraleap) with a Linux host processing unit. Control signals are transmitted via a Smoothieboard motion controller to the Opentrons OT-One actuators.

2.3 Research and Development Methodology

The research began by analyzing previous work that applied a Gaussian blur for color detection (red, green, blue) via an Intel RealSense camera. The initial implementation used MATLAB to control the robot by extracting relative coordinates from the camera frame. To improve efficiency and modularity, the project was migrated to Python and refactored into four distinct modules, as shown in the correlation diagram in Fig. 2:

- **app.py:** Manages a web-based user interface (built with HTML/CSS) for easier interaction with the robot, allowing users to input instructions and view a live feed.
- **camera.py:** Handles all camera operations, including frame capture and managing the live video feed during experiments.
- **biochem.py:** Automates backend tasks like pipetting by creating threads to run parallel tasks for the pipette and camera.
- **color.py:** Detects color and location in images using Gaussian blur techniques, defined by the equation:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \qquad (1)$$

where (x, y) are pixel coordinates and σ is the standard deviation of the Gaussian kernel, which controls the blur intensity.

This modular design enhanced code organization, making debugging and updates easier while improving system performance.

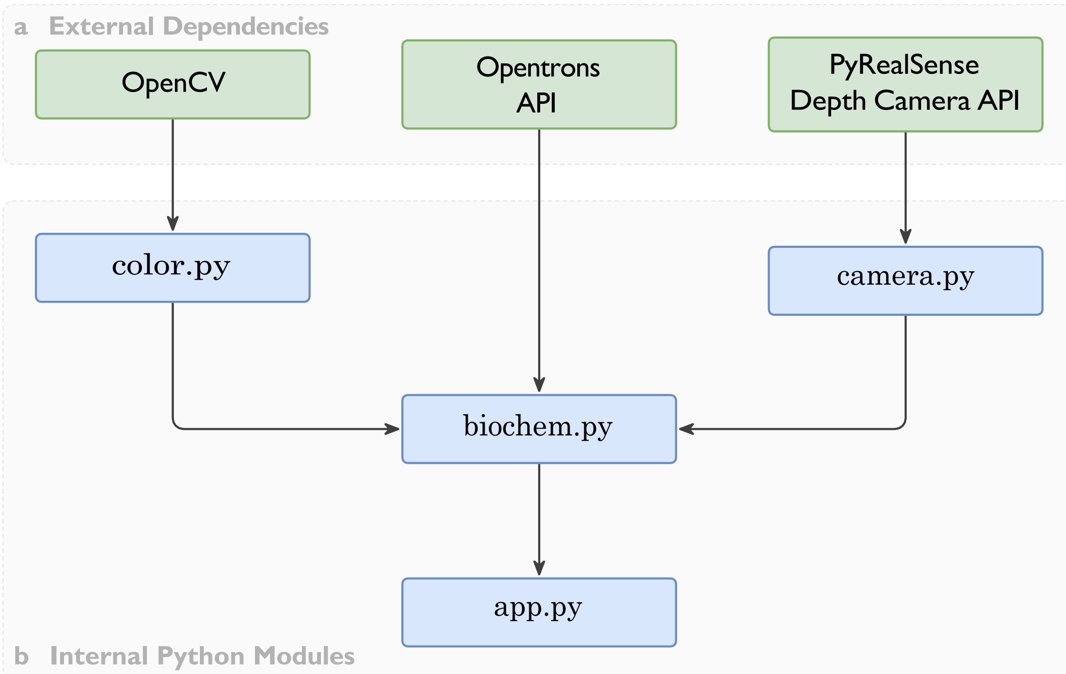

Figure 2: **System Dependency Graph.** The architecture is stratified into external dependencies (green) and internal Python modules (blue). The central biochem.py logic integrates computer vision and depth sensing data streams.

2.4 Refinement and User Experience

After refactoring, the Gaussian blur parameters were fine-tuned for greater accuracy in color detection, which is essential for precise robotic control. The coordinate calculations were improved by using relative coordinates based on the camera frame, increasing movement precision. The web-based application was developed to improve accessibility, allowing users without expertise in terminal commands to input mixing instructions, view a live feed, and interact with the system seamlessly. This design simplified user interaction and made the system more suitable for educational purposes. Migrating the system from MATLAB to Python significantly improved modularity and execution speed by enabling parallel threading for the pipette and camera tasks within the biochem.py logic.

2.5 Lab Module Development and Feedback Mechanism

A series of interactive lab modules were developed to enhance the system's usability. This comprehensive lab guide provides a step-by-step process for users to set up hardware, understand the code, and run experiments, covering everything from basic operation to advanced pipetting and computer vision techniques. The study was conducted at a four-year university open to both senior-level undergraduate and first-year graduate students introduced in a robot control course at approximately 20 students from mechanical, electrical, and computer engineering disciplines as well as computer science. Due to the complexity of hardware integration, prerequisites include undergraduate introductory into programming (C or Python) and control systems. While the core Python framework provided to the students was faculty-developed, it was specifically designed to be hardware-agnostic to allow for replication on any G-code-based gantry system.

In this pilot study, two OT-One units were available, with labs administered to teams of 3–4 students to ensure hands-on engagement. The curriculum was delivered over seven weeks, with each module conducted in a weekly three-hour session for a total of 21 contact hours. This timeline was structured to prioritize foundational hardware familiarization before introducing the more complex computer vision concepts in the later stages.

To evaluate the module's effectiveness, participant feedback was gathered through surveys focusing on three key areas: understanding of the OT-One's capabilities, level of interactivity, and overall user experience. The lab modules were structured to progressively build participants' skills through practical, hands-on learning. The content and outcomes of each module are detailed below.

- **Lab 01: Getting to Know the Machine** served as an introductory session, familiarizing participants with the physical components of the OT-One pipetting robot, including the motor system, pipette holder, containers, and the Intel RealSense camera. Objective is to familiarize students with the robot's 3D operational structure through hardware identification and spatial orientation, resulting in a foundational understanding of the physical layout necessary for subsequent automation tasks.
- **Lab 02: Understanding Python Code** aimed to develop participants' programming skills for controlling the OT-One robot. This module introduced essential Python concepts and libraries. Objective is to develop programming proficiency for laboratory hardware interaction using Python syntax and library management, enabling students to write scripts that communicate directly with the robot's firmware.
- **Lab 03: Setting Everything Up** guided students through the software and hardware configuration process, including installing Python and configuring a virtual environment. Objective is to successfully integrate the Smoothieboard and RealSense camera through software environment configuration and troubleshooting, resulting in a fully operational development environment.
- **Lab 04: Testing Movement Capabilities** introduced the robot's movement commands, where students wrote scripts to direct the pipette along the X, Y, and Z axes. Objective is to master precise robotic positioning and coordinate systems using G-code command implementation, ensuring successful execution of precise, collision-free movement across

the work envelope.

- **Lab 05: Testing Pipetting Procedure** focused on automating a complete liquid handling routine, including picking up tips, aspirating liquid, and dispensing into plates. Objective is to automate a multi-step liquid handling routine through protocol optimization and mechanical timing, achieving autonomous transfer of reagents with high repeatability and volume accuracy.
- **Lab 06: Testing Computer Vision** introduced advanced concepts using the Intel RealSense camera, OpenCV, and NumPy to recognize objects and process visual data. Objective is to implement visual feedback for autonomous adjustments using image processing and Gaussian blur to detect high-contrast targets (using food-grade dyes), resulting in the successful mapping of pixel coordinates to robotic G-code. Students utilize food-grade colored dyes in the fluids to provide high-contrast targets, which facilitates the OpenCV and Gaussian blur algorithms in achieving reliable object detection and coordinate mapping
- **Lab 07: End and Reflection** was a concluding session where participants reviewed key concepts and provided feedback through a comprehensive survey. Objective is to reflect interdisciplinary connections through technical self-assessment and critical analysis, providing a comprehensive survey that validates module effectiveness and identifies areas for future improvement.

3 Experimentation and Results

3.1 Pre- and Post-Lab Knowledge Assessment

A pilot study was conducted with five participants between two teams in a curriculum focused on automation mechanics and robotics. Due to equipment constraints (two OT-One units for a potential class of 20), small team sizes were used, resulting in this preliminary sample. While faculty provided the core modular architecture, consisting of the four internal Python modules (app.py, camera.py, biochem.py, and color.py), students were responsible for developing the specific control scripts for robotic movement and the final YOLO-based fluid detection project.

Participants completed a pre-lab survey to assess their initial knowledge and a post-lab survey to evaluate the program’s impact. The data reflects an indirect measurement of student self-assessment on a 5-point Likert scale, ranging from 1 (No Understanding) to 5 (Expert). The "improved biochemistry understanding" reported by students was based on an indirect self-assessment of their ability to implement specific biochemical protocols, such as PCR setup and reagent dispensing. The results are summarized in Table 1, and pre-lab survey questions can be found in Appendix A. To better represent the distribution of these scores, standard deviations have been included alongside the mean values in Tables 1 and 2.

Participants demonstrated observed improvements in their understanding of automation and biochemistry after completing the lab modules. Pre-lab survey results showed average ratings of 2.8 for automation and 2.0 for biochemistry understanding, indicating limited prior familiarity. Post-lab ratings increased to 3.6 and 3.2, respectively. Understanding of computer science and coding showed a slight decline from 3.4 pre-lab to 3.2 post-lab. This may reflect an increased awareness of the complexity of these skills rather than a reduction in ability, as participants with minimal programming experience gained a more realistic perspective on the technical challenges involved. While the n=5 sample size precludes the calculation of meaningful p-values, the qualitative success of the curriculum is evidenced by the students' ability to independently develop the high-precision YOLOv11 project using the skills scaffolded in these modules.

Table 1: **Comparison of Student Self-Assessment Scores.** Average ratings on a 5-point Likert scale before (Pre-Lab) and after (Post-Lab) the module.

Note: Scores represent mean values where 1 = No Understanding and 5 = Expert Understanding.

Topic of Understanding	**Pre-Lab**	**Post-Lab**	**Change (Δ)**
Computer Science & Coding	3.4 ± 1.14	3.2 ± 0.45	−0.2
Automation Workflow	2.8 ± 0.84	3.6 ± 0.55	0.8
Biochemistry Concepts	2.0 ± 0.71	3.2 ± 0.45	1.2

3.2 Effectiveness, Interactivity, and User Experience

The lab modules were rated highly for their educational value and engagement. The results from the participant surveys are detailed in Table 2. Descriptions and post lab survey questions can be found in Appendix A.

All modules received an average effectiveness score above 4.0, except for Lab 06. **Lab 01: Getting to Know the Machine** was the highest-rated (4.8), indicating its success in providing foundational knowledge. **Lab 05: Testing Pipetting Procedure** also received high ratings (4.6), reflecting the impact of hands-on liquid handling tasks. Conversely, **Lab 06: Testing Computer Vision** received the lowest score (3.2), suggesting participants found the advanced computer vision concepts more challenging.

Interactivity scores were consistently high, with all modules rated at 4.0 or above. **Lab 04: Testing Movement Capabilities** was the most interactive (4.8), indicating participants valued the hands-on activities and real-time feedback from controlling the robot's movements. Lab 01 and Lab 03 also scored highly (4.6), reinforcing the value of physical engagement and setup processes.

User experience ratings were uniformly positive, with all modules scoring 4.2 or higher. Lab 03 and Lab 06 received the highest scores (4.4), suggesting participants found these modules well-structured and easy to navigate. The high ratings underscore the program's success in delivering a well-organized and user-friendly experience.

Table 2: **Lab Module Evaluation.** Mean student ratings for effectiveness, interactivity, and overall user experience across all seven laboratory sessions.

	Student Ratings (Mean)		
Lab Module	**Effectiveness**	**Interactivity**	**User Exp.**
Lab 01: Getting to Know the Machine	4.8 ± 0.45	4.6 ± 0.55	4.2 ± 0.45
Lab 02: Understanding Python Code	4.4 ± 0.55	4.2 ± 0.84	4.2 ± 0.84
Lab 03: Setting Everything Up	4.4 ± 0.89	4.6 ± 0.55	4.4 ± 0.55
Lab 04: Testing Movement Caps.	4.2 ± 0.84	4.8 ± 0.45	4.4 ± 0.55
Lab 05: Testing Pipetting Proc.	4.6 ± 0.55	4.6 ± 0.55	4.2 ± 0.45
Lab 06: Testing Computer Vision	3.2 ± 1.30	4.2 ± 0.84	4.4 ± 0.55
Lab 07: End	4.0 ± 1.22	4.0 ± 1.22	4.2 ± 0.84

4 Discussion

The data reveal relationships between module design and participant engagement. Modules with a strong focus on foundational understanding and physical interaction, such as Lab 01 and Lab 04, received the highest ratings for effectiveness and interactivity. This suggests that early exposure to hardware and tangible feedback creates a solid base for learning. Conversely, the lower effectiveness score for Lab 06 (Testing Computer Vision) points to a disconnect between participant familiarity and task complexity, likely to stem from the advanced nature of computer vision concepts. This result may also reflect issues with instructional clarity or perceived relevance to the core robotics curriculum, rather than purely the conceptual difficulty of the material. These findings indicate a need for more substantial prior knowledge or simplified instruction to ensure optimal understanding in future iterations.

These findings align with broader educational literature. Se´ et al. (2008) emphasize the value of interactive, problem-based learning in biochemistry, which is mirrored in the hands-on success of this program's modules [6]. Similarly, Lang & Bodner (2020) highlight the importance of addressing interdisciplinary gaps, a goal achieved here through the integration of automation, coding, and biochemistry concepts [9].

The significance of these results lies in their implications for advancing laboratory automation education. The observed improvements in understanding highlight the potential of integrating affordable automation technologies, like the OT-One into educational settings. By providing a platform that bridges theoretical and practical learning, this program enhances student engagement and equips participants with skills relevant to modern scientific workflows. As this is a pilot study, scalability for larger cohorts would require an expanded budget to acquire additional Opentrons units, ensuring the two-robot-per-twenty-student ratio is improved for optimal hands-on time.

Student Project Example: Neural Network Detection of Well Fluid

The educational framework successfully fostered creativity and innovation, leading to a student-led project that expanded the OT-One's capabilities. This student-led project validates the laboratory scaffolding; the skills developed in earlier modules, specifically Python-based robotic control and computer vision processing, provided the foundational technical framework required for the students to independently develop the high-precision YOLOv11 neural network model for object detection and an OSHA-compliant remote E-Stop button with the OT-One robot to automate fluid detection in 96-well plates.

The developed system achieved high precision (99%) and recall (97%) in detecting fluid presence.

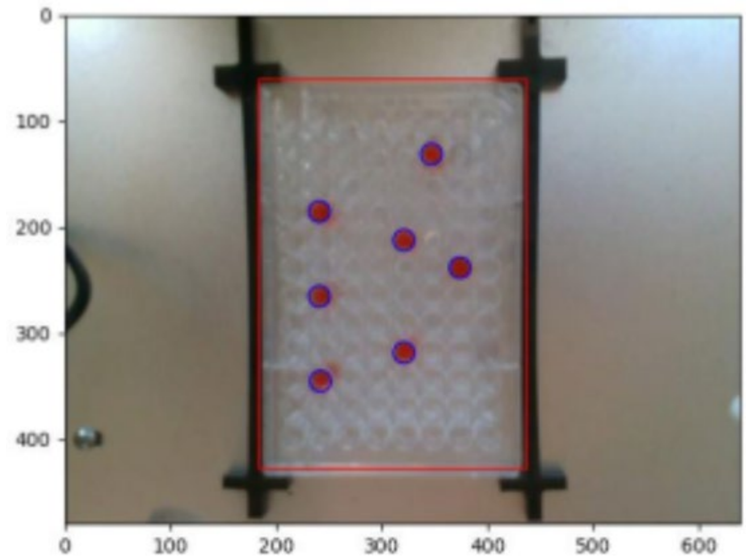

Figure 3: Example of Labeled Plate of Well Fluid

As illustrated in Fig. 3, the system captures a camera image, identifies the edges of the container, and detects fluid within the wells. The program then calculates the center of the fluid, marks it, and outputs its relative coordinates. This innovative approach addresses a critical challenge in automation, offering a cost-effective alternative to expensive sensors or manual intervention. This project exemplifies how hands-on, interdisciplinary learning can empower students to develop innovative solutions to real-world scientific challenges.

5 Conclusion

Developed lab modules demonstrated the effectiveness of integrating an OT-One pipetting robot with computer vision technologies in an educational context. Observed improvements in automation knowledge and biochemistry understanding highlight the success of this approach, while high ratings for effectiveness, interactivity, and user experience validate the curriculum design. While the small sample size of this pilot study is acknowledged as a limitation, these preliminary results serve as a successful proof-of-concept for the system's high interactivity and positive user experience. The modular framework is designed to be hardware-agnostic, the curriculum remains actionable for larger cohorts using any open-source gantry system. While the OT-One is an older, open-source model, this modular framework serves as a hardware-agnostic proof-of-concept that is highly transferable to newer systems, such as Opentrons OT-2 robot. This ensures the curriculum remains a relevant and scalable blueprint for interdisciplinary STEM education using modern automated liquid handling platforms [10]. Future work will focus on incorporating additional scaffolding for programming skills, expanding the program to a larger cohort, and exploring its scalability across diverse learning environments and skill levels. We aim to involve biochemistry students directly in the project scope, fostering a collaborative environment where they work alongside their engineering peers to solve real-world automation challenges.

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Appendix A: Laboratory Survey Instruments

Participants completed this survey prior to Lab 01 to establish a technical baseline.

Q1: How is your understanding of computer science and your coding level before the lab modules?

(1: Beginner — 5: Expert)

Q2: How is your understanding of automation before the lab modules?

(1: Beginner — 5: Expert)

Q3: How is your understanding of biochemistry before the lab modules?

(1: Beginner — 5: Expert)

Q4: What is your main goal in participating in this lab? (Open-ended)

Q5: What do you hope to learn from these lab modules? (Open-ended)

A.2. Post-Lab Evaluation and Impact Survey

Participants completed this survey after the conclusion of Lab 07.

Part I: Module-Specific Ratings

For each of the seven modules listed below, participants provided three distinct ratings based on Effectiveness, Interactivity, and User Experience using the scales defined in Part II.

- Lab 01: Getting to Know the Machine (Hardware identification and 3D layout)
- Lab 02: Understanding Python Code (Scripting basics, libraries, and functions)
- Lab 03: Setting Everything Up (Environment configuration and hardware connection)
- Lab 04: Testing Movement Capabilities (X, Y, Z axis coordinate verification)
- Lab 05: Testing Pipetting Procedure (Aspiration, dispensing, and tip disposal)
- Lab 06: Testing Computer Vision (Depth sensing and OpenCV color mapping)
- Lab 07: Reflection and Final Survey (Consolidation of learning)

Part II: Rating Scales

Score	Effectiveness (Educational Value)	Interactivity (Hands-on Engagement)	User Experience (Clarity/Ease of Use)
1	Not helpful at all	Not interactive at all	Poor user experience

2	Slightly helpful	Slightly interactive	Somewhat poor experience
3	Somewhat helpful	Somewhat interactive	Neutral / "It was okay"
4	Helpful	Interactive	Good user experience
5	Very helpful	Very interactive	Excellent user experience

Part III: Learning Outcomes Assessment

Participants rated their perceived growth in key areas compared to their pre-lab baseline.

Q1: How has your understanding of computer science and coding changed?

(1: Not Improved — 5: Improved Significantly)

Q2: How has your understanding of automation changed?

(1: Not Improved — 5: Improved Significantly)

Q3: How has your understanding of biochemistry changed?

(1: Not Improved — 5: Improved Significantly)

Q4: General feedback on the curriculum and suggestions for future iterations. (Open-ended)