Laboratory Automation Solution with Collaborative Robot and Deep Learning in Clinical Processing

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Abstract – During the outbreak of COVID-19, manual execution of clinical procedures encounters challenges in handling the surge in demand for pathological analysis in pandemic control, necessitating an accessible and reliable healthcare system. Clinical procedures such as pipette calibration, sample preparation, liquid handling, or pipetting are manipulation tasks demanding exceptional accuracy and experimental efficiency, which challenges the current traditional system with human factors [2,3]. To address this issue, the paper proposes a laboratory automation solution to optimise the workflow in clinical laboratories, leveraging cutting-edge technologies and techniques in collaborative robotics and object detection deep learning models in vision system.

Introducing a human-robot collaboration (HRC) workspace setting to perform low-frequency, high-repetition processes, this approach offers a promising resolution to uphold laboratory safety, mitigate error risks, ensure human-like operation and augment productivity within the laboratory environment. The research will be demonstrated to automate the pipette calibration process, a crucial procedure aimed at evaluating and guaranteeing the precision of the pipettes. The solution will be elaborated upon in subsequent papers through appropriate research endeavours[1].

Keywords – laboratory automation, collaborative robot, human-robot collaboration, object detection, deep learning, clinical processing

I. INTRODUCTION

For over the last decade, robotic technologies in industrial applications have created a new wave of migrating traditional systems into automated systems to improve efficacy and precision while ensuring the cost-effectiveness of the workflow [4]. In the health sector, a rise in the number of pathological tests during the 2020 pandemic crisis placed significant strain and obstacles on the healthcare infrastructure in which robotics and autonomous systems were applied to aid humans in managing medical procedures amidst these challenges. Within laboratory workstations, collaborative robots will be used to perform tasks alongside humans with high accuracy and better efficiency than traditional human labour. A machine learning model for object detection will be integrated into the system to serve as its cognitive component, directing the robot's interaction with the pipette within the physical lab environment.

To manage samplings and execute clinical procedures effectively, the collaborative robot must possess environmental awareness and comprehension of task progression. This is achieved through the design of an integration system comprising a fitting cobot, a high-quality camera, and a suitable object detection machine-learning model.

This paper will present recommendations for the selection of individual components and the integration system, to implement and advance laboratory automation. The most up-to-date and suitable collaborative robot for the system is ABB YuMi, a dual-arm robot with six degrees of freedom (6-DoF) using a vacuum gripper with suction cups, renowned for its flexibility and robustness, making it capable of maneuvering the pipette throughout the calibration process [6]. As for the vision system, an RGB-Depth camera will be employed to surveil the workspace and subsequently determine the x-y position of the pipette using the newest release You Only Look Once version 8 (YOLOv8) for the real-time object detection system [7].

II. BACKGROUND

A. COVID-19 outbreak and the need for laboratory automation

Throughout the COVID-19 outbreak, the need for laboratory automation increased significantly to help humans under the pressure of battling the pandemic. The stress in the healthcare system from the excessive pathological testing and a shortage of human resources among health and quarantine restrictions has caused the

[1] *The solution proposed in this paper will mention contemporary technologies that serve the purposes updated by 03/2024. Other innovations could be used to improve the design of the solution. Same approach could be applied to other repetitive procedure if appropriate.*

demand for a high availability, reliable and timely system. Laboratory automation provides a solution to continue social function and enhance overall productivity by facilitating rapid clinical processing and reducing reliance on human intervention in the laboratory environment while maintaining accuracy, availability, and cost-effectiveness within the workflow [1,5]. Laboratory automation has been shown to yield a substantial improvement in overall performance by 66% while reducing human hazardous activities by 62% [1]. This indicates the significant contribution of robotic applications in the healthcare system.

B. Pipette calibration procedure

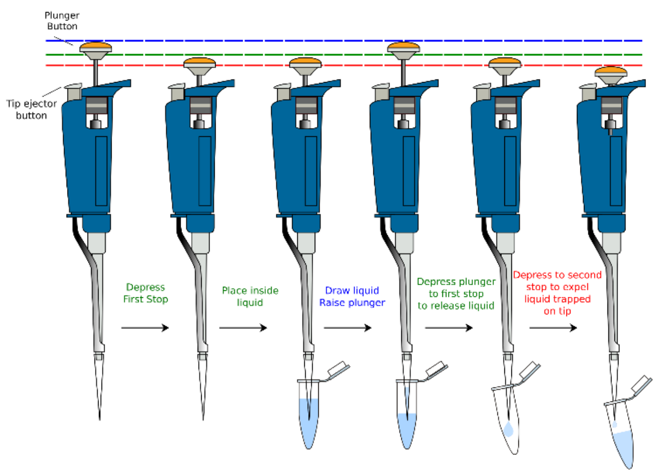


Fig. 1. Pipette calibration procedure

There are 2 stages of pipette calibration: taking the sample into the pipette (called aspiration) and dispensing which is sample delivery. It requires the pipette to go through a 2-stop pushing process with different forces on the plunger button. Each process requires high accuracy and multiple repetitions.

Accurate and precise scientific data is vital for all scientific discoveries and advancements across diverse fields, especially in the healthcare sector where poor quality or incorrect data would cause misleading/ wrong results which leads to resources and time wastage, or even disastrous events. This calibration process plays an important role in the workflow of medical processing that ensures the results from liquid dispensing of the pipette are consistent and precise [8]. In a laboratory environment, the pipette calibration procedure is used as a clinical regulatory requirement to assess the accuracy and precision of the pipette, which requires high accuracy, reliability, time and effort to carry out. Implementing an automated system for pipette calibration presents a method to address the existing challenges associated with the process. from minimizing human error, and saving time and costs, to improving task performance and enhancing the quality of the results.

Within the procedure, the lab technician will precisely aspirate and dispense the liquid to measure the reliability of the pipette performance (Fig.1). This procedure requires the robot to recognise the structure of the pipette and understand the kinematic control and movement of the aspiration and dispensing process.

III. LITERATURE REVIEW

A. Robot and computer vision

Collaborative robot arms equipped with computer vision technology are an evolving approach applied to perform specific tasks within automation systems. This methodology entails image processing and real-time robot control within physical workstations that require the cobot arms to visually perceive and interpret their surroundings, then collect and extract the data to perform actions respectively.

In the last few years, there are various studies have applied this solution to implement automated systems in different industries. YuMi dual-arm cobot, the most collaborative robot in the world introduced by ABB in 2015, has gained popularity in the robotics industry that most of the recent research chose to employ and develop their idea using this robot. In 2016, Kirschner et al. [9] integrated an RGB-D camera, the camera allows colour and depth real-time output, with YuMi for object detection and robot control, and one year later, Liang et al. [10] proposed dual quaternion-based kinematic control for more effective Yumi robot control. Five years later, Yang et al. [11] proposed the same approach as Kirschner (2016) but utilised the UR5 robot arm integrated with intel RealSense D435 camera using the YOLOv3 model to detect objects. In 2021, Lelachaicharoeanpan and Vongbunyong [12] applied YOLOv5 to the UR5 robot for the classification of the surgical device, disregarding the similarity of the object appearances. The camera has been changed throughout the years to meet the requirements of the system from basic image processing for depth image segmentation using Intel RealSense R200 (2019) to superior compactness, lower noise, and higher resolution in the L515 camera.

B. Computer vision with YOLO

Published in 2015, the real-time object detection system YOLO is among one of the best object detection recently, with high detection accuracy and high inference speed. Based on the Convolutional neural network (CNN), YOLO inherited all the best features of the deep learning algorithm and even surpassed the performance of R-CNN due to its ability to detect objects directly from feature maps instead of region-based detection. They have improved rapidly and released 8 versions of the model, the newest one is YOLOv8 Jan 2023 with the best mean average precision (mAP) of object detection and better performance.

In 2020, Wu et al. [13] applied YOLO to implement an object detection system on robots utilising the robot operating system (ROS) and Python, while, Zhao and Li [14] enhanced YOLOv3 to achieve improved mean average precision (mAP) in object detection tasks. The application of the object detection model trained using different versions of the YOLO family has been used in numerous research works, for instance, Benjdira et al. [15] showed the superior performance of the YOLOv3 by comparing faster R-CNN and YOLOv3 in detecting cars for unmanned aerial vehicle applications

IV. DISCUSSION

A. *Collaborative robot arm*

YuMi is s collaborative robot (cobot) developed by ABBRobotics and designed to work alongside humans as an assistant. YuMi is equipped with a high-quality sensing system and advanced control system that creates a robot-friendly environment for humans to interact and work with within a human-robot collaborative workstation setting. This cobot is known for its flexibility which allows the system to adapt to dynamic environments, versatility and ease of programming. It is able to work in the workspace of 560x320 mm on the x-y plane, with objects with a payload of 500g for each arm and is equipped with a customized gripper to serve different purposes.

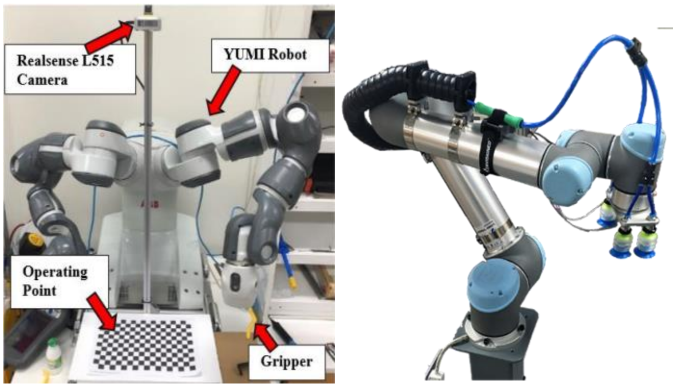


Fig. 2. Robot arm Yumi and vacuum gripper

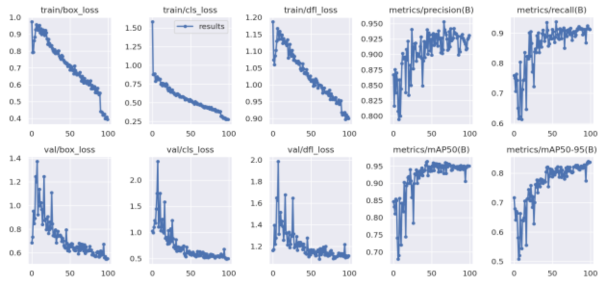
Kijdech et al.[6] presented their set-up for the pick-and-place application of object detection using the YuMi robot and RealSense L515 camera equipped above the robot arms to allow the robot to "see" the surrounding area. The camera is one of the best RGB-D cameras at a frame rate of 30fps with 1024x769 pixels for the depth images and 1920x1080 pixels for the colour ones. Using a depth camera alongside with robot control system, the cobot will be able to identify the position of the object and then proceed with the pre-programmed sequence of actions respectively. To apply in the pipette calibration use case, we propose the application of a vacuum gripper with suction cups in one hand to perform aspiration and dispensing tasks within the calibration procedure (Fig. 2). The normal friction gripper arm will find and pick up the targeted pipette then place it in the pipette holder and wait for the other arm to perform the aspiration and dispensing operations. The vacuum gripper will be responsible for executing the "push" action, where there has to be a precise amount of force to press down the button to make it stop at the wanted positions. The control valve of the component will regulate the airflow in and out of the gripper to create a vacuum environment between the "finger" and the plunger button, therefore, controlling the strength to just right to get the plunger to move to the expected position.

B. *Object detection Machine Learning model*

YOLOv8 is the latest model of the YOLO family of object detection models published in Jan 2023 by Ultralytics. Developed by the same company, YOLOv8 has the most similar architecture to YOLOv5 which has been known as one of the highly successful YOLO models. It has proved to be superior in tackling various vision tasks such as real-time object detection, segmentation, pose estimation and classification. YOLOv8 is a cutting-edge and extendable model that allows boosting performance and versatility by supporting CPU and GPU and being comparable with all previous YOLO versions.

Model	Size (pixels)	mAP	Speed CPU	Speed TensorRT
YOLOv8n	640	37.3	80.4	0.99
YOLOv8s	640	44.9	128.4	1.20
YOLOv8m	640	50.2	234.7	1.83
YOLOv8l	640	52.9	375.2	2.39
YOLOv8x	640	53.9	479.1	3.53

Fig. 3. Compare YOLOv8 pre-trained models



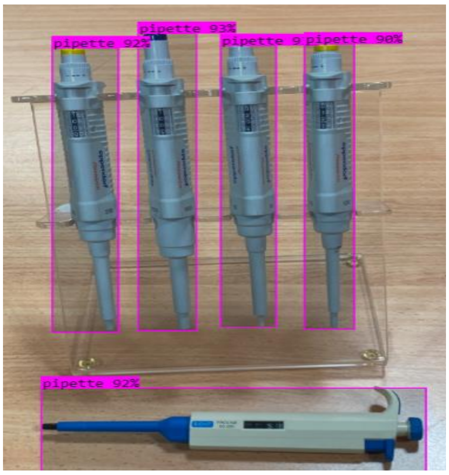


Fig.4. Pipette Detection using YOLOv8

In this research, we have utilised YOLOv8x pre-trained model as it has the highest mAP@50 value (Fig. 3) to perform the object detection on only realising pipettes. The model was trained on 917 augmented annotated image data, with a batch size of 16 and 100 epochs (Fig.4). The dataset was the combination of all types of pipettes that will be used in the procedure and their multiple 360 angles, then was split into 3 subsets: training, validating and testing data to ensure the diversity and prevent overfitting in the ML model. The ML model of YOLOv8 shows its high accuracy and efficiency in real-time object detection, with the mAP@.50 value for the pipette detection in this experiment is 96.6% accurate. This model is high in flexibility and accessibility and supports running training and referencing on both API hosted on roboflow and local devices,

V. CONCLUSION

In this era of high technology, automating the system using robotics and AI is the way to achieve better efficiency, quality, cost-effectiveness and safety in the improvement of the industry. Similarly, laboratory automation is the innovation of applying robotics technology into healthcare systems to enhance productivity, and accuracy while ensuring the availability and scalability of the system. Automated systems in the laboratory environment are a vital factor in helping the world battle against the pandemic, where robots can assist humans in working on highly accurate and repetitive tasks without human intervention. Recently, technology in robotics and AI have developed rapidly to provide innovative solutions for laboratory automation. The invention of a reliable generation of collaborative robots like ABB YuMi, myCobots or UR5 in the mid-2010s has marked the opening of the new automation era. Machine Learning and Deep Learning models to support computer vision are promptly evolving and getting stronger over time to catch up with the needs of the system requirements and applications. Soon, it is expected to achieve a fully comprehensive human-robot collaboration environment where the human and robot can “discuss” and work together as a team integrating Natural Language Processing NLP using the Large Langaue Model LLM to convey a proper workspace for both human and robot to cooperate.

VI. REFERENCES

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