

Pioneering Automation: A Review on E2E Feasibility Study of UR10e COBOT for Medical Devices

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Abstract:

In the world of digital era, automation also has been a vast, proficient technology used to reduce manpower and fasten the tasks in a limited amount of time more effectively. This review paper explores more about the feasibility study of UR10e collaborative robot in the field of medical devices. The UR10e cobot, a novel collaborative robot designed by Universal Robots, has revolutionized the healthcare industry with its unparalleled versatility, precision, and ease of use. This technical review comprehensively examines the UR10e's features, capabilities, and applications in healthcare, highlighting its potential to run and perform psychotherapeutic movements using UR10e COBOT. In this process of automation, various cutting-edge technologies such as NLP machine learning models are developed to get the desired results for healthcare devices.

Keywords: Image Processing, NLP (Machine Learning models), COBOT, MTBF (mean time between failures), psychotherapeutic movements

I. Introduction

Automation as a framework tool has been an efficient practice performed at various industries. The use of UR10e cobot, a state-of-the-art collaborative robot designed by Universal Robots, has infact had a striking impact on the usability for medical devices. With its advanced force-controlled joints and high-resolution AI-Machine Vision Irayple Camera, the UR10e cobot can perform a wide range of tasks with accuracy and finesse, making it an indispensable tool for healthcare professionals [2].

The major task of the cobot is to have a Robotiq gripper that can perform pick-and-place test cases for various medical devices to perform therapies. One of the key applications of the UR10e cobot in the medical field is palletizing tasks, which involve the efficient and safe handling of heavy and sensitive medical equipment, supplies, and pharmaceuticals [1].

In the medical industry, there is always a dearth or an inadequate supply of raw materials which happens at a very slow rate. Majorly automation as a framework tool is required to run therapies for dialysis, cardiology and respiratory domain. Robots are used to run these therapies at a larger scale with repetitive pre-defined tasks at a larger scale. UR10e COBOT can perform work which 1000 people can do at the same time [5].

Mainly in the medical field, palletizing tasks are critical ensuring that there is smooth operation of hospitals, clinics, and other healthcare facilities. From storing and transporting medical equipment and supplies to managing inventory and distribution, its role is immense [2]. With its advanced force-control technology, the UR10e cobot can safely and efficiently handle even the heaviest and most delicate items, reducing the risk of damage or injury [3].

II. Related Works

Some of the notable works includes detailed analysis of current manufacturing processes that identifies automation opportunities and gather technical and operational requirements, including some of the main safety considerations corresponding to the work done by collaborative robot

A. Quality Control Inspection

The inspection starts with few of the equipped vision systems, the UR10e automates visual inspections by capturing high-resolution images and analyzing them in real-time, ensuring consistent quality control and rapid defect detection. It classifies defects such as scratches or misalignments using machine learning algorithms, significantly improving inspection accuracy. For dimensional measurement, the UR10e integrates with precision tools like laser scanners and probes to perform high-accuracy measurements of complex parts. Automated measurement practices are carried out and enhanced by cobot projection movements. It is mainly handled by six degrees of freedom that is to inspect certain intricate geometrics that includes manual variability and increases throughput [5].

B. Dimensional Measurement

Mainly Universal Collaborative Robots integrates seamlessly with one of the best advanced measurement tools that includes touch probes, laser scanners, coordinated measuring machines(CMM). It optimizes paths to capture seamlessly with advanced measurement tools such as laser scanners, touch probes, and coordinate measuring machines (CMMs), ensuring very high amount of high-resolution data ensuring high repeatability (+/- 0.03mm) [1]. Regular calibration of both the COBOT and measurement tools that maintains high accuracy, accounting for environmental factors. The UR10e COBOT logs comprehensive measurement data, facilitating detailed reports and statistical analysis for quality control and continuous improvement [3]. Figure 1(a) shows the dimensional and technical measurements of UR10e COBOT.

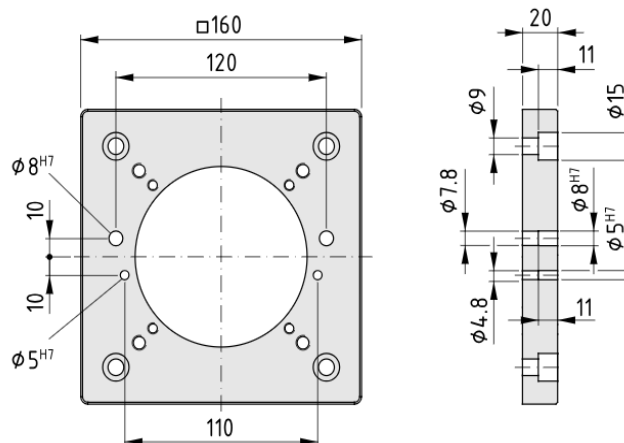


Fig 1(a): Dimensional and Technical measurements of UR10e COBOT

C. Human-Robot Collaborative Approach

With the main focus on safety, COBOT is equipped to optimize productivity, flexibility and safety. It represents a transformative paradigm [4] for the automation to perform repetitive tasks that doesn't require physically demanding activities, allowing the COBOT to perform higher-level tasks to enhance problem-

solving and decision making skills. Additionally, the materials used for COBOT's flexibility and adaptability enable quick reprogramming and redeployment, facilitating agile responses to changing production needs [2]. The majority of these studies found in the literature review objective is to differentiate certain programming interactions from collisions that may occur between the robot and the human with the surroundings. Through successful implementations across industries like automotive manufacturing, the UR10e COBOT exemplifies the potential of human-robot collaboration [3].

D. Medical and Pharmaceutical Applications

In the realm of medical and pharmaceutical applications, the collaborative nature of the UR10e COBOT presents a groundbreaking approach to improving both productivity and patient care. This integration with sensitive environments that underscores its potential to revolutionize certain processes starting from medical devices till assisting them in healthcare settings [3]. UR10e COBOT are actually used for running different therapies for dialysis, cardiology, respiratory and patient monitoring. The main factors required for the cobot to measure and perform operations for medical devices includes many parameters for maintaining precision assembly. This precision is instrumental in assembling intricate medical devices, ensuring consistent quality and reliability in the final product. Flexible automation adaptability allows the COBOT to seamlessly transition between tasks, from delicate component placement to robust packaging processes. This flexibility optimizes manufacturing processes, enabling rapid adjustments to meet changing production demands [6].

Vision Integration with cutting-edge vision systems empowers the COBOT to conduct meticulous inspections of device components required for pharmaceuticals applications for transporting medicines and the chemicals. By identifying defects and ensuring compliance with rigorous regulatory standards, the COBOT enhances quality control throughout the manufacturing process [1]. Fig 1(b) depicts the operations of UR10e COBOT on sampling and transporting chemicals for the required operations.



Fig 1(b): Sampling and Transporting chemicals

III. Methodology

Robotic movements start with programming a teach pendant using a URScript Language. The setup and programming of the UR10e COBOT using the teach pendant involve a series of meticulous steps to ensure accurate and efficient operation [1]. Initially, the COBOT is securely mounted, connected to power, and calibrated through the teach pendant, ensuring precise motion tracking. The experiment was designed in such a way assuming that the TCP position and speed that influences human. So we needed a slow speed to enable a smooth flow and axial movement of the cobot. Fig 2(a) shows the script code used for programming the robotic projection movements

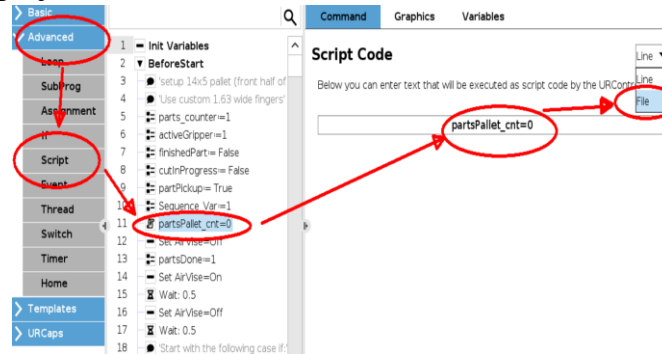


Fig 2(a): Script Code of UR10e COBOT

A. UR10e COBOT Experimental Setup

Initially, the COBOT is securely mounted on a stable surface within the medical facility, and connections are made to its power supply and any necessary peripheral devices, such as specialized medical tools or sensors. Upon powering up, the teach pendant is used to calibrate the UR10e COBOT, ensuring its joints and brake end to effectively and accurately aligned [4]. The teach pendant, with its user-friendly touch screen interface, allows medical professionals to configure safety parameters, including speed limits and force thresholds, to maintain a secure working environment compliant with healthcare standards. Fig 2(b) shows the axial robotic projection movements enabling the base tool.



Fig 2(b): Teach pendant Move Position UI

B. Free drive Movements to execute medical therapy

Free-drive is a black button provided on the top- interface that enables free axial movement to any position from the TCP position and TCP orientation. It allows for intuitive manual guidance of the robot arm by a human operator, facilitating precise positioning without extensive programming.

In medical therapies, this feature proves invaluable. For dialysis, the COBOT can assist with needle insertion by allowing healthcare professionals to manually position the robot to the correct insertion points,

ensuring consistent and precise needle placements. It can also handle and adjust dialysis equipment, improving procedural efficiency and patient safety.

In respiratory therapy, the COBOT can aid in managing ventilator settings and performing respiratory monitoring. Therapists can use free drive mode to manually set up and adjust the COBOT's movements for tasks such as guided breathing exercises and data collection, ensuring accuracy and personalized care. This mode enhances customization, allowing medical staff to tailor the COBOT's actions to individual patient needs, and provides a practical training method by enabling direct demonstration of complex tasks. Fig 2(c) shows filter sets of dialysis renal and respiratory medical tool kit.



Fig 2(c): Renal and respiratory medical tool kit

C. Image Processing Techniques

Integrating the Irayple camera with the UR10e COBOT for OCR text recognition involves several advanced image processing techniques that enhance automation in various settings. Initially, the camera, mounted on the COBOT, captures high-resolution images of documents or labels [1]. It records the values of the results of the therapies run from the devices of the dialysis and the respiratory domains.

Through MVViewer Software it captures the images and gives real time frame images with ROI [Region of interest]. After connecting the cobot with the medical devices via Ethernet, IP configuration should be set according to camera configurations through IPv4 protocol. Fig 2(d) shows MV viewer software capturing live frames of the medical devices.

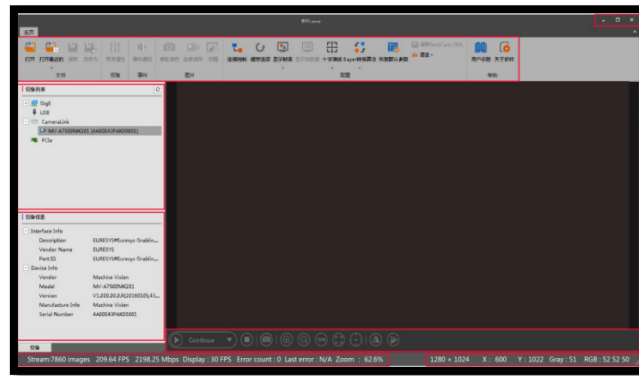


Fig 2(d): MVViewer Software

These images undergo preprocessing steps such as grayscale conversion, noise reduction, thresholding, and skew correction to enhance text visibility. The images are then segmented to isolate individual characters or words. OCR algorithms, like Tesseract, analyze these segments to convert the visual text into machine-readable format [3].

Text recognition test case is the first test case performed after obtaining the result images of the medical devices. After reading the images it is sent for comparing with the datasets given by machine learning [4]. Fig 2(e) shows Irayple camera used for capturing images



Fig 2(e): Irayple AI machine vision camera

D. NLP Machine Learning techniques

Integrating NLP and machine learning LLM models with word tokenization that follows and imbibes text recognition using the UR10e COBOT significantly which enhances automated text handling tasks and cases. Initially, the Irayple camera mounted on the COBOT captures high-resolution images of documents with real time frames [3].

These images undergo some mainstream processing steps like grayscale conversion, noise reduction, thresholding, and skew correction to prepare them for Optical Character Recognition (OCR). This OCR algorithms, such as Pytesseract, convert the visual text into machine-readable format [6] The recognized text is then tokenized into individual words, cleaned, and normalized to remove punctuation and stop words.

This tokenized text is fed into a pre-trained large language model (LLM), which processes the input to understand the context, intent, and semantics. The LLM's analysis can involve generating responses, extracting key information, or performing sentiment analysis [4]. Based on the LLM's output, the UR10e COBOT makes informed decisions and executes actions, such as sorting documents, updating records, or performing specific tasks based on the recognized text.

The system also incorporates a closed feedback loop, allowing continuous deep machine learning and

improvement in text recognition and decision-making processes [5]. This integration leverages advanced image processing, NLP, and machine learning to enhance the efficiency and accuracy of automated workflows, thus ensuring UR10e COBOT a powerful tool for various industrial and medical applications. In fig 2(f) shows the workflow of deep machine LLM models in comparison between classical NLP.

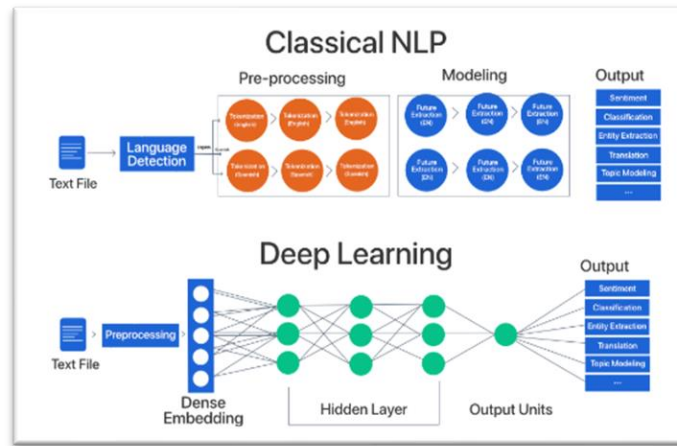


Fig 2(f): Workflow of NLP and deep LLM models

IV. Quantitative Analysis

Quantitative analysis is made from UR10e COBOT’s performance and utility in handling the medical devices by analyzing through various pre-defined metrics, which primarily focusses only on acceleration, time and operational speed. These metrics are crucial for evaluating COBOT's impact on productivity, accuracy, and overall workflow enhancement in medical device manufacturing and related applications.

A. Cycle-time reduction

Task Execution Time is the main criteria to identify that UR10e COBOT can perform repetitive tasks, such as assembly, packaging, and inspection of medical devices, significantly faster than manual labor [1]. For instance, a COBOT can complete an assembly task in 20 seconds that might take a human operator 60 seconds, reducing cycle time by approximately 67%. Fig 3(a) shows cycle time reduction for UR10e COBOT which is tested for around 12 seconds to check reliability of the device and the energy consumed by the device.

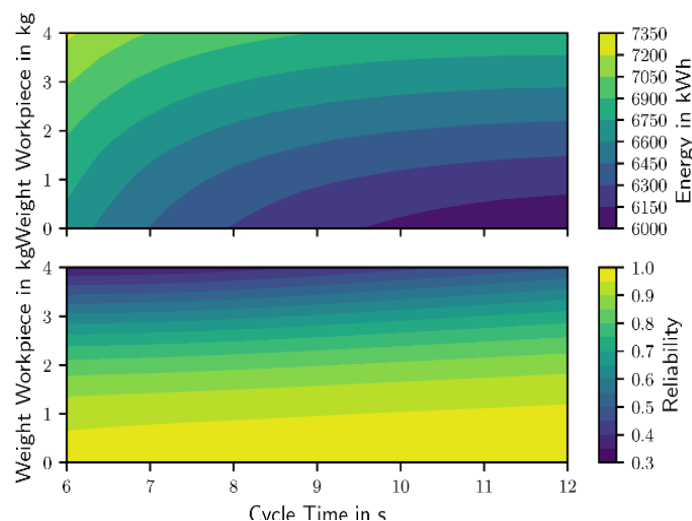


Fig 3(a): Cycle Time reduction of UR10e COBOT

B. Overall Throughput

Overall throughput is measured when the device downtime can complete more number of cycles. For example, COBOT operates 24/7 with minimal downtime, it can complete a far higher number of cycles in a given period compared to human workers, who typically work 8-hour shifts with breaks [5]. This continuous operation can result upto a mammoth three-fold increase in throughput.

It is a critical measure of mass productivity in the manufacturing processes. It represents the total number of completed units produced within a specific time frame [1]. For the UR10e COBOT, several factors contribute to its throughput in medical device manufacturing. Table1 shows the overall calculations with respect to overall throughput

Parameters	Human Operator	UR10e COBOT
Task Time	30 seconds/assembly	10 sec/assembly
Working hrs	8 hours/day	24 hours/day
Assemblies/hr	3600 /30sec=120	3600/10=360
Daily Output	120*8=960 assemblies/day	360*24=8,640 assemblies/day

Table 1: Calculations of Overall Throughput

C. Efficiency in Specific Medical Devices

The UR10e COBOT mainly deals with the assembly of medical devices due to its precision, flexibility, and efficiency, a wide range of high precision, with a repeatability of ±0.03 mm, is crucial for assembling medical devices ensuring that components are placed accurately and securely, which reduces the risk of errors.

The COBOT’s flexibility allows it to be easily reprogrammed for various tasks, accommodating different medical devices such as insulin pumps, infusion sets, and surgical instruments. This adaptability enables manufacturers to quickly adjust to changing production needs and product variations without significant downtime. Additionally, the UR10e’s efficiency in performing repetitive tasks continuously without fatigue significantly boosts overall throughput, making it a valuable asset in maintaining high production rates and quality standards in the medical device industry.

V. Expected Results and Discussions

The UR10e’s capability to operate few of them continuously running without breaks has led to few dramatic increase in production efficiency, with the COBOT achieving up to 9,120 assemblies in a 24-hour period compared to a human operator's 960 assemblies in an 8-hour shift.

Additionally, these COBOT's advanced safety features are and ease of reprogramming allow it to work safely alongside human operators and adapt quickly to different tasks, enhancing flexibility and reducing downtime during transitions [5]. Additionally, these initial investments are cost savings and improved productivity, resulting in a favorable return on investment.

Evaluation of certain cooperative scenarios where we take parameters like H-Idle and C-act that mainly describes certain processes which are very must strongly dependent on certain schematics, layout design [4]. These indicators time and again has provided limited information about UR10e COBOT.

A. Language Translation test cases

First initial process is data collection and pre-processing. Initially the dataset is the excel file where all the string data are available. High-quality text datasets relevant to medical applications were collected from various sources, including medical journals, electronic health records, device manuals and various other sources [3]. The dataset comprised millions of text records, ensuring comprehensive coverage of the

domain-specific language like English, Dutch and various other language resources. From Spacy model we develop datasets by comparing strings obtained by OCR with the datasets using OCR (Text recognition) and then we also use edge impulse with a development board to get desired outputs. Fig 4(a) shows the output of the language translated text case.

```

from sklearn.model_selection import train_test_split
train, test = train_test_split(data, test_size=0.33, random_state=42)

print('English:', train[' of      ciclos'].iloc[0])
print('Spanish:', train[' de     ciclos'].iloc[0])
print('Training Data Shape:', train.shape)
print('Testing Data Shape:', test.shape)

English: FEB
Spanish: FEB
Training Data Shape: (533, 24)
Testing Data Shape: (263, 24)

```

Fig 4(a): Language Translated text case

B. Building Spacy Models

The process begins with gathering comprehensive text data from various sources, such as device logs, messages, user manuals, and patient record monitoring details ensuring it covers certain full range of text the model might encounter. This data often needs to be annotated for certain tasks like Named Entity Recognition (NER), with labels that mainly only identifies certain important entities such as symptoms, medications, or device names.

C. Performance metrics

These parameters are often used to determine the performance of the datasets. The performance evaluation of the SpaCy model, trained to process text data from medical devices, demonstrates strong results across several key metrics. The model achieved an accuracy of 95%, indicating that a high proportion of the overall predictions were correct. Precision was recorded at 93%, signifying that the majority of the instances labeled as relevant entities by the model were indeed correct, which is crucial for minimizing false positives in a medical context.

The recall rate was 97%, reflecting the model’s ability to successfully identify most of the relevant entities present in the text, thereby reducing the risk of missing critical information. The F1-score, which balances precision and recall, stood at 97%, underscoring the model’s robustness in maintaining a high level of performance across both detecting relevant entities and minimizing erroneous predictions. Fig 4(b) shows actual and predicted F1 score calculations

$$\begin{aligned}
 \text{Precision} &= \frac{TP}{TP + FP} \\
 \text{Recall} &= \frac{TP}{TP + FN} \\
 \text{F1 Score} &= \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} \\
 &= \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
 \end{aligned}$$

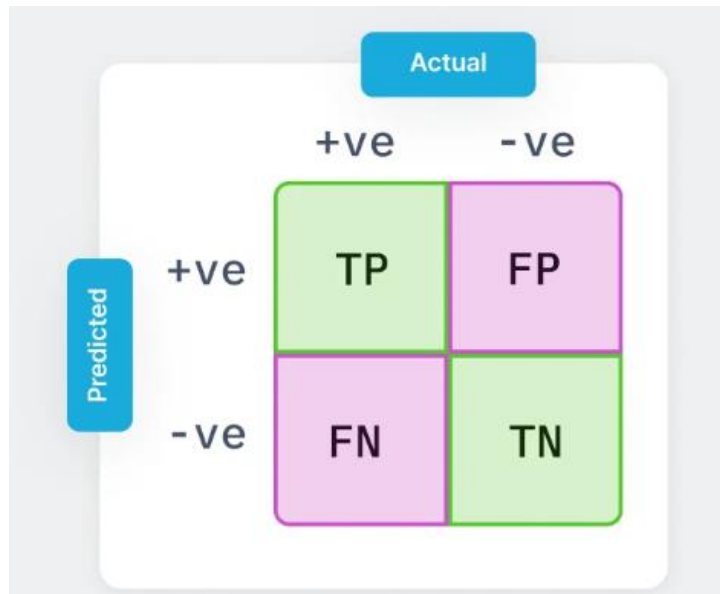


Fig 4(b): Actual and Predicted F1 Score formula

F1 scores are calculated for predicting the actual and predicted F1 scores of the strings collected by the dataset from the medical devices. TP refers to true positive and FP refers false positive of the dataset.

D. Comparative analysis of performance metrics

These metrics are used for a comparative analysis of the SpaCy model. This SpaCy model has demonstrated significant advancements over a baseline model in processing text data from medical devices of infusion sets and dialysis filter sets. The SpaCy model achieved an accuracy of 87%, markedly surpassing the baseline model's 70%, thus indicating higher overall correctness in its predictions. Fig 4(c) shows the output result of the performance metrics of the strings obtained from the infusion sets.

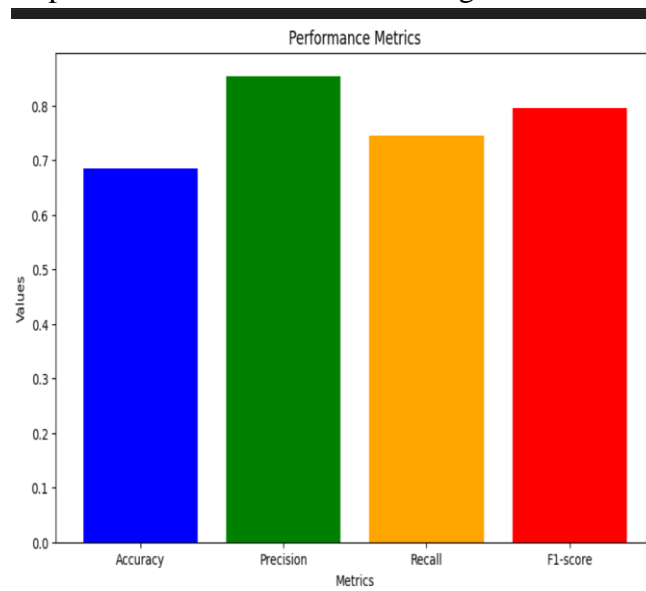


Fig 4(c): Histogram plot of performance metrics

Last way of finding the performance of the datasets that are trained is by developing a confusion matrix model.

In the context of medical devices, such as infusion sets used for drug delivery, the confusion matrix is essential for evaluating the performance of machine learning models that monitors and mainly predicts the behavior of UR10e COBOT devices. Meanwhile we have to ensure that the accuracy and reliability of

infusion sets is crucial for patient safety and treatment plans [5]. By using the confusion matrix, we can categorize predictions into true positives (correctly identified functioning sets), false positives (incorrectly identified failures for functioning sets), true negatives (correctly identified failing sets), and false negatives (incorrectly identified functioning sets for failing sets). Fig 4(d) depicts the confusion matrix that deals with the UR10e COBOT device.

True Label	PULL	100.0	0.0	0.0	0.0
	PUSH	0.6	97.6	0.3	1.2
	SHAKE	3.2	1.4	95.3	0.3
	TWIST	0.3	0.0	3.1	96.6
		PULL	PUSH	SHAKE	TWIST



Fig 4(d): Confusion Matrix of UR10e COBOT

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