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Roboswab: A COVID-19 Thermal Imaging Detector Based on Oral and Facial Temperatures

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***Abstract*—The SARS-CoV-2 virus has been the precursor of the coronavirus disease (COVID-19). The symptoms of COVID-19 begin with the common cold and then become very severe, such as those of Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS). Currently, polymerase chain reaction (PCR) is used to detect COVID-19 accurately, but it causes some side effects to the patient when the test is performed. Therefore, the proposed "Roboswab" was developed that uses thermal imaging to measure non-contact facial and oral temperature. This study focuses on the performance of the proposed equipment in measuring facial and oral temperature from various distances. Face detection also involves checking whether the subject is wearing a mask or not. Image processing methods with thermal imaging and robotic manipulators are integrated into a contact-free detector that is inexpensive, accurate, and painless. This research has successfully detected masked or non-masked faces and accurately detected facial temperature. The results showed that the accurate measurement of facial temperature with a mask is 90% with an error of +/- 0.05%, while it was 100% without a mask. On the other hand, the oral temperature was measured with 97% accuracy and an error of less than 5%. The optimal distance of the Roboswab to the face for measuring temperature is an average of 60 cm. The Roboswab tool equipped with masked or non-masked face detection can be used for early detection of COVID-19 without direct contact with patients.**

***Keywords*— Thermal imaging; face and oral temperature; COVID-19; mask; Roboswab.**

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I. INTRODUCTION

A marked increase in pneumonia cases with unknown etiologic in early 2020 originated in Wuhan, China, and was eventually declared as a new coronavirus, startling the World Health Organization (WHO) [1]. WHO declared COVID-19 a Public Health Emergency of International Concern (PHEIC) [2] and officially designated this novel coronavirus disease in humans as Coronavirus Disease (COVID-19) [3]. It is caused by SARS-COV 2, which belongs to the same large family of coronaviruses that causes SARS but is of a different type of virus [4], [5]. It has a very high mortality rate due to its rapid and extensive spread [4] and was eventually declared a national disaster in Indonesia [6]. Lockdowns were implemented worldwide to break its rapid spread, but they seriously affected a country's economic situation. Society was also forced to implement changes in its norms to prevent the further spread of COVID-19 through social distancing, which involves wearing masks, using hand sanitizers, periodic temperature measurements, etc. The spread of COVID-19 has not yet been stopped but keeps increasing due to discoveries of new variants.

Many technological innovations that are effective and efficient in fighting COVID-19 have been designed and manufactured. Information Technology (IT), the Internet of Things (IoT), Artificial intelligence (AI), as well as wireless aspects of smart technology are some of those that have been widely utilized in medical equipment to support paramedics in to fight against COVID-19 [7], [8]. Real-time polymerase chain reaction (RT-PCR) is a widely-used tool for COVID-19 detection [9], [10]. However, the risk of medical personnel being infected by aerosols from patients is quite high since there is still direct contact during the sampling process [11].

Additionally, RT-PCRs are expensive, painful, and relatively take a long time for the results to come out, aside from the occasional inconsistent results that lead to misdiagnosis [12].

In this study, an innovative COVID-19 early detection tool was developed to address the previously mentioned weaknesses and shortcomings. Roboswab is an innovation in diagnosing early indications of COVID-19 infection by detecting the temperature in the face area (with and without mask) and the oral cavity area. Image processing methods with thermal imaging and robotic manipulators are integrated into a contact-free detector that is inexpensive, accurate, and painless. The technological innovation is focused on the design and investigation of Roboswab's accuracy, sensitivity, and recall in facial and oral temperature scanning. The reliability value of the Roboswab device is the response to the result of temperature measurement of the facial and oral cavity areas.

II. MATERIAL AND METHOD

A. SWAB on The Robot Development Framework

In the present information, the PCR is the most effective in diagnosing COVID-19 [13] and is carried out by swabbing the oral or nasal area (Fig 1.a and 1.b) [10]. This method is strongly influenced by how those are carried out, thus affecting the results of the PCR examination and eventually can lead to false negatives/positives. Also, operators do not truly do it because they are afraid of being infected. Researchers departing through those factors agreed that robot mechanisms during the COVID-19 pandemic helped medical personnel in patients' healthcare by avoiding direct contact.

Industry 4.0 explored image processing and artificial intelligence in the detection of COVID-19. A swab device that integrates a manipulator robot to prevent local transmission of COVID-19 has been studied by Wang et al. [14]. It consisted of an active end-effector, a passive position arm, and a detachable gripper, but the drawback is in its use of a swabbing device that could cause pain and discomfort to the patient aside from the additional waste of cotton swabs.

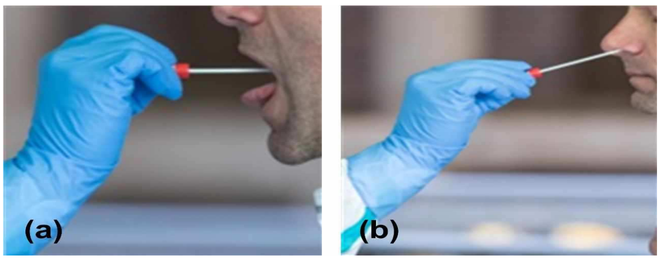

Fig. 1 Swab process

Wang and Wang [15] proposed a remote scanning system that integrated a thermal imaging camera and robot system in an attempt to avoid direct contact between swab operators and possible COVID-19 patients. It provided fast scan results and satisfactory collection data with a sampling rate success of 95%. Podpora studies the concept of robots using artificial intelligence (AI) that can identify humans based on audio-visual [16]. Chen et al. [17] presented a robot that combined the automatic phase and teleoperation phase, which allowed it to avoid transmission to the clinical staff due to direct contact when carrying out a swab. This system has a particular advantage in sampling determination, but the sterility of the robotic arm can be a source of transmission of COVID-19.

B. Roboswab Tools and Equipment

Our study proposes that Roboswab has two main parts: the 6DOF-RM robot manipulator and the thermal imaging camera (CTI) (Fig. 2). The RM is the seat of the CTI which moves to control the accuracy of the scan distance. It is equipped with a stepper motor and a proximity sensor for setting the optimum scanning distance.

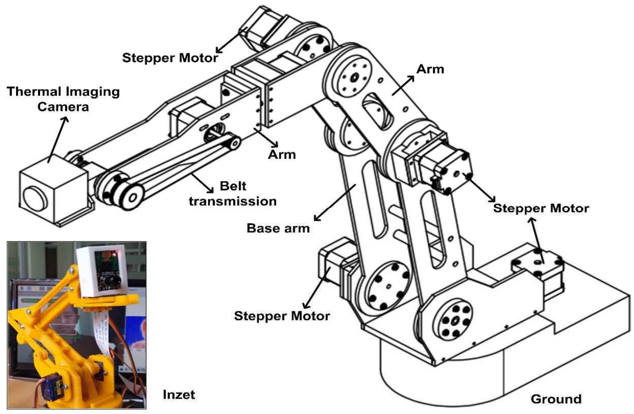

Fig. 2 Structure of Roboswab

C. Intelligent Framework Innovation

An analysis of COVID-19 using an intelligent framework to help healthcare teams make rapid decisions in hospitals, in terms of quarantine, identifying and treating patients with a typical cold has been studied by Abdel-Basset, Chang, and Nabeeh [8]. The study proposed a hybrid Computational Intelligent Algorithm (CI) using Moth-Flame Optimization and Marine Predators Algorithms (MOMPA) to detect the shortest path to the emergency location of COVID-19 without direct interaction with other subjects [18]. Several studies related to reducing the risk of COVID-19 transmission via swabbing through the use of IoT and intelligent frameworks were also conducted [19], [22].

Innovations in scanning for COVID-19 were also developed in Indonesia, including the Gajah Mada Electronic Nose (GeNose) implemented for the passenger of the railway system [23]. Its process involves storing human breath in a plastic bag, then measuring on available instruments. It was, however, very risky to cause new transmission due to the waste (plastic bags, etc.). Another innovation is the Real Time Lamp (RT-Lamp) and LFIA by LIPI as well as the CePAD by the UnPad and ITB Consortium [6].

Theoretically stating, body temperature is the most important vital sign in regulating the human body's metabolism. When the human body temperature increases beyond the normal limit of 36.5~37°C, it might be dangerous since it will disturb the immune system. The reliability and accuracy of temperature measurement are influenced by the subject and the measurement area, with the most precise being the oral and rectal areas. Another precise and common way to rapidly detect body temperature is by touching the forehead, although it might be very inaccurate. The mercury-in-glass thermometer is commonly used, but it needs many treatments and a long time to provide a truthful temperature. An infrared thermometer (also called a thermometer gun) was used to reduce contact during temperature measurement.

Image processing through camera scanning has been widely recommended as a body temperature detector, whether or not the subject has contracted the coronavirus. The morphology of the thermal imager (TI) on the face is shown in Fig. 3.

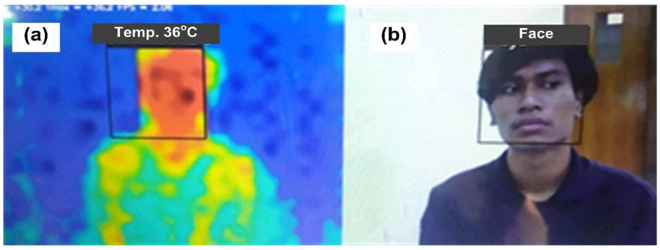

Fig. 3 Morphology of thermal imaging

The thermal imager is a thermal imaging technique in the form of color distribution like spectrum illumination (red (R), Green (G), & Blue (B)) that is visualized as thermography. Similarly, it can also refer to an RGB image [24]. The visualization is caused by electromagnetic energy emission, referred to as infrared radiation or thermal radiation, with a range of 0.75-1000 µm [25]. IT has the advantage of being fast, non-invasive, cheap [26], and safe based on surface temperature [27]. IT has become the choice in many domains because of these advantages, especially in the fight against COVID-19. Furthermore, artificial intelligence has been widespread use in combating the COVID-19 pandemic, such as big data, intelligent devices and systems, and intelligent robots [28]. Some of these were on the quick, efficient and contactless early coronavirus detection [29], [30].

Another interesting work was by Barnawi et al. [31] proposed an IoT-UAV with an onboard thermal sensor that determines possible exposure to COVID-19 based on the recorded temperature. It has an average accuracy of 99.5% showing its practical application in real-world scenarios. On the other hand, Sorto worked on software that performed facial recognition and temperature registration for patients [32].

In this innovation, the MLX90640 thermal camera, functioning as the heat and facial temperature detector, is connected to the Raspberry Pi 4 Model B w/c is connected to all other components (Fig.4).

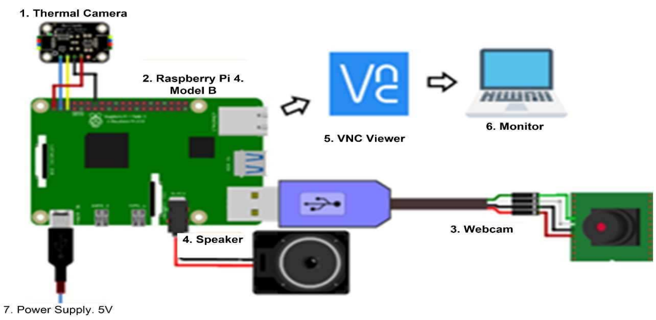

Fig. 4 Thermal imaging cameras

The 8MP web camera module for detecting the face is connected via USB to the Raspberry Pi. VNC, a remote desktop tool, is utilized to connect to the Raspberry via Wi-Fi to view the output.

D. Measurement Testing

This work tested various distances (50, 60, 70, 80, 90, and 100 cm) of the Roboswab from the forehead and throat in measuring the temperature with the thermo-gun set as the control. The scanning process begins with acquiring facial and background images, wherein the Open CV face detection scans the face area with or without a mask. The detection was carried out of face image datasets with or without their respective masks. Furthermore, a labeling process was conducted to provide notation based on the class that has been determined and as a reference for the training process.

Determining the architectural model of the detection object is first carried out using the efficient net-Lite model wherein the Google Drive is linked to Google Colab. XML PASCAL VOC formatted data in Google Drive are then sampled as input datasets to the Google Colab Library Model Maker. These datasets are stored in three folders, namely: train (containing 80% of the data set), test (10% of the data set), and validation (10% of the data set). During the validation process, the invisible image is used to decide when training should stop and to prevent overfitting. Regarding the training process, the Efficient Det-Lite (EDL) model used an epoch value of 50, which means it will train the dataset 50 times.

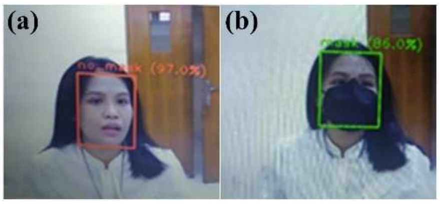

Fig. 5 Patient face imaging

Fig. 5.a and 5.b show an image capture of a face without and with a mask detected by the web camera. The confidence score method was applied based on the confusion matrix in order to determine the face with and without a mask. This method has three characteristics that show the detector's accuracy, recall, and precision [7], [30]. Accuracy is the percentage of data that is classified correctly compared with the entire date. Precision is the accuracy of the classification, while recall is the success rate of data recognized from all the detected data. The estimation of the performance of an automated system depends upon the measurement in a human-machine system, whose values are calculated as follows:

$$\text{Accuracy} = \frac{T_{(+)}+T_{(-)}}{T_{(+)}+T_{(-)}+F_{(+)}+F_{(-)}} \quad (1)$$

$$\text{Precision} = \frac{T_{(+)}}{T_{(+)}+F_{(+)}} \quad (2)$$

$$\text{Recall} = \frac{T_{(+)}}{T_{(+)}+F_{(-)}} \quad (3)$$

Precision and recall are parameters widely used in classifier performance evaluation. Precision expresses the predicted significant cases that are calculated as follows:

$$F_{measure} = 2x\frac{\left(\frac{T_{(+)}+T_{(-)}}{T_{(+)}+T_{(-)}+F_{(+)}+F_{(-)}}\right)\left(\frac{T_{(+)}}{T_{(+)}+F_{(-)}}\right)}{\left(\frac{T_{(+)}+T_{(-)}}{T_{(+)}+T_{(-)}+F_{(+)}+F_{(-)}}\right)+\left(\frac{T_{(+)}}{T_{(+)}+F_{(-)}}\right)} \quad (4)$$

Where; $T_{(+)}$ is a true positive (patient with mask); $T_{(-)}$ indicates a true negative (patient without mask), $F_{(+)}$ is a False positive (with mask), and $F_{(-)}$ is a false negative (without mask), as well as F_m is Statistical measure its calculation with a value between 0 and 1 as its output.

Fig. 6 shows a temperature scan of a face image for the forehead and mouth areas. Three boxes were identified during the observation: green box for the face, orange box for the forehead, and white box for the oral cavity. Haar cascades method, HOG + Linear support vector machines (SVM), and convolutional neural network (CNN) was used in order to determine the relationship between these three scanning areas [30].

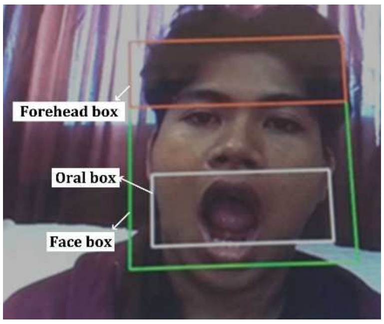

Fig. 6 Face and mouth area temperature detection

The system performs a temperature array mapping process based on the forehead and mouth bounding box. It reads the temperature in the open mouth and takes the hottest temperature in that area. The system displays thermal and facial images as well as measurement results in real-time that are displayed above the bounding box as decimal numbers (Fig.7). The factors that affect temperature scanning of the forehead and oral cavity areas are calibration of temperature readings, measurement distance, and room temperature. The biometric thermal imaging process can be categorized into detection, monitoring, recognition, and identification. The biometric thermal image applications are defined in four categories, namely: detection, monitoring, and recognition, as well as identification. The face imaging and thermal scanning are shown in Fig. 7.

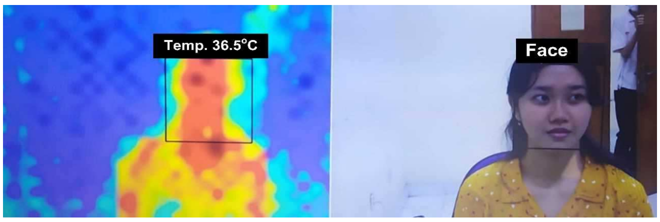

Fig. 7 Thermal imaging of the detected face

In terms of face detection, using visual photos for face identification can easily be made cascade and then classified as inoperable due to non-uniform illumination. But, the thermal frames shown in the visual photo are not influenced by this problem. On the other hand, the measurement of the face area is affected by the environment, and it plays an important role in the measurement of the face and forehead temperatures which are carried out by calibrating and compensating based on the impact of environmental factors. This thermal imaging process is also used for measuring the oral area temperature. The Roboswab detection in the face area with varying distances is given in Fig. 8.

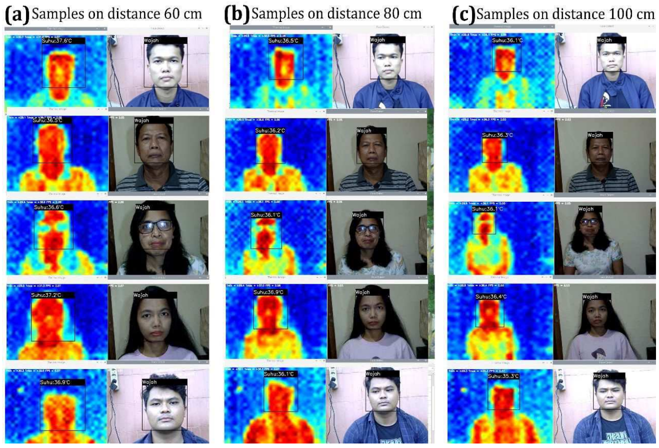

Fig. 8 Frame in different thermal imaging conditions

We can see how the measured temperature varies with respect to the distances for five individuals of different ages. At 60 cm, the subject can be seen with a wide area for the thermal imaging camera to work. However, the subject wearing eyeglasses has some effect, especially on the thermal imaging aspect. Similar results were observed even if the measurement distance was changed to 80 cm and 100 cm. Based on these results, the infrared cameras can be installed at a distance from the subjects and still measure the temperature of the facial area with an accuracy of 94% - 95%.

III. Result and Discussion

A. *Characteristics of Thermal Camera Detection*

The average accuracy, precision, and recall for the face area temperature measurement of 20 subjects with and without a mask are given in Fig 9. The 85% accuracy with a mask is lower than for without, which reached 100%. On the other hand, the precision for both with and without masks was up to 100%, while the recall was calculated to be 85% and 100% for with mask and without masks, respectively.

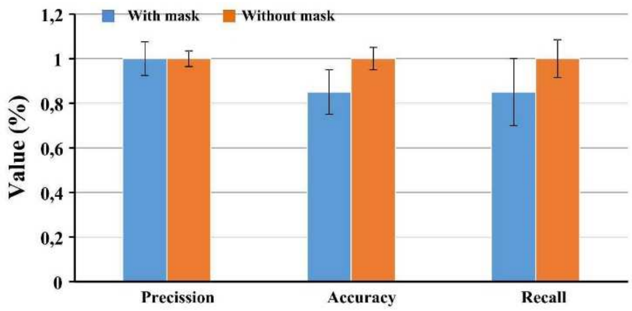

Fig. 9 Roboswab performance

It can be concluded that the system recognized faces without masks as well as those with masks, including the shape and color of the masks. Additionally, the light intensity around the face area affects the recall value, and it is similar to the results of previous research works [33], [35]. The accuracy and recall values and the Fm depend on the mask type and the material used. Using the confidence score analysis method for facial temperature measurement, both with and without a mask, obtained a 100% accuracy, meaning that the Roboswab tool has fairly good accuracy.

B. Roboswab Measurements Distance

Fig.10 shows that there is a linear relationship between distance and temperature. In this case, the farther the scanning distance is, the lower the measured temperature compared to the actual temperature (36.5°C).

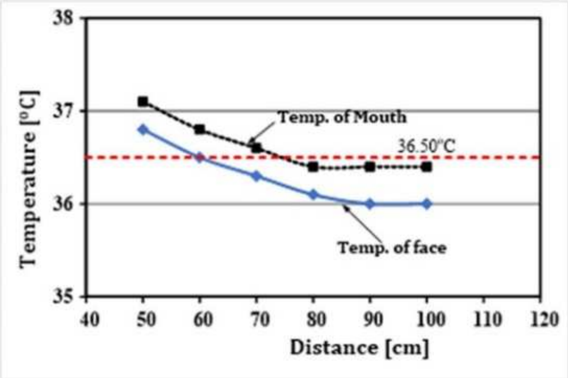

Fig. 10 Average value for face and oral detection

The decrease in measured temperature is due to environmental interference such that the scanned temperature becomes unstable at distances above 70 cm. The measured temperature between the facial and oral cavity areas demonstrated the same decreasing trend. However, the measured temperature of the oral cavity is higher than that of the face. The most stable measured values for the facial area occur at 60 cm while at 75 cm for the oral cavity. The difference in the most stable measurement distance between the face and the oral cavity areas is due to environmental factors in measurement, while the difference in measured temperature is because the oral cavity is more closed; hence external effects can be avoided.

It can be seen in Figure 11 that at 50 – 60 cm away, the facial and oral cavity measured temperature errors are almost the same. The further away from the scanner camera, there is an increase in measurement error for that the face and a slight deviation in the measured value for that the oral cavity. The deviation in measurement results with a longer measurement distance is 0.5°C for the face and 0.1°C for the oral cavity. The smallest measurement error for the forehead area was obtained at a distance of 60 cm with an error value of 0.50, while it was at a distance of 70 cm with an error value of 0.45 for the oral cavity area. From these results, the optimum distance for measuring temperature to determine whether someone is infected with COVID-19 is 60 cm for facial temperature and 70 cm for oral cavity temperature. This is in relation to the temperature obtained above the control temperature of 36.5°C.

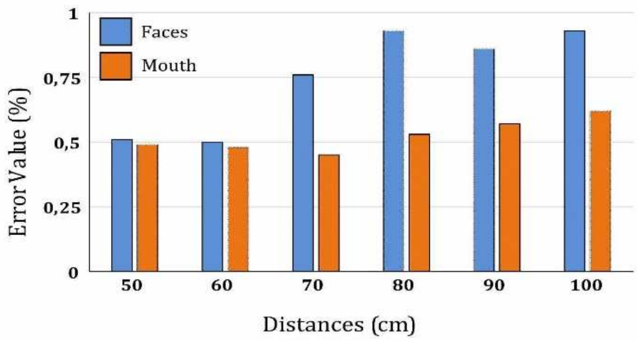

Fig. 11 Measurement error

In this work, we found that industry 4.0 has provided a clear view of smart technology applications, especially in efforts to fight the COVID-19 pandemic [7], [8]. Body temperature is vital because it affects the body's immune system, thus facilitating the spread of the coronavirus. The rapid spread of the coronavirus is caused by a decrease in the body's immune system when the temperature rises above 37°C. The coronavirus generally spreads in several ways, including saliva and breathing [36]. This can be very dangerous for infected individuals with a history of other illnesses since it is very likely to end in death. Since 2020, the coronavirus has spread with various variants that have appeared, although the effect is not as severe as COVID-19. However, it is necessary to be aware that COVID-19 is not over and continues to evolve with new variants.

The swab method is the most effective technique in breaking the chain and spread of the coronavirus [9], [37]. However, some of the swab's weaknesses are its high cost, waste created, direct contact between patients and medical personnel, and often can cause trauma, with the test results taking quite a long to come out.

The application of RT-PCR is quite effective and is the most accurate and efficient in scanning, but it is expensive and not evenly available in pandemic areas. Considering the lack of available tools to detect COVID-19, the development of IoT, AI, and IT, as well as other smart technologies, have pushed for innovations in COVID-19 detection tools that are cheap, accurate, efficient, and contact-free [29]. The internet of things (IoT) has become the choice for COVID-19 detection tools without direct contact between sufferers and medical staff [29], [38], [39].

Roboswab (see Figure 3) is one of the innovations in detecting COVID-19 that puts forward the measurement of the face area (without and with a mask) and the oral cavity temperature. This tool consists of a robot mechanism (manipulator robot with 6-DOF) and a web camera based thermal imaging. The structure of the Roboswab consists of a robot manipulator that places the camera and controls the measurement distance. While the web camera functions to scan the temperature of the face, forehead and oral cavity. The display from the camera scan is utilized for image processing based on RGB. The scan is applied to three areas, namely: the face (with and without a mask), the forehead area, and the oral cavity. The scan is displayed in the form of a white box for the oral cavity, green for the face, and orange for the forehead. The measurement results are reviewed based on the characteristics of the scan, namely: accuracy 100%, precision 100%, and recall 100%, wherein an average value of 100% for without mask. While the face with a mask is: 85% accuracy, 100% precision, and recall 85%, where the average value is 90%. The results helped us conclude that temperature scanning is limited by the presence of masks and also influenced by environmental factors such as light, ambient air, and the scanning distance of the subject from the camera.

IV. Conclusions

Since COVID-19 has become a global pandemic, Roboswab is proposed for primary detection of COVID-19 based on thermal imaging that removes direct contact between medical personnel and the patient. The result of the image processing from the scan gives meaning to the high and low body temperatures. The results for detecting masked and unmasked faces are very satisfying. The effect of measuring distance has a significant impact on measuring errors. This research found that the most effective distance for measuring with and without the mask in the mouth cavity is 60~70 cm with an error of 0.45%, while for a forehead, it is 60 cm with an error of 0.5%. The results show that the proposed Roboswab can achieve high accuracy with the possibility of performing additional real-time tasks.

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