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Development Of Facemask Recognition-Based Access Control System For Covid-19 Safety Using Machine Learning

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***Abstract*— In this paper, development of a 'facemask recognition-based access control system for covid-19 safety is presented. The system is an embedded system and the design is divided into two phases, the face mask recognition phase and the access control phase. The facemask detection is implemented using Raspberry Pi microprocessor and USB webcam, and the status of detection is sent to the Arduino microcontroller which handles the access control phase. A non-contact temperature sensor technology is interfaced with the Arduino microcontroller handling the temperature detection aspect of the system. Algorithms were written and implemented in Python and C++ frameworks; python is used for the facemask development model and deployment while the C++ is used for the Hardware programming. Sample face dataset were used to evaluate the system and the results showed that the system was able to identify facemask on eight out of ten participants used for the testing while taking heavily bearded face, skin color and gender into consideration, however, the system failed in classifying torn facemasks and handkerchiefs into the "No Face Mask" category,. Hence, this calls for development of a more robust system to address such cases.**

Keywords: Facemask Recognition, Arduino Microcontroller , Access Control System , A Non-Contact Temperature Sensor, Covid-19 Safety, Python And C++ Frameworks , Raspberry Pi Microprocessor, Machine Learning

1. Introduction

In the recent past few years, corona virus pandemic has been causing global health crisis. One of the effective protection methods advocated is wearing a facemask in public areas [1,2,3,4, 5,6,7,8, 9,10,11,12]. This has given rise to COVID-19 safety measures and policies in many organizations which require that facemask must be worn by individuals seeking to enter the premises of the organization [13,14,15,16,17,18,19]. In addition, high body temperature has been identified as one of the obvious sign of COVID-19 infection [20,21,22,23,24,25]. As such, the COVID-19 safety measures and policies refuses access for individuals with high body temperature. However, measuring body temperature for individuals has to be non-contact measurement to avoid COVID-19 infection through contact [26,27,28,29,30,31,32].

Accordingly, in this paper, a machine learning model is developed for implementation on a Raspberry Pi and the pi-based access control hardware device [33,34,35,36,37]. The Raspberry Pi and the pi-based access control hardware device has non-contact temperature for contactless body temperature measurement along with facemask recognition framework that uses USB webcam to capture the image of individual face and subject the image to the machine learning-based facemask recognition process. The individual is granted access by the system only if facemask is detected on the face image and the body temperature is within the acceptable range of body temperature that does not indicate possibility of COVID-19 infection. The details of the development of the machine learning model and the Raspberry Pi and the pi-based access control hardware device are presented along with the data and procedure used to demonstrate how effective the system is in detecting facemask and acceptable body temperature as required for enforcing the access control policy.

2. Methodology

2.1 Model Development Stages

The access control mechanism developed in this paper is meant to use machine learning to determine if a person is wearing facemask or not and thereby giving access to only the person that is detected as wearing facemask why denying access to the person that is detected as not wearing facemask. The development of the machine learning-based mechanism for facemask recognition –based access control system is divided into three segments, namely, model development, model testing, and model deployment stages.

The machine learning model was developed using Real World Masked Face Dataset (RMFD). The procedure used for the development of the model for facemask recognition is shown in Figure 1.

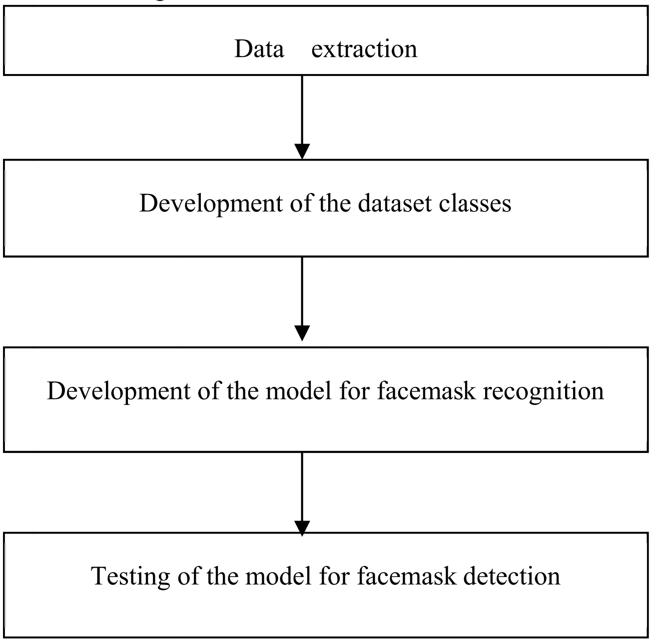

Figure 1 The procedure used for the development of the model for facemask recognition

2.2 Data extraction: The Real World Masked Face Dataset (RMFD) used for the model development has dataset of images of masked and unmasked faces which comprises of 5,000 masked face images along with 90,000 unmasked face images [38,39,40,41]. The screenshot in Figure 2 shows sample images of masked and unmasked faces from the RMFD dataset. At this point, pandas data frame was created by conducting iteration over the masked and the unmasked face images in the RMFD dataset whereby face images in the dataset with no facemask is labeled 0 whereas face images in the dataset with facemask is labeled 1. Development of the dataset classes: Particularly, in this paper, the machine learning model requires the input images to be in Tensor form with size of 100x100 and. So, dataset class is developed and used to query the image dataset and transform each of the images in the process to conform to the required 100x100 size and afterwards convert the image samples to a Tensor.

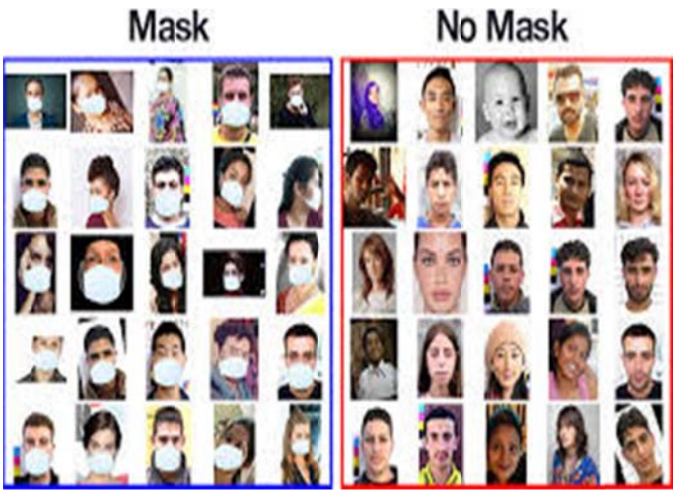

Figure 2: The screenshot showing sample images of masked and unmasked faces from the RMFD dataset

2.3 Development of the model for facemask recognition: This phase entails defining the model architecture along with forward pass. The accuracy class adopted is the one available in touchMetrics package and it is used for the model train and validation accuracy commutation. The model architecture consists of 2 convolutional layers followed by two linear layers along with ReLu activation function while the pooling layer adopted is the maxpool2d (Figure 3). The weight of the layers is initialized using Xavier_uniform function. Since an imbalanced RMFD dataset consisting of 5000 images with facemask and 90, 000 images without facemask is used, the same proportion of masked and unmasked images is maintained in the splitting of the dataset into train and validation datasets. Specifically, train_test_split function contained in the sklearn library is used to implement the splitting of the dataset. Notably, the splitting of the dataset is such that 70% is for training and 30% is for validation. The model training is conducted using batch size set to 32 along with Adams optimizer with learning rate value set to 0.00001.The training accuracy and training log are also computed so as to enable visualization the progress of the training process. To train the facemask recognition model, the mask detector object is initialized and then passed to the fit() method. In this case, the facemask detector model was trained with 10 epochs. The screenshot of Figure 4 shows the validation loss graph while the validation accuracy graph is shown in Figure 5.

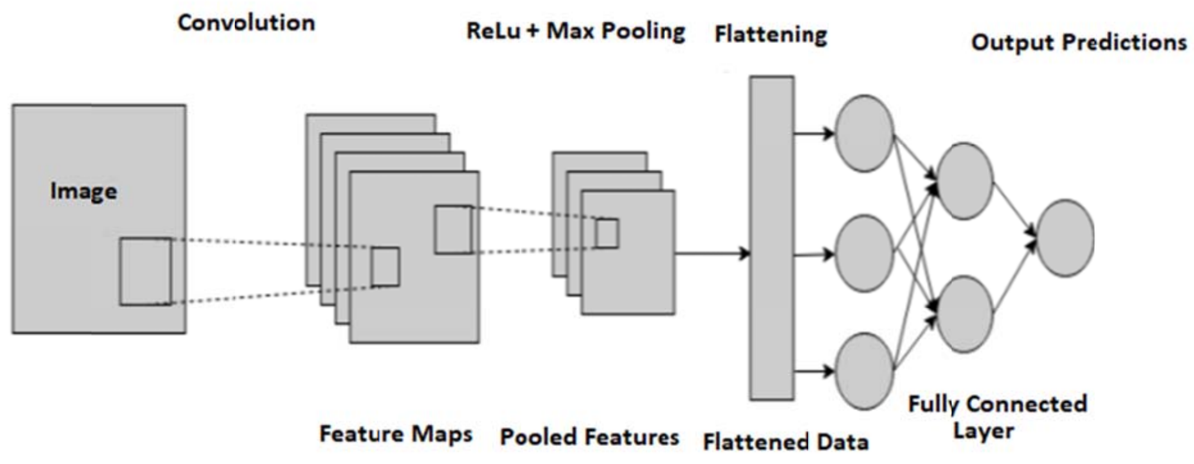

Figure 3. Model development diagram

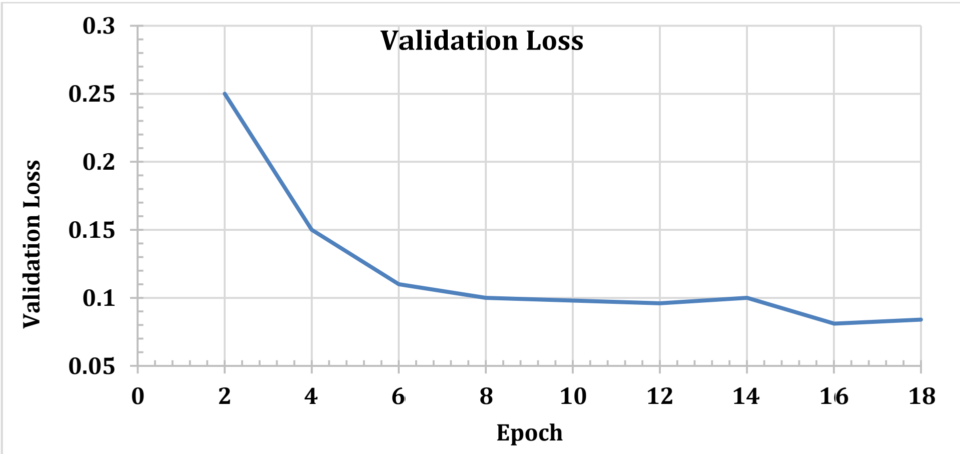

Figure 4 Screenshot of the validation loss graph

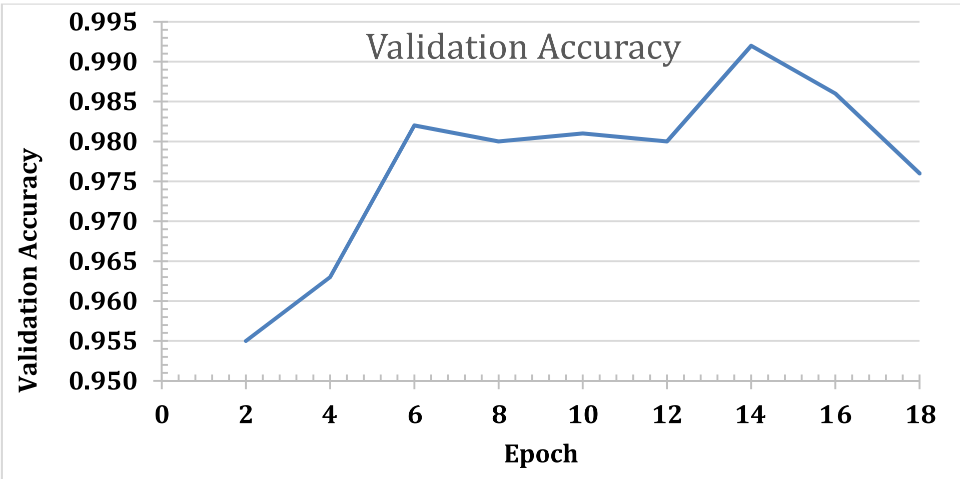

Figure 5 Performance accuracy of the proposed model

2.4 Testing of the model for facemask detection: In order to test the facemask recognition model on real face image data, openCV library is used. The RGB colour values are employed in setting the color for the bounding rectangle and also green colour is used to indicate "mask" bounding rectangle box while red colour is sued to indicate "no mask" bounding rectangle box. The result has two probabilities, namely, "mask" or "no mask" and this will be indicated in green rectangular box or in rectangular red box respectively when the result is displayed.

2.5 Model Deployment Stage

The facemask recognition model is deployed with the aid of a Raspberry Pi and the pi-based hardware device which has the architecture as shown in Figure 6. The hardware device uses USB camera that is connected through the serial port to capture face images and pass the image data in bytes to the Arduino microcontroller. In operation, the controller passes a digital value of 1 when it detect a facemask otherwise it passes a value of 0 when no facemask is detected in the image data. The hardware device is also equipped with a non-contact temperature sensor module which it uses to capture the body temperature of the user. The non-contact temperature sensor module is connected to the digital input pins of the Arduino microcontroller. In addition, the hardware device has liquid-crystal (LCD) display, push button, light emitting diodes (LED), servo motor and buzzer connected through the various digital input pins of the Arduino microcontroller.

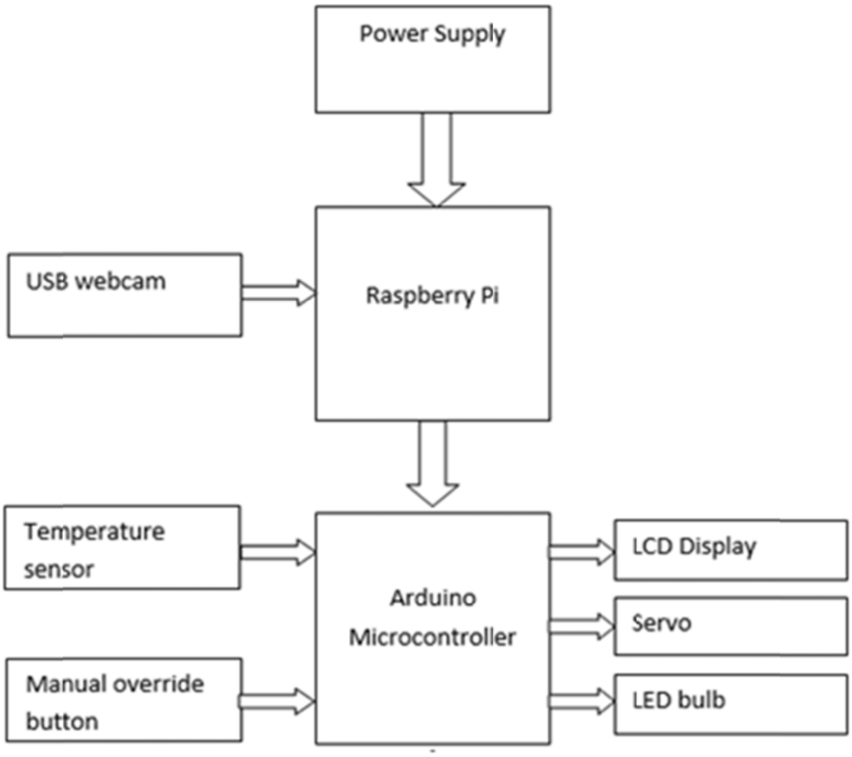

Figure 6 The architecture of the Raspberry Pi and the pi-based hardware device for the facemask recognition system

The flowchart for the operation of the Raspberry Pi and the pi-based hardware device for the facemask recognition system is given in Figure 7. According to Figure 7, the system notifies the user and prompts the user to wait for some seconds while it checks if the user wears a facemask or not. If the condition of "mask on" is satisfied, it is displayed on the LCD screen and the system goes ahead to check the user's temperature, if temperature is less than 37^{o} Celsius (which is the average human body temperature),the users temperature is displayed on the LCD screen then the servo motor moves upwards. If the system check for facemask and no facemask is detected, the LCD displays "no facemask detected" and the system remains locked.

On the other hand, if the system checks for facemask and the condition of "mask on" is satisfied, it is displayed on the LCD screen and the system goes ahead to check the user's temperature, if temperature is more than 37^{o} Celsius (which is the average human body temperature), the users temperature is displayed on the LCD screen and the system remains locked.

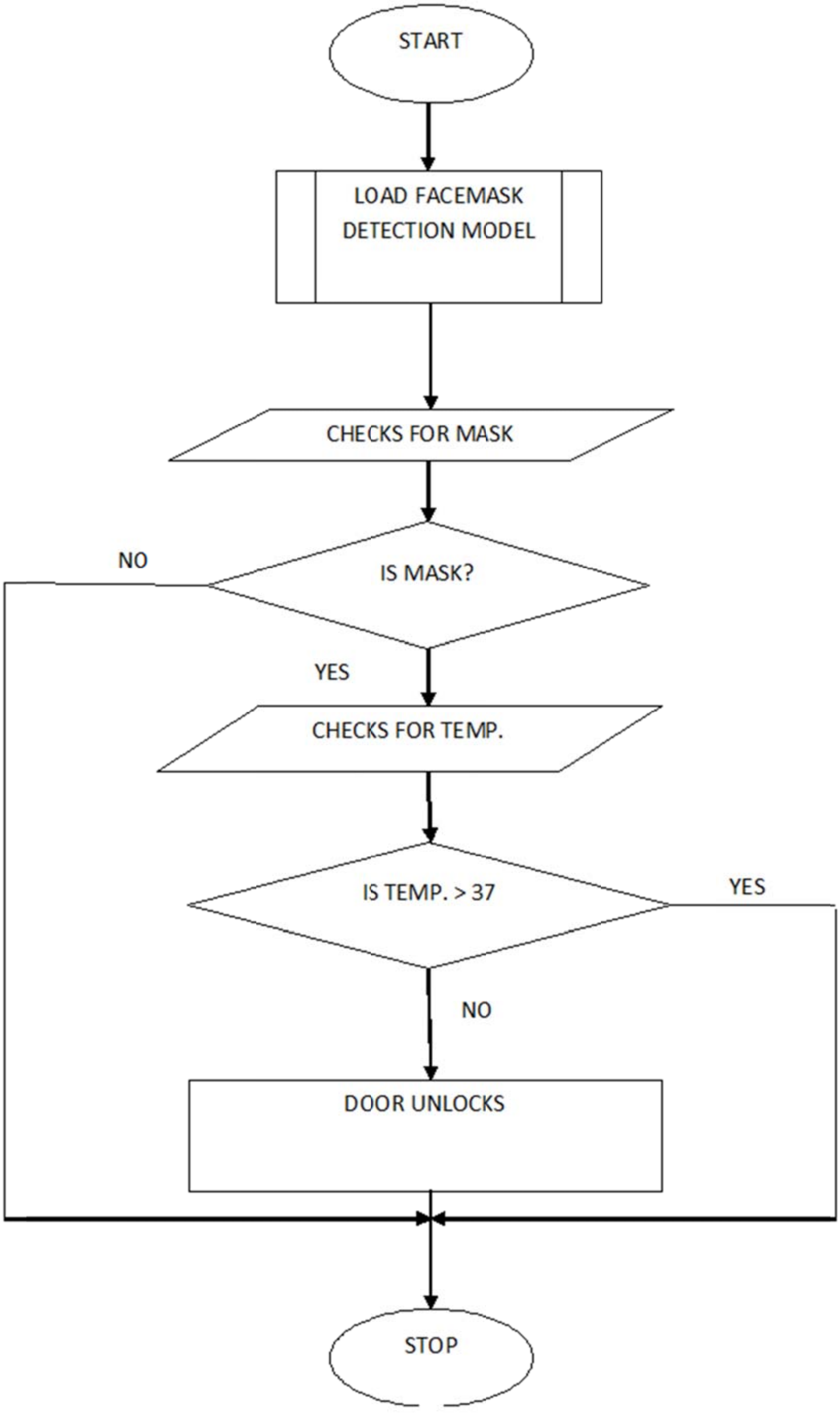

Figure 7 The flowchart for the operation of the Raspberry Pi and the pi-based hardware device for the facemask recognition system

3. Result and discussions

The results of the Raspberry Pi and the pi-based hardware device for the facemask recognition system are presented according to the two core stages of the developed system, namely, the facemask recognition model and the hardware access control mechanism. The results also illustrate the working of each of the system's component and their inter-dependency on each other.

The picture showing the developed Raspberry Pi and the pi-based hardware device for the facemask recognition system is shown in Figure 8. After the system was setup, it was tested with some sample participants with facemask amd without facemask. When a participant with a facemask on was scanned by the system, the feedback from the system indicated that a face mask was detected on the participant. The picture showing the system's response when facemask is detected on the participant.is shown in Figure 9. Again, when a participant without a facemask on was scanned by the system, the feedback from the system indicated that no face mask was detected on the participant. The picture showing the system's response when facemask is not detected on the participant.is shown in Figure 10.

For the temperature detection test, a sample participant was used; the temperature sensor read the participant's temperature and displayed it as 30.15 degrees on the LCD (as shown in Figure 11), the user's temperature falls within the allowable temperature of the system design which is 36.0°C. Similarly, the picture showing the system's response when the participant's temperature falls is higher than the allowable temperature set by the system is shown in Figure 12.

Figure 8 The picture showing the developed Raspberry Pi and the pi-based hardware device for the facemask recognition system

Figure 9 Picture showing the system's response when facemask is detected

Figure 10 Picture showing the system's response when facemask is not detected

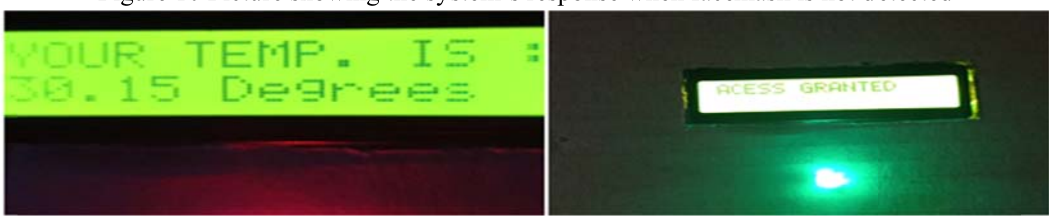

Figure 11 Picture showing the system's response when the participant's temperature falls within the allowable temperature set by the system

Figure 12 Picture showing the system's response when the participant's temperature falls is higher than the allowable temperature set by the system

Eventually, the extent to which the system performed on different users was explored; to this end, ten (10) participants were tested with upright faces, while the faces were either masked or non-masked. Gender, as a between-subject variable was also included in the system's test. The participants were randomly picked and each of the participants completed the facemask recognition test twice. The summary of the results obtained from the facemask recognition test conducted on the ten (10) participants using the Raspberry Pi and the pi-based hardware device for the facemask recognition system are shown in Table 1.

The results in Table 1 is based on the principle of operation of the system, namely, for the system to get to the temperature detection phase, the user has to pass the facemask recognition test, in other words the system has to detect facemask on the user first. In addition, for the user to pass the temperature detection test, the users temperature must fall in the allowable temperature range of less than or equal to thirty seven degrees Celsius (<= 37^{o}C). If the user's temperature is above the allowable temperature say 38^{o}C, "High temperature" is displayed on the LCD screen, hence Access denied.

The overall system results (as presented in Table 1) are in line with the aims and objectives of the developed system. However, for the facemask detection test, the developed system did not completely determine the result status of participants 9 and 10 respectively. Participant 9 wore a facemask but it is torn, the system should have classified a torn facemask into the "no mask detected" category. Also participant 10 tied a handkerchief around the face region; a handkerchief is not classified into the facemask category, but the developed system recognized the handkerchief as a facemask. This two false results (number 9 and 10) dropped the system accuracy to 80%.

Finally, the speed of operation of the system took about five seconds to completely detect and determine if a user is wearing a facemask or not. This outcome is too slow for a decision making system.

Table 1 The summary of the results obtained from the facemask recognition test conducted on the ten (10) participants using the Raspberry Pi and the pi-based hardware device for the facemask recognition system

S/N	GENDER	FACE MASK WORN?	COLOUR OF MASK	RESULT FROM MODEL
1	M	No, but heavily bearded	-	No mask detected
2	M	Yes, but worn below the nose region	blue	No mask detected
3	F	Yes, but light skinned	white	Face mask detected
4	F	No, but heavily fixed hair that covers a good part of the face region	-	No facemask detected
5	F	No	-	No facemask detected
6	M	No	-	No facemask detected
7	M	No	-	No facemask detected
8	F	Yes, but torn	white	Face mask detected
9	M	Yes, but dark in completion	black	Face mask detected
10	M	No, but tied handkerchief around the face region	white	Facemask detected

4. Conclusion

The development of machine learning model for facemask recognition for access control system used to enforce COVID-19 safety policy is presented. Also, the development of the Raspberry Pi-based hardware device that is used to implement the access control based on the outcome of the facemask test conducted on participants seeking access to the protected region is presented. The system was tested using a number of randomly sampled participants and the results gave accuracy of about 80 % for facemask detection. Apart from facemask detection, the system also has non-contact body temperature measurement sensor module that is used to capture the participant's body temperature and hence enforce the body temperature component of the COCID-19 safety policy. In all, the results show that the system can effectively be used for access control to enforce COVID-19 safety protocol.

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