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Short Paper*

Prototype Model Development using Python for Detection of Transparent Face Mask and Identification of the State of Usage of Transparent Face Mask

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Special Issue on International Research Conference on Computer Engineering and Technology Education 2023 (IRCCETE 2023). Guest Associate Editors:* **Dr. Nelson C. Rodelas, PCpE (*Computer Engineering Department, College of Engineering, University of the East-Caloocan City; nelson.rodelas@ue.edu.ph*) and **Engr. Ana Antoniette C. Illahi**, PCpE *(Asst. Professor & Vice Chair, Department of Computer and Electronics Engineering, Gokongwei College of Engineering, De La Salle University, Taft Ave., Manila; ana.illahi@dlsu.edu.ph*).

Abstract

Purpose – The right use of face masks is one of the health practices that have been implemented in response to the COVID-19 pandemic danger. The automated monitoring of face mask usage is aided using face mask detection models.

Methodology – A prototype model that can detect and identify the state of usage of a transparent face mask was developed using the object detection model Resnet50. It was trained with datasets containing people wearing proper and improper way of transparent masks and people who do not wear masks. The proponents also employed OpenCV to enable computer vision, which is utilized for methods of image processing like reading and resizing.

Result – The prototype model's overall accuracy and precision were tested on 19 distinct test scenarios, with the prototype model obtaining an average of 50.21% accuracy and 49.96% precision. The worst-case scenario for the prototype model's responsiveness is 2 frames per second.

Conclusion – The prototype model was developed as part of a pilot study to detect and identify the state of use of a transparent face mask. The test demonstrated that the prototype model can detect and identify the state of use of transparent face masks, namely proper, improper, and no mask, accurately, precisely, and responsively.

Recommendation – Future researchers must consider utilizing new techniques to further train the model; this may be accomplished by adding more images to the dataset as well as applying various types of pre-trained/hybrid models that are more optimal.

Practical Implications – The prototype model promotes health security and public safety and adheres to standard data privacy protections in the usage of a transparent face mask.

Keywords – Object Detection, ResNet50, Transparent Face mask

INTRODUCTION

COVID-19 is a respiratory illness that poses a significant danger to global health today. The World Health Organization (WHO) has recommended several safety measures due to the threats of COVID-19. One of the WHO's suggestions for personal protection and minimizing the transmission of COVID-19 is to use a face mask. According to the Centers for Disease Control and Prevention (CDC, 2022), wearing a mask has become an essential public health measure for COVID-19 mitigation. As a result, face masks became an essential part of people's everyday lives, and many countries adopted them. A face mask, however, can only be useful provided it is worn properly. In terms of improper face mask use, a 2020 survey in Japan found that just 23.1% of 2,141 persons followed all instructions for proper face mask wear. This led to the conclusion that many people utilize improper measurements when using face masks (Machida, et al., 2020). A plethora of face mask recognition models have emerged to aid in the automated monitoring of face masks usage. These models, however, can only detect common types of masks, such as surgical masks, N95 respirators, and fabric masks. The CDC recommends a transparent face mask (Machida et al., 2020). One study found that even for persons with normal hearing, a transparent mask can considerably increase auditory-visual identification of phrases, reducing the challenge in pandemic communication experienced in medical, educational, and employment. On the other hand, the dataset used by existing face mask detection models does not include a transparent face mask.

Therefore, existing face mask detection can only detect common types of masks, leading to recommendations from existing research to include the transparent face mask as part of improving existing face mask detection and developing new models that include the transparent face mask (Hussain et al., 2021). Due to the future demand for transparent face masks, proponents saw the necessity to develop a prototype model that can identify transparent face masks and incorporate the identification of the state of usage of detected face masks. Aside from the model, the proponents will also contribute to producing the dataset for a transparent face mask for future studies.

General Objectives

The proponents aim to develop a prototype model using Python that can detect transparent face masks and identify the state of usage of the transparent face mask.

Specific Objectives

- To develop a model that precisely detects and identifies the state of usage of transparent face mask
- To develop a responsive model that processes the frames
- To evaluate the model accuracy (F1-Score) in detecting and identifying the state of usage of a transparent face mask in a frame

Scope and Delimitation

The prototype model focuses on Python as its programming language. The prototype model's scope is to detect transparent face masks and identify their states of usage namely proper, improper, and no face masks. Proponents will be the ones to create a transparent face mask dataset. Furthermore, the prototype will not consider masks with printed images.

Significance of the Study

While wearing a mask is useful for infection management, numerous researchers also have noted unfavorable negative effects in interpersonal interaction because important parts of the face are partially blocked. Occlusion has a substantial impact on face emotion identification and intensity perception (Miyazaki et al., 2022).

This study may aid the community in terms of following health protocols, most specifically in terms of following the proper state of usage of a transparent face mask. By providing an improved face mask detection that can detect transparent face masks. This can then be used by larger establishments that have stricter preferences for a transparent face mask that they allow within their buildings/premises.

In addition, this study may aid future researchers in developing studies related to the detection of the proper way of wearing transparent face masks with the inclusion of emotion identification and intensity perception, which is critical for face-to-face communication inside interactive settings such as classrooms.

Conceptual Framework

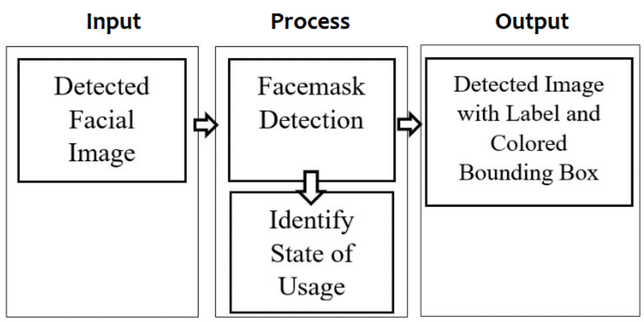

Figure 1. Conceptual Framework

Figure 1 illustrates the procedural sequence of the prototype model. The input of the prototype model is the acquired facial image; it will then undergo the two main processes of the model: first, it will determine if a face mask is present in the acquired image; next, it will identify the state of usage of a transparent face mask (it can be proper, improper, or no mask); and lastly, the output will be the detected face with a label and colored bounding box that corresponds to its specific state of usage.

LITERATURE REVIEW

Mandatory Wearing of Face masks in the Philippines

Memorandum Circular No 2020-071 was Officially released on April 09, 2020, by the Department of Interior and Local Government DILG in the Republic of Philippines (Department of the Interior and Local Government, 2020). The subject of this Memorandum is the requirement to wear a face mask or other protective equipment in public places. This memorandum was addressed to all provincial governors, city municipalities, and all others concerned. The memorandum was produced and formally released to reduce the risk of new Covid19 cases in the country. Local Government Units are encouraged to undertake the measures outlined in this memorandum, given that positive cases have been verified in all areas across the country. The key points of the memorandum are to firmly enforce the use of a face mask by all citizens, to encourage locals to produce their face masks to maintain supply and to regularly check the public to ensure they are using a face mask.

Transparent Face mask

A Clear or Transparent face mask is a type of face mask where the mouth of the people wearing it can be seen. According to CDC, the main function of this type of mask is that it can be used by a specific group of people, this includes deaf or hard of hearing people, a student or a child that is currently learning how to read, people with impairments, and people who need to observe the exact shape of the lips to make good vowel sounds (Centers for Disease Control and Prevention, 2022).

Purpose of Wearing Face mask

- Reduced propagation of infectious virus particles in respiratory droplets, including from infected people before they show symptoms (Milton et al., 2013).
- Wearing a mask reduces the danger of stigma and increases acceptability, whether it's to avoid infecting others or persons caring for COVID-19 patients in non-clinical settings. (Bion et al., 2010).
- Making people believe that they can help to stop the spread of the disease (Chen et al., 2020).
- Encouragement of concurrent transmission-reducing behaviors, such as hand hygiene and avoiding contact with the eyes, nose, and mouth (Betsch et al., 2020).
- While there is a pandemic, stop the spread of other respiratory illnesses like tuberculosis and influenza and lessen the burden of these conditions (Cowling et al., 2020).

Deep Learning

Deep learning is a subset of machine learning that uses three or more layers of artificial neural networks to study processes similar to those of the human brain. These neural networks attempt to emulate human brain function by allowing it to "learn" from vast amounts of data, yet they are incredibly inadequate to do so (Guillermo et al., 2020). Although a single-layer neural network may produce approximate predictions, extra layers can assist optimize and improve accuracy. Many artificial intelligence (AI) systems and services rely on deep learning to increase automation by executing analytical and physical activities without human interaction. Deep learning lowers some of the data preparation required by machine learning. These algorithms can ingest and understand unstructured data such as text and photos, as well as automate feature extraction, eliminating the need for human specialists.

Face Mask Detection using Deep Learning: An Approach to Reduce Risk of Coronavirus Spread

The researchers of this study employed three models ResNet50, MobileNet, and Alex Net. Approximately 26000 photos from the MAFA dataset, which had been augmented with data, were used in the training. As a result, as seen in the figure below, this model was able to detect proper and improper surgical masks and cloth masks. However, it does not necessarily identify the type of face mask that is detected, and the face mask that is recognized by the model is only limited to two types: specifically cloth mask and surgical mask (Sethi et al., 2021).

IoT and Deep Learning Based Approach for Rapid Screening and Face Mask Detection for Infection Spread Control of COVID-19

This paper incorporates real-time deep-learning models for detection and classification. Using a transfer learning technique, the model identified persons who wore the face mask appropriately, incorrectly, and without a face mask using VGG-16, MobileNetV2, Inception v3, ResNet- 50, and CNN. Using VGG-16, the investigation obtained the best accuracy of 99.81%. For future researchers, some of the recommendations of this study are to include the transparent face mask in the dataset, to expound on the type of face mask covered by the enhanced model (Hussain et al., 2021). It was stated in this study that they are recommending this type of transparent face mask since this model is only limited to two types of face masks namely surgical and N95 masks. Enhancing the model that includes the transparent face mask will also be beneficial for people who have problems with hearing and those people who require proper lip reading to communicate well.

Facial Recognition and Face Mask Detection Using Machine Learning Techniques

This study utilized CNN and transfer learning to create a model that can recognize face masks and identify people's facial traits even when half of their faces are covered by masks. The dataset used to train the model was obtained from Kaggle, which contains around 8000 photos with a roughly equal number of images of faces with and without face masks (Boulos, 2021).

The Face Mask Detection for Preventing the Spread of COVID-19 at Politeknik Negeri Batam

As a broad definition for face masks, this study built a face mask detector that can recognize surgical masks and fabric masks. The model was able to recognize a moving person even when there was a disruption in the area—it was surrounded by items of similar hue. Although the model can recognize them as generic face masks and distinguish between proper and improper, as illustrated in the image below, it cannot identify the type of face masks (surgical mask, cloth mask, etc.). A YOLO V4 deep learning mask identification technique was utilized to recognize these facial masks. They then trained and tested the model using the FDDB dataset. The experimental findings were obtained in a real-time application, and the Average Precision of YOLO v3 was increased by 10% (Susanto et al., 2020).

An Automatic System to Monitor the Physical Distance and Face Mask Wearing of Construction Workers in the COVID-19 Pandemic

The researchers of this study created a system for computers to identify face mask violations and physical separation in this investigation. This was done in connection with the safety of construction workers on projects. The face mask identification uses R-CNN Inception ResNet V2, which was trained with an existing dataset before adding their own 1000 photos, generating 3300 image-containing datasets. The vision system can distinguish between suitable and incorrect surgical and textile masks.

However, the system does not necessarily identify and label the type of face masks that were worn by the people in the images. The project's researchers compiled a face mask collection that included photographs of people wearing masks, without masks, and improper masks. To expand the training dataset, 1,000 photos of people wearing various types of masks were gathered and uploaded to the dataset. Then, using a variety of data augmentation techniques, the project's researchers raised the size of the dataset to 3300 photos in total (Razavi et al., 2021).

METHODOLOGY

Figure 2. Shows the overall functions of the prototype model. From the figure, we can see that after acquiring a facial image, it will go directly to face detection, after which it will generate ROI. The resizing of images will be dependent on the acquired ROI coordinates. The image that will be processed in resizing will only be within the ROI coordinates, after which it will go to the function of adding padding into the image to meet the desired input of the model, which is 224x224 pixels. The output of the function add padding will serve as the input in the identification of the state of usage which is the model for the identification of usage of a transparent face mask. The predicted state will be shown on a label along with its corresponding bounding box.

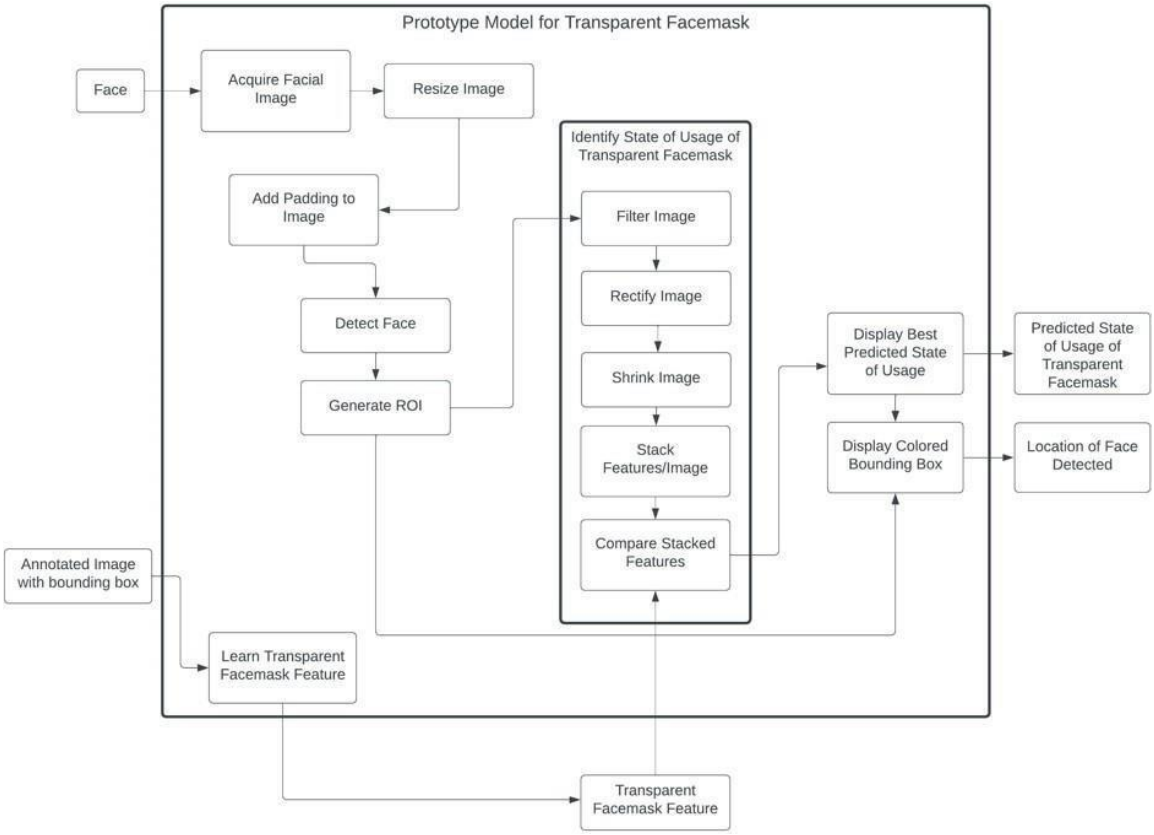

Figure 2. Functional Analysis of the Prototype Model

Automation of Dataset Gathering

The researchers first decided to train the model with manually captured images. However, the researchers decided that there was a need for more datasets because the model that was developed struggled with accuracy. Because face detection is already finished, the researchers opted to automate dataset creation. The script captures and saves images of the researchers wearing transparent face masks properly and improperly, as well as those who are not wearing any masks. The region of interest, which is the face, is the only area of the image that the script crops and resizes by 224 pixels. In total, the proponents have produced datasets containing 600 images without a mask, 600 images with improper usage of transparent face mask, and 600 images with proper usage of transparent face mask, in total the dataset contains 1800 images which are then used to train the model. The class distribution of the gathered dataset is shown in Table 1 below.

Table 1. Class Frequency Distribution per Class

Test Scenario Subgroup	Proper	Improper	*No Mask*
Angle of Face	120	120	120
Background	120	120	120
Accessories	120	120	120
Distance	120	120	120
Lighting	120	120	120

OpenCV for Computer Vision and Localization

The importation of OpenCV was utilized in this project. This library enables video stream which is required for the acquired facial image. OpenCV searches for faces in images using machine learning methods. The proponents utilize it to identify face images and general ROI or regions of interest within the collected facial picture. The resulting ROI was then utilized to build a bounding box in the identified face, together with its associated label, as an output of the prototype model.

ResNet50

The prototype model's means to Identify the State of Usage of Transparent Face mask is the ResNet50 as the base model, the ResNet50 architecture is followed which performs the 5 secondary functions needed by the prototype model: Filter Image, Rectify Image, Shrink Image, Stack Features, Compare stacked features.

The input layer has an input requirement of 224x224 RGB images. Afterward, the output proceeds to the ZeroPadding layer where the image is padded with zero values around such that the output image is a 230x230 image. Consecutively, every ResNet architecture performs early convolution and max pooling. In the Conv0 layer, the RGB channels of the image are convolved with 64 7x7 kernels with stride 2 outputting 64 convolved images with a size of 112x112. These images proceed to max-pooling in the Max Pool layer which performs pooling on a 3x3 area of each image with stride 2 outputting 64 shrunken images with a size of 56x56 (Dwivedi, 2019).

Filtered Image in Conv Layers

A convolution layer is responsible for filtering the image. Referring to figure 3, in the Conv1 layer, the 64 channels of 56x56 images are convolved with a 1x1 kernel with stride 1 still outputting images of size 56x56. Similarly, in the Conv2 layer, the 256 channels of 28x28 images are convolved with a 1x1 kernel with stride 1 still outputting images of size 28x28 (Patel, 2019).

Rectified Image in ReLU Layers

A ReLU layer is responsible for rectifying the image. Referring to figure 3, in the ReLU1 layer, the input images are rectified. Rectify pertains to converting all the negative values of the image into zero. This then outputs rectified images of size 56x56. Similarly, in the ReLU2 layer, the negative values in the input images are replaced with zeros outputting rectified images of size 28x28 (Patel, 2019).

Shrink Image in Pool Layers

A Pool layer is responsible for shrinking the image. This performs pooling on a 3x3 area of each image with stride 2 outputting shrunken image with a size of 28x28. Similarly, in the Pool2 layer, the model performs pooling on a 3x3 area of each image with stride 2 outputting a shrunken image with a size of 14x14 (Patel, 2019).

Compare Stacked Features in SoftMax Layer

A Softmax layer is responsible for comparing stacked features/images. Referring to figure 3, there are fully connected layers before the softmax layer. The fully connected layer receives the flattened image and performs calculations using the learned bias and weight of the layer to reduce the number to 1x512 and ultimately down to 1x2 (Koech, 2020). These 2 values are the confidence values returned by the model, in this case, with a mask or without a mask.

Hyperparameters

Before a learning algorithm is trained, a hyperparameter's value is selected. Table 2 below shows the values of the hyperparameters used in the study.

Table 2. Hyperparameters of the Model

Hyperparameter	Value
Learning Rate	0.0001
Epoch	100
Batch Size	32
Optimizer	Adam
Activation	Softmax
Loss	Binary Cross Entropy
Metrics	Accuracy
Neurons	256 (input layer) 2 (output layer)

RESULTS

Figure 3 depicts sample findings from testing in recognizing the state of use of a transparent face mask in conjunction with the no face mask condition. The number of fps, the confidence level, and the categorized condition are displayed for each output. Green shows that the transparent face mask is being worn correctly, light blue suggests that it is being worn incorrectly, and red denotes the absence of a face mask.

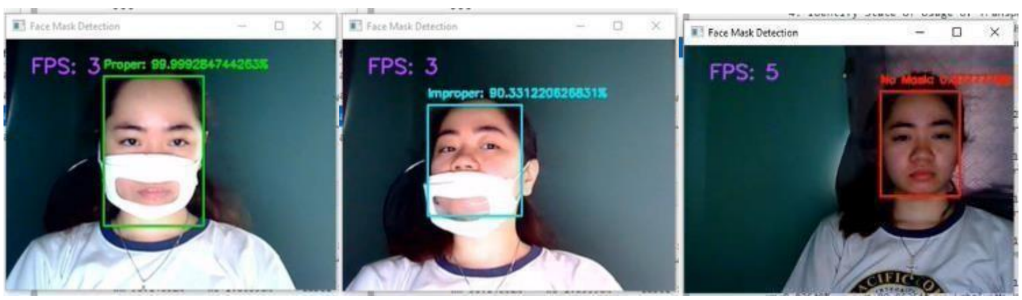

Figure 3. Results of Detection

Tables 3 and 4 show the prototype model's overall accuracy and precision. Each of the specific rates, namely accuracy, and precision, were displayed in a distinct table to allow for accurate differentiation of the results of each rate as well as seeing the results of each of the test group situations. The average result was computed per test group scenario in the fifth column of Tables 3 and 4, while the average result for each of the states of usage of transparent face mask, namely proper, improper, and no mask, is in the last row of Tables 3 and 4. The average result is calculated by combining all the values for each state and dividing them by the number of test groups, which is five. The cell located at the lower right corner contains the results for the overall average of each rate: Accuracy and Precision.

Table 3. Overall Accuracy

Test Scenario Subgroup	**Proper (%)**	**Improper (%)**	***No Mask (%)***	**Average (%)**
Angle of Face	44.83	51.66	46.15	47.21
Background	48.78	63.95	56.79	56.51
Accessories	40.42	48.14	0	29.52
Distance	34.78	64.67	43.67	47.71
Lighting	37.77	73.04	52.19	54.67
Average (%)	41.92	61.65	47.05	50.21

Table 4. Overall Precision

Test Scenario Subgroup	**Proper (%)**	**Improper (%)**	***No Mask (%)***	**Average (%)**
Angle of Face	33.33	76.92	35.48	48.58
Background	38.46	81.81	45.09	55.12
Accessories	25.67	70.27	0	31.98
Distance	44.44	73.97	32.20	50.20
Lighting	32.07	81.74	46.29	53.37
Average (%)	32.76	78.21	38.91	49.96

The number of frames per second is determined directly from the system by adjusting the codes to produce the raw obtained image's frames per second. In recording the results of FPS, a duration of 1-minute video recording per test scenario was used. The listing of the FPS was done by applying an automatic listing generator code. In this way, all the FPS within the 1-minute video recording will be recorded and saved in a CSV file automatically. The minimum FPS of each test scenario (refer to Table 5) under 1 minute was recorded in one of the columns of this table.

Table 5. Responsiveness

Light Intensity Level	**State of Usage of Transparent Face mask**	***Minimum FPS under 1 minute***
0.108 lux	Proper	2 fps
	Improper	2 fps
	No Mask	3 fps
10.8 lux	Proper	3 fps
	Improper	3 fps
	No Mask	3 fps
1075 lux	Proper	3 fps
	Improper	2 fps
	No Mask	3 fps
10700 lux	Proper	3 fps
	Improper	2 fps
	No Mask	2 fps

The minimum, maximum, and average results are provided in Table 6 along with the proponents' evaluation of the Summary of Results regarding the study's objectives.

Table 6. Summary of Findings

Objectives	**Measured Parameters**		
	Minimum	**Maximum**	**Average**
Precision (%)	0 %	81.81 %	49.96 %
Responsiveness (fps)	2 fps	3 fps	2.5 fps
Accuracy (%)	0 %	73.04 %	50.21 %

DISCUSSION

Accuracy

The prototype model's accuracy refers to the ability of the model to accurately detect and identify the state of usage of transparent face masks present in a frame considering the imbalanced classification distribution of the training dataset. A total of 19 test scenarios which are subdivided into 5 main groups were conducted. Table 3 shows that the prototype model can fairly detect and identify faces with improper, proper, and no transparent face masks with 50.21% overall accuracy. The model's accuracy is significantly impacted by the test subject's face's distance from the camera, the angle at which it faces the camera and the presence of any accessories on the subject's face.

Precision

The prototype model’s precision was measured by the proportion of true positive prediction over the total positive prediction of a face mask. Precision refers to the ability of the model to correctly detect and identify the state of usage of a transparent face mask present in a frame without providing false positives. A total of 19 test scenarios which are subdivided into 5 main groups were conducted. Table 4 shows that the prototype model can fairly detect and identify faces with improper, proper, and no transparent face masks with 49.96% overall precision. The model's precision is significantly impacted by the test subject's face angle at which it faces the camera and the presence of any accessories on the subject's face.

Responsiveness

The responsiveness test considers the different light setting while testing the different states of usage of a transparent face mask. Among all the test scenarios, the light condition with 10 Lux has a value of 3 for all the states of usage of transparent face mask, by this, it has the highest minimum value of FPS. The minimum FPS of each of the test scenarios ranges from 2 to 3, where 2 is the minimum value of FPS since it is the lowest value among all the minimum FPS. As a result, proponents can conclude that the light setting has no effect on the fps value and that the prototype model's rating of 2 fps represents the worst-case situation.

Summary of Findings

The average precision of the detection and identification result is 49.96%. The average accuracy of the prototype to detect and identify the use of a transparent face mask as a measure of its overall performance is 50.21%. Lastly, the prototype's average responsiveness resulted in a score of 2.5 fps.

CONCLUSIONS AND RECOMMENDATIONS

The prototype model was a pilot project for detecting and identifying the state of usage of a transparent face mask. The test has shown that the prototype model can accurately, precisely, and responsively detect and identify the state of usage of a transparent face mask, namely: proper, improper, and no mask. These results have satisfied all the general objectives and specific objectives. The prototype model is rated as fairly accurate, with 49.96% overall accuracy, precise, with 50.21% overall precision, and very poorly responsive, with at least 2 fps. Future researchers must consider utilizing new techniques to further train the model; this may be accomplished by adding more images to the dataset as well as applying various types of pre-trained/hybrid models that are more optimal.

IMPLICATIONS

The prototype model promotes health security and public safety by identifying the three conditions under which a transparent face mask may be used while adhering to COVID-19 health regulations. Standard data privacy protections are followed by the prototype model.

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DECLARATIONS

Conflict of Interest

All authors declare that they have no conflicts of interest.

Informed Consent

The researchers' photos were included in the research paper, which ensures their full consent to have them published in an international journal.

Ethics Approval

The conducted research uses only the researchers' photos and did not include other humans as participants hence it does not violate any ethical issues.

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