Convolutional neural network-based Face Mask Detection

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Abstract- The Covid-19 pandemic has adversely affected our lives. Movements and trading activities have been paralyzed. People have been forced to normalize into the new normal. The pandemic has shaped the way we live. In an attempt to fight against the pandemic, governments and other health organizations have fostered restrictive measures to reduce the spread of Covid-19. Some of these restrictions include but are not limited to total lockdown, limited social gatherings and the use of face masks. The use of face masks called for the need to have facial detection machines which can be developed from Keras, Scikit-learn and OpenCV. This paper examines the Convolutional Neural Network (CNN), which is utilized for detecting and classifying an individual wearing a mask.

Index Terms- Convolutional Neural Network (CNN), OpenCV, Keras.

I. INTRODUCTION

The pandemic, since its onset, has been considered among the most threatening viruses in the history of humankind. According to statistics, the virus spreads faster simply by getting exposed to contaminated surfaces. Social interactions are ranked top as means of spreading the virus. From the onset of the pandemic, lack of consciousness contributed to increased cases. Covid-19 was a new phenomenon ever reported in many parts of the world. In this case, many people were not well prepared and had little knowledge about the virus—this paralyzed efforts against the pandemic. As a result, we had to adapt to the situation and develop appropriate measures to minimize the adverse effects of Covid-19. One of the key measures was putting on face masks during social interactions. This literature review provides a better understanding of the Convolutional Neural Network while efforts to protect against Covid-19 remain a priority. Convolutional Neural Network is mainly utilized to recognize people's faces putting on their masks as far as safety measures are concerned (Upadhyay & Rudra, 2021).

Deep learning methods have created a significant background for artificial intelligence. The literature review shows that the Convolutional Neural Network is effective for face masks detection. The mechanism can be vital in critical areas such as railway stations, airports and other crowded social places. The Convolutional Neural Network has helped create a safer environment for populations in the current scenario. Face mask detection mainly involve locating the face and stating whether a mask covers the face or not. This process using the Convolutional Neural Network is suitable for proving the identity of individuals while wearing face masks. The process is essential for surveillance, education and autonomous driving purposes. Farman et al. (2022) suggest machine learning and deep learning to detect faces among individuals wearing face masks. The study reveals excellent results regarding the effectiveness of ML and DL. Also, it is reported that DL-based mechanisms are typical amid the crisis to detect individuals without masks. This has helped control the spread of the virus.

II. LITERATURE REVIEW

Amid Covid-19, various studies have proposed several hybrid designs that utilize the DL to detect individuals without masks. The hybrid design is said to have two major sections; Resnet50 and the Vector support machine. The first design is utilized for extraction, while the other ensembles decision trees and algorithms intended for recording and classifying the accuracy of tests. However, other studies reveal that wearing face masks modifies the faces of individuals, thus interfering with the face resonance. Furthermore, for actual face recognition, Ramachandra et al. propose using a 3D silicone mask. Based on the visual refractive analysis, Li et al. suggest a 3D face mask to measure the image reflectance.

Notably, Keras is an open-source machine that renders a Python interface for man-made neural networks. Keras operates as a Tensor Flow interface. The models and layers are considered core data structures. Keras provides a site for the implementation of the CNN model. On the other hand, Tensor flow is mainly utilized for a wide range of activities but specifically on the interface and training of the deep neural networks. Besides, Tensor Flow reshapes the image within image processing amid facial detection. CNN network reveals the relationship between raw image pixels and their rating classification. CNN is primarily a deep neural network which treats images as input. This input goes through processes involving convolution layers, kernels, fully connected layers and pooling layers in an effort to provide a definition of an image in terms of stochastic values ranging between zero to one. The convolution is the crucial layer where data is first obtained from the input image. The pooling layers optimize the parameter

counts, especially when the images are extra-large in size (Farman et al., 2022).
CNN has proved to be effective in facilitating face mask detection through surveillance. This has significantly helped reduce the spread of Covid-19 through social interactions as individuals without masks are encouraged to wear them. According to various studies, it is revealed that the Convolutional Neural Network is accurate enough in detecting faces without masks in critical areas such as airports, railway stations and other public domains. In workplaces with vast numbers of workers, the Convolutional Neural Network can be implemented for face mask detection. The Convolutional Neural Network attains an accuracy of 93.9 percent (Upadhyay & Rudra, 2021). Currently, there are many uses inclined to Convolutional Neural networks in preventing damage and loss of lives. The facility can be utilized in fire disasters, analysis of facial features, and health care, among other fields. Since more emphasis on this literature is directed towards Covid-19 and prevention measures, CNN has helped address the Covid-19 situation by detecting and establishing the identity of faces wearing masks. The studies provide more significant insights into how individuals without masks can be placed in public to emphasize the use of face masks in preventing the spread of the pandemic.

III. PROPOSED WORKS

The proposed paper will detail the use of convolutional neural system model for face masking among people in public places. The system will help to detect if people are wearing their face mask properly. It will also help detect those who are wearing their masks wrongly or do not have a mask. The paper discusses the processes that will be involved in the system as well as the technology that will be used to help prevent the spread of covid-19. The process starts with data preparation and processing, which finally ends with the possible outcomes of the real-time face mask prediction. The figure below shows the process involved.

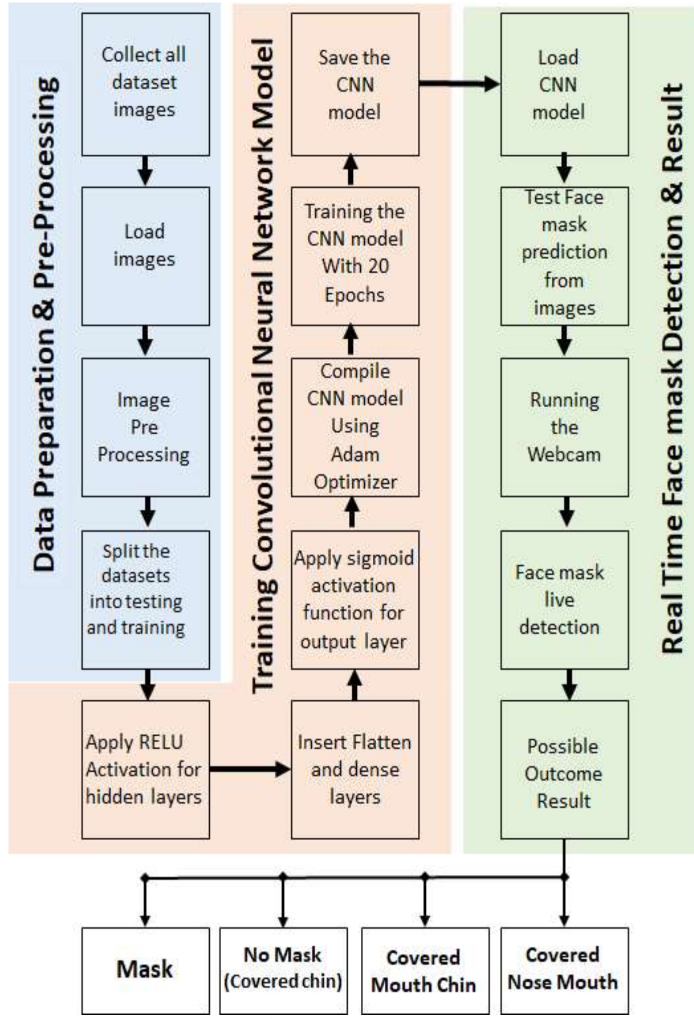

Figure 1 *'Facemask Detection System Block Diagram'*

IV. DATA PREPARATION

Different proper ways of putting on mask pictures were taken, as well as the improper ways of putting on a mask. The system was then trained on these different masking ways for better accurate results of how people are wearing their masks. Fifteen thousand pictures of the data were used on the system. The used data was gotten from (P. Bhandary) "MaskedFace-Net (https://github.com/cabani/MaskedFace-Net)".
The used data had different categories, which included "Correctly Masked Face Dataset (CMFD)," which contained the data for proper ways of masking, and the "Incorrectly Masked Face Dataset (IMFD)" for wrong masking ways. The wrong masking ways were further divided into sections of the position of the mask where these categories include:

- ❖ No mask.
- ❖ Covered mouth chin
- ❖ Covered nose mouth.

The collected image data was labeled into the different masking ways, which consisted of about 3500 pictures for each category in proper masking, without a mask, covering only the mouth chin, and nose mouth covered.

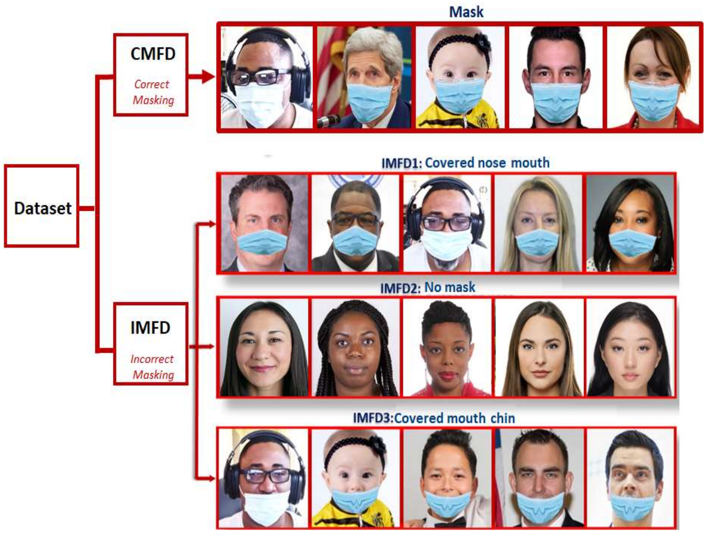

Figure 2 *Masking Categories*

V. DATA PREPROCESSING

The quality of the data pictures into the system will determine the accurateness of the model. In this section, the data is cleaned to remove defective pictures so wrong predictions would not be made. Secondly, the images are sized 100 by 100 for optimum result. High-sized photos and low hardware resources may result to memory errors and poor accuracy. The array of images is then transformed to a Numpy array for quicker computation.

The image processing involves techniques such as face detection, cropping, and blob from the images which facilitate the data processing. For any specific image detected, 'Single Short MultiBox Detector (SSD) framework' is applied to detect the location of the face using pre-trained deep neural network model in OpenCV called Floating-point 16 version (res10_300x300_ssd_iter_140000_fp16.caffemodel). The model may be downloaded from GitHub (https://github.com/opencv/opencv_3rdparty/raw/19512576c112aa2c7b6328cb0e8d589a4a90a26d/res10_300x300_ssd_iter_140000_fp16.caffemodel). The images within Single Short MultiBox Detector (SSD) will be cropped and resize using blob from image (Bhadani & Sinha 2020) as shown in figure 3.

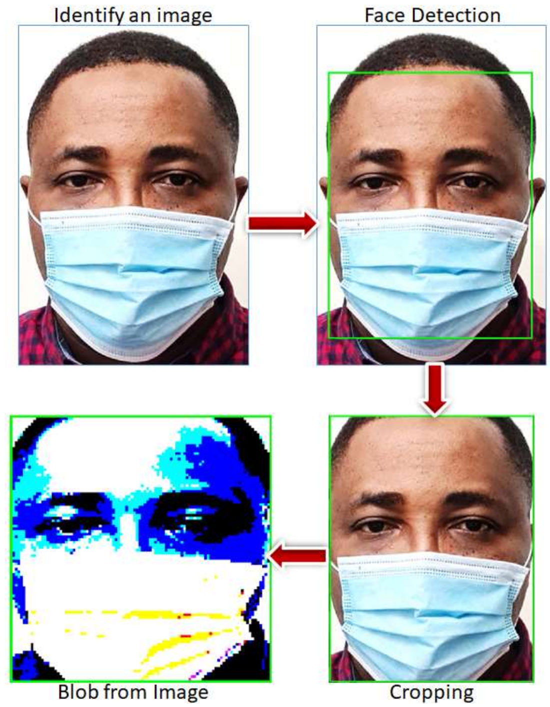

Figure 3: *Image preprocessing*

VI. SPLITTING DATA FOR MODEL TRAINING

The collected data of 15 000 were used for the proposed model. The model must be trained precisely using a certain dataset and tested alongside different data using the Scikit-learn. The splitting of data during training is mainly used to set the machine into the learning model, and testing is used to calculate the accuracy of the machine. 80% (12,000) of the data were used for the model's training, while the rest for testing.

VII. MODEL ARCHITECTURE AND TRAINING

The organization of a managed learning CNN system is done after its process of training to categorize the proficient images to their particular classes by knowing important pictorial patterns by the use of "TensorFlow" as the main building blocks for the model proposed. The study used 80%, equivalent to 12,000 image data for training and the rest for testing. The input image is preprocessed and augmented. The model architecture illustrated in figure 4 below is a consecutive model established with 'TensorFlow.keras' and compiled with 'Adam optimizer.' More optimizers will be discussed in the following section.

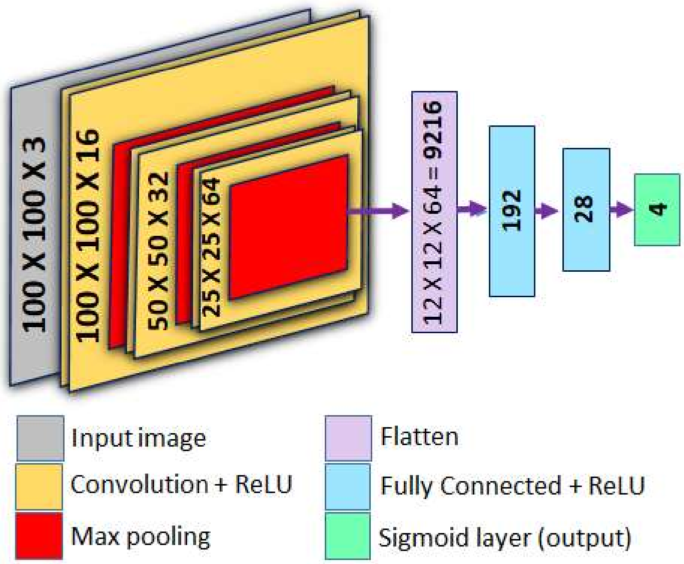

Figure 4. *Proposed Facemask Detection CNN Model Architecture*

```
# convolution neural network

model = Sequential([
    layers.Conv2D(16,3,padding='same',input_shape=(100,100,3),activation='relu'),
    layers.MaxPool2D(),
    layers.Conv2D(32,3,padding='same',activation='relu'),
    layers.MaxPool2D(),
    layers.Conv2D(64,3,padding='same',activation='relu'),
    layers.MaxPool2D(),
    layers.Flatten(),
    layers.Dense(192,activation='relu'),
    layers.Dense(28,activation='relu'),
    layers.Dense(4,activation='sigmoid')
])
# compiling CNN
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
              loss=tf.keras.losses.categorical_crossentropy,metrics=['accuracy'])
```

Table 1: *Illustrate the python code used to develop the sequential CNN model for proposed Facemask detection described in figure 4*

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 100, 100, 16)	448
max_pooling2d (MaxPooling2D)	(None, 50, 50, 16)	0
conv2d_1 (Conv2D)	(None, 50, 50, 32)	4640
max_pooling2d_1 (MaxPooling2D)	(None, 25, 25, 32)	0
conv2d_2 (Conv2D)	(None, 25, 25, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 12, 12, 64)	0
flatten (Flatten)	(None, 9216)	0
dense (Dense)	(None, 192)	1769664
dense_1 (Dense)	(None, 28)	5404
dense_2 (Dense)	(None, 4)	116

Table 2: *Illustrate the proposed sequential CNN model parameters described in figure 4*

The above model is separated into convolutional part (feature abstraction) and fully connected part (classifier). The convolutional part is used to separate and identify the numerous features of the pictorial for investigation in the Feature Extraction process. In contrast, the fully connected part utilizes the convolution method's results and predicts the image category according to the extracted features.

The proposed model is created when convolutional parts extract the features of the input image, pooling layers reduce the magnitude of the convolved map feature, which helps to reduce the computational costs, and lastly, fully-connected layers connecting the neurons between the hidden layers are connected. The Kernel size is fixed to 3 x 3, which stipulates the height and breadth of the 2D convolution gap, the stride is established to 1, and padding is fixed to 1 for all convolution arranged layers. The filter dimensions differ from the first, with 16 and 32 for the second, while the third layer has 64. The input image dimension to the planned model is 100 x 100 x 3. The activation function used for the system are "Rectified Linear Unit (ReLU) and Sigmoid for the output layer." After the convolutional process, all the image dimensions are flattened and serve as the input to fully connected (FC) two hidden neural network layers, where the number of neurons in each layer is calculated using the pyramidal rule formula given below.

Number of neurons = *sqrt(m*m)*
Where m = number of inputs
n = number of outputs

VIII. OPTIMIZERS COMPARISON ON THE PROPOSED MODEL

The optimization algorithm discovers the value of the weights that reduces the error in planning inputs to outputs. These algorithms or optimizers largely affect the deep learning model's correctness, accuracy and computation time.

This segment emphasizes various optimizers examples such as Adam, SGD, Adagrad and RMSProp, which were practically analyzed using 20 epochs. The optimizers are used as part of compiler to build the face mask detection model, increase the system's accuracy, and improve speed and efficiency.

After running the proposed model with 15,000 images data on different optimizers, the accuracy, the loss and the computation time at 20 epochs are shown in the tables and figures below.

Optimizers Comparison For Training Accuracy				
Epochs	Adam	Adagrad	RMSprop	SGD
0	0.929977	0.654584	0.890758	0.445503
1	0.972659	0.855499	0.969071	0.745763
2	0.982927	0.905604	0.981814	0.822219
3	0.986762	0.923667	0.987999	0.865396
4	0.990103	0.939626	0.992824	0.889274
5	0.993567	0.945565	0.994309	0.90746
6	0.99666	0.949524	0.996412	0.919213
7	0.998392	0.953977	0.996412	0.926884
8	0.998763	0.955833	0.996907	0.932575
9	0.99233	0.95806	0.998021	0.938018
10	0.995917	0.96004	0.997897	0.944699
11	0.998021	0.960782	0.999381	0.943833
12	0.99901	0.964493	0.998639	0.947915
13	1	0.964493	0.99901	0.950019
14	1	0.965731	0.999505	0.95274
15	1	0.968205	0.999505	0.952864
16	1	0.969442	0.999134	0.954101
17	1	0.970927	0.998763	0.955215
18	1	0.969937	0.999134	0.957442
19	1	0.973772	0.999381	0.96004

Table 3: *Illustrate the optimizers comparison for training accuracy*

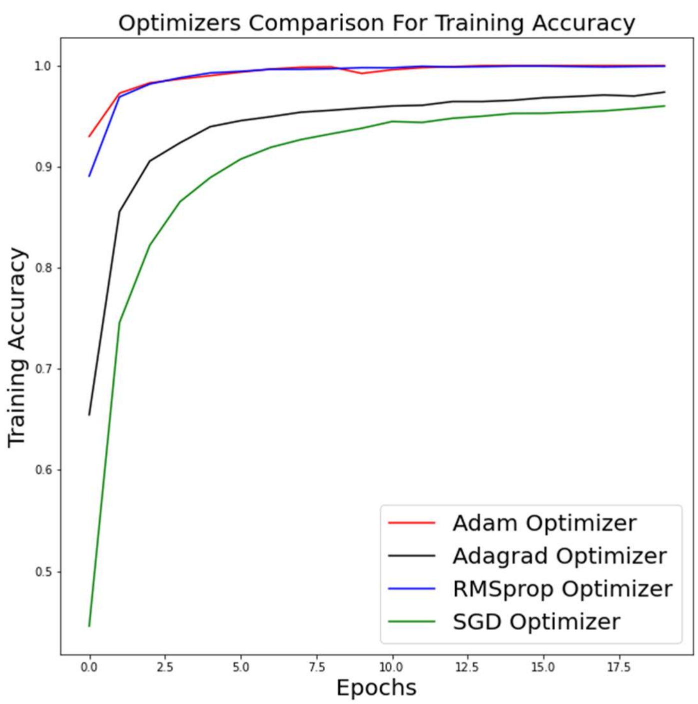

Figure 5: *Optimizers comparison for Training Accuracy*

Optimizers Comparison For Training Loss				
Epochs	Adam	Adagrad	RMSprop	SGD
0	0.201516	1.121326	0.292194	1.332685
1	0.083347	0.455191	0.089989	1.040651
2	0.048756	0.29924	0.053115	0.590936
3	0.041646	0.234404	0.034416	0.417159
4	0.029594	0.198728	0.024695	0.337263
5	0.018105	0.176975	0.018567	0.287963
6	0.010293	0.162949	0.014283	0.252783
7	0.006416	0.15128	0.01127	0.226847
8	0.004085	0.142037	0.009095	0.205373
9	0.021839	0.134393	0.004859	0.189497
10	0.013739	0.128492	0.007395	0.17883
11	0.006947	0.121764	0.001783	0.168239
12	0.003946	0.117135	0.007724	0.159153
13	0.000534	0.112864	0.006504	0.152785
14	0.000056	0.107878	0.002752	0.145528
15	0.000019	0.105696	0.001607	0.139719
16	0.000014	0.099987	0.003633	0.135576
17	0.00001	0.095878	0.009058	0.13027
18	0.000008	0.095213	0.001745	0.125534
19	0.000007	0.08977	0.002389	0.122385

Table 4: *Illustrate the optimizers comparison for training loss*

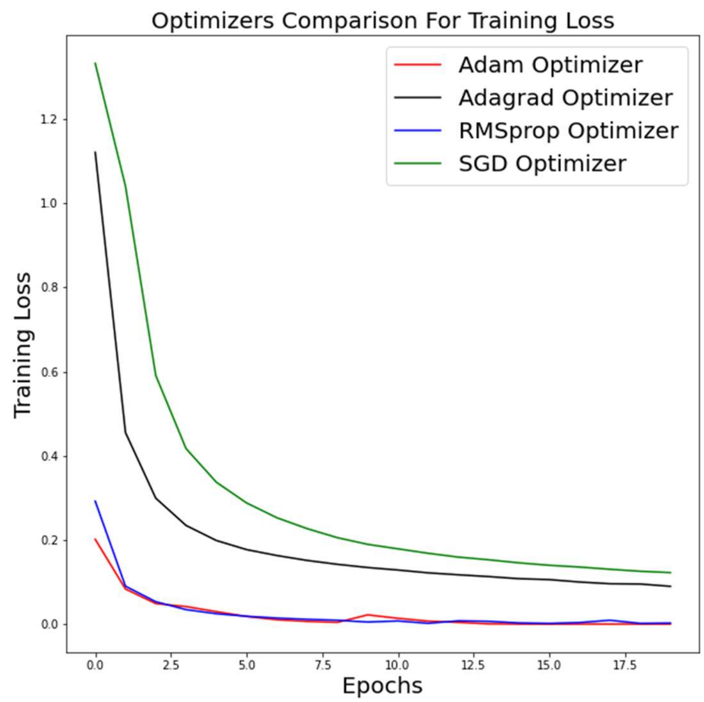

Figure 6: *Optimizers comparison for Training Loss*

Computation Time	
Adam	14.30 min
Adagrad	14.59 min
RMSprop	15:33 min
SGD	14.05 min

Table 5: *Illustrate computation time for optimizers*

From the results above, Adam optimizer proved the best result regarding training accuracy of 1 and training loss of 0.000007. RMSprop displays similar accuracy to Adam's, but with comparatively much longer computation time, and lastly, SGD contains lowest accuracy and computation time. From the above result, the Adam optimizer was selected in this research paper as an optimizer for the proposed face mask detection CNN model for the best probability of getting the best result.

IX. RESULT AND ANALYSIS

The model was executed with 20 epochs and compiled with Adam optimizer, resulting in high accuracy. The model accuracy increased and the loss decreased as the epochs reached maximum count.

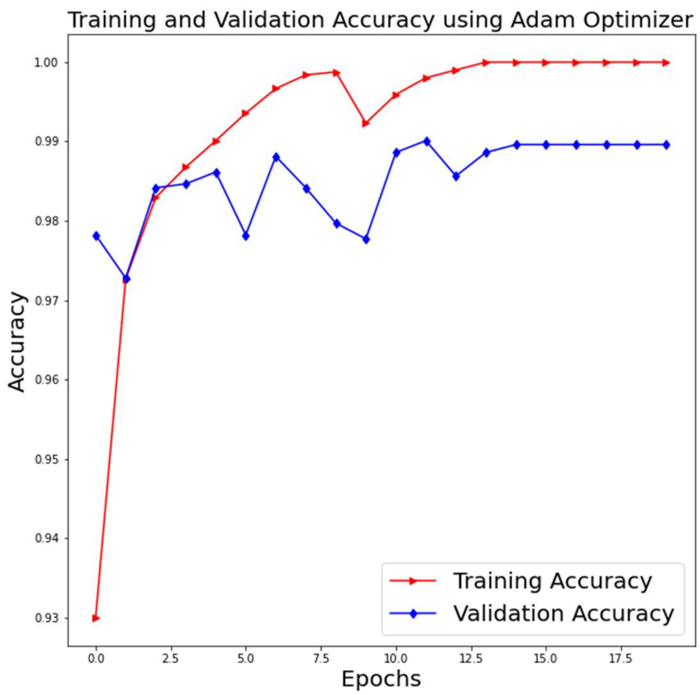

Figure 7: *Training and Validation Accuracy using Adam optimizer*

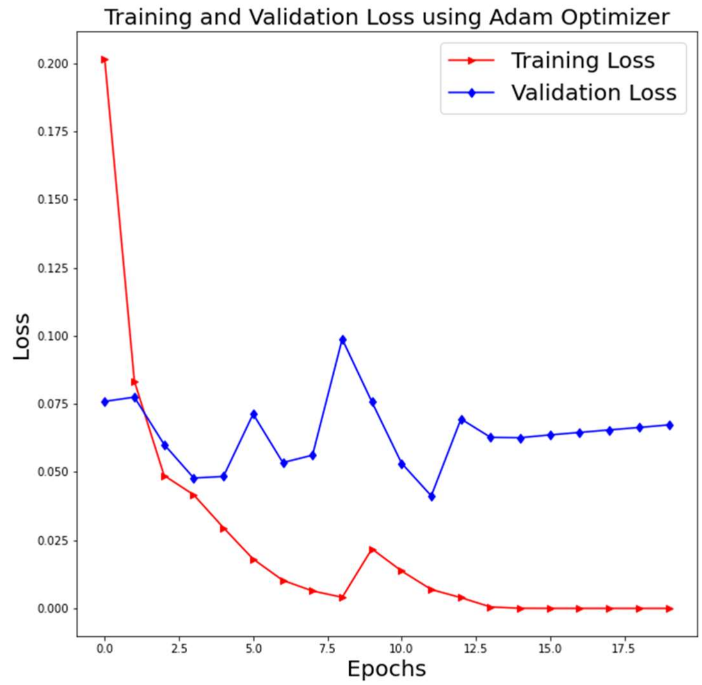

Figure 8: *Training and Validation Loss using Adam optimizer*

Finally, the proposed model was integrated with live webcam to recognize the real-time facial mask status and then predict the result based on the four possible different output categories as mentioned in section IV. Figure 7 and figure 8 illustrate that the model achieved high level of training accuracy of 100% and least training loss of 0.0007% at the end of 20 epochs, which implies that the proposed model achieved high level of accuracy of getting the best prediction and result as demonstrated in figure 9.

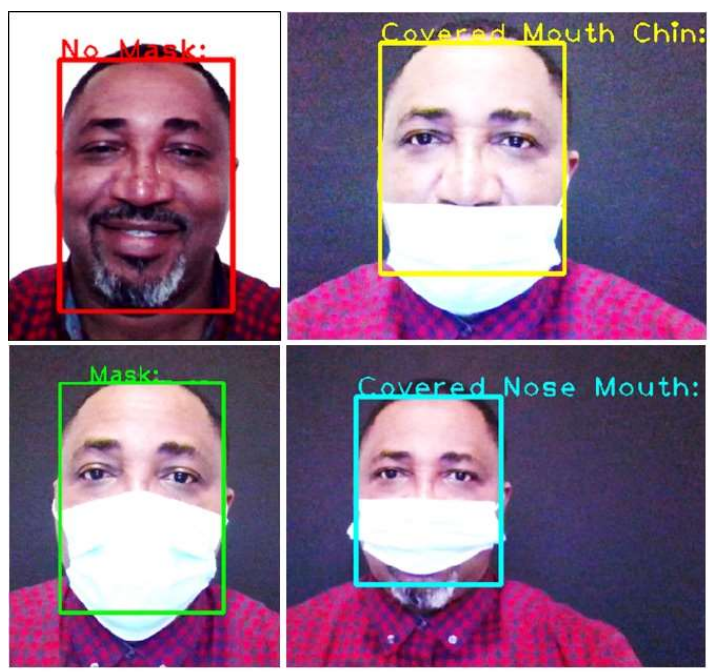

Figure 9: *Proposed facemask model final output result*

X. FUTURE IMPROVEMENT

This model can be developed and integrated onto neuromorphic hardware (chip) like IBM TrueNorth that uses spiking neural networks for better computation, energy efficiency, execution speed, robustness and ability to learn from computation to produce more accurate result and performance. Also, the integration of an improved facial recognition system to support the identification of a person while on a mask.

XI. CONCLUSION

To control COVID-19 pandemic in the societies, this publication suggests a face mask identification system using CNN to detect people's faces and the state of wearing face masks in the public domains. The proposed model can determine whether a face mask is present or not using Keras, OpenCV, and CNN, and the model provides accurate and prompt result. In workplaces where many workers are, employers and companies are encouraged to use this proposed model to improve the safety and reduce the risk of related to COVID-19 exposure.

The trained model produces a training accuracy of 100% as discussed in section VIII and IX which implies that the proposed model achieved high level of accuracy of getting the best prediction and result. Because of its accuracy and processing effectiveness, this proposed model is a strong contender for a real-time face mask detection monitoring system.

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