Live Face Mask Detection Using IBM Watson

1 INTRODUCTION

1.1 Overview

The world is fighting with Covid19 pandemic. There are so many essential types of equipment needed to fight against the Coronavirus. One such essential is Face Mask. Firstly face mask was not mandatory for everyone but as the day progresses scientists and Doctors recommended everyone wear a face mask. Now To detect whether a person is wearing Face Mask or not we will be training a deep learning model and building a flask app for video streaming and detection.

1.2 Purpose

In current times, after the rapid expansion and spread of the COVID-19 outbreak globally, people have experienced severe disruption to their daily lives. One idea to manage the outbreak is to enforce people wear a face mask in public places. Therefore, automated and efficient face detection methods are essential for such enforcement. In this paper, a face mask detection model for static and real time videos has been presented which classifies the images as "with mask" and "without mask". The model is trained and evaluated using the Kaggle data-set. The gathered data-set comprises approximately about 4,000 pictures and attained a performance accuracy rate of 98%. The proposed model is computationally efficient and precise as compared to DenseNet-121, MobileNet-V2, VGG-19, and Inception-V3. This work can be utilized as a digitized scanning tool in schools, hospitals, banks, and airports, and many other public or commercial locations.

Keywords OpenCV · Convolutional neural network (CNN) · COVID-19 · Deep learning · Real-time face mask detection

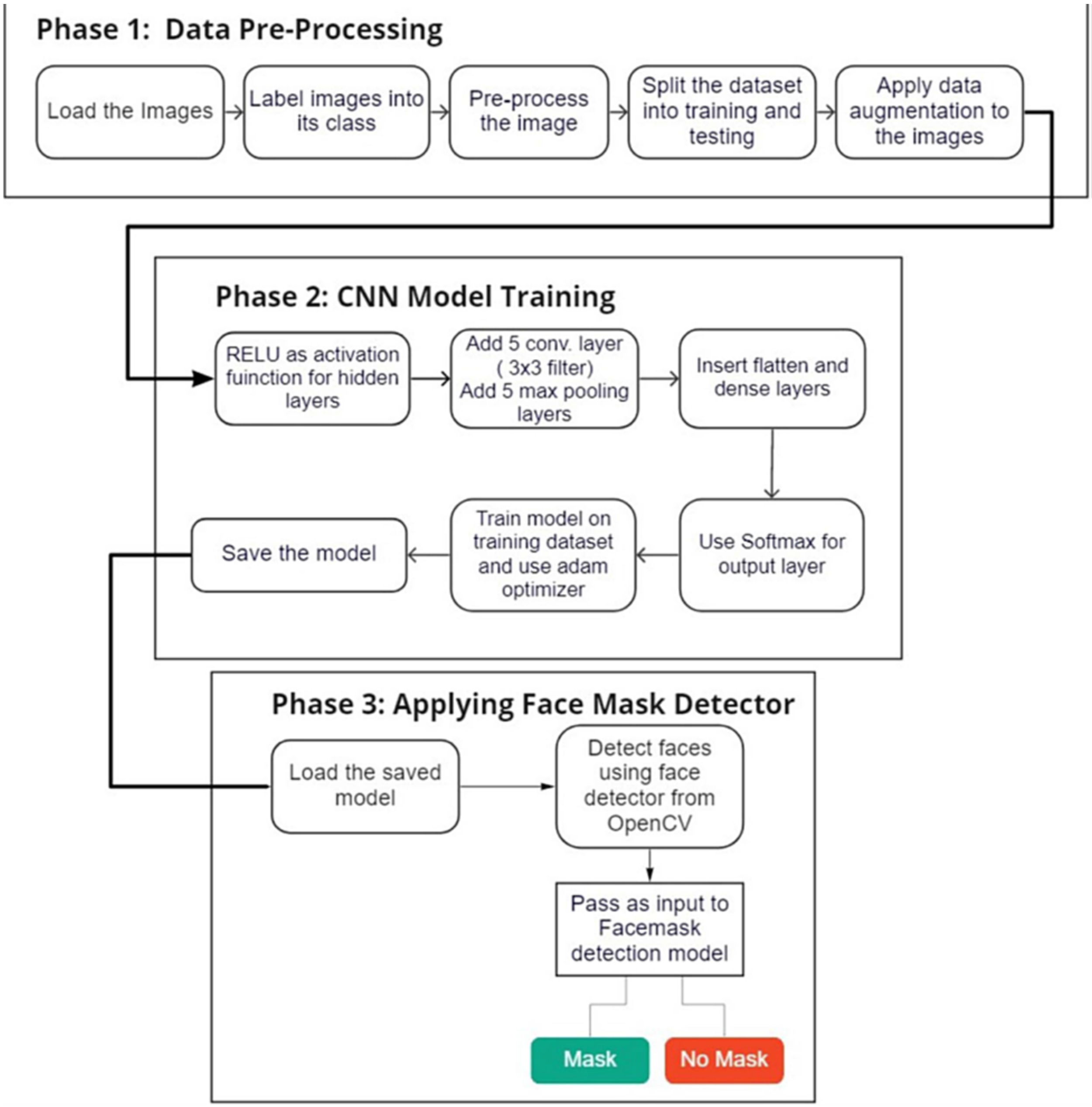
2 LITERATURE SURVEY

2.1 Proposed methodology

In order to predict whether a person has put on a mask, the model requires learning from a well-curated dataset, as discussed later in this section. The model uses Convolution Neural Network layers (CNN) as its backbone architecture to create different layers. Along with this, libraries such as OpenCV, Keras, and Streamlit are also used. The proposed model is designed in three phases: Data pre-processing, CNN model training and Applying face mask detector as described

3 THEORITICAL ANALYSIS

3.1 Block Diagram



3.2 Hardware / Software designing

Hardware requirements

1. Processor – i5
2. RAM – 8GB

Software requirements

1. Anaconda3

2. Jupyter Notebook

3. Browsers

4. Spyder

4 EXPERIMENTAL INVESTIGATIONS

The model architecture adopted for the research is described. The main components
of the architecture are 2D convolutional layers (conv2D), pooling layer, activation functions and fully-connected layers. The proposed model comprises of a total of *5 Conv2D*
layers with padding 'same' and stride of 1. At each conv2D layer, feature map of 2D input
data is extracted by "sliding input" across a filter or kernel and perform following operation:

$$C(Z) = (P \times Q)(x) = \int_{-\infty}^{\infty} P(Z) \times Q(Z - x)\, dZ$$

(

In the above, P represents the matrix of the input image, and Q is convolutional kernel
giving C as output.

Pooling layers decrease the size of the feature map. Thus, the number of trainable parameters
is reduced, resulting in rapid calculations without losing essential features. Two major

kinds of pooling operations can be carried out: max pooling and average pooling. Max pooling implies making the most significant value present in the specific location where the kernel resides. On the other hand, average pooling computes the mean of every value in that region.

Activation functions are the nodes that are placed at the end or among neuronal networks (layers). They decide whether or not the neuron fires. Choice of activation function at hidden layers as well as at output layer is important as it controls the quality of model learning. The ReLU activation function is primarily used for hidden layers; whereas, Softmax is used for the output layer and calculates probability distribution from a real number vector. The latter is the preferred choice for multi-class classification problems. Regarding ReLU, it offers better performance and widespread depth learning compared to the function of sigmoid and tanh.

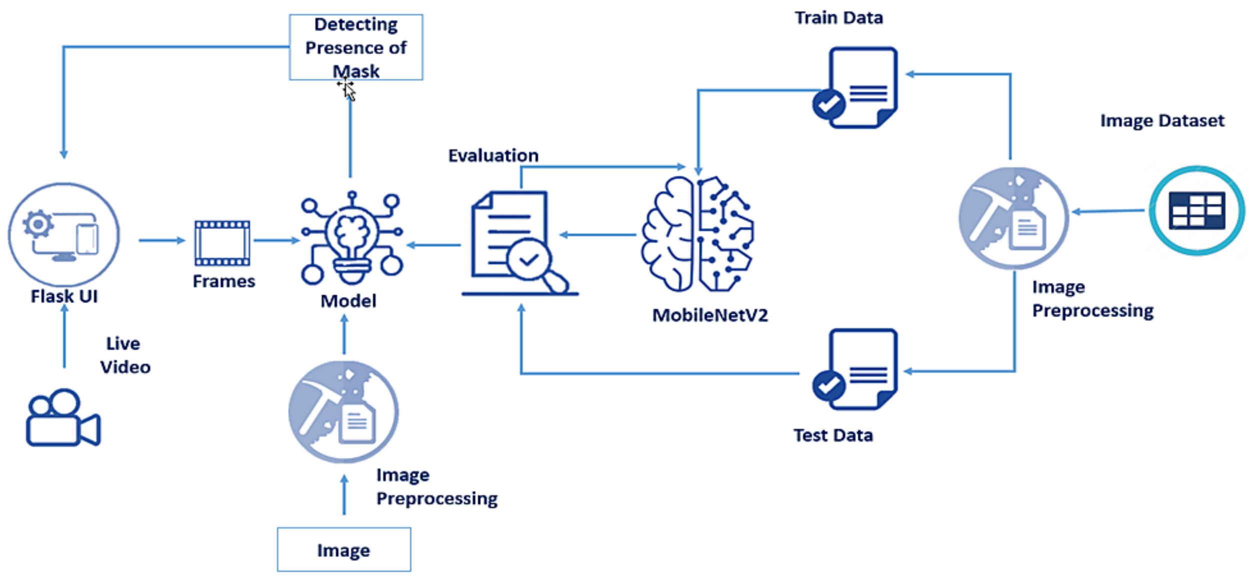
After all Convolutional layers have been implemented, the FC layers are applied. These layers help to classify pictures in both the multi class and binary categories. In these layers, the softmax activation function is the choice of preference to produce probabilistic results.

$$ReLU : f(x) = max(0, x) \quad (2)$$

$$Softmax : (x_i) = \_\exp(x_i)$$

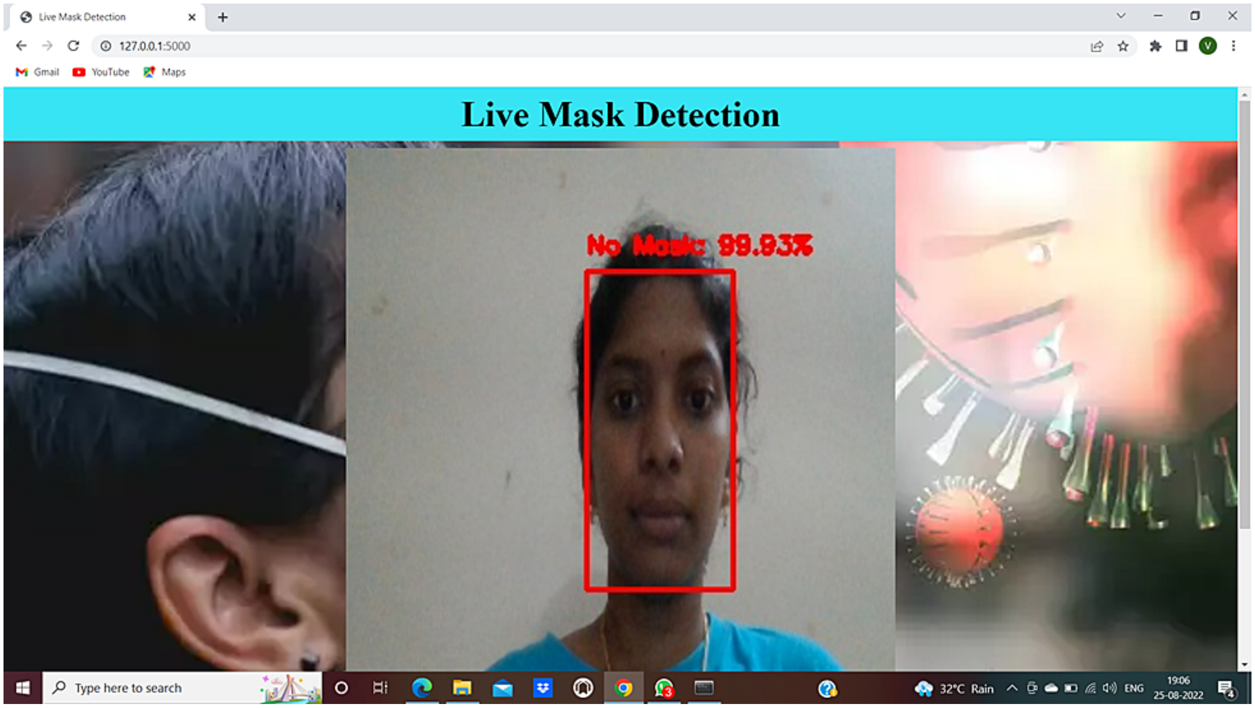
$$j \exp(x_j)$$

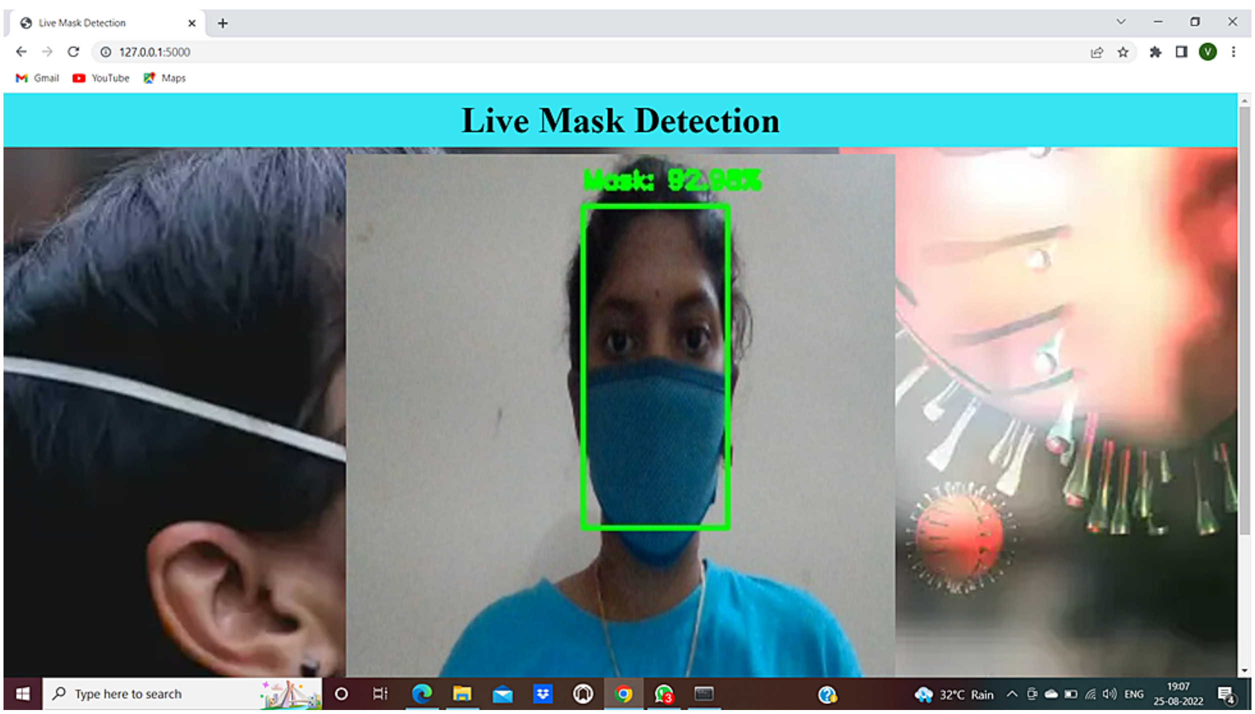
5 FLOWCHART

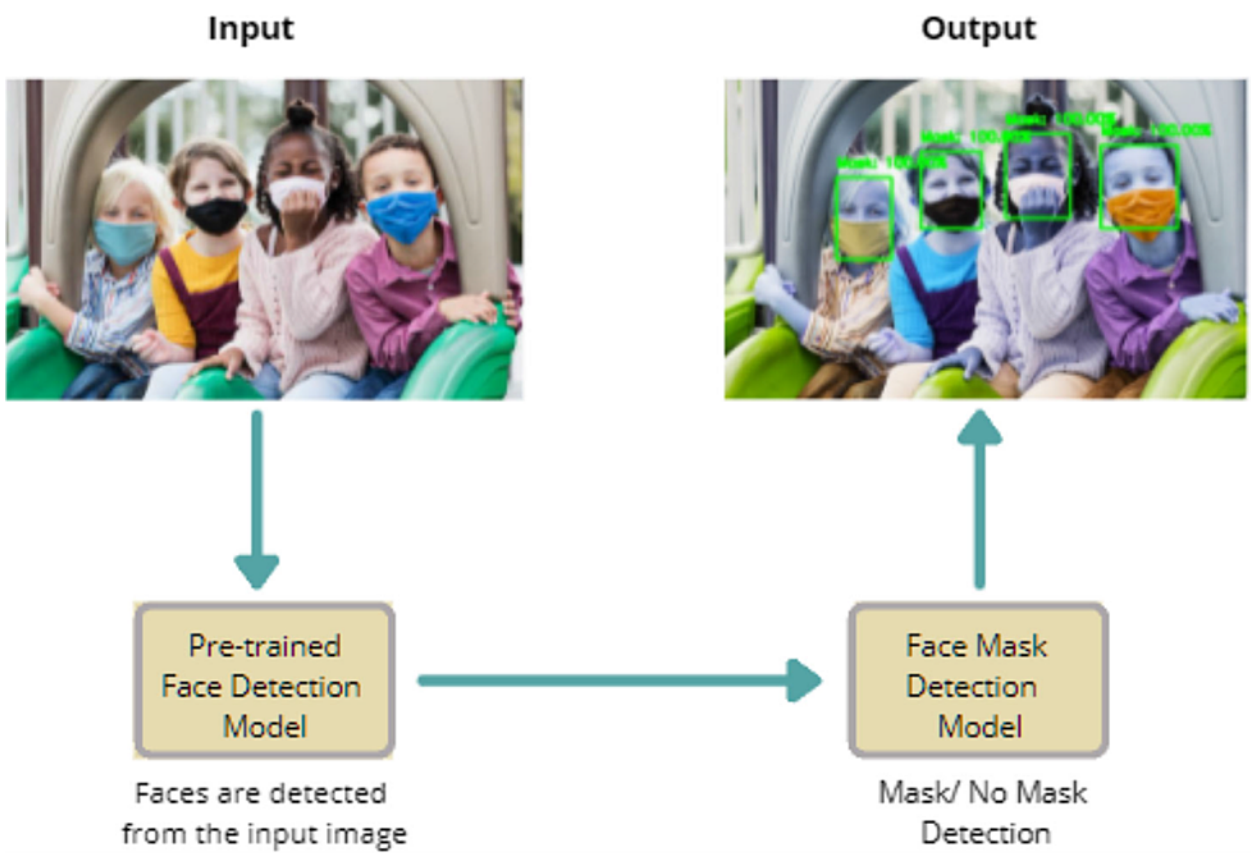


6 RESULT

The final results, were achieved after multiple experiments using various hyper-parameter values such as learning-rate, epoch size, and batch size. It depicts the hyper-parameters used.


Live Mask Detection
127.0.0.1:5000
Gmail
YouTube
Maps
Live Mask Detection
No Mask: 99.93%
Type here to search
32°C Rain
ENG
19:06
25-08-2022


Live Mask Detection
127.0.0.1:5000
Gmail
YouTube
Maps
Live Mask Detection
Mask:
Type here to search
32°C Rain
ENG
19:07
25-08-2022



7 ADVANTAGES & DISADVANTAGES

7.1 Advantages

1. No mouth leaks
2. Effective in mouth breathers
3. More stable always pressure
4. Lower resistance to airflow
5. Less need for patient cooperation

7.2 Disadvantages

1. Claustrophobic
2. Increased risk of aspiration
3. Difficult communication
4. Impossible to eat and drink

8 APPLICATIONS

Information results displayed via the LCD are mask detector, which means that the person is wearing a mask. The system can detect when the person is not using a mask. Information results displayed via the LCD are no mask, which means that the person is not wearing a mask.

9 CONCLUSION

This manuscript proposes a face mask recognition system for static images and real-time video that automatically identifies if a person is wearing a mask, which is an excellent solution for deterring the spread of the COVID-19 pandemic. By using Keras, OpenCV, and CNN, the proposed system is able to detect the presence or absence of a face mask and the model gives precise and quick results. The trained model yields an accuracyof around 98%. Trials were conducted to compare it with other pre-existing popularmodels which demonstrates that the proposed model performs better than DenseNet-121, MobileNet-V2, VGG-19, and Inception-V3 in terms of processing time and accuracy. This methodology is an excellent contender for a real-time monitoring system because of its precision and computing efficiency.

10 FUTURE SCOPE

In the future, physical distance integration could be introduced as a feature, or coughing and sneezing detection could be added. Apart from detecting the face mask, it will also compute the distances among each individual and see any possibility of coughing or sneezing. If the mask is not worn properly, a third class can be introduced that labels the image as ‘improper mask’. In addition, researchers could propose a better optimiser, improved parameter configuration, and the use of adaptive models.

11 REFERENCES

1. Chen D, Hua G, Wen F, Sun J (2016) Supervised transformer network for efficient face detection.In: European conference on computer vision. Springer, pp 122–138. https://doi.org/10.1007/978-3-319-46454-1 8

2. Chen Y, Menghan Hu, Hua C, Zhai G, Zhang J, Li Q, Yang SX (2021) Face mask assistant: detection of face mask service stage based on mobile phone. IEEE Sensors J 21(9):11084–11093. https://doi.org/10.1109/JSEN.2021.3061178

3. Cruz AP, Jaiswal J (2021) Text-to-image classification using attngan with densenet architecture. In: Proceedings of international conference on innovations in software architecture and computational systems.Springer, pp 1–17

4. Ejaz MS, Islam MR, Sifatullah M, Sarker A (2019) Implementation of principal component analysis on masked and non-masked face recognition. In: 2019 1St international conference on advances in science, engineering and robotics technology (ICASERT). IEEE, pp 1–5. https://doi.org/10.1109/ICASERT.2019.8934543

5. He K, Zhang X, Ren S, Sun J (2016) Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 770–778. https://doi.org/10.1109/ v

6. Huang Y, Qiu C, Wang X, Wang S, Yuan K (2020) A compact convolutional neural network for surface defect inspection. Sensors 20(7):1974. https://doi.org/10.3390/s20071974

7. Hussain SA, Al Balushi ASA (2020) A real time face emotion classification and recognition using deep learning model. In: Journal of physics: Conference series, vol 1432. IOP Publishing, Bristol, p 012087