Face Mask Detector

Final Report

Ese Emuraye, Pragya Srivastava, Sheldon Sebastian

Introduction

The goal of our project is to identify whether a person is **correctly** wearing a mask or not. A person correctly wears a mask when the mask completely covers his mouth and nose.

COVID-19, as we know, is a pandemic that has claimed millions of lives in the year 2020. Wearing a face mask has been identified as a successful method of preventing the spread of COVID amongst people. It is strongly recommended to wear a mask in public places. Most people follow the guidelines and wear masks. Some people do not wear it while others wear it incorrectly which doesn't cover their nose/mouth as it should.

Our project aims to train a model on images of people wearing masks and develop an interface to identify faces of people wearing the mask correctly, wearing it incorrectly or not wearing a mask.

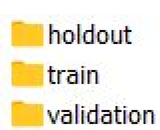
Dataset

For our project we used the MaskedFace-Net dataset[1]. This dataset is a synthetic dataset created using Generative Adversarial Network (GAN) on the Flickr-Faces-HQ Dataset[2]. The MaskedFace-Net model created synthetic images of people wearing the mask correctly and incorrectly. For our project we also wanted to identify whether the person was wearing a mask or not. So we added the original Flickr-Faces-HQ dataset images of people not wearing a mask to achieve this task.

The data was downloaded using CURL command and the python scripts are available in the Data Download Scripts Folder of the Github repository. The final combined dataset contains 60,000 images and is 15 GB in size.

Of the 60,000 images 20,000 images were of incorrect worn masks, 20,000 images were of correct worn masks and 20,000 images were of uncovered faces.

80% of the dataset was used for training and 20% was used as holdout or test set. The script to split into train-validation and holdout is found in DataPreprocessing.py. The data was organized such that it was accessible using the ImageFolder API of Pytorch.



And inside each folder of holdout(test), train, and validation we have following folders:

The dataset contains the following 3 image labels:

covered

incorrect

uncovered

Network and Training

For the purposes of this project we are planning to use Convolutional Neural Networks, in its standard form. We explored pre-trained models - Resnet18, Resnet50, Alexnet, VGG, Densenet and Inception. We trained all of these models for 20 epochs with standard hyperparameters and then then selected the one that gave us highest validation accuracy for further enhancements.

ResNet50 gave us the highest validation accuracy of about 88% without any tuning and hence was selected for this project. ResNet50 is a 50 layer Residual Network. ResNet, short for Residual Networks, is a classic neural network used for many computer vision tasks. This model was the winner of the ImageNet challenge in 2015. The fundamental breakthrough with ResNet was it allows training of extremely deep neural networks with 150+layers. Prior to ResNet training very deep neural networks were difficult due to the problem of vanishing gradients.

Experimental Setup

We selected ResNet50 because of the reasons mentioned above. The data was fed into the network with the following train, test and validation splits - 80:20 train and test, the validation was 20% of the train. The network was then fine tuned to increase accuracy. Since the dataset was balanced we did not need too many augmentations.

Transformations

Resize instead of RandomResizedCrop for train data - We used the pre-processing resize transform instead of the augmentation random resized crop because our data consisted of images which contain human faces in the entire frame in most cases, so our object of interest is within the frame.

ColorJitter Transformation - We used the ColorJitter transformation on the training data which randomly changes the color saturation of images to any percentage between zero and hundred. This helps in generalizing better masks of different colors.

We tried a few other augmentations like flipping images but since the data was balanced those augmentations only worsened accuracy.

Hyperparameters

Learning Rate - Learning rate of 0.001 was used for this model. We tried 0.0001 as well but that worsened the accuracy metrics.

Batch Size - Batch size of 512 was used. In some cases if the cuda ran out of memory we reduced the batch size to 256 or 128 to run the model.

Optimizer - Adam was used as the optimizer.

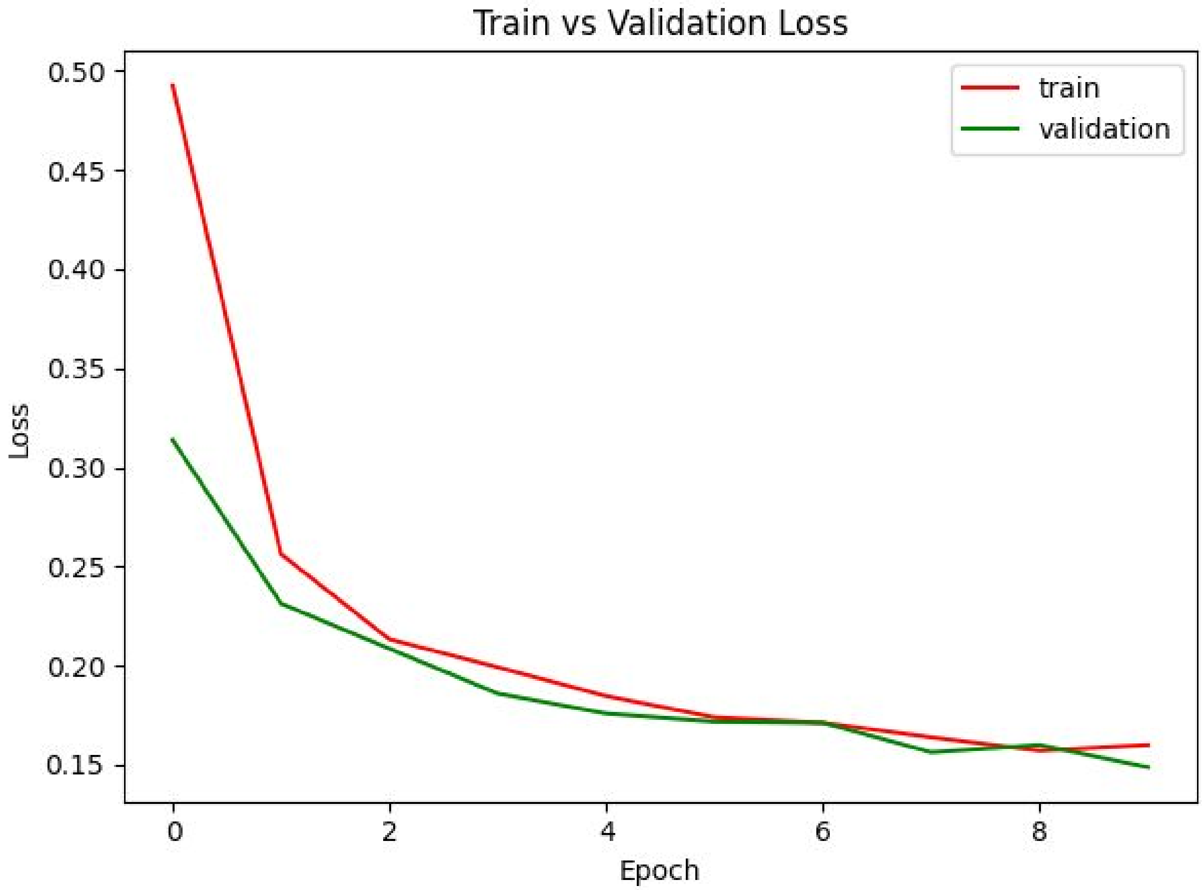
Epochs - The model was run for 10 epochs.

Regularization

Regularizing with Dropout - We have used 30% dropout rate in our model to prevent overfitting. We tried using 20% but 30% gives us the optimum results.

Model Accuracy

The performance of the model was judged based on accuracy and loss values for train, validation and holdout set. The loss on train and validation sets for ten epochs is given below -



The model does well since both train and validation loss are moving in the same direction for ten epochs and the validation loss decreases throughout the training.

Since the dataset was balanced, we have used accuracy as a metric to evaluate the model. The F1 score is using the option average='micro' and since the dataset is balanced, it is equal to the accuracy. The results for the final model are given below -

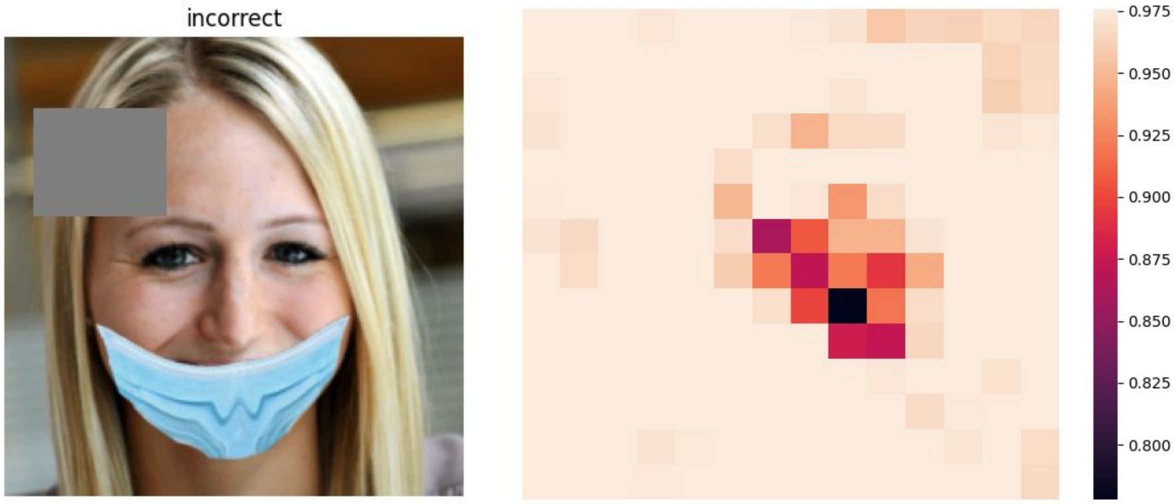
```
Train Evaluation Metrics
----------
Accuracy::0.9545066666666666
F1 Score::0.9545066666666666
Confusion Matrix::[[11726   598    38]
 [  658 11495   185]
 [   14   213 12573]]

Validation Evaluation Metrics
----------
Accuracy::0.9509228635442227
F1 Score::0.9509228635442227
Confusion Matrix::[[2935  147    8]
 [ 170 2846   68]
 [   2   65 3132]]

Holdout Evaluation Metrics
----------
Accuracy::0.9522143527604744
F1 Score::0.9522143527604744
Confusion Matrix::[[3663  187   13]
 [ 200 3589   67]
 [  11   82 3907]]
```

Model Interpretation

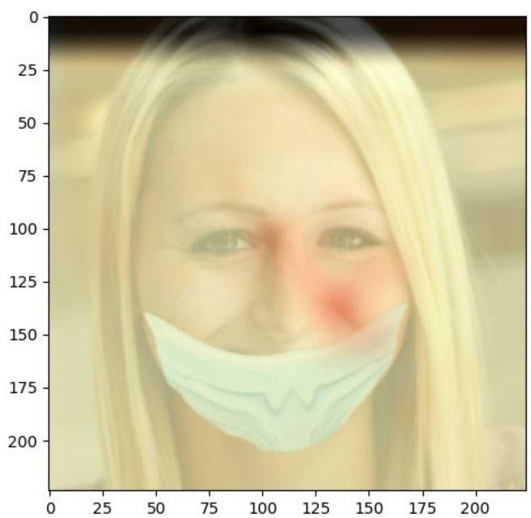
Once the model was trained with strong validation accuracy and low validation loss, we interpreted the CNN model on the training dataset using Occlusion experiment[3].

Occlusion experiments are performed to determine which patches of the image contribute maximally to the output of the neural network.

In the occlusion experiment, we iterate over all the regions of the image systematically by occluding(blocking) a part of the image with a grey patch and monitor the probability of the classifier using a heatmap.

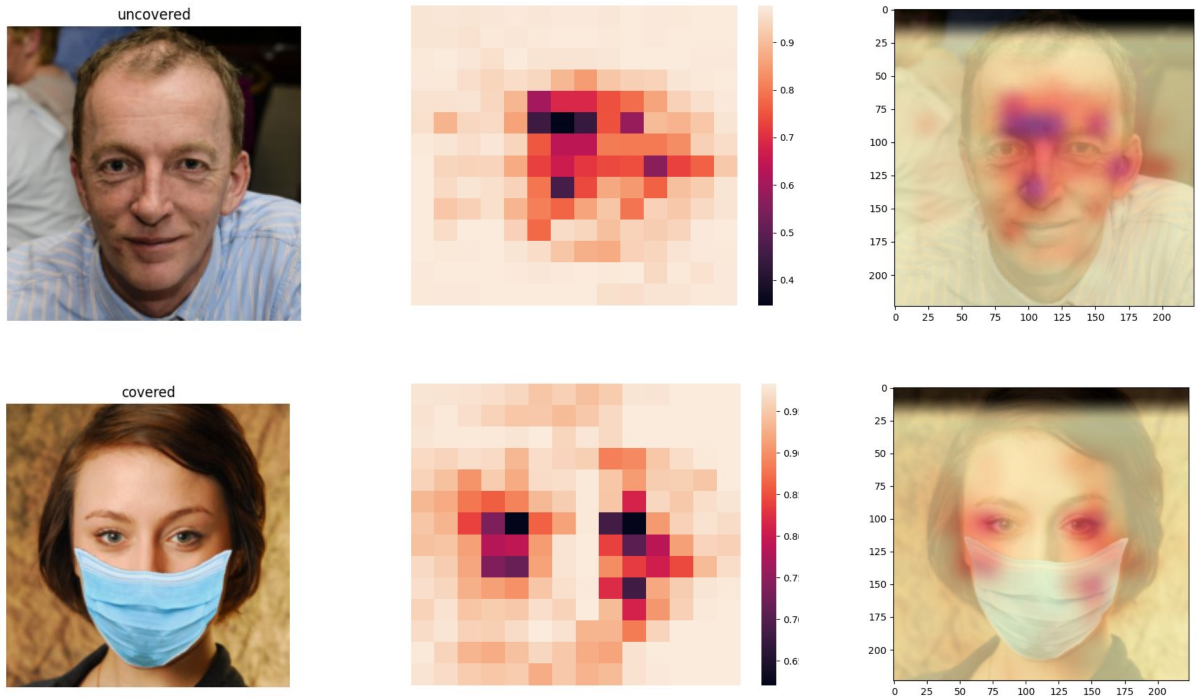


After blending the probability heatmap and the original image we get the following output:



We notice that we get low probability for the classifier when the patches of images containing nose or upper mouth are occluded. Thus, the occlusion experiment tells us that the CNN model is learning relevant patterns in the image.

For other image labels the occlusion experiment results are as follows:

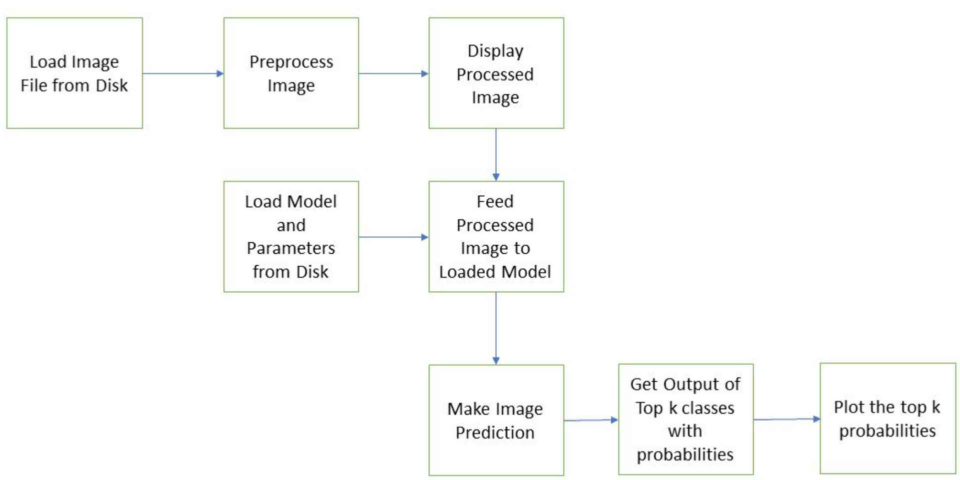


From above results we can conclude that the model is identifying relevant features to make classification predictions.

Results: Inference for Classification

To understand how well the model performs and make predictions on real world face images, we performed an inference for classification on images captured with a camera, with different samples of face images: without a face mask, with a face mask and with an incorrectly worn face mask.

A predict function was written that takes a processed image and returns the top k most likely classes along with their probabilities. The block diagram for this procedure is shown below:



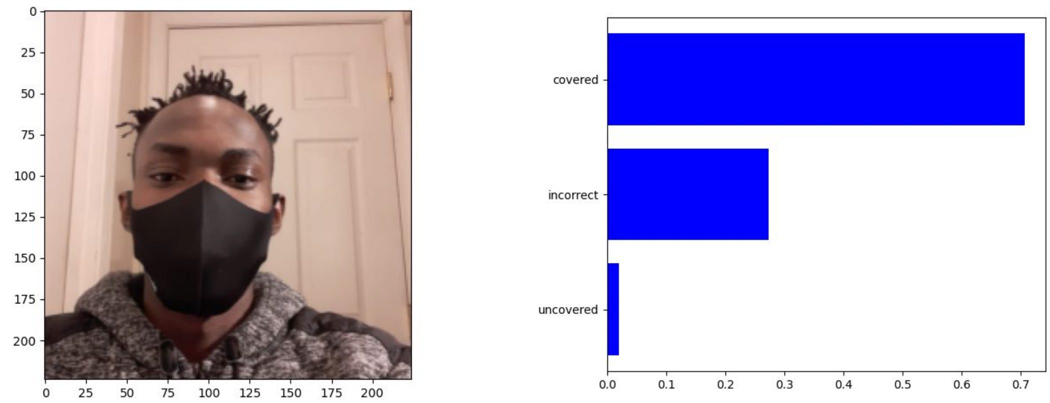


Figure 6.1 Face mask prediction with face image covered

We observed for an image with a face mask, the model gave a correct prediction with a probability of about 0.7. Other predictions were made with the model with the results shown below:

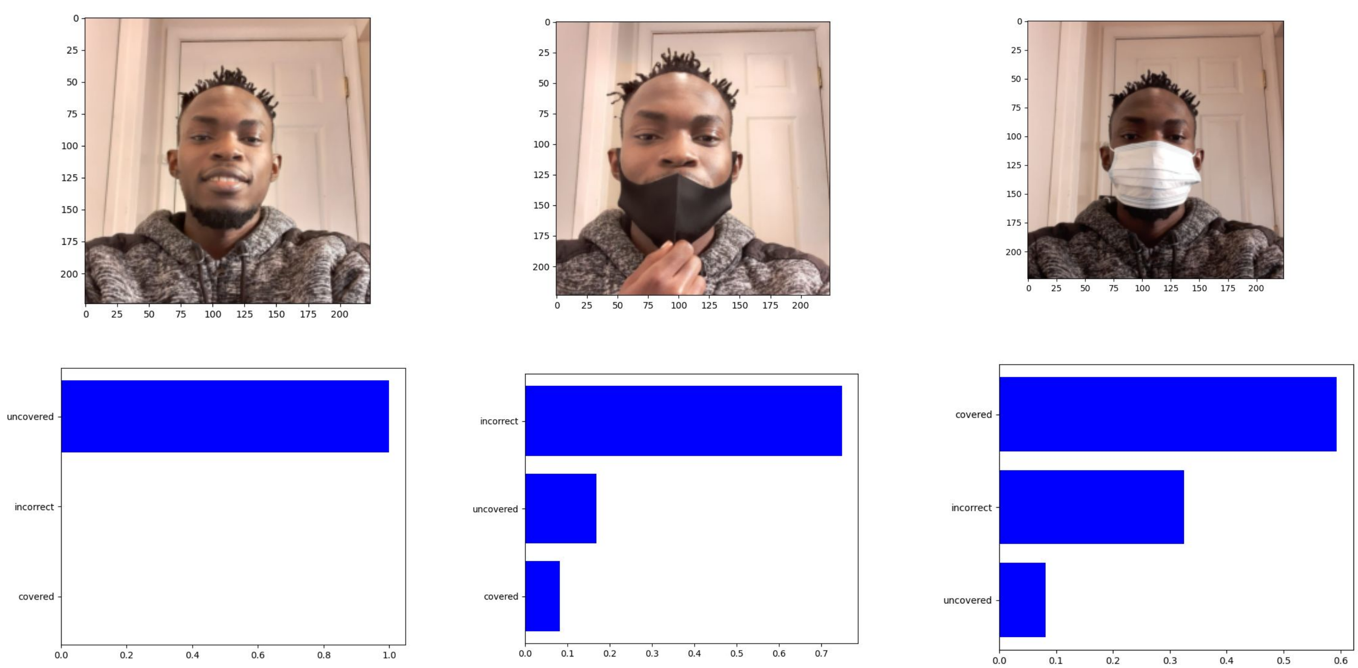


Figure 6.2 Face mask prediction with face image uncovered, incorrect and covered

We observed for an image without a face mask, the model gave a correct prediction with a probability of 1.0, while the prediction with an incorrectly worn face mask gave a correction prediction with a probability of about 0.75. We tested the model with a different color of face mask (white) to observe if there was any significant difference in the prediction with the black face mask used earlier, The model gave a reduced probability of about 0.6 with a correct prediction of a covered facemask.

We investigated further by cropping the image to reveal the face of the person only. The result of the prediction is shown below:

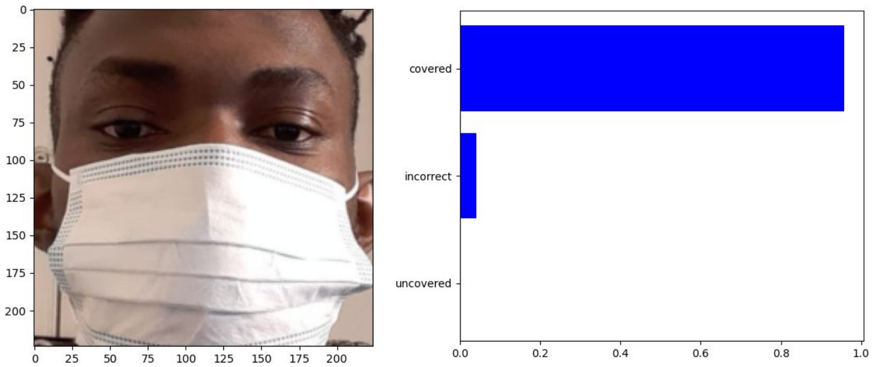


Figure 6.3 Face mask prediction with cropped face image

The model produced a correct prediction for a covered face mask with a probability of approximately 0.95, an improvement on previously classification results.

Summary and Conclusions

From the results, we conclude that the model performs better when the input image is processed to reveal the face only. This is because the model was trained to make classification based on face mask coverings as we observed in the occlusion experiment. From figure 6.3 a cropped face image produced a correct prediction with a probability of approximately 0.95, which is consistent with accuracy of 0.9522 obtained for the held-out dataset. In figures 6.1 and 6.2, other features, like the surrounding environment and the body of the human, contributed to the features fed to the model which reduced the prediction performance.

Further work will require the development of a primary model to detect faces in an image, before applying the face mask model developed in this project. The primary model should be able to predict a bounding box around the face for detection. The face can then be fed to the face mask detector model for classification.

References

1. Adnane Cabani, Karim Hammoudi, Halim Benhabiles, and Mahmoud Melkemi, "MaskedFace-Net - A dataset of correctly/incorrectly masked face images in the context of COVID-19", Smart Health, ISSN 2352-6483, Elsevier, 2020

2. A Style-Based Generator Architecture for Generative Adversarial Networks Tero Karras (NVIDIA), Samuli Laine (NVIDIA), Timo Aila (NVIDIA)

3. Kumar, N. (2019, December 17). Visualizing Convolution Neural Networks using Pytorch. Retrieved December 07, 2020, from https://towardsdatascience.com/visualizing-convolution-neural-networks-using-pytorch-3dfa8443e74e

Appendix (Code)

The files given below can be found on the project GitHub repository.

Data Download Scripts: To download the images from one drive and google drive using CURL.

DataProcessing.py: To split the downloaded images into train-validation-holdout and organize the files for ImageFolder.

MaskDetector_Final.py: Training of the final resnet50 model.

Inference.py: To view the inference probability of each class based on input image passed.

OcclusionExperiment.py: To interpret and visualize the CNN based on occlusion experiment

Order to run the files:

1. Data Download Scripts
2. DataProcessing.py
3. MaskDetector_Final.py
4. Inference.py
5. OcclusionExperiment.py