Facial Recognition - But With Masks

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1 Project Summary

As a part of this project, we have implemented facial recognition with masks. Ever since the pandemic, masks have become an everyday essential attire. However, facial recognition technology struggles with this new norm. We plan to address this issue by making use of Machine Learning models, combined with Computer Vision methods.

We use One Shot learning, implemented using Siamese networks to build a model to successfully recognize faces both with and without masks.

2 Goals and objectives

Our objective is to build a model using Siamese Networks that can perform facial recognition on masked faces as well as unmasked faces. This is done with one-shot learning.

Another objective to address during this project is the issue of data collection. We use methods such as image editing to explicitly add masks to unmasked faces.

3 Approach

1. Firstly, train a model with Siamese Networks that uses a binary classifier, to recognise faces
2. Then, we try and expand this model to work with faces that have masks on. To get the data for this, we use image editing to generate more samples.
3. We re-train the previous model to detect faces with masks on.

4 Training on Unmasked Faces

Our model has a InceptionResnet backbone that has been pre-trained on VGGFace2 dataset. We use this network to generate embedding for each of the two images passed for the identification task. We then pass the difference of these embeddings to a fully-connected layer and a Sigmoid activation function (Binary Classifier). Because, we have less data and are using transfer learning, we only trained this model for 20 epochs using the Adam Optimization Algorithm with learning rate = 0.001 and weight decay = 0.0075, and the Binary Cross Entropy loss.

4.1 Results

Figure 1: Training Losses over 20 Epochs

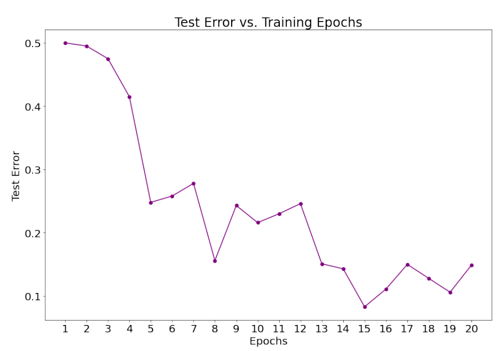

Figure 2: Test Error over 20 Epochs

Our model produced a 91% accuracy on the unmasked dataset (Labeled Faces in the Wild-Pairs Data set). From Figure 1 and Figure 2, we can see a downward trend of the loss and test error vs. training over 20 epochs.

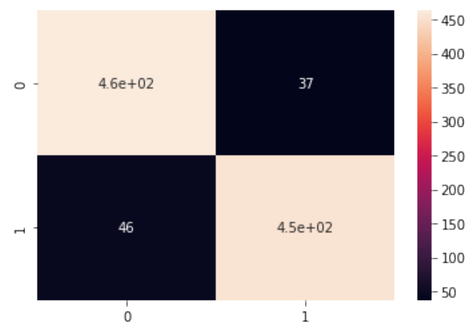

Figure 3: Confusion Matrix for Unmasked Faces

In the confusion matrix in Figure 3, we can see our model did fairly well in in predicting the correct label in both positive and negative examples.

5 Masked Dataset Creation

5.1 Model Description

This model was created using face landmarks to identify six key features on the face in order to place the mask, and also, measure the head and face tilt. Based on the tilt of the head, the appropriate mask is selected from a library of masks, and then transformed based on the six key features to fit the face.

5.2 Results

Using the above model, we were able to successfully mask all the faces available in our original paired faces dataset.

Figure 4: Images of Adam Sandler before applying masks vs after applying masks

6 Training on Masked Faces

Using the same model as our unmasked data, we now train it on the masked we faces we generated. The model architecture was exactly the same as the unmasked model, but we now use learning rate = 0.001 and weight decay = 0.01. We are still training over 20 epochs using the Adam Optimization Algorithm and Binary Cross Entropy loss.

6.1 Results

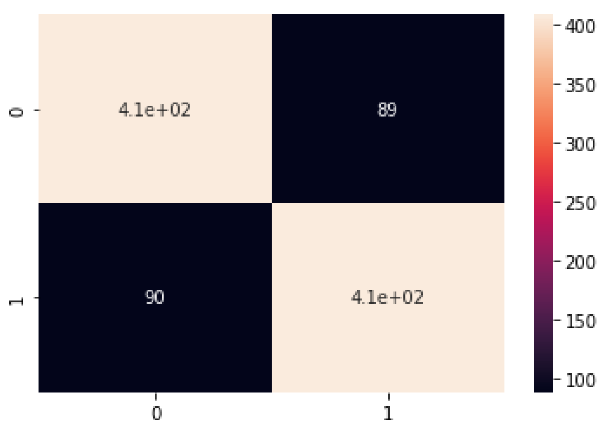

Figure 5: Confusion Matrix for Masked Faces

Our model produced an 82% accuracy on the test set for masked faces. From Figures 6 and 7 we can see a downward trend in loss and test error over 20 epochs. From the confusion matrix in Figure 5 we can see our model also does very well by correctly classifying the examples for majority of the data.

Figure 6: Training Losses over 20 Epochs for Masked Faces

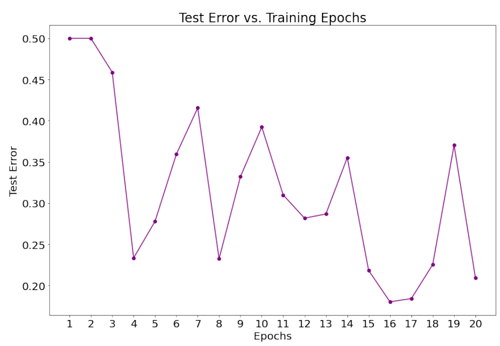

Figure 7: Test Error over 20 Epochs for Masked Faces

7 Demo

We can now use our model to test whether it can recognize two photos are of the same person or of different people.

With our unmasked faces, we passed in 2 photos of the same person (Figures 8(a) and (b)) to see if the model can recognize they are the same person, and it did so. Then we passed in photos of 2 different people (Figures 8(a) and (c)) and the model recognized they were different people. Finally we passed in photos of 2 different people, but this time with similar physical features (Figures 8(a) and (d)), and our model correctly detected they are different people.

For our masked faces model, we passed in 2 photos of the same person (Figures 10(a) and (b)) and the model correctly outputted they were the same person. Then we passed in photos of 2 different people in masks (Figures 10(a) and (b)) and the model correctly outputted that they were photos of 2 different people.

(a) (b) (c) (d)

Figure 8: Example Photos of Unmasked Faces, (a) and (b) are of the same person, (c) and (d) are different from (a) and (b)

```
verify('Vaibhav/Vaibhav_0001.jpeg', 'Vaibhav/Vaibhav_0002.jpeg')
```

```
1
```

```
verify('Vaibhav/Vaibhav_0001.jpeg', 'Jianbo/Jianbo_0001.jpeg')
```

```
0
```

```
verify('Vaibhav/Vaibhav_0001.jpeg', 'Varun/Varun_0001.jpeg')
```

```
0
```

Figure 9: Results from Unmasked Demo

(a) (b) (c)

Figure 10: Example Photos of Masked Faces, (a) and (b) are of the same person, while (c) is different

```
verify('Rasya/Rasya_0001.JPG', 'Rasya/Rasya_0002.JPG')
```

```
1
```

```
verify('Rasya/Rasya_0001.JPG', 'Cassie/Cassie_0001.JPG')
```

```
0
```

Figure 11: Results from Masked Demo

8 Conclusion

We were successfully able to build a model to do face recognition whether or not people are wearing their masks. Working on this project enlightened us to the various complexities involved in building machine learning models. Some of the takeaways from this project include the following:

1. The dataset we used was a very good one. We realized the importance of the quality of data in training a machine learning model. Good data yields good results.

2. We faced a number of challenges while training our models. Not only is it difficult to understand complex models, it is also a painstaking and time consuming process to train a model, even when using powerful resources.

3. We did not have to change the model that recognized faces without masks a lot to yield good results with masked faces. This truly shows how effective the "learning" part of machine learning is.

9 Future Scope and Improvements

Given more time to work on this projects, there are several ways we can improve our results.

1. The pairwise dataset is not the largest dataset there is. More data would certainly increase the accuracy of our model.

2. We could attempt to build a better model by unfreezing the last few layers of the InceptionResnet backbone network.

10 References

1. Y. Taigman, M. Yang, M. Ranzato and L. Wolf, "DeepFace: Closing the Gap to Human-Level Performance in Face Verification," 2014 IEEE Conference on Computer Vision and Pattern Recognition, 2014, pp. 1701-1708, doi: 10.1109/CVPR.2014.220.
   The paper on using Siamese Networks for Facial recognition

2. MaskTheFace - Convert face dataset to masked dataset

3. Labeled Faces in the Wild dataset.