MGTA611 – Deep Learning Assignment Report

Prepared by Farzan – 235819710

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Introduction:

While the ideas of toying with facial recognition models and convincing people to cover their faces if they are sick is not something new, the rise and impact of COVID-19 pushed both factors into the limelight to reduce the probability of people getting infected by the virus, especially in public places.

To curb raspatory viruses, numerous places mandated a rule of only letting masked people access certain premises to keep the number of infected people at bay, but there was a constant challenge in ensuring that such a rule is followed. Such civil issues led to people experimenting with facial recognition models and expanding the scope to utilize such models to detect if an individual is wearing a mask.

The oldest documented model (Arjya Das Department of Information Technology, Ansari, & Basak, 10-13 December 2020) that uses and references a Machine Learning Model based on packages such as TensorFlow, Keras and OpenCV dates to December 2020. This references a conference that itself cites a project that uses Facial Mask Detection using Semantic Segmentation that was published in 2019 as a basis for their workings. One of the reasons that I found this paper interesting was due to their approach towards rendering images; while CNN 2D layers were used, the authors went an extra step to convert images in their dataset to grayscale.

Business Implications of the Project

One of the major reasons that I chose to work on face mask detection for my Deep Learning project is the level of versatility that this project offers. While the use-case scenario in this case may be restricted to a certain cause, the scope can easily be modified to fulfill a different purpose.

For example, instead of facemasks, the models can be trained to detect whether someone is equipped with Personal Protective Equipment (PPE) or not – a case especially useful in industries where workers may be exposed to hazardous material. Such cases can also be paired up with other security measures to promote a safer workspace.

Data Set and Methodology

The dataset for this project is obtained from Kaggle. It comprises of nearly 7,500 images that are divided between faces of people wearing a mask and faces without a mask. This was the only publicly available dataset that consisted of copyright-free images, so I decided to use this as a base for my model.

To ensure that the dataset is fit for use, all images were converted to 128x128 pixels and in RGB format followed by a conversion of image lists to numpy arrays. With the help of arrays and appropriate scaling, I completed the groundwork for the complex and simple models that I had chosen.

Complex Models

Sequential CNN

The first complex model that was tested consisted of a Convolution Neural Network (CNN) that uses Tensorflow and Keras as a base for its working. The goal was to create a sequential CNN model with multiple layers on top which consist of:

- Conv2D Layers with 32 filters and a 3x3 kernel size.

- MaxPooling2D layers to reduce spatial dimensions of the Conv2D layers.
- A flatten layer to convert 2D layers to 1D layers.
- Dense layers that are fully connected to perform classification.
- Dropout layers to help prevent overfitting.

The training process consists of a 10% validation split and 5 epochs after which the training and performance of the model is evaluated on a different test set. The model hereby achieves a training accuracy of 93%, validation accuracy of 91% and test evaluation accuracy of 90%.

Keras/Pretrained Transfer Model Learning using Mobilenet

Since my dataset can be classified as a binary dataset (a person is either wearing or not wearing a mask – there is no middle ground), I decided to use Mobilenet for a binary pretrained CNN. Base layers were frozen, and the following layers were added to the model:

- GlobalAveragePooling2D to reduce feature map to a single value and make the model slightly less complicated, and
- Two dense layers. One with 1024 neurons, the other with 2 neurons to help keep the values binary.

Data augmentation was used as a preprocessing tool to artificially increase the size of the dataset and data generators were used to train the model on 3 epochs. Evaluation of the model takes place by loading and preprocessing a single image to demonstrate the practical application of the model.

As a result, the model achieved high accuracy and showcases how relevant features from an image can be extracted towards effective usage for a binary task. The approach also highlights the potential need for large training datasets to prevent overfitting as well as how pretrained models can speed up the overall processing.

Simple Learning Models.

Simple Sequential Model using MNIST

This was a rather basic approach towards the model that only consists of a Flatten layer to convert 2D images followed by a dense layer for non-linear transformations. This was done to keep the outcome binary even though MNIST models are generally multi-class classifications.

As a result, the training and testing logs with 10 epochs and a validation split of 20% demonstrated unusual negative losses with a decreasing trend, which indicates that this is not a suitable approach for this model since loss values typical point towards zero. However, a second attempt corrected this, but the approach remains ambiguous. While this may count as a practical demonstration of MNIST, the peculiarities in the result make it unsuitable for further analysis.

Support Vector Machine (SVM) Approach

Once again, I decided to treat this as a binary classification model using SVM and avoiding the use of Convolutional Neural Networks altogether to keep this approach simple. The preparation stage consists of images being converted to RGB and 128x128 pixels along with assigning labels for with/without mask.

A Histogram of Oriented Gradients (HOG) feature has been used to capture edge and structure of gradients (Kh Tohidul Islam, 2017) and generally works well in terms of content detection. This was followed by a train-test split with 20% of the data reserved for testing. As mentioned in this paper, image processing that used a combination of Artificial Neural Networks (ANNs) and HOG features achieved accuracy levels as high as 99.0% in practical applications.

With the help of feature scaling and SVM training with a linear kernel (since I opted for a binary approach), the trained model is evaluated by its ability to predict the label (either 0 for without mask, or 1 with mask), and accuracy is measured with the help of precision, recall, and F1-score for each class. The model and approach resulted in an overall accuracy of approximately 83%, strongly showcasing that simple models can be just as effective towards such problems.

Comparative Analysis between the Methodologies

The comparison between CNN and SVM highlights several fascinating insights. As demonstrated in the code in the technical appendix of this report, CNN models rely on their deep learning capabilities and perform well in terms of directly learning from raw images. Such models can highlight complex patterns and select relevant features without manual feature extraction. However, this comes at the cost of large amounts of computing power as well as the need for labeled data for training.

On the other hand, SVM models perform their best when a careful, structured approach is taken (such as in the case of an HOG-based approach). Feature selection is of paramount importance, as the case with traditional Machine Learning approaches. While a greater degree of preprocessing and domain knowledge is required, they still end up taking less computational power to execute.

Conclusion

To conclude, we can use our approaches towards each type of model to demonstrate identical accuracy figures regardless of the approach. CNNs perform their best when computational resources are not limited, whereas SVMs with the right feature engineering manage to catch pace with less overheads. Keeping such factors aside, it remains imperative to observe broader themes, such as the impact of trade-offs in model complexity, approaches taken towards preprocessing data, and the potential impact of feature scaling with complex models.

References

Arjya Das Department of Information Technology, J. U., Ansari, M. W., & Basak, R. (10-13 December 2020). Covid-19 Face Mask Detection Using TensorFlow, Keras and OpenCV. New Delhi, India: IEEE.

Kh Tohidul Islam, R. G.-M. (2017). Performance of SVM, CNN, and ANN with BoW, HOG, and Image Pixels in Face Recognition. *International Conference on Electrical & Electronic Engineering (ICEEE)*. Rajshahi, Bangladesh: IEEE.

Technical Appendix

```
#Installing Kaggle to load API/JSON file and download the dataset
!pip install kaggle
```

```
Requirement already satisfied: kaggle in
/usr/local/lib/python3.10/dist-packages (1.5.16)
Requirement already satisfied: six>=1.10 in
/usr/local/lib/python3.10/dist-packages (from kaggle) (1.16.0)
Requirement already satisfied: certifi in
/usr/local/lib/python3.10/dist-packages (from kaggle) (2024.2.2)
Requirement already satisfied: python-dateutil in
/usr/local/lib/python3.10/dist-packages (from kaggle) (2.8.2)
Requirement already satisfied: requests in
/usr/local/lib/python3.10/dist-packages (from kaggle) (2.31.0)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-
packages (from kaggle) (4.66.2)
Requirement already satisfied: python-slugify in
/usr/local/lib/python3.10/dist-packages (from kaggle) (8.0.4)
Requirement already satisfied: urllib3 in
/usr/local/lib/python3.10/dist-packages (from kaggle) (2.0.7)
Requirement already satisfied: bleach in
/usr/local/lib/python3.10/dist-packages (from kaggle) (6.1.0)
Requirement already satisfied: webencodings in
/usr/local/lib/python3.10/dist-packages (from bleach->kaggle) (0.5.1)
Requirement already satisfied: text-unidecode>=1.3 in
/usr/local/lib/python3.10/dist-packages (from python-slugify->kaggle)
(1.3)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->kaggle)
(3.3.2)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.10/dist-packages (from requests->kaggle) (3.6)
```

```
# configuring the path of Kaggle.json file
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
```

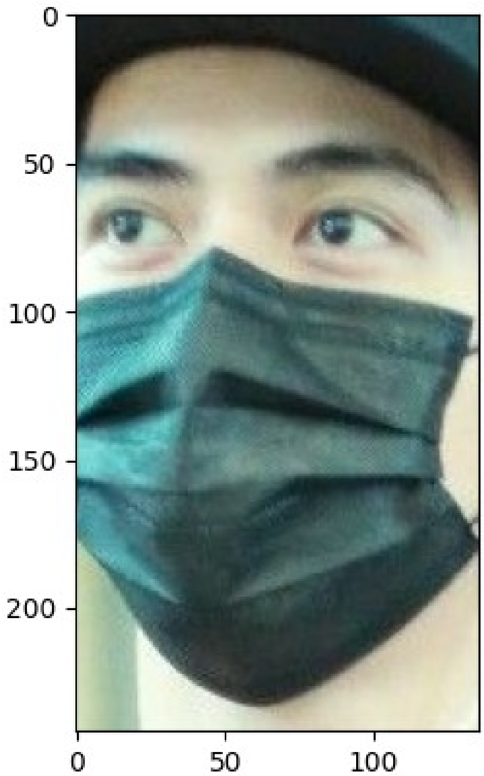
```
# API to fetch the dataset from Kaggle
!kaggle datasets download -d omkargurav/face-mask-dataset
```

```
face-mask-dataset.zip: Skipping, found more recently modified local
copy (use --force to force download)
```

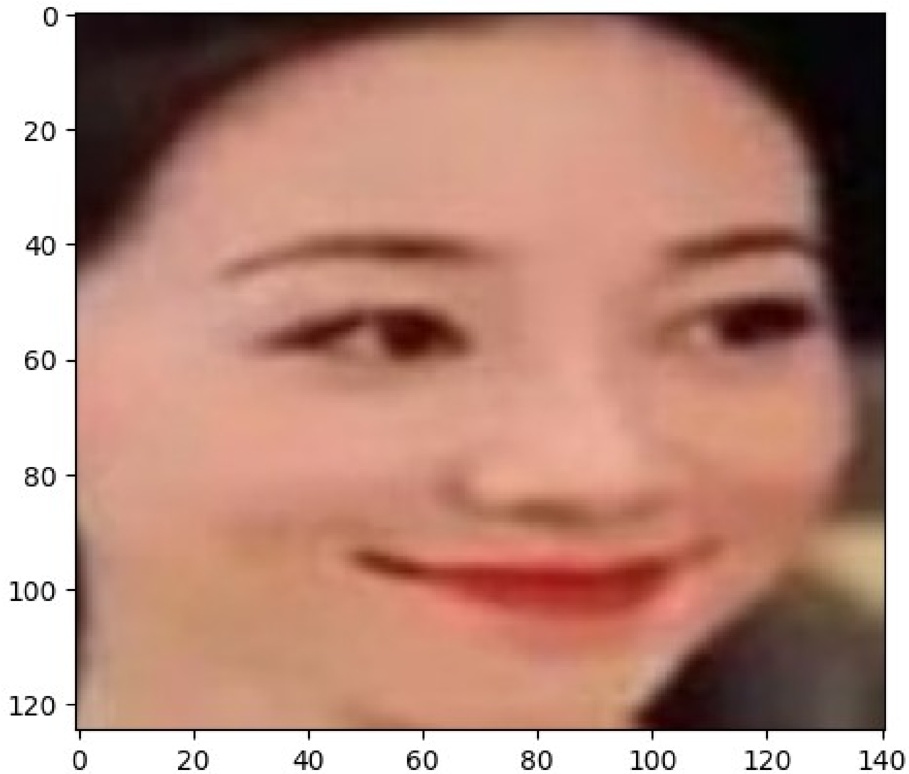
```
# extracting the compessed Dataset
from zipfile import ZipFile
dataset = '/content/face-mask-dataset.zip'

with ZipFile(dataset,'r') as zip:
  zip.extractall()
  print('The dataset is extracted')
```

```
The dataset is extracted

!ls

data  face-mask-dataset.zip  kaggle.json  sample_data

#Load dependencies

import os
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import cv2
from google.colab.patches import cv2_imshow
from PIL import Image
from sklearn.model_selection import train_test_split

#Verify file names
with_mask_files = os.listdir('/content/data/with_mask')
print(with_mask_files[0:5])
print(with_mask_files[-5:])

['with_mask_2486.jpg', 'with_mask_1354.jpg', 'with_mask_69.jpg',
'with_mask_601.jpg', 'with_mask_831.jpg']
['with_mask_3289.jpg', 'with_mask_1268.jpg', 'with_mask_3695.jpg',
'with_mask_3364.jpg', 'with_mask_2881.jpg']

without_mask_files = os.listdir('/content/data/without_mask')
print(without_mask_files[0:5])
print(without_mask_files[-5:])

['without_mask_2715.jpg', 'without_mask_305.jpg',
'without_mask_750.jpg', 'without_mask_2529.jpg',
'without_mask_1670.jpg']
['without_mask_1048.jpg', 'without_mask_951.jpg',
'without_mask_2344.jpg', 'without_mask_1649.jpg',
'without_mask_720.jpg']

print('Number of with mask images:', len(with_mask_files))
print('Number of without mask images:', len(without_mask_files))

Number of with mask images: 3725
Number of without mask images: 3828

#Creating Labels for the two class of Images#

#with mask --> 1#

#without mask --> 0#

# create the labels
```

```
with_mask_labels = [1]*3725

without_mask_labels = [0]*3828

print(with_mask_labels[0:5])

print(without_mask_labels[0:5])

[1, 1, 1, 1, 1]
[0, 0, 0, 0, 0]

print(len(with_mask_labels))
print(len(without_mask_labels))

3725
3828

labels = with_mask_labels + without_mask_labels

print(len(labels))
print(labels[0:5])
print(labels[-5:])

7553
[1, 1, 1, 1, 1]
[0, 0, 0, 0, 0]

#display the images

# displaying with mask image
img = mpimg.imread('/content/data/with_mask/with_mask_1354.jpg')
imgplot = plt.imshow(img)
plt.show()
```




```
# displaying without mask image
img = mpimg.imread('/content/data/without_mask/without_mask_354.jpg')
imgplot = plt.imshow(img)
plt.show()
```



```
#Use image processing to resize the images and convert images to numpy
arrays

# convert images to numpy arrays+

with_mask_path = '/content/data/with_mask/'

data = []

for img_file in with_mask_files:

  image = Image.open(with_mask_path + img_file)
  image = image.resize((128,128))
  image = image.convert('RGB')
  image = np.array(image)
  data.append(image)



without_mask_path = '/content/data/without_mask/'


for img_file in without_mask_files:

  image = Image.open(without_mask_path + img_file)
  image = image.resize((128,128))
```

```
  image = image.convert('RGB')
  image = np.array(image)
  data.append(image)
```

```
/usr/local/lib/python3.10/dist-packages/PIL/Image.py:996: UserWarning:
Palette images with Transparency expressed in bytes should be
converted to RGBA images
  warnings.warn(
```

```
type(data)
```

```
list
```

```
len(data)
```

```
7553
```

```
data[0]
```

```
array([[[ 89,  94,  98],
        [ 91,  96, 100],
        [ 90,  94,  98],
        ...,
        [ 49,  46,  57],
        [ 49,  46,  57],
        [ 49,  46,  57]],

       [[101, 106, 110],
        [103, 108, 112],
        [102, 106, 110],
        ...,
        [ 49,  46,  57],
        [ 49,  46,  57],
        [ 49,  46,  57]],

       [[109, 114, 117],
        [111, 116, 119],
        [110, 114, 117],
        ...,
        [ 49,  46,  57],
        [ 49,  46,  57],
        [ 49,  46,  57]],

       ...,

       [[  2,  75, 114],
        [  1,  74, 112],
        [  1,  75, 109],
        ...,
        [184, 200, 213],
        [177, 196, 210],
```

```
        [169, 189, 204]],

       [[  5,  68, 105],
        [  5,  69, 103],
        [  5,  68, 101],
        ...,
        [185, 200, 212],
        [177, 192, 204],
        [170, 186, 197]],

       [[ 17,  68, 102],
        [ 16,  68, 101],
        [ 16,  68,  98],
        ...,
        [174, 189, 201],
        [169, 183, 194],
        [166, 180, 189]]], dtype=uint8)
```

```
type(data[0])
```

```
numpy.ndarray
```

```
data[0].shape
```

```
(128, 128, 3)
```

```
# converting image list and label list to numpy arrays

X = np.array(data)
Y = np.array(labels)
```

```
type(X)
```

```
numpy.ndarray
```

```
type(Y)
```

```
numpy.ndarray
```

```
print(X.shape)
print(Y.shape)
```

```
(7553, 128, 128, 3)
(7553,)
```

```
print(Y)
```

```
[1 1 1 ... 0 0 0]
```

```
#Train Test Split

X_train, X_test, Y_train, Y_test = train_test_split(X, Y,
test_size=0.2, random_state=2)
```

```
print(X.shape, X_train.shape, X_test.shape)
```

```
(7553, 128, 128, 3) (6042, 128, 128, 3) (1511, 128, 128, 3)
```

```
# scaling the data

X_train_scaled = X_train/255

X_test_scaled = X_test/255

X_train[0]
```

```
array([[[ 46,  36,  27],
        [ 46,  36,  27],
        [ 46,  36,  27],
        ...,
        [ 40,  35,  29],
        [ 42,  37,  32],
        [ 42,  37,  33]],

       [[ 46,  36,  27],
        [ 46,  36,  27],
        [ 45,  35,  26],
        ...,
        [ 37,  32,  26],
        [ 40,  35,  30],
        [ 40,  36,  32]],

       [[ 44,  34,  25],
        [ 44,  34,  25],
        [ 42,  33,  24],
        ...,
        [ 39,  32,  26],
        [ 40,  33,  29],
        [ 40,  33,  30]],

       ...,

       [[146, 103,  76],
        [149, 106,  79],
        [153, 112,  84],
        ...,
        [ 59,  50,  41],
        [ 63,  54,  43],
        [ 64,  56,  45]],

       [[144, 104,  75],
        [148, 107,  79],
        [154, 113,  85],
        ...,
        [ 59,  50,  41],
```

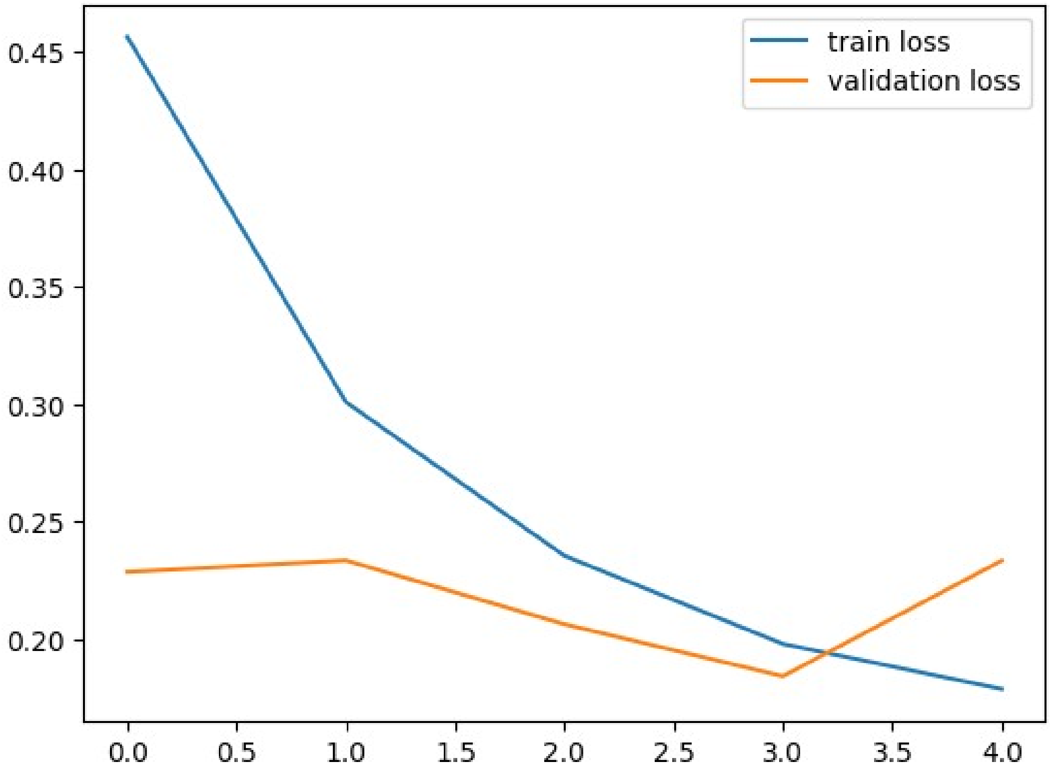
```
        [ 62,  54,  43],
        [ 63,  55,  44]],

       [[143, 104,  73],
        [147, 108,  77],
        [153, 114,  83],
        ...,
        [ 60,  52,  41],
        [ 62,  54,  43],
        [ 62,  54,  43]]], dtype=uint8)
```

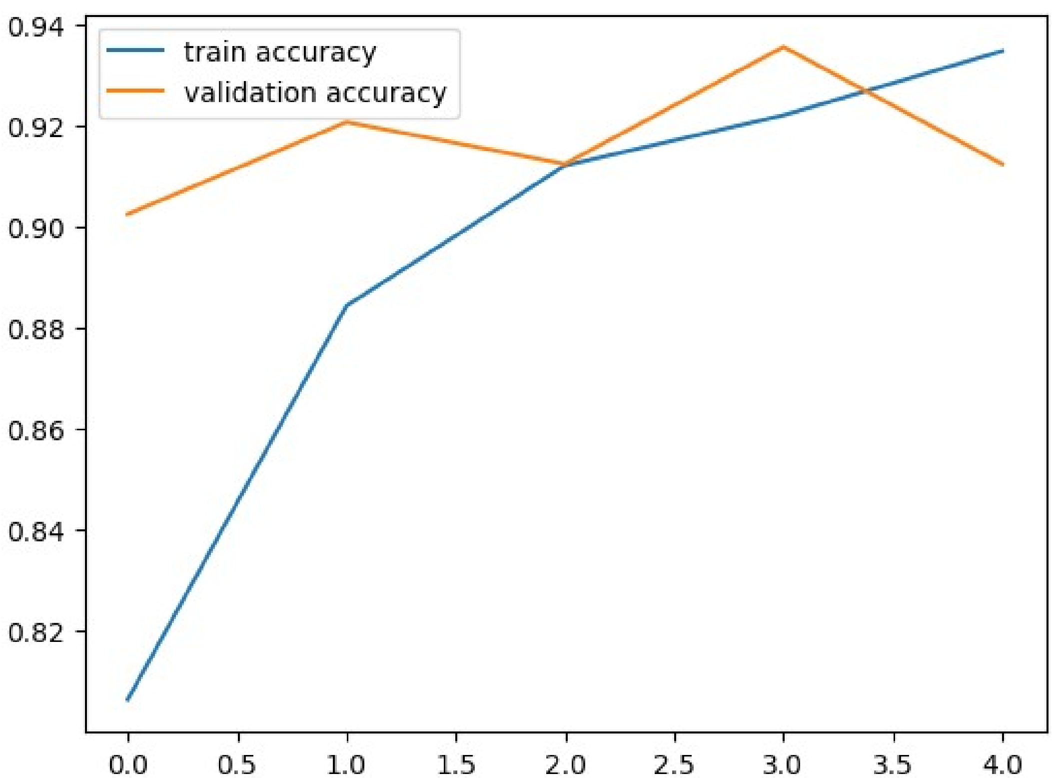
```
X_train_scaled[0]
```

```
array([[[0.18039216, 0.14117647, 0.10588235],
        [0.18039216, 0.14117647, 0.10588235],
        [0.18039216, 0.14117647, 0.10588235],
        ...,
        [0.15686275, 0.1372549 , 0.11372549],
        [0.16470588, 0.14509804, 0.1254902 ],
        [0.16470588, 0.14509804, 0.12941176]],

       [[0.18039216, 0.14117647, 0.10588235],
        [0.18039216, 0.14117647, 0.10588235],
        [0.17647059, 0.1372549 , 0.10196078],
        ...,
        [0.14509804, 0.1254902 , 0.10196078],
        [0.15686275, 0.1372549 , 0.11764706],
        [0.15686275, 0.14117647, 0.1254902 ]],

       [[0.17254902, 0.13333333, 0.09803922],
        [0.17254902, 0.13333333, 0.09803922],
        [0.16470588, 0.12941176, 0.09411765],
        ...,
        [0.15294118, 0.1254902 , 0.10196078],
        [0.15686275, 0.12941176, 0.11372549],
        [0.15686275, 0.12941176, 0.11764706]],

       ...,

       [[0.57254902, 0.40392157, 0.29803922],
        [0.58431373, 0.41568627, 0.30980392],
        [0.6       , 0.43921569, 0.32941176],
        ...,
        [0.23137255, 0.19607843, 0.16078431],
        [0.24705882, 0.21176471, 0.16862745],
        [0.25098039, 0.21960784, 0.17647059]],

       [[0.56470588, 0.40784314, 0.29411765],
        [0.58039216, 0.41960784, 0.30980392],
        [0.60392157, 0.44313725, 0.33333333],
```

```
         ...,
         [0.23137255, 0.19607843, 0.16078431],
         [0.24313725, 0.21176471, 0.16862745],
         [0.24705882, 0.21568627, 0.17254902]],

        [[0.56078431, 0.40784314, 0.28627451],
         [0.57647059, 0.42352941, 0.30196078],
         [0.6       , 0.44705882, 0.3254902 ],
         ...,
         [0.23529412, 0.20392157, 0.16078431],
         [0.24313725, 0.21176471, 0.16862745],
         [0.24313725, 0.21176471, 0.16862745]]]])

#Building a Convolutional Neural Networks (CNN)

import tensorflow as tf
from tensorflow import keras

num_of_classes = 2

model = keras.Sequential()

model.add(keras.layers.Conv2D(32, kernel_size=(3,3),
activation='relu', input_shape=(128,128,3)))
model.add(keras.layers.MaxPooling2D(pool_size=(2,2)))


model.add(keras.layers.Conv2D(64, kernel_size=(3,3),
activation='relu'))
model.add(keras.layers.MaxPooling2D(pool_size=(2,2)))

model.add(keras.layers.Flatten())

model.add(keras.layers.Dense(128, activation='relu'))
model.add(keras.layers.Dropout(0.5))

model.add(keras.layers.Dense(64, activation='relu'))
model.add(keras.layers.Dropout(0.5))


model.add(keras.layers.Dense(num_of_classes, activation='sigmoid'))

# compiling the neural network
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['acc'])

# training our neural network
history = model.fit(X_train_scaled, Y_train, validation_split=0.1,
epochs=5)
```

```
Epoch 1/5
170/170 [==============================] - 143s 827ms/step - loss:
0.4565 - acc: 0.8065 - val_loss: 0.2287 - val_acc: 0.9025
Epoch 2/5
170/170 [==============================] - 138s 814ms/step - loss:
0.3010 - acc: 0.8843 - val_loss: 0.2336 - val_acc: 0.9207
Epoch 3/5
170/170 [==============================] - 133s 784ms/step - loss:
0.2355 - acc: 0.9121 - val_loss: 0.2064 - val_acc: 0.9124
Epoch 4/5
170/170 [==============================] - 142s 837ms/step - loss:
0.1980 - acc: 0.9220 - val_loss: 0.1843 - val_acc: 0.9355
Epoch 5/5
170/170 [==============================] - 131s 771ms/step - loss:
0.1788 - acc: 0.9347 - val_loss: 0.2334 - val_acc: 0.9124

#Evaluating our model

loss, accuracy = model.evaluate(X_test_scaled, Y_test)
print('Test Accuracy =', accuracy)

48/48 [==============================] - 10s 198ms/step - loss: 0.2816
- acc: 0.9007
Test Accuracy = 0.9007279872894287

h = history

# plot the loss value
plt.plot(h.history['loss'], label='train loss')
plt.plot(h.history['val_loss'], label='validation loss')
plt.legend()
plt.show()

# plot the accuracy value
plt.plot(h.history['acc'], label='train accuracy')
plt.plot(h.history['val_acc'], label='validation accuracy')
plt.legend()
plt.show()
```






```
#Testing our predictions
```

```
input_image_path = input('Path of the image to be predicted: ')

input_image = cv2.imread(input_image_path)

cv2_imshow(input_image)

input_image_resized = cv2.resize(input_image, (128,128))

input_image_scaled = input_image_resized/255

input_image_reshaped = np.reshape(input_image_scaled, [1,128,128,3])

input_prediction = model.predict(input_image_reshaped)

print(input_prediction)


input_pred_label = np.argmax(input_prediction)

print(input_pred_label)


if input_pred_label == 0:

  print('The person in the image is wearing a mask')

else:

  print('The person in the image is not wearing a mask')
```

```
Path of the image to be predicted:
/content/data/with_mask/with_mask_1354.jpg
```

```
1/1 [==============================] - 0s 32ms/step
[[0.8516464 0.0411257]]
0
The person in the image is wearing a mask
```

```
input_image_path = input('Path of the image to be predicted: ')

input_image = cv2.imread(input_image_path)

cv2_imshow(input_image)

input_image_resized = cv2.resize(input_image, (128,128))

input_image_scaled = input_image_resized/255

input_image_reshaped = np.reshape(input_image_scaled, [1,128,128,3])

input_prediction = model.predict(input_image_reshaped)

print(input_prediction)


input_pred_label = np.argmax(input_prediction)

print(input_pred_label)


if input_pred_label == 0:

  print('The person in the image is wearing a mask')
```

```
else:

  print('The person in the image is not wearing a mask')
```

```
Path of the image to be predicted:
/content/data/without_mask/without_mask_1354.jpg
```

```
1/1 [==============================] - 0s 52ms/step
[[0.4755757 0.532472 ]]
```

```
1
The person in the image is not wearing a mask

# Complex Model # 2 - Keras/Pretrained Transfer Model Learning using
Mobilenet

from tensorflow.keras.applications import MobileNet
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import matplotlib.pyplot as plt

# Load MobileNet with weights pre-trained on ImageNet, exclude top
layers
base_model = MobileNet(weights='imagenet', include_top=False,
input_shape=(128, 128, 3))

Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/mobilenet/mobilenet_1_0_128_tf_no_top.h5
17225924/17225924 [==============================] - 0s 0us/step

# Freeze the base model layers to prevent them from being updated
during training
base_model.trainable = False

# Create a new model on top
model = Sequential([
    base_model,
    GlobalAveragePooling2D(),
    Dense(1024, activation='relu'),  # Fully connected layer with 1024
units and ReLU activation
    Dense(2, activation='softmax')   # Output layer for two classes
with softmax activation
])

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])

# Data preprocessing and augmentation
train_datagen = ImageDataGenerator(rescale=1./255, shear_range=0.2,
zoom_range=0.2, horizontal_flip=True)
test_datagen = ImageDataGenerator(rescale=1./255)

from google.colab import drive
drive.mount('/content/drive')

Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force_remount=True).

# Load and apply preprocessing to datasets
train_generator =
```

```
train_datagen.flow_from_directory('/content/drive/MyDrive/data',
target_size=(128, 128), batch_size=32, class_mode='categorical')
validation_generator =
test_datagen.flow_from_directory('/content/drive/MyDrive/data',
target_size=(128, 128), batch_size=32, class_mode='categorical')
```

```
Found 7563 images belonging to 2 classes.
Found 7563 images belonging to 2 classes.
```

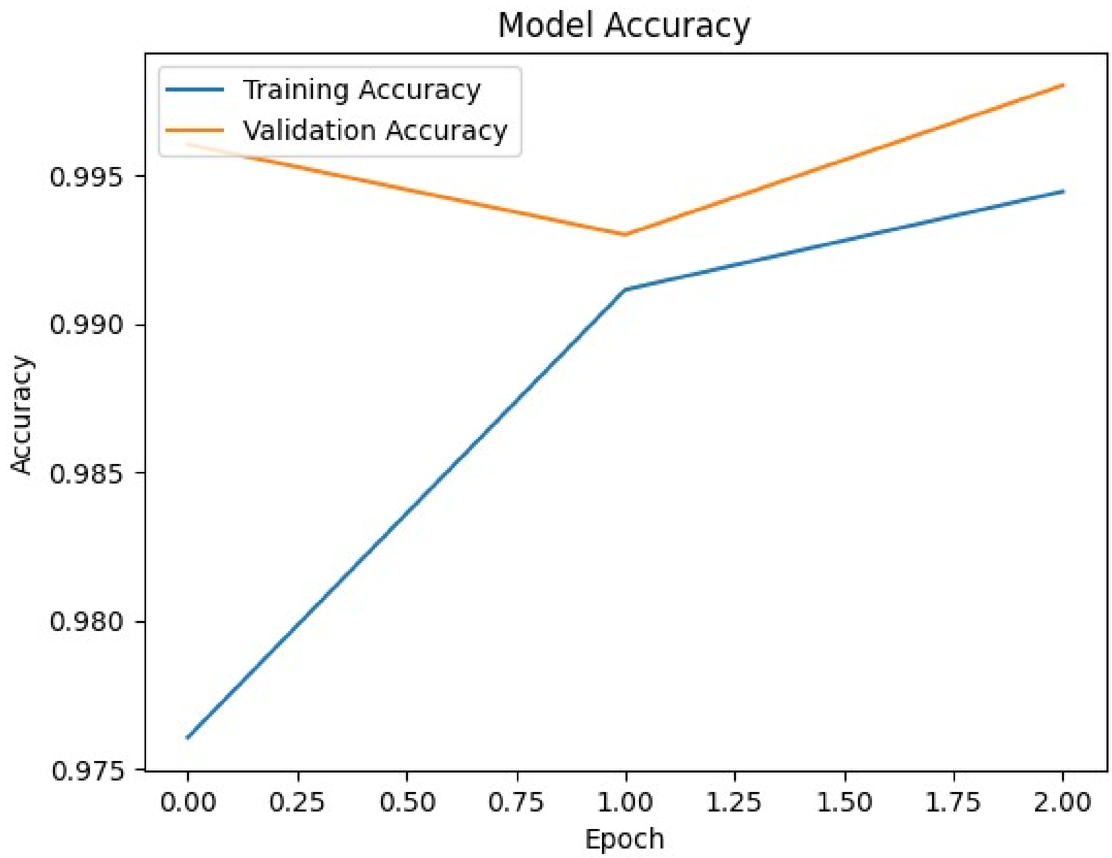
```
# Train the model and save the history
history = model.fit(train_generator,
steps_per_epoch=len(train_generator), epochs=3,
validation_data=validation_generator,
validation_steps=len(validation_generator))
```

```
Epoch 1/3
 63/237 [======>.......................] - ETA: 15:18 - loss: 0.1490 -
accuracy: 0.9489
```

```
/usr/local/lib/python3.10/dist-packages/PIL/Image.py:996: UserWarning:
Palette images with Transparency expressed in bytes should be
converted to RGBA images
  warnings.warn(
```

```
237/237 [==============================] - 1182s 5s/step - loss:
0.0713 - accuracy: 0.9761 - val_loss: 0.0124 - val_accuracy: 0.9960
Epoch 2/3
237/237 [==============================] - 274s 1s/step - loss: 0.0281
- accuracy: 0.9911 - val_loss: 0.0183 - val_accuracy: 0.9930
Epoch 3/3
237/237 [==============================] - 290s 1s/step - loss: 0.0191
- accuracy: 0.9944 - val_loss: 0.0070 - val_accuracy: 0.9980
```

```
# Plotting the training and validation accuracy
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(loc="upper left")
plt.show()
```




```
#Testing the above model

from tensorflow.keras.preprocessing import image
import numpy as np

#Loading the image
image_path = '/content/drive/MyDrive/data/with_mask/with_mask_1.jpg'
img = image.load_img(image_path, target_size=(128, 128))

# Convert the image to a numpy array and scale it
img_array = image.img_to_array(img) / 255.0

# Expand dimensions to make it compatible with the model input
img_array = np.expand_dims(img_array, axis=0)

#Prediction output
predictions = model.predict(img_array)
predicted_class = np.argmax(predictions, axis=1)
if predicted_class[0] == 0:
    print("The model predicts: Class 0") #with mask
else:
    print("The model predicts: Class 1") #without mask
```

```
1/1 [==============================] - 0s 103ms/step
The model predicts: Class 0
```

```
#Trying a simple method - simple sequential model using MNIST

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Flatten, Dense

# Define a simple Sequential model for binary classification
model = Sequential([
    Flatten(input_shape=(28, 28)),  # Assuming 28x28 input size
    Dense(128, activation='relu'),
    Dense(1, activation='sigmoid')  # Output layer for binary
classification
])

model.compile(optimizer='adam',
              loss='binary_crossentropy',  # Use binary_crossentropy
for binary classification
              metrics=['accuracy'])

history = model.fit(train_images, train_labels, epochs=10,
validation_split=0.2)
```

```
Epoch 1/10
1500/1500 [==============================] - 9s 5ms/step - loss: -
45531.2461 - accuracy: 0.1140 - val_loss: -132948.7656 - val_accuracy:
0.1060
Epoch 2/10
1500/1500 [==============================] - 6s 4ms/step - loss: -
292487.2188 - accuracy: 0.1140 - val_loss: -479167.3125 -
val_accuracy: 0.1060
Epoch 3/10
1500/1500 [==============================] - 7s 5ms/step - loss: -
723545.8750 - accuracy: 0.1140 - val_loss: -983868.5625 -
val_accuracy: 0.1060
Epoch 4/10
1500/1500 [==============================] - 6s 4ms/step - loss: -
1301845.6250 - accuracy: 0.1140 - val_loss: -1626400.1250 -
val_accuracy: 0.1060
Epoch 5/10
1500/1500 [==============================] - 6s 4ms/step - loss: -
2015257.6250 - accuracy: 0.1140 - val_loss: -2401020.0000 -
val_accuracy: 0.1060
Epoch 6/10
1500/1500 [==============================] - 7s 4ms/step - loss: -
2856782.7500 - accuracy: 0.1140 - val_loss: -3299980.7500 -
val_accuracy: 0.1060
Epoch 7/10
```

```
1500/1500 [==============================] - 6s 4ms/step - loss: -
3825139.0000 - accuracy: 0.1140 - val_loss: -4326086.0000 -
val_accuracy: 0.1060
Epoch 8/10
1500/1500 [==============================] - 7s 5ms/step - loss: -
4919712.5000 - accuracy: 0.1140 - val_loss: -5474363.5000 -
val_accuracy: 0.1060
Epoch 9/10
1500/1500 [==============================] - 7s 4ms/step - loss: -
6136760.5000 - accuracy: 0.1140 - val_loss: -6747469.0000 -
val_accuracy: 0.1060
Epoch 10/10
1500/1500 [==============================] - 7s 5ms/step - loss: -
7480479.0000 - accuracy: 0.1140 - val_loss: -8144362.0000 -
val_accuracy: 0.1060
```

```python
history = model.fit(train_images, train_labels, epochs=10,
validation_split=0.2)

# Plot training and validation accuracy
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

```
Epoch 1/10
1500/1500 [==============================] - 13s 7ms/step - loss:
0.2851 - accuracy: 0.9185 - val_loss: 0.1492 - val_accuracy: 0.9573
Epoch 2/10
1500/1500 [==============================] - 6s 4ms/step - loss:
0.1280 - accuracy: 0.9623 - val_loss: 0.1200 - val_accuracy: 0.9643
Epoch 3/10
1500/1500 [==============================] - 7s 5ms/step - loss:
0.0885 - accuracy: 0.9739 - val_loss: 0.1032 - val_accuracy: 0.9683
Epoch 4/10
1500/1500 [==============================] - 7s 5ms/step - loss:
0.0654 - accuracy: 0.9805 - val_loss: 0.1028 - val_accuracy: 0.9693
Epoch 5/10
1500/1500 [==============================] - 7s 5ms/step - loss:
0.0502 - accuracy: 0.9852 - val_loss: 0.0840 - val_accuracy: 0.9743
Epoch 6/10
1500/1500 [==============================] - 6s 4ms/step - loss:
0.0403 - accuracy: 0.9875 - val_loss: 0.0879 - val_accuracy: 0.9736
Epoch 7/10
1500/1500 [==============================] - 8s 5ms/step - loss:
0.0303 - accuracy: 0.9909 - val_loss: 0.0898 - val_accuracy: 0.9745
Epoch 8/10
1500/1500 [==============================] - 6s 4ms/step - loss:
```

```
0.0253 - accuracy: 0.9924 - val_loss: 0.0944 - val_accuracy: 0.9727
Epoch 9/10
1422/1500 [===========================>..] - ETA: 0s - loss: 0.0198 -
accuracy: 0.9938

#Testing our model
from tensorflow.keras.preprocessing import image
import numpy as np

# Load and preprocess image for binary classification
img_path = '/content/drive/MyDrive/data/with_mask/with_mask_100.jpg'
img = image.load_img(img_path, target_size=(28, 28),
color_mode='grayscale')
img_array = image.img_to_array(img) / 255.0
img_array = np.expand_dims(img_array, axis=0)  # Model expects a batch

# Predict
prediction = model.predict(img_array)
predicted_class = (prediction > 0.5).astype(int)  # Since we're using
sigmoid
print(f"The model predicts: {predicted_class[0][0]}")

1/1 [==============================] - 0s 20ms/step
The model predicts: 1

#Simple method 2 - Using SVM

from skimage import feature, io
from sklearn import svm
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, accuracy_score
import numpy as np
import os
from PIL import Image

# Linking datasets
mask_path = '/content/drive/MyDrive/data/with_mask'
no_mask_path = '/content/drive/MyDrive/data/without_mask'

images = []
labels = []

# Function to load images from a directory and assign labels
def load_images_from_directory(directory, label):
    for img_name in os.listdir(directory):
        img_path = os.path.join(directory, img_name)
        img = Image.open(img_path).convert('RGB')  # Convert to RGB
        img = img.resize((128, 128))  # Resize images
        images.append(np.array(img))
        labels.append(label)
```

```python
# Load 'without mask' images
load_images_from_directory(no_mask_path, 0)  # 0 for 'without mask'

#Load images with masks (modified code to exclude other formats)
def load_images_from_directory(directory, label):
    for img_name in os.listdir(directory):
        if img_name.lower().endswith('.jpg'):  # Check if the file is
a .jpg image
            img_path = os.path.join(directory, img_name)
            img = Image.open(img_path).convert('RGB')  # Convert to
RGB
            img = img.resize((128, 128))  # Resize images
            images.append(np.array(img))
            labels.append(label)

# Convert lists to numpy arrays
images = np.array(images)
labels = np.array(labels)

# Extract HOG features
hog_features = [feature.hog(image, pixels_per_cell=(16, 16),
cells_per_block=(1, 1), visualize=False, multichannel=True) for image
in images]
hog_features = np.array(hog_features)
```

```
<ipython-input-80-077d908040ed>:2: FutureWarning: `multichannel` is a
deprecated argument name for `hog`. It will be removed in version 1.0.
Please use `channel_axis` instead.
  hog_features = [feature.hog(image, pixels_per_cell=(16, 16),
cells_per_block=(1, 1), visualize=False, multichannel=True) for image
in images]
```

```python
# Split the dataset
X_train, X_test, y_train, y_test = train_test_split(hog_features,
labels, test_size=0.2, random_state=42)

# Feature scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train SVM
clf = svm.SVC(kernel='linear')
clf.fit(X_train_scaled, y_train)
```

```
SVC(kernel='linear')
```

```python
# Predict
y_pred = clf.predict(X_test_scaled)
```

```python
# Evaluation
print(f"Accuracy: {accuracy_score(y_test, y_pred)}")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.8387953941541186
              precision    recall  f1-score   support

           0       0.80      0.70      0.75       766
           1       0.86      0.91      0.88      1492

    accuracy                           0.84      2258
   macro avg       0.83      0.81      0.81      2258
weighted avg       0.84      0.84      0.84      2258
```