```
In [1]: """This program trains a binary classification model on image data (human face images saves the trained model, and classifies new/test images using the model. Also called b It utilizes the Keras library and follows the typical structure of a Convolutional Neu The trained model predicts/classifies the test/new images as: 0 - No Eye glasses & 1 - This program will be hosted online via Streamlit community cloud. Streamlit web app will be created that allows users to upload an image, classify it us display the result."""
```

'This program trains a binary classification model on image data (human face images w ith and without glasses), \nsaves the trained model, and classifies new/test images u sing the model. Also called binary image classification model.\nIt utilizes the Keras library and follows the typical structure of a Convolutional Neural Network (CNN) mod el. \nThe trained model predicts/classifies the test/new images as: 0 - No Eye glasses s & 1 - Eye glasses present.\n\nThis program will be hosted online via Streamlit comm unity cloud. \nStreamlit web app will be created that allows users to upload an imag e, classify it using pre-trained models, and\ndisplay the result.'

```
In [1]: # Importing all necessary libraries
   import h5py
   import os
   from keras.preprocessing.image import ImageDataGenerator
   from keras.models import Sequential
   from keras.layers import Conv2D, MaxPooling2D
   from keras.layers import Activation, Dropout, Flatten, Dense
   from keras import backend as K
   from sklearn.model_selection import train_test_split
   import warnings
   warnings.filterwarnings('ignore')
   import matplotlib.pyplot as plt
   import seaborn as sns
```

```
In [2]: # Setting up training and validation directories
    train_data_dir = 'train'
    validation_data_dir = 'test'

# Counting the number of images in training and validation directories
    train_count = len(os.listdir('train/none')) + len(os.listdir('train/present'))
    test_count = len(os.listdir('test/none')) + len(os.listdir('test/present'))

# Setting up image counts for training and validation
    nb_train_samples = train_count
    nb_validation_samples = test_count

# Setting up training parameters
    epochs = 100  # specific for Model 2
    batch_size = 100

# Setting image dimensions
    img_width, img_height = 224, 224
```

```
In [3]: # Checking the image data format
   if K.image_data_format() == 'channels_first':
        input_shape = (3, img_width, img_height)
   else:
        input_shape = (img_width, img_height, 3)
```

```
In [4]: # Creating a Sequential model
        model = Sequential()
        # Adding Convolutional and Pooling Layers
        model.add(Conv2D(32, (2, 2), input_shape=input_shape))
        model.add(Activation('relu'))
        model.add(MaxPooling2D(pool size=(2, 2)))
        model.add(Conv2D(32, (2, 2)))
        model.add(Activation('relu'))
        model.add(MaxPooling2D(pool_size=(2, 2)))
        model.add(Conv2D(64, (2, 2)))
        model.add(Activation('relu'))
        model.add(MaxPooling2D(pool size=(2, 2)))
        # Flattening and adding Dense Layers
        model.add(Flatten())
        model.add(Dense(64))
        model.add(Activation('relu'))
        model.add(Dropout(0.5))
        model.add(Dense(1))
        model.add(Activation('sigmoid'))
In [5]: # Compiling the model
        model.compile(loss='binary_crossentropy',
                                 optimizer='rmsprop',
                                 metrics=['accuracy'])
In [6]: # Setting up data augmentation for training
        train datagen = ImageDataGenerator(
                rescale=1. / 255,
                shear range=0.2,
                zoom range=0.2,
                horizontal flip=True)
        # Setting up data normalization for testing
        test datagen = ImageDataGenerator(rescale=1. / 255)
        # Creating data generators for training and validation
        train_generator = train_datagen.flow_from_directory(train_data_dir,target_size=(img_wi
        batch size=batch size, class mode='binary')
        validation generator = test datagen.flow from directory(
                validation_data_dir,
                target size=(img width, img height),
                batch size=batch size,
                class_mode='binary')
        # Training the model
        history=model.fit generator(
            train generator,
                 steps_per_epoch=nb_train_samples // batch_size,
                epochs=epochs,
                validation data=validation generator,
                validation steps=nb validation samples // batch size)
```

```
Found 4418 images belonging to 2 classes.
Found 2371 images belonging to 2 classes.
Epoch 1/100
44/44 [============== ] - 171s 4s/step - loss: 0.5695 - accuracy: 0.74
87 - val_loss: 0.2595 - val_accuracy: 0.9013
Epoch 2/100
44/44 [============== ] - 128s 3s/step - loss: 0.2752 - accuracy: 0.89
65 - val loss: 0.1315 - val accuracy: 0.9574
Epoch 3/100
44/44 [================ ] - 121s 3s/step - loss: 0.2107 - accuracy: 0.92
68 - val loss: 0.1480 - val accuracy: 0.9530
Epoch 4/100
44/44 [============== ] - 121s 3s/step - loss: 0.1819 - accuracy: 0.93
49 - val loss: 0.1014 - val accuracy: 0.9643
Epoch 5/100
44/44 [============== ] - 118s 3s/step - loss: 0.1592 - accuracy: 0.94
84 - val loss: 0.0983 - val accuracy: 0.9696
Epoch 6/100
44/44 [============== ] - 124s 3s/step - loss: 0.1463 - accuracy: 0.94
77 - val loss: 0.1127 - val accuracy: 0.9661
Epoch 7/100
44/44 [================ ] - 122s 3s/step - loss: 0.1441 - accuracy: 0.94
97 - val_loss: 0.1936 - val_accuracy: 0.9357
Epoch 8/100
44/44 [============== ] - 128s 3s/step - loss: 0.1418 - accuracy: 0.94
97 - val loss: 0.0989 - val accuracy: 0.9691
Epoch 9/100
44/44 [================ ] - 115s 3s/step - loss: 0.1248 - accuracy: 0.95
85 - val_loss: 0.1032 - val_accuracy: 0.9709
Epoch 10/100
51 - val_loss: 0.0944 - val_accuracy: 0.9687
Epoch 11/100
44/44 [============== ] - 134s 3s/step - loss: 0.1200 - accuracy: 0.95
81 - val_loss: 0.0892 - val_accuracy: 0.9726
Epoch 12/100
44/44 [============== ] - 128s 3s/step - loss: 0.1159 - accuracy: 0.96
09 - val loss: 0.0877 - val accuracy: 0.9730
Epoch 13/100
44/44 [================ ] - 123s 3s/step - loss: 0.1157 - accuracy: 0.95
97 - val_loss: 0.0958 - val_accuracy: 0.9683
Epoch 14/100
44/44 [================ ] - 121s 3s/step - loss: 0.1099 - accuracy: 0.96
11 - val loss: 0.0983 - val accuracy: 0.9687
Epoch 15/100
44/44 [================= ] - 128s 3s/step - loss: 0.1127 - accuracy: 0.96
18 - val loss: 0.0790 - val accuracy: 0.9743
44/44 [============== ] - 127s 3s/step - loss: 0.0993 - accuracy: 0.96
36 - val_loss: 0.0789 - val_accuracy: 0.9774
Epoch 17/100
44/44 [============== ] - 126s 3s/step - loss: 0.0932 - accuracy: 0.96
11 - val loss: 0.0877 - val accuracy: 0.9696
Epoch 18/100
44/44 [================ ] - 122s 3s/step - loss: 0.0998 - accuracy: 0.96
39 - val_loss: 0.0849 - val_accuracy: 0.9735
Epoch 19/100
44/44 [================ ] - 131s 3s/step - loss: 0.0911 - accuracy: 0.96
41 - val loss: 0.0991 - val accuracy: 0.9722
Epoch 20/100
```

```
44/44 [============== ] - 123s 3s/step - loss: 0.0918 - accuracy: 0.96
60 - val loss: 0.0773 - val accuracy: 0.9765
Epoch 21/100
44/44 [============== ] - 131s 3s/step - loss: 0.0936 - accuracy: 0.96
50 - val_loss: 0.0832 - val_accuracy: 0.9748
Epoch 22/100
44/44 [============== ] - 123s 3s/step - loss: 0.0901 - accuracy: 0.96
60 - val loss: 0.0870 - val accuracy: 0.9770
Epoch 23/100
44/44 [================ ] - 121s 3s/step - loss: 0.0917 - accuracy: 0.96
57 - val loss: 0.1164 - val accuracy: 0.9687
Epoch 24/100
67 - val loss: 0.0744 - val accuracy: 0.9778
Epoch 25/100
44/44 [============== ] - 120s 3s/step - loss: 0.0806 - accuracy: 0.96
87 - val loss: 0.0963 - val accuracy: 0.9674
Epoch 26/100
44/44 [============== ] - 126s 3s/step - loss: 0.0800 - accuracy: 0.97
29 - val loss: 0.0813 - val accuracy: 0.9717
Epoch 27/100
44/44 [================ ] - 121s 3s/step - loss: 0.0833 - accuracy: 0.96
85 - val_loss: 0.0889 - val_accuracy: 0.9765
Epoch 28/100
44/44 [============== ] - 136s 3s/step - loss: 0.0760 - accuracy: 0.96
92 - val_loss: 0.0757 - val_accuracy: 0.9796
Epoch 29/100
44/44 [================= ] - 126s 3s/step - loss: 0.0770 - accuracy: 0.97
24 - val loss: 0.0796 - val accuracy: 0.9787
Epoch 30/100
04 - val_loss: 0.0892 - val_accuracy: 0.9761
Epoch 31/100
44/44 [============== ] - 130s 3s/step - loss: 0.0742 - accuracy: 0.97
31 - val loss: 0.0869 - val accuracy: 0.9765
Epoch 32/100
44/44 [============== ] - 129s 3s/step - loss: 0.0755 - accuracy: 0.97
29 - val loss: 0.0825 - val accuracy: 0.9791
Epoch 33/100
44/44 [================ ] - 127s 3s/step - loss: 0.0711 - accuracy: 0.97
38 - val_loss: 0.0884 - val_accuracy: 0.9774
Epoch 34/100
44/44 [================ ] - 135s 3s/step - loss: 0.0679 - accuracy: 0.97
55 - val loss: 0.0804 - val accuracy: 0.9765
Epoch 35/100
44/44 [================= ] - 139s 3s/step - loss: 0.0681 - accuracy: 0.97
55 - val loss: 0.0951 - val accuracy: 0.9752
44/44 [============== ] - 135s 3s/step - loss: 0.0657 - accuracy: 0.97
55 - val_loss: 0.0884 - val_accuracy: 0.9778
Epoch 37/100
44/44 [============== ] - 133s 3s/step - loss: 0.0586 - accuracy: 0.97
82 - val loss: 0.0986 - val accuracy: 0.9748
Epoch 38/100
44/44 [================= ] - 126s 3s/step - loss: 0.0636 - accuracy: 0.97
48 - val_loss: 0.0975 - val_accuracy: 0.9787
Epoch 39/100
44/44 [================ ] - 131s 3s/step - loss: 0.0636 - accuracy: 0.97
82 - val loss: 0.0955 - val accuracy: 0.9796
Epoch 40/100
```

```
44/44 [============== ] - 136s 3s/step - loss: 0.0569 - accuracy: 0.97
71 - val loss: 0.1105 - val accuracy: 0.9674
Epoch 41/100
44/44 [============== ] - 134s 3s/step - loss: 0.0597 - accuracy: 0.97
71 - val_loss: 0.0871 - val_accuracy: 0.9791
Epoch 42/100
44/44 [============== ] - 133s 3s/step - loss: 0.0513 - accuracy: 0.98
03 - val loss: 0.0995 - val accuracy: 0.9748
Epoch 43/100
44/44 [================ ] - 135s 3s/step - loss: 0.0519 - accuracy: 0.97
94 - val loss: 0.0886 - val accuracy: 0.9796
Epoch 44/100
44/44 [============== ] - 128s 3s/step - loss: 0.0526 - accuracy: 0.97
85 - val loss: 0.0912 - val accuracy: 0.9800
Epoch 45/100
44/44 [============== ] - 133s 3s/step - loss: 0.0598 - accuracy: 0.97
71 - val loss: 0.0873 - val accuracy: 0.9783
Epoch 46/100
44/44 [============== ] - 132s 3s/step - loss: 0.0518 - accuracy: 0.98
17 - val loss: 0.0930 - val accuracy: 0.9791
Epoch 47/100
44/44 [================ ] - 133s 3s/step - loss: 0.0537 - accuracy: 0.98
15 - val_loss: 0.1695 - val_accuracy: 0.9617
Epoch 48/100
44/44 [============== ] - 132s 3s/step - loss: 0.0590 - accuracy: 0.97
82 - val loss: 0.0809 - val accuracy: 0.9770
Epoch 49/100
44/44 [================= ] - 135s 3s/step - loss: 0.0521 - accuracy: 0.98
12 - val loss: 0.1083 - val accuracy: 0.9787
Epoch 50/100
44/44 [============== ] - 132s 3s/step - loss: 0.0515 - accuracy: 0.98
08 - val_loss: 0.1079 - val_accuracy: 0.9778
Epoch 51/100
44/44 [============== ] - 126s 3s/step - loss: 0.0488 - accuracy: 0.98
31 - val loss: 0.0979 - val accuracy: 0.9770
Epoch 52/100
44/44 [============== ] - 126s 3s/step - loss: 0.0548 - accuracy: 0.98
10 - val loss: 0.0848 - val accuracy: 0.9791
Epoch 53/100
44/44 [================ ] - 127s 3s/step - loss: 0.0497 - accuracy: 0.98
10 - val_loss: 0.1011 - val_accuracy: 0.9783
Epoch 54/100
44/44 [================ ] - 132s 3s/step - loss: 0.0476 - accuracy: 0.98
17 - val loss: 0.0928 - val accuracy: 0.9783
Epoch 55/100
44/44 [================= ] - 126s 3s/step - loss: 0.0432 - accuracy: 0.98
43 - val loss: 0.1101 - val accuracy: 0.9778
44/44 [============== ] - 126s 3s/step - loss: 0.0466 - accuracy: 0.98
08 - val_loss: 0.1163 - val_accuracy: 0.9791
Epoch 57/100
44/44 [============== ] - 126s 3s/step - loss: 0.0492 - accuracy: 0.98
38 - val loss: 0.1051 - val accuracy: 0.9757
Epoch 58/100
44/44 [================= ] - 125s 3s/step - loss: 0.0423 - accuracy: 0.98
45 - val loss: 0.1021 - val accuracy: 0.9778
Epoch 59/100
44/44 [================ ] - 126s 3s/step - loss: 0.0415 - accuracy: 0.98
43 - val loss: 0.1227 - val accuracy: 0.9757
Epoch 60/100
```

```
44/44 [============== ] - 125s 3s/step - loss: 0.0434 - accuracy: 0.98
54 - val loss: 0.1129 - val accuracy: 0.9778
Epoch 61/100
44/44 [============== ] - 125s 3s/step - loss: 0.0366 - accuracy: 0.98
49 - val_loss: 0.1149 - val_accuracy: 0.9770
Epoch 62/100
44/44 [============== ] - 128s 3s/step - loss: 0.0430 - accuracy: 0.98
33 - val loss: 0.1094 - val accuracy: 0.9839
Epoch 63/100
44/44 [================ ] - 126s 3s/step - loss: 0.0383 - accuracy: 0.98
40 - val loss: 0.1257 - val accuracy: 0.9774
Epoch 64/100
44/44 [============== ] - 125s 3s/step - loss: 0.0403 - accuracy: 0.98
31 - val loss: 0.1034 - val accuracy: 0.9826
Epoch 65/100
44/44 [============== ] - 127s 3s/step - loss: 0.0351 - accuracy: 0.98
55 - val loss: 0.1221 - val accuracy: 0.9770
Epoch 66/100
44/44 [============== ] - 125s 3s/step - loss: 0.0406 - accuracy: 0.98
61 - val loss: 0.1226 - val accuracy: 0.9796
Epoch 67/100
44/44 [================ ] - 125s 3s/step - loss: 0.0386 - accuracy: 0.98
75 - val_loss: 0.1092 - val_accuracy: 0.9809
Epoch 68/100
44/44 [============== ] - 126s 3s/step - loss: 0.0385 - accuracy: 0.98
52 - val loss: 0.1273 - val accuracy: 0.9778
Epoch 69/100
44/44 [================ ] - 125s 3s/step - loss: 0.0405 - accuracy: 0.98
47 - val loss: 0.1353 - val accuracy: 0.9800
Epoch 70/100
44/44 [============== ] - 125s 3s/step - loss: 0.0384 - accuracy: 0.98
66 - val_loss: 0.1128 - val_accuracy: 0.9817
Epoch 71/100
44/44 [============== ] - 126s 3s/step - loss: 0.0393 - accuracy: 0.98
49 - val_loss: 0.1462 - val_accuracy: 0.9752
Epoch 72/100
44/44 [============== ] - 125s 3s/step - loss: 0.0363 - accuracy: 0.98
63 - val loss: 0.1037 - val accuracy: 0.9830
Epoch 73/100
44/44 [================ ] - 125s 3s/step - loss: 0.0331 - accuracy: 0.98
56 - val_loss: 0.1262 - val_accuracy: 0.9800
Epoch 74/100
44/44 [================ ] - 125s 3s/step - loss: 0.0300 - accuracy: 0.98
96 - val loss: 0.1375 - val accuracy: 0.9770
Epoch 75/100
44/44 [============== ] - 126s 3s/step - loss: 0.0352 - accuracy: 0.98
77 - val loss: 0.1083 - val accuracy: 0.9809
44/44 [============== ] - 125s 3s/step - loss: 0.0316 - accuracy: 0.98
75 - val_loss: 0.1245 - val_accuracy: 0.9804
Epoch 77/100
44/44 [============== ] - 127s 3s/step - loss: 0.0408 - accuracy: 0.98
66 - val loss: 0.1154 - val accuracy: 0.9791
Epoch 78/100
44/44 [================ ] - 126s 3s/step - loss: 0.0290 - accuracy: 0.98
82 - val_loss: 0.1243 - val_accuracy: 0.9778
Epoch 79/100
44/44 [================ ] - 125s 3s/step - loss: 0.0372 - accuracy: 0.98
82 - val loss: 0.1461 - val accuracy: 0.9791
Epoch 80/100
```

```
44/44 [============== ] - 125s 3s/step - loss: 0.0358 - accuracy: 0.98
80 - val loss: 0.1163 - val accuracy: 0.9778
Epoch 81/100
44/44 [============== ] - 125s 3s/step - loss: 0.0307 - accuracy: 0.98
80 - val_loss: 0.1372 - val_accuracy: 0.9774
Epoch 82/100
44/44 [============== ] - 125s 3s/step - loss: 0.0290 - accuracy: 0.98
77 - val loss: 0.1203 - val accuracy: 0.9800
Epoch 83/100
44/44 [================ ] - 126s 3s/step - loss: 0.0307 - accuracy: 0.98
98 - val loss: 0.1442 - val accuracy: 0.9800
Epoch 84/100
44/44 [============== ] - 125s 3s/step - loss: 0.0335 - accuracy: 0.98
89 - val loss: 0.1452 - val accuracy: 0.9787
Epoch 85/100
44/44 [============== ] - 125s 3s/step - loss: 0.0295 - accuracy: 0.98
82 - val loss: 0.1337 - val accuracy: 0.9783
Epoch 86/100
44/44 [============== ] - 127s 3s/step - loss: 0.0303 - accuracy: 0.98
84 - val loss: 0.1299 - val accuracy: 0.9817
Epoch 87/100
44/44 [================ ] - 127s 3s/step - loss: 0.0311 - accuracy: 0.98
96 - val_loss: 0.1373 - val_accuracy: 0.9783
Epoch 88/100
44/44 [============== ] - 145s 3s/step - loss: 0.0308 - accuracy: 0.98
80 - val loss: 0.1329 - val accuracy: 0.9787
Epoch 89/100
44/44 [================ ] - 138s 3s/step - loss: 0.0246 - accuracy: 0.99
14 - val loss: 0.1340 - val accuracy: 0.9791
Epoch 90/100
44/44 [=============== ] - 140s 3s/step - loss: 0.0295 - accuracy: 0.98
87 - val_loss: 0.1225 - val_accuracy: 0.9796
Epoch 91/100
44/44 [============== ] - 157s 4s/step - loss: 0.0289 - accuracy: 0.98
87 - val_loss: 0.1544 - val_accuracy: 0.9787
Epoch 92/100
44/44 [============== ] - 135s 3s/step - loss: 0.0334 - accuracy: 0.98
54 - val loss: 0.1288 - val accuracy: 0.9787
Epoch 93/100
44/44 [================= ] - 132s 3s/step - loss: 0.0306 - accuracy: 0.98
93 - val_loss: 0.1411 - val_accuracy: 0.9796
Epoch 94/100
03 - val loss: 0.1122 - val accuracy: 0.9800
Epoch 95/100
44/44 [============== ] - 129s 3s/step - loss: 0.0274 - accuracy: 0.99
14 - val loss: 0.1495 - val accuracy: 0.9830
44/44 [============== ] - 129s 3s/step - loss: 0.0284 - accuracy: 0.99
12 - val_loss: 0.1215 - val_accuracy: 0.9796
Epoch 97/100
44/44 [============== ] - 131s 3s/step - loss: 0.0285 - accuracy: 0.98
84 - val loss: 0.1333 - val accuracy: 0.9817
Epoch 98/100
44/44 [================ ] - 128s 3s/step - loss: 0.0282 - accuracy: 0.99
00 - val_loss: 0.1495 - val_accuracy: 0.9813
Epoch 99/100
44/44 [================ ] - 130s 3s/step - loss: 0.0258 - accuracy: 0.98
98 - val loss: 0.1665 - val accuracy: 0.9770
Epoch 100/100
```

```
44/44 [================ ] - 196s 4s/step - loss: 0.0235 - accuracy: 0.99
         17 - val loss: 0.1434 - val accuracy: 0.9817
In [7]:
        # Plotting loss and accuracy over epochs
         plt.figure(figsize=(20,5))
         # Plotting loss & validation loss
         plt.subplot(1,2,1)
         sns.lineplot(x=history.epoch, y=history.history['loss'], color='red', label='Train Los
         sns.lineplot(x=history.epoch, y=history.history['val_loss'], color='orange', label='Va
         plt.title('Loss on train vs test')
         plt.legend(loc='best')
         # Plotting accuracy and validation accuracy
         plt.subplot(1,2,2)
         sns.lineplot(x=history.epoch, y=history.history['accuracy'], color='blue', label='Trai
         sns.lineplot(x=history.epoch, y=history.history['val accuracy'], color='green', label=
         plt.title('Accuracy on train vs test')
         plt.legend(loc='best')
         plt.show()
                         Loss on train vs test
                                                                         Accuracy on train vs test
                                                        1.00

    Train Loss

                                              Val Loss
                                                        0.95
                                                        0.90
        0.3
                                                        0.85
        0.2
                                                        0.80
                                                                                            Val Accuracy
In [8]:
        # Saving the trained model
         model.save('Model3.h5')
         # Generating Classification report
In [3]:
         from sklearn.metrics import classification report
         # Setting up data augmentation for training
         train_datagen = ImageDataGenerator(
                 rescale=1. / 255,
                 shear range=0.2,
                 zoom range=0.2,
                 horizontal_flip=True)
         # Setting up data normalization for testing
         test_datagen = ImageDataGenerator(rescale=1. / 255)
         # Creating data generators for training and validation
         train generator = train datagen.flow from directory(train data dir,target size=(img wi
         batch size=batch size, class mode='binary')
         validation_generator = test_datagen.flow_from_directory(
                 validation data dir,
                 target_size=(img_width, img_height),
                 batch size=batch size,
```

class_mode='binary')

```
from keras.models import load model
         model = load_model('Model3.h5')
         # Generate predictions for the validation dataset
         validation_generator.reset() # Reset generator to start from beginning
         y pred = model.predict generator(validation generator, steps=len(validation generator)
         y_pred_binary = (y_pred > 0.5).astype(int) # Convert probabilities to binary predicti
         # Get true labels
         y_true = validation_generator.classes
         # Generate classification report
         print(classification_report(y_true, y_pred_binary))
         Found 4418 images belonging to 2 classes.
         Found 2371 images belonging to 2 classes.
         24/24 [========= ] - 17s 670ms/step
                       precision recall f1-score support
                           0.64
                    0
                                     0.64
                                               0.64
                                                         1502
                    1
                            0.38
                                      0.39
                                               0.38
                                                          869
                                               0.55
                                                         2371
             accuracy
                           0.51
                                      0.51
                                               0.51
                                                         2371
            macro avg
         weighted avg
                           0.55
                                      0.55
                                               0.55
                                                         2371
In [4]: # Loading the trained model for predictions
         from keras.models import load_model
         from tensorflow.keras.utils import load_img
         from tensorflow.keras.utils import img to array
         from keras.applications.vgg16 import preprocess_input
         from keras.applications.vgg16 import decode predictions
         from keras.applications.vgg16 import VGG16
         import os
         import numpy as np
         model = load model('Model3.h5')
         # Making predictions on test/new images using the trained model from the above.
In [11]:
         import glob
         # Setting the directory for testing images
         folder_dir = "/Users/tabal/OneDrive/Desktop/Data Capstone/Pictures for Testing"
         # Looping through each image in the directory
         for image in glob.iglob(f'{folder_dir}/*'):
             # Loading and preprocessing the image
             load image = load img(image, target size=(224, 224))
             img = img to array(load image)
             img = preprocess_input(img.reshape(1,224,224,3))
             # Making predictions using the loaded model
             label = model.predict(img)
             # Displaying the predicted class (0 - No Eye glasses , 1 - Eye glasses present) fd
             print("Predicted Class (0 - None , 1- Present) for ", os.path.basename(image), " i
```

Load the saved model

```
Predicted Class (0 - None , 1- Present) for 1.jpg is: 0
1/1 [======= ] - 0s 25ms/step
Predicted Class (0 - None , 1- Present) for 10.jpg is: 0
1/1 [=======] - 0s 23ms/step
Predicted Class (0 - None , 1- Present) for 11.png is: 1
1/1 [======= ] - 0s 23ms/step
Predicted Class (0 - None , 1- Present) for 12.png
                                   is: 1
Predicted Class (0 - None , 1- Present) for 13.jpg is: 1
1/1 [======= ] - 0s 22ms/step
Predicted Class (0 - None , 1- Present) for 14.jpg
1/1 [======] - 0s 25ms/step
Predicted Class (0 - None , 1- Present) for 15.jpg
                                    is: 0
Predicted Class (0 - None , 1- Present) for 16.jpg is: 1
1/1 [======= ] - 0s 25ms/step
Predicted Class (0 - None , 1- Present) for 17.jpg
                                    is: 1
1/1 [======] - 0s 33ms/step
Predicted Class (0 - None , 1- Present) for 18.jpg
Predicted Class (0 - None , 1- Present) for 19.jpg is: 1
1/1 [======] - 0s 23ms/step
Predicted Class (0 - None , 1- Present) for 2.jpg is: 0
1/1 [======] - 0s 25ms/step
Predicted Class (0 - None , 1- Present) for 20.jpg is: 1
1/1 [======] - 0s 21ms/step
Predicted Class (0 - None , 1- Present) for 21.jpg is: 0
Predicted Class (0 - None , 1- Present) for 22.jpg
Predicted Class (0 - None , 1- Present) for 23.jpg
                                    is: 1
1/1 [=======] - 0s 20ms/step
Predicted Class (0 - None , 1- Present) for 24.png is: 0
1/1 [======= ] - 0s 25ms/step
Predicted Class (0 - None , 1- Present) for 25.png is: 1
1/1 [======] - 0s 24ms/step
Predicted Class (0 - None , 1- Present) for 26.png
1/1 [======] - 0s 20ms/step
Predicted Class (0 - None , 1- Present) for 27.png
                                    is: 1
Predicted Class (0 - None , 1- Present) for 28.png is: 0
1/1 [======= ] - 0s 16ms/step
Predicted Class (0 - None , 1- Present) for 29.png is: 0
1/1 [======] - 0s 25ms/step
Predicted Class (0 - None , 1- Present) for 3.png is: 0
1/1 [======] - 0s 35ms/step
Predicted Class (0 - None , 1- Present) for 30.png is: 0
Predicted Class (0 - None , 1- Present) for 31.png
                                    is: 0
Predicted Class (0 - None , 1- Present) for 32.png
                                    is: 0
1/1 [======= ] - 0s 25ms/step
Predicted Class (0 - None , 1- Present) for 33.jpg is: 1
1/1 [======] - 0s 22ms/step
Predicted Class (0 - None , 1- Present) for 34.jpg
                                    is: 1
Predicted Class (0 - None , 1- Present) for 35.jpg is: 0
1/1 [======= ] - 0s 31ms/step
Predicted Class (0 - None , 1- Present) for 4.jpg is: 0
```

```
Predicted Class (0 - None , 1- Present) for 5.jpg is: 0
        1/1 [======] - 0s 21ms/step
        Predicted Class (0 - None , 1- Present) for 6.jpg is: 0
        1/1 [======] - 0s 24ms/step
        Predicted Class (0 - None , 1- Present) for 7.jpg is: 0
        1/1 [======] - 0s 21ms/step
        Predicted Class (0 - None , 1- Present) for 8.jpg is: 0
        1/1 [======] - 0s 21ms/step
        Predicted Class (0 - None , 1- Present) for 9.png is: 0
        # Making predictions on test/new images using the trained model from the above and exp
In [10]:
        # results to an Excel file.
        import glob
        import pandas as pd
        # Setting the directory for testing images
        # folder_dir = "/Users/tabal/OneDrive/Desktop/Data Capstone/Pictures for Testing"
        folder dir = "/Users/tabal/OneDrive/Desktop/Data Capstone/Occulusion jpg"
        # Create an empty list to store prediction results
        prediction_results = []
        # Looping through each image in the directory
        for image in glob.iglob(f'{folder_dir}/*'):
            # Loading and preprocessing the image
            load image = load img(image, target size=(224, 224))
            img = img to array(load image)
            img = preprocess_input(img.reshape(1,224,224,3))
            # Making predictions using the loaded model
            label = model.predict(img)
            # Append the prediction results to the list
            prediction_results.append({
                'Image Name': os.path.basename(image),
                'Prediction': round(label[0][0])})
        # Create a DataFrame from the list
        df = pd.DataFrame(prediction_results)
        # Save the DataFrame to an Excel file
        df.to_excel('prediction_results_Model3', index=False)
```

1/1	[======]	_	0s	14ms/step
1/1	[=======]	_	0s	39ms/step
1/1	[=======]			•
1/1	[=======]			
1/1	[=======]			
1/1	[=======]			
1/1	[=======]			•
1/1	[=======]			•
1/1	[=======]			
1/1	[=======]			•
1/1	[=======]			-
1/1	[=======]			
1/1	[=======]			•
1/1	[=======]			•
1/1	[=======]			-
1/1	[=======]			
1/1	[=======]			
1/1	[=======]	-	0s	18ms/step
1/1	[=======]			•
1/1	[=======]			17ms/step
1/1	[=======]			22ms/step
1/1	[=======]	-		
1/1	[======]	-	0s	23ms/step
1/1	[=======]	-	0s	25ms/step
1/1	[=======]	-	0s	23ms/step
1/1	[=======]	-	0s	32ms/step
1/1	[======]	-	0s	22ms/step
1/1	[=======]	-	0s	22ms/step
1/1	[=======]	-	0s	21ms/step
1/1	[========]	-	0s	21ms/step
1/1	[======]	-	0s	33ms/step
1/1	[========]	-	0s	32ms/step
1/1	[======]	-	0s	17ms/step
1/1	[======]	-	0s	32ms/step
1/1	[======]	-	0s	19ms/step
1/1	[======]	-	0s	34ms/step
1/1	[======]	-	0s	17ms/step
1/1	[======]	-	0s	17ms/step
1/1	[======]	-	0s	32ms/step
	[======]			
	[======]			
1/1	[======]			•
1/1	[======]			
1/1	[======]			•
1/1	[======]			•
1/1	[======]	-	0s	21ms/step
1/1	[]			
1/1	[======]			•
1/1	[======]			
1/1	[=======]			•
1/1	[======]			
1/1	[=========]			•
1/1	[========]			
1/1	[=========]			•
1/1	[========]			•
1/1	[========]			•
1/1	[=======]			•
1/1	[=======]			
1/1	[=======]			•
1/1	[]	-	US	241113/3ceh

1/1	[======]	-	0s	22ms/step
1/1	[==========]	-	0s	23ms/step
1/1	[=======]	_	0s	22ms/step
1/1	[========]	_	0s	23ms/step
1/1	[=======]	-	0s	33ms/step
	[=======]			•
	[=======]			
-	[========]			
-	[=======]			
	[=======]			
	[=======]			•
1/1	[========]	_	0s	21ms/step
1/1	[=======]	-	0s	22ms/step
1/1	[========]	-	0s	22ms/step
1/1	[=======]	-	0s	37ms/step
1/1	[=======]	-	0s	23ms/step
1/1	[=======]	-	0s	21ms/step
1/1	[========]	-	0s	22ms/step
1/1	[=======]	-	0s	22ms/step
1/1	[=======]	-	0s	22ms/step
1/1	[========]	-	0s	22ms/step
1/1	[=========]	-	0s	32ms/step
1/1	[======]	-	0s	22ms/step
1/1	[=========]	-	0s	22ms/step
1/1	[=========]	-	0s	22ms/step
1/1	[=======]	-	0s	35ms/step
1/1	[======]	-	0s	22ms/step
1/1	[=========]	-	0s	23ms/step
1/1	[=======]	-	0s	33ms/step
1/1	[======]	-	0s	22ms/step
1/1	[=======]	-	0s	22ms/step
1/1	[======]	-	0s	22ms/step
1/1	[======]	-	0s	34ms/step
1/1	[======]	-	0s	22ms/step
1/1	[=======]	-	0s	21ms/step
1/1				
	[======]			•
	[======]			•
	[======]			•
	[======]			
	[======]			
	[======]			
	[======]			
	[======]			
	[======]			•
	[========]			•
•	[=======]			, ,
	[=========]			•
	[=========]			•
	[=========]			
	[======]			•
	[=========]			•
	[==========]			•
	[========]			
	[=========]			•
	[=========]			•
	[========]			•
	[========]			•
	[========]			
-/ -			J J	JJ, J CCP

1/1	[======]	_	۵s	22ms/sten
	[======]			
1/1	<u> </u>			
1/1				
	[======]			
	[======]			
1/1				22ms/step
1/1				23ms/step
1/1				33ms/step
1/1				
1/1	[======]			25ms/step
1/1				33ms/step
1/1				, ,
1/1	[======]			•
1/1	[======]		0s	32ms/step
1/1				, ,
1/1	[=======]			
1/1	[======]			
1/1	[======]		_	
1/1	: :		0s	/
1/1	[======]			37ms/step
1/1	[=======]		_	23ms/step
1/1	[========]			23ms/step
1/1	[=======]			23ms/step
1/1	[======]			30ms/step
1/1	[=======]	_	_	22ms/step
1/1				30ms/step
1/1	[======]			25ms/step
1/1	[======]			22ms/step
1/1			_	23ms/step
1/1				34ms/step
1/1	[=======]			22ms/step
1/1	<u> </u>		_	22ms/step
1/1	: :			21ms/step
1/1				27ms/step
,	[========]			, ,
	[=======]			
	[=======]			
	[=======]			
	[========]			
	[========]			
	[=======]			
	[=======]			
	[=======]			
	[========]			
-/ -	[]		03	э -н шэ <i>,</i> эсср