Submission

April 7, 2023

1 Project 3

Subject: Deep Learning

Date: 2023-04-07

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2 Introduction

In this project, we use a modified version of the FairFace dataset to build five neural networks in order to classify three attributes: race, gender and age. All images are converted to gray scale and resized them to 32 × 32 to decrease the training time.

[ ]:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
import keras
from keras.models import Sequential
from keras.layers import Dense
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
from PIL import Image
from concurrent.futures import ThreadPoolExecutor
import os
import time
import random
```

[ ]:
```
# import Keras layers
from keras.layers import Conv2D
from keras.layers import MaxPooling2D
from keras.layers import Flatten
from keras.layers import Dropout
from keras.layers import Dense
from keras.layers import BatchNormalization
```

3 Task 0: Load Images

3.0.1 Functions for one-hot-encoding Age, Gender and Ethnicity

[ ]:
```
def convert_age(age):
    age_dict = {'0-2': 0, '3-9': 1, '10-19': 2, '20-29': 3, '30-39': 4, '40-49':
 ↪ 5, '50-59': 6, '60-69': 7, 'more than 70': 8}
    return np.eye(9)[[age_dict[a] for a in age]]

def convert_gender(gender):
    gender_dict = {'Male': 0, 'Female': 1}
    return np.eye(2)[[gender_dict[g] for g in gender]]

def convert_race(race):
    race_dict = {'Black': 0, 'Latino_Hispanic': 1, 'East Asian': 2, 'White': 3,␣
 ↪'Southeast Asian': 4, 'Middle Eastern': 5, 'Indian': 6}
    return np.eye(7)[[race_dict[r] for r in race]]
```

3.0.2 Reading in images in parallel

[ ]:
```
# function to read image
def read_image(image_path):
    with Image.open(image_path) as image:
        return np.asarray(image)

# function to read image
def read_image(image_path):
    with Image.open(image_path) as image:
        return np.asarray(image)

# read data, labels in lists
def get_dataset(DATA_DIR, mode, sample=False):
    if mode == 'train':
        df = pd.read_csv(os.path.join(DATA_DIR, 'fairface_label_train.csv'))
    elif mode == 'val':
        df = pd.read_csv(os.path.join(DATA_DIR, 'fairface_label_val.csv'))
    else:
        raise ValueError

    age = df['age'].values.tolist()
    gender = df['gender'].values.tolist()
    race = df['race'].values.tolist()
    filenames = df['file'].values.tolist()

    image_paths = [os.path.join(DATA_DIR, name) for name in filenames]

    if sample:
        sample_size = int(len(image_paths) * 0.05) # 5% of total images
        sampled_indexes = random.sample(range(len(image_paths)), sample_size)
```

```
        image_paths = [image_paths[i] for i in sampled_indexes]
        age = [age[i] for i in sampled_indexes]
        gender = [gender[i] for i in sampled_indexes]
        race = [race[i] for i in sampled_indexes]

    with ThreadPoolExecutor() as executor:
        all_img = list(executor.map(read_image, image_paths))

    onehot_age = convert_age(age)
    onehot_gender = convert_gender(gender)
    onehot_race = convert_race(race)

    return all_img, onehot_age, onehot_gender, onehot_race
```

[ ]:
```
DATA_DIR = '/Users/harshvardhan/Library/CloudStorage/Dropbox/Academics/UTK␣
 ↪Classes/Spring 2023/Deep Learning/Project 3/project3_COSC525'
```

[ ]:
```
train_img, train_age, train_gender, train_race = get_dataset(DATA_DIR,'train')
val_img, val_age, val_gender, val_race = get_dataset(DATA_DIR,'val')
```

[ ]:
```
# Normalize the data with MinMaxScaler
flattened_train_img = [img.reshape(32*32) for img in train_img]
flattened_val_img = [img.reshape(32*32) for img in val_img]

scaler = MinMaxScaler()
scaler.fit(flattened_train_img)
print(len(scaler.data_max_), len(scaler.data_min_))

scaled_train_img = scaler.transform(flattened_train_img)
scaled_val_img = scaler.transform(flattened_val_img)
```

```
1024 1024
```

4 Task 1: Fully Connected Neural Network

1. Build a feed forward neural network with the following specifications (Test on two different tasks):

- Hidden layer 1: 1024 neurons with hyperbolic tangent activation function in each neuron.
- Hidden layer 2: 512 neurons, with sigmoid activation function in each of the neuron.
- 100 neurons, with rectified linear activation function in each of the neuron.
- Output layer: n (depending on the task) neurons representing the n classes, using the softmax activation function.

2. Using Min-Max scaling to scale the training dataset and using the same Min and Max values from the training set scale the test dataset

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

.

3. sing mini-batch gradient descent to optimize the loss function: "categorical cross-entropy" on the training dataset. Please record the loss value for each of the epochs and create an epoch-loss plot and an accuracy-loss plot for both the training and validation set.

4. Report the following:
   - Final classification accuracy.
   - n-class confusion matrix.

```
[ ]: # Building the model
def get_model(output_dim):
    model = Sequential()
    model.add(Dense(1024, input_dim=32*32, activation='tanh'))
    model.add(Dense(512, activation='sigmoid'))
    model.add(Dense(100, activation='relu'))
    model.add(Dense(output_dim, activation='softmax'))
    return model
```

4.1 Classifying Gender

```
[ ]: lr = 0.001
opt = keras.optimizers.Adam(learning_rate=lr)
bs = 32
epochs = 50
```

```
[ ]: gender_model = get_model(2)
gender_model.compile(loss='categorical_crossentropy', optimizer=opt,␣
 ↪metrics=['accuracy'])
train_history = gender_model.fit(scaled_train_img, np.array(train_gender),
                    batch_size=32, epochs=10,
                    verbose=1, shuffle=True, validation_data=(scaled_val_img,␣
 ↪np.array(val_gender)))
loss = train_history.history['loss']
val_loss = train_history.history['val_loss']
acc = train_history.history['accuracy']
val_acc = train_history.history['val_accuracy']
```

```
2023-04-07 12:56:48.047986: I tensorflow/core/platform/cpu_feature_guard.cc:193]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
operations:  SSE4.1 SSE4.2
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.

Epoch 1/10
2711/2711 [==============================] - 20s 7ms/step - loss: 0.6211 -
accuracy: 0.6470 - val_loss: 0.5699 - val_accuracy: 0.6874
Epoch 2/10
```

```
2711/2711 [==============================] - 20s 7ms/step - loss: 0.5822 -
accuracy: 0.6805 - val_loss: 0.6024 - val_accuracy: 0.6387
Epoch 3/10
2711/2711 [==============================] - 20s 7ms/step - loss: 0.5659 -
accuracy: 0.6908 - val_loss: 0.5523 - val_accuracy: 0.7060
Epoch 4/10
2711/2711 [==============================] - 19s 7ms/step - loss: 0.5583 -
accuracy: 0.6961 - val_loss: 0.5376 - val_accuracy: 0.7129
Epoch 5/10
2711/2711 [==============================] - 19s 7ms/step - loss: 0.5529 -
accuracy: 0.7027 - val_loss: 0.5558 - val_accuracy: 0.6955
Epoch 6/10
2711/2711 [==============================] - 19s 7ms/step - loss: 0.5496 -
accuracy: 0.7032 - val_loss: 0.5370 - val_accuracy: 0.7087
Epoch 7/10
2711/2711 [==============================] - 19s 7ms/step - loss: 0.5459 -
accuracy: 0.7067 - val_loss: 0.5537 - val_accuracy: 0.7145
Epoch 8/10
2711/2711 [==============================] - 19s 7ms/step - loss: 0.5446 -
accuracy: 0.7088 - val_loss: 0.5274 - val_accuracy: 0.7289
Epoch 9/10
2711/2711 [==============================] - 19s 7ms/step - loss: 0.5406 -
accuracy: 0.7124 - val_loss: 0.5491 - val_accuracy: 0.6785
Epoch 10/10
2711/2711 [==============================] - 20s 7ms/step - loss: 0.5384 -
accuracy: 0.7125 - val_loss: 0.5412 - val_accuracy: 0.7165
```

Model Architecture

[ ]:
```
gender_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 1024)              1049600

 dense_1 (Dense)             (None, 512)               524800

 dense_2 (Dense)             (None, 100)               51300

 dense_3 (Dense)             (None, 2)                 202

=================================================================
Total params: 1,625,902
Trainable params: 1,625,902
Non-trainable params: 0
_________________________________________________________________
_________________________________________________________________
```

```
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 1024)              1049600

 dense_1 (Dense)             (None, 512)               524800

 dense_2 (Dense)             (None, 100)               51300

 dense_3 (Dense)             (None, 2)                 202

=================================================================
Total params: 1,625,902
Trainable params: 1,625,902
Non-trainable params: 0
_________________________________________________________________
```

4.1.1 Validation and Training Loss and Accuracy

[ ]:
```
# creating a data frame for the loss and accuracy
df = pd.DataFrame({'epoch': np.arange(1,11), 'loss': loss, 'val_loss':␣
↪val_loss, 'acc': acc, 'val_acc': val_acc})
```

[ ]:
```
df
```

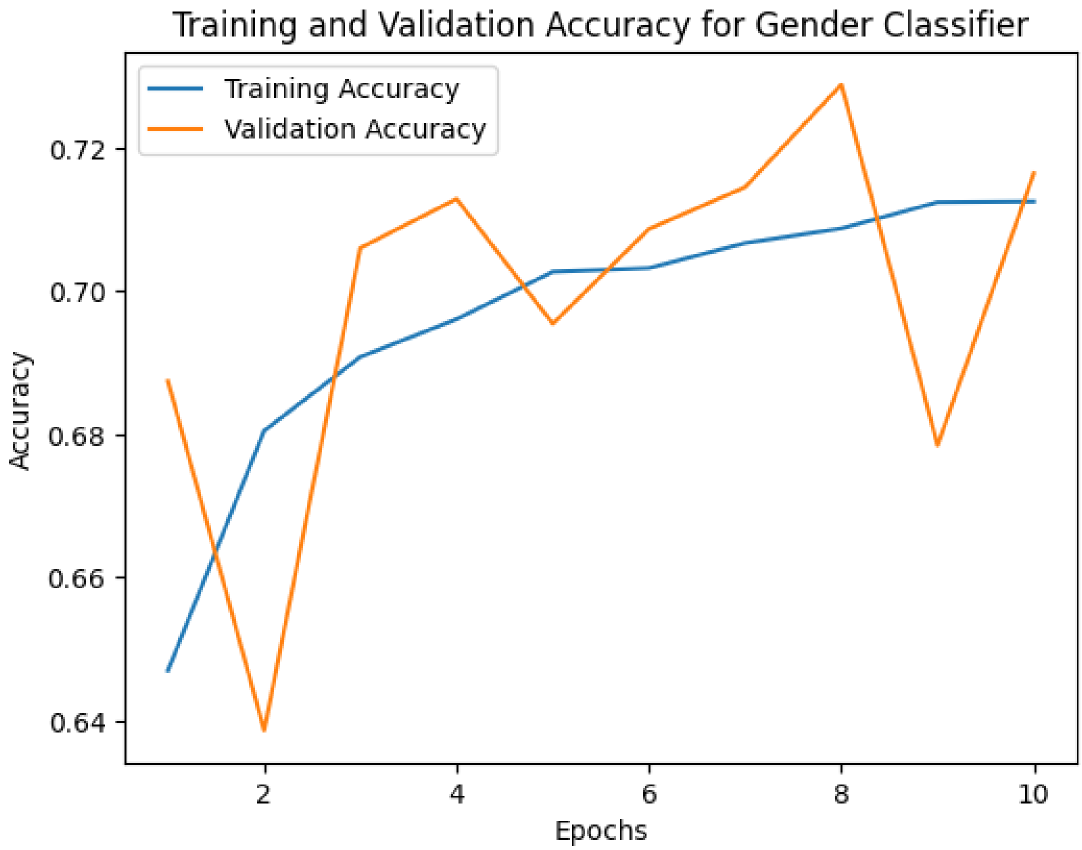
[ ]:

	epoch	loss	val_loss	acc	val_acc
0	1	0.621132	0.569863	0.647042	0.687420
1	2	0.582183	0.602352	0.680508	0.638671
2	3	0.565928	0.552272	0.690826	0.706043
3	4	0.558314	0.537600	0.696094	0.712890
4	5	0.552851	0.555792	0.702711	0.695454
5	6	0.549578	0.537050	0.703230	0.708691
6	7	0.545871	0.553694	0.706723	0.714534
7	8	0.544581	0.527407	0.708764	0.728866
8	9	0.540597	0.549149	0.712430	0.678474
9	10	0.538360	0.541181	0.712533	0.716451

[ ]:
```
# plotting validation and training loss
plt.plot(df['epoch'], df['loss'], label='Training Loss')
plt.plot(df['epoch'], df['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training and Validation Loss for Gender Classifier')
plt.legend()
plt.show()
```

[ ]:
```
# plotting validation and training accuracy
plt.plot(df['epoch'], df['acc'], label='Training Accuracy')
plt.plot(df['epoch'], df['val_acc'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title("Training and Validation Accuracy for Gender Classifier")
plt.legend()
```

[ ]:
```
<matplotlib.legend.Legend at 0x7fabc29cde70>
```



4.1.2 Confusion Matrix on Predictions

[ ]:
```
gender_pred = gender_model.predict(scaled_val_img)
val_gender = np.array(val_gender)
matrix = confusion_matrix(y_true=val_gender.argmax(axis=1), y_pred=gender_pred.
  ↪argmax(axis=1))
```

```
343/343 [==============================] - 1s 3ms/step
```

[ ]:
```
matrix
```

[ ]:
```
array([[5117,  675],
       [2431, 2731]])
```

[ ]:
```
Accuracy = (matrix[0][0] + matrix[1][1]) / (matrix[0][0] + matrix[0][1] +␣
  ↪matrix[1][0] + matrix[1][1])
print("Accuracy: ", Accuracy)
```

```
Accuracy:  0.7164506116487128
```

Accuracy The accuracy of the model is 71.7%, which is the percentage of correct predictions made by the model.

Confusion Matrix The confusion matrix presented here is a table that indicates the performance of a gender prediction model on a validation set of face images. The model is tasked with predicting the gender of each face image, and 'Male' is labeled as 0 while 'Female' is labeled as 1.

The matrix indicates that the model correctly predicted 5117 male images and 2731 female images, representing the true positives for each class. However, the model misclassified 675 male images as female and 2431 female images as male, which are the false positives for females and males, respectively.

From this matrix, we can see that the model has a higher accuracy in predicting males than in predicting females.

4.2 Classifying Age

[ ]:
```
lr = 0.001
opt = keras.optimizers.Adam(learning_rate=lr)
bs = 32
epochs = 50
```

[ ]:
```
age_model = get_model(9)
age_model.compile(loss='categorical_crossentropy', optimizer=opt,␣
 ↪metrics=['accuracy'])
train_history = age_model.fit(scaled_train_img, np.array(train_age),
                    batch_size=bs, epochs=epochs,
                    verbose=1, shuffle=True, validation_data=(scaled_val_img,␣
 ↪np.array(val_age)))
loss = train_history.history['loss']
val_loss = train_history.history['val_loss']
acc = train_history.history['accuracy']
val_acc = train_history.history['val_accuracy']
```

```
Epoch 1/50
2711/2711 [==============================] - 493s 182ms/step - loss: 1.7841 -
accuracy: 0.3070 - val_loss: 1.7399 - val_accuracy: 0.3329
Epoch 2/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.7188 -
accuracy: 0.3301 - val_loss: 1.6997 - val_accuracy: 0.3381
Epoch 3/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.7015 -
accuracy: 0.3378 - val_loss: 1.7179 - val_accuracy: 0.3286
Epoch 4/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6927 -
accuracy: 0.3404 - val_loss: 1.6683 - val_accuracy: 0.3543
Epoch 5/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6863 -
accuracy: 0.3397 - val_loss: 1.6635 - val_accuracy: 0.3596
```

```
Epoch 6/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6771 -
accuracy: 0.3432 - val_loss: 1.6551 - val_accuracy: 0.3546
Epoch 7/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6671 -
accuracy: 0.3475 - val_loss: 1.6555 - val_accuracy: 0.3613
Epoch 8/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6618 -
accuracy: 0.3484 - val_loss: 1.6454 - val_accuracy: 0.3697
Epoch 9/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6555 -
accuracy: 0.3517 - val_loss: 1.6811 - val_accuracy: 0.3498
Epoch 10/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6527 -
accuracy: 0.3502 - val_loss: 1.6664 - val_accuracy: 0.3564
Epoch 11/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6484 -
accuracy: 0.3518 - val_loss: 1.6486 - val_accuracy: 0.3590
Epoch 12/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6481 -
accuracy: 0.3529 - val_loss: 1.6786 - val_accuracy: 0.3494
Epoch 13/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6404 -
accuracy: 0.3541 - val_loss: 1.6670 - val_accuracy: 0.3499
Epoch 14/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6382 -
accuracy: 0.3550 - val_loss: 1.6427 - val_accuracy: 0.3643
Epoch 15/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6342 -
accuracy: 0.3570 - val_loss: 1.6274 - val_accuracy: 0.3643
Epoch 16/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6348 -
accuracy: 0.3583 - val_loss: 1.6250 - val_accuracy: 0.3620
Epoch 17/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6340 -
accuracy: 0.3576 - val_loss: 1.6402 - val_accuracy: 0.3600
Epoch 18/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6330 -
accuracy: 0.3579 - val_loss: 1.6275 - val_accuracy: 0.3663
Epoch 19/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6322 -
accuracy: 0.3585 - val_loss: 1.6539 - val_accuracy: 0.3587
Epoch 20/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6340 -
accuracy: 0.3551 - val_loss: 1.6405 - val_accuracy: 0.3608
Epoch 21/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6299 -
accuracy: 0.3587 - val_loss: 1.6617 - val_accuracy: 0.3472
```

```
Epoch 22/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6281 -
accuracy: 0.3581 - val_loss: 1.6481 - val_accuracy: 0.3529
Epoch 23/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6265 -
accuracy: 0.3589 - val_loss: 1.6783 - val_accuracy: 0.3529
Epoch 24/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6263 -
accuracy: 0.3598 - val_loss: 1.6649 - val_accuracy: 0.3642
Epoch 25/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6227 -
accuracy: 0.3601 - val_loss: 1.6526 - val_accuracy: 0.3597
Epoch 26/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6203 -
accuracy: 0.3610 - val_loss: 1.6319 - val_accuracy: 0.3696
Epoch 27/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6195 -
accuracy: 0.3615 - val_loss: 1.6497 - val_accuracy: 0.3601
Epoch 28/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6167 -
accuracy: 0.3616 - val_loss: 1.6193 - val_accuracy: 0.3694
Epoch 29/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6184 -
accuracy: 0.3607 - val_loss: 1.7282 - val_accuracy: 0.3416
Epoch 30/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6162 -
accuracy: 0.3609 - val_loss: 1.6529 - val_accuracy: 0.3635
Epoch 31/50
2711/2711 [==============================] - 19s 7ms/step - loss: 1.6194 -
accuracy: 0.3613 - val_loss: 1.6342 - val_accuracy: 0.3648
Epoch 32/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6166 -
accuracy: 0.3610 - val_loss: 1.6234 - val_accuracy: 0.3661
Epoch 33/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6146 -
accuracy: 0.3630 - val_loss: 1.6311 - val_accuracy: 0.3676
Epoch 34/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6148 -
accuracy: 0.3631 - val_loss: 1.6262 - val_accuracy: 0.3695
Epoch 35/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6087 -
accuracy: 0.3652 - val_loss: 1.6273 - val_accuracy: 0.3602
Epoch 36/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6120 -
accuracy: 0.3639 - val_loss: 1.6349 - val_accuracy: 0.3643
Epoch 37/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6082 -
accuracy: 0.3647 - val_loss: 1.6479 - val_accuracy: 0.3546
```

```
Epoch 38/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6102 -
accuracy: 0.3603 - val_loss: 1.6327 - val_accuracy: 0.3670
Epoch 39/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6098 -
accuracy: 0.3617 - val_loss: 1.6467 - val_accuracy: 0.3604
Epoch 40/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6049 -
accuracy: 0.3642 - val_loss: 1.6265 - val_accuracy: 0.3676
Epoch 41/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6039 -
accuracy: 0.3665 - val_loss: 1.6356 - val_accuracy: 0.3620
Epoch 42/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6047 -
accuracy: 0.3658 - val_loss: 1.6370 - val_accuracy: 0.3651
Epoch 43/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6111 -
accuracy: 0.3625 - val_loss: 1.6486 - val_accuracy: 0.3538
Epoch 44/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6086 -
accuracy: 0.3627 - val_loss: 1.6370 - val_accuracy: 0.3593
Epoch 45/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6029 -
accuracy: 0.3653 - val_loss: 1.6561 - val_accuracy: 0.3579
Epoch 46/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6041 -
accuracy: 0.3652 - val_loss: 1.6179 - val_accuracy: 0.3672
Epoch 47/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6019 -
accuracy: 0.3649 - val_loss: 1.6284 - val_accuracy: 0.3569
Epoch 48/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6041 -
accuracy: 0.3649 - val_loss: 1.6188 - val_accuracy: 0.3686
Epoch 49/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6052 -
accuracy: 0.3644 - val_loss: 1.6321 - val_accuracy: 0.3641
Epoch 50/50
2711/2711 [==============================] - 20s 7ms/step - loss: 1.6041 -
accuracy: 0.3647 - val_loss: 1.6247 - val_accuracy: 0.3615
```

Model Architecture

[ ]:
```
age_model.summary()
```

```
Model: "sequential_1"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_4 (Dense)             (None, 1024)              1049600
```

```
 dense_5 (Dense)             (None, 512)               524800

 dense_6 (Dense)             (None, 100)               51300

 dense_7 (Dense)             (None, 9)                 909

=================================================================
Total params: 1,626,609
Trainable params: 1,626,609
Non-trainable params: 0
_________________________________________________________________
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_4 (Dense)             (None, 1024)              1049600

 dense_5 (Dense)             (None, 512)               524800

 dense_6 (Dense)             (None, 100)               51300

 dense_7 (Dense)             (None, 9)                 909

=================================================================
Total params: 1,626,609
Trainable params: 1,626,609
Non-trainable params: 0
_________________________________________________________________
```

4.2.1 Validation and Training Loss and Accuracy

[ ]:
```python
# creating a data frame for the loss and accuracy
df = pd.DataFrame({'epoch': np.arange(1,epochs+1), 'loss': loss, 'val_loss': val_loss, 'acc': acc, 'val_acc': val_acc})
```

[ ]:
```python
df
```

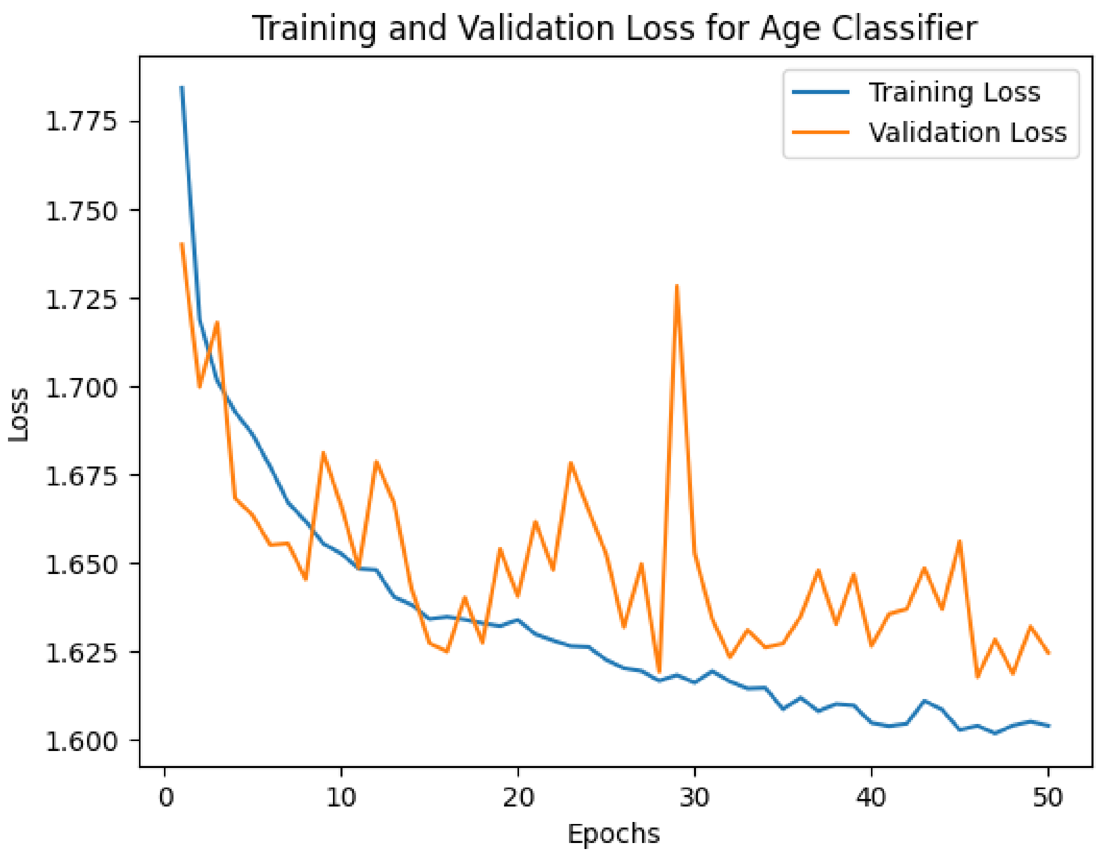
[ ]:

	epoch	loss	val_loss	acc	val_acc
0	1	1.784089	1.739939	0.306961	0.332938
1	2	1.718761	1.699723	0.330098	0.338141
2	3	1.701464	1.717879	0.337752	0.328647
3	4	1.692725	1.668296	0.340392	0.354300
4	5	1.686306	1.663491	0.339747	0.359595
5	6	1.677106	1.655090	0.343228	0.354574
6	7	1.667095	1.655548	0.347517	0.361329
7	8	1.661780	1.645443	0.348439	0.369728
8	9	1.655452	1.681100	0.351690	0.349827

9	10	1.652693	1.666366	0.350226	0.356399
10	11	1.648434	1.648569	0.351828	0.359047
11	12	1.648055	1.678622	0.352866	0.349370
12	13	1.640399	1.666952	0.354146	0.349918
13	14	1.638224	1.642665	0.355045	0.364251
14	15	1.634168	1.627394	0.356958	0.364342
15	16	1.634817	1.624980	0.358330	0.361968
16	17	1.634026	1.640207	0.357592	0.359960
17	18	1.632990	1.627468	0.357904	0.366259
18	19	1.632184	1.653913	0.358515	0.358682
19	20	1.633952	1.640548	0.355114	0.360781
20	21	1.629894	1.661667	0.358676	0.347179
21	22	1.628130	1.648064	0.358111	0.352930
22	23	1.626547	1.678258	0.358861	0.352930
23	24	1.626300	1.664866	0.359771	0.364159
24	25	1.622661	1.652556	0.360106	0.359686
25	26	1.620305	1.631929	0.361016	0.369637
26	27	1.619497	1.649723	0.361524	0.360142
27	28	1.616749	1.619304	0.361627	0.369363
28	29	1.618358	1.728195	0.360740	0.341610
29	30	1.616249	1.652870	0.360913	0.363520
30	31	1.619439	1.634171	0.361258	0.364798
31	32	1.616565	1.623377	0.361005	0.366076
32	33	1.614593	1.631104	0.363034	0.367628
33	34	1.614785	1.626173	0.363091	0.369545
34	35	1.608731	1.627284	0.365247	0.360234
35	36	1.611958	1.634925	0.363852	0.364342
36	37	1.608174	1.647948	0.364694	0.354574
37	38	1.610194	1.632698	0.360348	0.366989
38	39	1.609792	1.646743	0.361731	0.360416
39	40	1.604890	1.626529	0.364164	0.367628
40	41	1.603947	1.635603	0.366515	0.361968
41	42	1.604662	1.637008	0.365835	0.365072
42	43	1.611074	1.648555	0.362550	0.353752
43	44	1.608596	1.636957	0.362746	0.359321
44	45	1.602875	1.656123	0.365316	0.357860
45	46	1.604055	1.617853	0.365213	0.367172
46	47	1.601903	1.628427	0.364947	0.356947
47	48	1.604123	1.618791	0.364936	0.368632
48	49	1.605248	1.632087	0.364406	0.364068
49	50	1.604089	1.624733	0.364717	0.361512

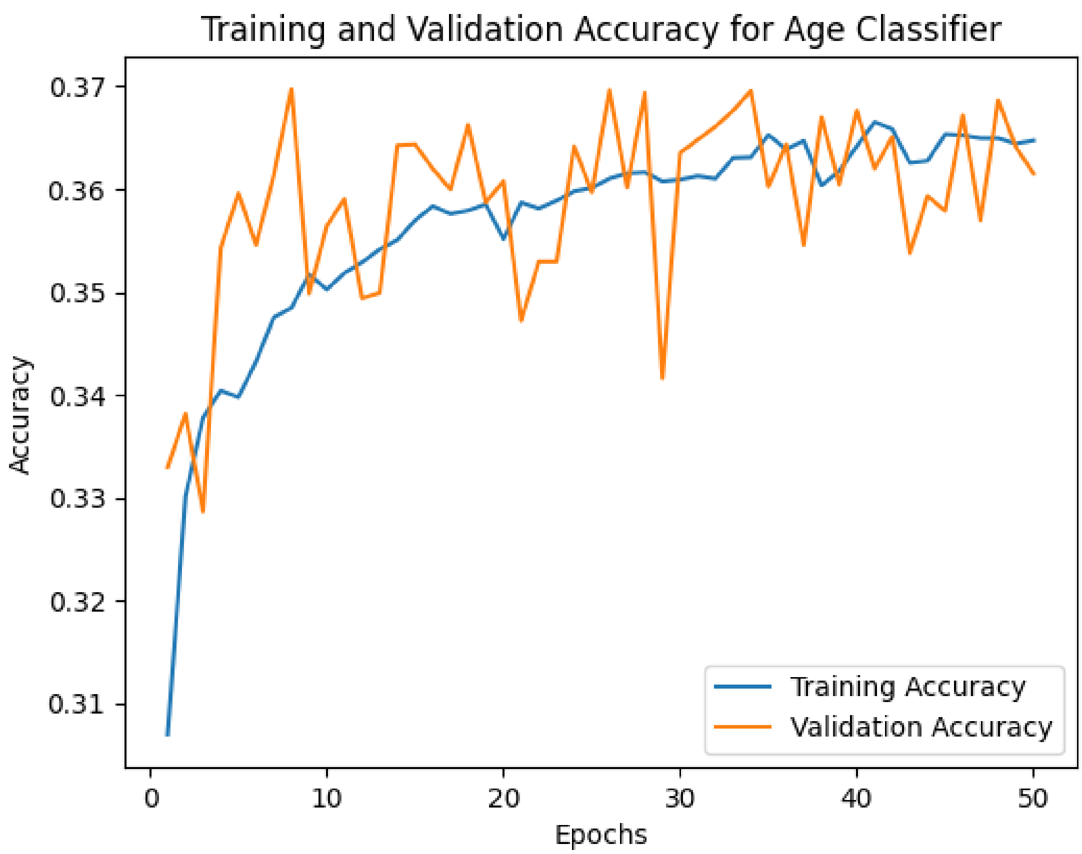
[ ]:
```
# plotting validation and training loss
plt.plot(df['epoch'], df['loss'], label='Training Loss')
plt.plot(df['epoch'], df['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
```

```
plt.title('Training and Validation Loss for Age Classifier')
plt.legend()
plt.show()
```



[ ]:
```
# plotting validation and training accuracy
plt.plot(df['epoch'], df['acc'], label='Training Accuracy')
plt.plot(df['epoch'], df['val_acc'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title("Training and Validation Accuracy for Age Classifier")
plt.legend()
```

[ ]: <matplotlib.legend.Legend at 0x7fabd5c8f280>



4.2.2 Confusion Matrix on Predictions

[ ]:
```
age_pred = age_model.predict(scaled_val_img)
val_age = np.array(val_age)
matrix = confusion_matrix(y_true=val_age.argmax(axis=1), y_pred=age_pred.
 ↪argmax(axis=1))
```

```
343/343 [==============================] - 1s 3ms/step
```

[ ]:
```
matrix
```

[ ]:
```
array([[   0,  139,    0,   44,   12,    0,    4,    0,    0],
       [   0,  679,   13,  572,   80,    0,   12,    0,    0],
       [   0,  149,   11,  878,  130,    0,   13,    0,    0],
       [   0,  115,    5, 2512,  601,    3,   64,    0,    0],
       [   0,   51,    3, 1543,  635,   10,   88,    0,    0],
       [   0,   34,    2,  723,  485,    7,  102,    0,    0],
       [   0,   15,    0,  305,  355,    5,  116,    0,    0],
       [   0,    2,    0,  105,  130,    2,   82,    0,    0],
       [   0,    2,    0,   36,   49,    1,   30,    0,    0]])
```

[ ]:
```
Accuracy = (matrix[0][0] + matrix[1][1]) / (matrix[0][0] + matrix[0][1] +␣
↪matrix[1][0] + matrix[1][1])
print("Accuracy: ", Accuracy)
```

```
Accuracy:  0.8300733496332519
```

Accuracy The accuracy of the model is 83%, which is the percentage of correct predictions made by the model. However, the accuracy is not balanced between different classes as it can be observed from the confusion matrix.

Confusion Matrix This confusion matrix represents the performance of a model that predicts the age range of people from face images. The model is trained to predict ages in 9 categories, ranging from '0-2' to 'more than 70'. The matrix shows the number of true positives, false positives, false negatives, and true negatives for each age category.

From this matrix, we can see that the model has a higher accuracy in predicting middle age groups than young babies or old adults.

5 Task 2: Small Convolutional Neural Network

1. Build a convolutional neural network with the following specifications (Test on two different tasks):

- Convolution layer having 40 feature detectors, with kernel size 5 x 5, and ReLU as the activation function, with stride 1 and no-padding.
- A max-pooling layer with pool size 2x2.
- Fully connected layer with 100 neurons, and ReLU as the activation function.
- Output layer: n (depending on the task) neurons representing the n classes, using the softmax activation function. function for each of the 10 neurons.

2. Using Min-Max scaling to scale the training dataset and using the same Min and Max values from the training set scale the test dataset

$$\frac{X - X_{min}}{X_{max} - X_{min}}.$$

3. Using mini-batch gradient descent to optimize the loss function: "categorical cross- entropy" on the training dataset. Please record the loss value for each of the epochs and create an epoch-loss plot and an accuracy-loss plot for both the training and validation set.

4. Report the following:

- Final classification accuracy.
- The n-class confusion matrix.

[ ]:
```
# Define model for task 2
def get_model_2(output_dim):
    model = Sequential()
    model.add(Conv2D(filters=40, kernel_size=5, strides=(1, 1),␣
↪padding="valid", input_shape=(32,32,1), activation='relu'))
```

```
    model.add(MaxPooling2D(pool_size=(2, 2), strides=None, padding="valid"))
    model.add(Flatten())
    model.add(Dense(100, activation='relu'))
    model.add(Dense(output_dim, activation='softmax'))
    return model
```

5.1 Classfying Gender

[ ]:
```
lr = 0.001
opt = keras.optimizers.Adam(learning_rate=lr)
bs = 32
epochs = 50
```

[ ]:
```
scaled_train_img = [img.reshape(32,32,1) for img in scaled_train_img]
scaled_val_img = [img.reshape(32,32,1) for img in scaled_val_img]
```

Model Architecture

[ ]:
```
gender_model.summary()
```

```
Model: "sequential_3"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_1 (Conv2D)           (None, 28, 28, 40)        1040

 max_pooling2d_1 (MaxPooling  (None, 14, 14, 40)       0
 2D)

 flatten_1 (Flatten)         (None, 7840)              0

 dense_10 (Dense)            (None, 100)               784100

 dense_11 (Dense)            (None, 2)                 202

=================================================================
Total params: 785,342
Trainable params: 785,342
Non-trainable params: 0

_________________________________________________________________
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_1 (Conv2D)           (None, 28, 28, 40)        1040

 max_pooling2d_1 (MaxPooling  (None, 14, 14, 40)       0
 2D)

 flatten_1 (Flatten)         (None, 7840)              0
```

```
 dense_10 (Dense)            (None, 100)               784100


 dense_11 (Dense)            (None, 2)                 202

=================================================================
Total params: 785,342
Trainable params: 785,342
Non-trainable params: 0
_________________________________________________________________
```

5.2 Training

```
[ ]: # create and compile the gender model
     gender_model = get_model_2(2)
     gender_model.compile(loss='categorical_crossentropy', optimizer=opt,␣
      ↪metrics=['accuracy'])

     # train the model and record training history
     train_history = gender_model.fit(x=np.array(scaled_train_img), y=np.
      ↪array(train_gender),
                                      batch_size=bs, epochs=epochs,
                                      verbose=1, shuffle=True,
                                      validation_data=(np.array(scaled_val_img), np.
      ↪array(val_gender)))
     loss = train_history.history['loss']
     val_loss = train_history.history['val_loss']
     acc = train_history.history['accuracy']
     val_acc = train_history.history['val_accuracy']


     # make gender predictions on the validation set and compute confusion matrix
     gender_pred = gender_model.predict(np.array(scaled_val_img))
     val_gender = np.array(val_gender)
     matrix = confusion_matrix(y_true=val_gender.argmax(axis=1), y_pred=gender_pred.
      ↪argmax(axis=1))
```

```
Epoch 1/50
2711/2711 [==============================] - 20s 7ms/step - loss: 0.5310 -
accuracy: 0.7245 - val_loss: 0.4691 - val_accuracy: 0.7710
Epoch 2/50
2711/2711 [==============================] - 19s 7ms/step - loss: 0.4519 -
accuracy: 0.7759 - val_loss: 0.4420 - val_accuracy: 0.7870
Epoch 3/50
2711/2711 [==============================] - 19s 7ms/step - loss: 0.4172 -
accuracy: 0.7980 - val_loss: 0.4344 - val_accuracy: 0.7893
Epoch 4/50
2711/2711 [==============================] - 19s 7ms/step - loss: 0.3899 -
```

```
accuracy: 0.8134 - val_loss: 0.4205 - val_accuracy: 0.7948
Epoch 5/50
2711/2711 [==============================] - 20s 7ms/step - loss: 0.3669 -
accuracy: 0.8283 - val_loss: 0.4118 - val_accuracy: 0.8016
Epoch 6/50
2711/2711 [==============================] - 20s 7ms/step - loss: 0.3414 -
accuracy: 0.8420 - val_loss: 0.4289 - val_accuracy: 0.7946
Epoch 7/50
2711/2711 [==============================] - 20s 7ms/step - loss: 0.3170 -
accuracy: 0.8553 - val_loss: 0.4394 - val_accuracy: 0.8027
Epoch 8/50
2711/2711 [==============================] - 20s 7ms/step - loss: 0.2913 -
accuracy: 0.8693 - val_loss: 0.4617 - val_accuracy: 0.7965
Epoch 9/50
2711/2711 [==============================] - 20s 7ms/step - loss: 0.2661 -
accuracy: 0.8824 - val_loss: 0.4742 - val_accuracy: 0.7921
Epoch 10/50
2711/2711 [==============================] - 20s 7ms/step - loss: 0.2397 -
accuracy: 0.8953 - val_loss: 0.5114 - val_accuracy: 0.7953
Epoch 11/50
2711/2711 [==============================] - 20s 7ms/step - loss: 0.2159 -
accuracy: 0.9078 - val_loss: 0.5558 - val_accuracy: 0.7890
Epoch 12/50
2711/2711 [==============================] - 20s 7ms/step - loss: 0.1936 -
accuracy: 0.9182 - val_loss: 0.5658 - val_accuracy: 0.7900
Epoch 13/50
2711/2711 [==============================] - 20s 7ms/step - loss: 0.1710 -
accuracy: 0.9286 - val_loss: 0.6354 - val_accuracy: 0.7859
Epoch 14/50
2711/2711 [==============================] - 22s 8ms/step - loss: 0.1530 -
accuracy: 0.9373 - val_loss: 0.7343 - val_accuracy: 0.7892
Epoch 15/50
2711/2711 [==============================] - 21s 8ms/step - loss: 0.1350 -
accuracy: 0.9451 - val_loss: 0.7399 - val_accuracy: 0.7883
Epoch 16/50
2711/2711 [==============================] - 21s 8ms/step - loss: 0.1197 -
accuracy: 0.9519 - val_loss: 0.8204 - val_accuracy: 0.7880
Epoch 17/50
2711/2711 [==============================] - 23s 8ms/step - loss: 0.1071 -
accuracy: 0.9573 - val_loss: 0.8762 - val_accuracy: 0.7848
Epoch 18/50
2711/2711 [==============================] - 26s 9ms/step - loss: 0.0963 -
accuracy: 0.9624 - val_loss: 0.9198 - val_accuracy: 0.7835
Epoch 19/50
2711/2711 [==============================] - 23s 9ms/step - loss: 0.0881 -
accuracy: 0.9655 - val_loss: 1.0112 - val_accuracy: 0.7879
Epoch 20/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.0790 -
```

```
accuracy: 0.9698 - val_loss: 1.0200 - val_accuracy: 0.7875
Epoch 21/50
2711/2711 [==============================] - 29s 11ms/step - loss: 0.0744 -
accuracy: 0.9722 - val_loss: 1.0688 - val_accuracy: 0.7844
Epoch 22/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0683 -
accuracy: 0.9741 - val_loss: 1.1678 - val_accuracy: 0.7906
Epoch 23/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0608 -
accuracy: 0.9773 - val_loss: 1.2026 - val_accuracy: 0.7774
Epoch 24/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0608 -
accuracy: 0.9778 - val_loss: 1.2259 - val_accuracy: 0.7854
Epoch 25/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0568 -
accuracy: 0.9799 - val_loss: 1.3275 - val_accuracy: 0.7834
Epoch 26/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0530 -
accuracy: 0.9808 - val_loss: 1.3572 - val_accuracy: 0.7817
Epoch 27/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0485 -
accuracy: 0.9825 - val_loss: 1.4371 - val_accuracy: 0.7825
Epoch 28/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0473 -
accuracy: 0.9830 - val_loss: 1.4483 - val_accuracy: 0.7795
Epoch 29/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0458 -
accuracy: 0.9840 - val_loss: 1.5074 - val_accuracy: 0.7788
Epoch 30/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0433 -
accuracy: 0.9850 - val_loss: 1.5201 - val_accuracy: 0.7839
Epoch 31/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0439 -
accuracy: 0.9852 - val_loss: 1.5540 - val_accuracy: 0.7837
Epoch 32/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0407 -
accuracy: 0.9855 - val_loss: 1.5947 - val_accuracy: 0.7863
Epoch 33/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0412 -
accuracy: 0.9860 - val_loss: 1.6392 - val_accuracy: 0.7833
Epoch 34/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0405 -
accuracy: 0.9866 - val_loss: 1.6728 - val_accuracy: 0.7845
Epoch 35/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0366 -
accuracy: 0.9873 - val_loss: 1.6298 - val_accuracy: 0.7783
Epoch 36/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0373 -
```

```
accuracy: 0.9870 - val_loss: 1.7227 - val_accuracy: 0.7856
Epoch 37/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0358 -
accuracy: 0.9881 - val_loss: 1.7212 - val_accuracy: 0.7810
Epoch 38/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0357 -
accuracy: 0.9882 - val_loss: 1.7603 - val_accuracy: 0.7863
Epoch 39/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0364 -
accuracy: 0.9877 - val_loss: 1.8188 - val_accuracy: 0.7820
Epoch 40/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0333 -
accuracy: 0.9896 - val_loss: 1.8622 - val_accuracy: 0.7825
Epoch 41/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0288 -
accuracy: 0.9900 - val_loss: 1.8857 - val_accuracy: 0.7831
Epoch 42/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0319 -
accuracy: 0.9896 - val_loss: 1.8358 - val_accuracy: 0.7843
Epoch 43/50
2711/2711 [==============================] - 24s 9ms/step - loss: 0.0313 -
accuracy: 0.9901 - val_loss: 1.9286 - val_accuracy: 0.7779
Epoch 44/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.0267 -
accuracy: 0.9912 - val_loss: 1.9703 - val_accuracy: 0.7790
Epoch 45/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.0291 -
accuracy: 0.9906 - val_loss: 1.9834 - val_accuracy: 0.7815
Epoch 46/50
2711/2711 [==============================] - 23s 9ms/step - loss: 0.0307 -
accuracy: 0.9903 - val_loss: 2.0298 - val_accuracy: 0.7857
Epoch 47/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.0268 -
accuracy: 0.9916 - val_loss: 1.9300 - val_accuracy: 0.7789
Epoch 48/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.0273 -
accuracy: 0.9916 - val_loss: 2.0773 - val_accuracy: 0.7792
Epoch 49/50
2711/2711 [==============================] - 23s 9ms/step - loss: 0.0265 -
accuracy: 0.9918 - val_loss: 2.0818 - val_accuracy: 0.7859
Epoch 50/50
2711/2711 [==============================] - 23s 8ms/step - loss: 0.0246 -
accuracy: 0.9917 - val_loss: 2.0164 - val_accuracy: 0.7822
343/343 [==============================] - 1s 3ms/step
```

5.2.1 Validation and Training Loss and Accuracy

[ ]:
```
# creating a data frame for the loss and accuracy
df_task2 = pd.DataFrame({'epoch': np.arange(1,epochs+1), 'loss': loss,␣
 ↪'val_loss': val_loss, 'acc': acc, 'val_acc': val_acc})
df_task2
```

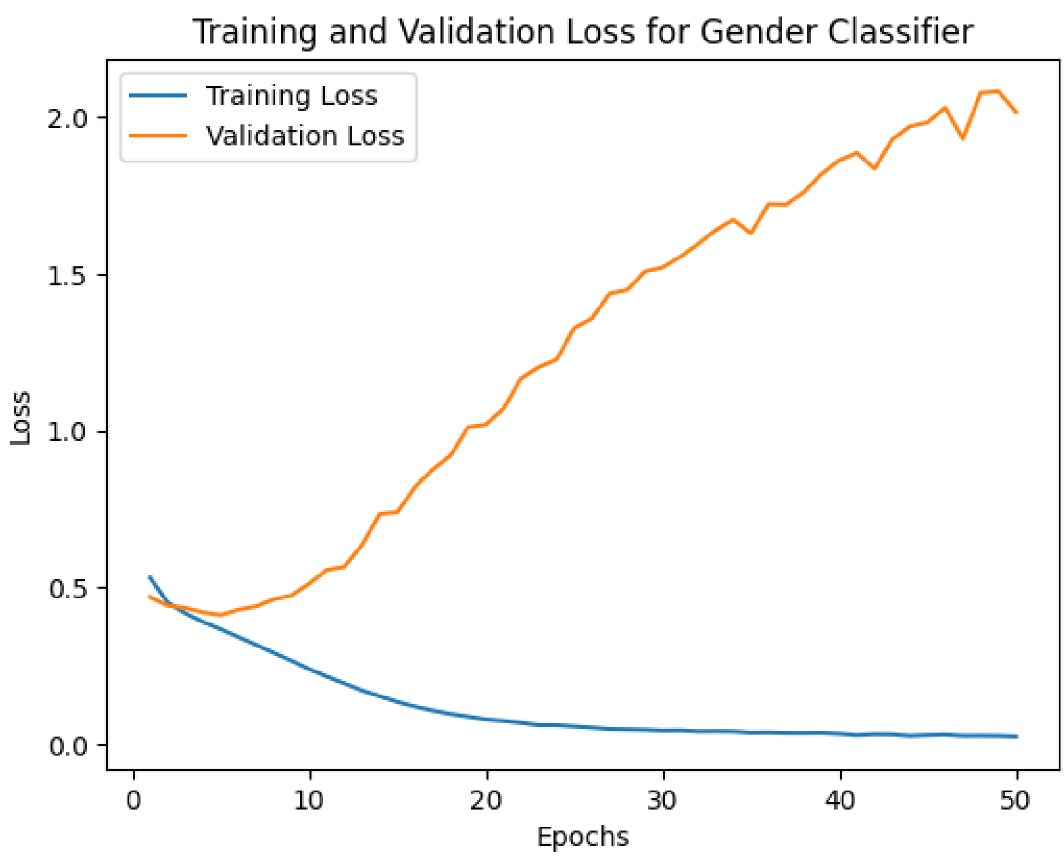
[ ]:

	epoch	loss	val_loss	acc	val_acc
0	1	0.530987	0.469073	0.724523	0.771043
1	2	0.451874	0.442004	0.775938	0.787018
2	3	0.417215	0.434399	0.798026	0.789301
3	4	0.389947	0.420510	0.813440	0.794778
4	5	0.366860	0.411779	0.828288	0.801625
5	6	0.341443	0.428858	0.841983	0.794596
6	7	0.317029	0.439398	0.855252	0.802720
7	8	0.291306	0.461719	0.869340	0.796513
8	9	0.266103	0.474214	0.882378	0.792131
9	10	0.239709	0.511446	0.895336	0.795326
10	11	0.215893	0.555761	0.907809	0.789027
11	12	0.193645	0.565839	0.918185	0.790031
12	13	0.170997	0.635397	0.928629	0.785923
13	14	0.152968	0.734279	0.937287	0.789209
14	15	0.134991	0.739920	0.945114	0.788297
15	16	0.119718	0.820417	0.951870	0.788023
16	17	0.107115	0.876211	0.957346	0.784827
17	18	0.096259	0.919845	0.962361	0.783458
18	19	0.088093	1.011249	0.965450	0.787931
19	20	0.079042	1.019982	0.969808	0.787475
20	21	0.074351	1.068838	0.972194	0.784371
21	22	0.068338	1.167788	0.974096	0.790579
22	23	0.060760	1.202612	0.977301	0.777433
23	24	0.060768	1.225919	0.977762	0.785375
24	25	0.056775	1.327529	0.979906	0.783367
25	26	0.053026	1.357197	0.980806	0.781724
26	27	0.048498	1.437119	0.982512	0.782545
27	28	0.047257	1.448327	0.982984	0.779533
28	29	0.045816	1.507385	0.983964	0.778802
29	30	0.043303	1.520138	0.985025	0.783915
30	31	0.043891	1.553993	0.985152	0.783732
31	32	0.040701	1.594686	0.985486	0.786288
32	33	0.041220	1.639151	0.985970	0.783276
33	34	0.040548	1.672801	0.986639	0.784462
34	35	0.036616	1.629809	0.987273	0.778255
35	36	0.037318	1.722697	0.987031	0.785649
36	37	0.035823	1.721221	0.988091	0.780993
37	38	0.035696	1.760266	0.988172	0.786288
38	39	0.036401	1.818822	0.987699	0.781997

39	40	0.033343	1.862183	0.989590	0.782545
40	41	0.028840	1.885692	0.990028	0.783093
41	42	0.031865	1.835755	0.989648	0.784280
42	43	0.031301	1.928624	0.990143	0.777889
43	44	0.026674	1.970273	0.991204	0.778985
44	45	0.029110	1.983395	0.990616	0.781541
45	46	0.030706	2.029773	0.990293	0.785740
46	47	0.026810	1.929988	0.991642	0.778894
47	48	0.027274	2.077311	0.991631	0.779167
48	49	0.026459	2.081816	0.991838	0.785923
49	50	0.024620	2.016369	0.991746	0.782180

5.2.2 Accuracy Metrics

[ ]:
```
# plotting validation and training loss
plt.plot(df_task2['epoch'], df_task2['loss'], label='Training Loss')
plt.plot(df_task2['epoch'], df_task2['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training and Validation Loss for Gender Classifier')
plt.legend()
plt.show()
```



```
[ ]: # Output the results for gender classification
print(matrix)
print("Accuracy: ", (matrix[0][0] + matrix[1][1]) / (matrix[0][0] +␣
 ↪matrix[0][1] + matrix[1][0] + matrix[1][1]))
print("Precision: ", matrix[0][0] / (matrix[0][0] + matrix[0][1]))
```

```
[[4536 1256]
 [1130 4032]]
Accuracy:  0.7821800255614387
Precision:  0.7831491712707183
```

Accuracy The accuracy of the model is 78.21%, which is the percentage of correct predictions made by the model.

Precision The precision of the model is 78.31%, a metric that measures the accuracy of positive predictions.

Confusion Matrix This confusion matrix represents the performance of a model that predicts people's gender from face images. From the output, we can see that this model performs better when it predicts the male gender.

5.3 Classfying Age

```
[ ]: # create and compile the age model
age_model = get_model_2(9)
age_model.compile(loss='categorical_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])

# train the model and record training history
train_history = age_model.fit(np.array(scaled_train_img), np.array(train_age),
                    batch_size=bs, epochs=epochs,
                    verbose=1, shuffle=True,
                    validation_data=(np.array(scaled_val_img), np.
 ↪array(val_age)))
loss = train_history.history['loss']
val_loss = train_history.history['val_loss']
acc = train_history.history['accuracy']
val_acc = train_history.history['val_accuracy']

# make age predictions on the validation set and compute confusion matrix
age_pred = age_model.predict(np.array(scaled_val_img))
val_age = np.array(val_age)
matrix = confusion_matrix(y_true=val_age.argmax(axis=1), y_pred=age_pred.
 ↪argmax(axis=1))
```

```
Epoch 1/50
2711/2711 [==============================] - 23s 9ms/step - loss: 1.6514 -
accuracy: 0.3551 - val_loss: 1.5616 - val_accuracy: 0.3949
Epoch 2/50
2711/2711 [==============================] - 24s 9ms/step - loss: 1.5108 -
accuracy: 0.3991 - val_loss: 1.4834 - val_accuracy: 0.4056
Epoch 3/50
2711/2711 [==============================] - 25s 9ms/step - loss: 1.4430 -
accuracy: 0.4191 - val_loss: 1.4623 - val_accuracy: 0.4183
Epoch 4/50
2711/2711 [==============================] - 25s 9ms/step - loss: 1.3969 -
accuracy: 0.4340 - val_loss: 1.4789 - val_accuracy: 0.4062
Epoch 5/50
2711/2711 [==============================] - 26s 9ms/step - loss: 1.3607 -
accuracy: 0.4459 - val_loss: 1.4234 - val_accuracy: 0.4248
Epoch 6/50
2711/2711 [==============================] - 26s 10ms/step - loss: 1.3274 -
accuracy: 0.4564 - val_loss: 1.4338 - val_accuracy: 0.4218
Epoch 7/50
2711/2711 [==============================] - 27s 10ms/step - loss: 1.2957 -
accuracy: 0.4670 - val_loss: 1.4425 - val_accuracy: 0.4260
Epoch 8/50
2711/2711 [==============================] - 25s 9ms/step - loss: 1.2650 -
accuracy: 0.4786 - val_loss: 1.4316 - val_accuracy: 0.4215
Epoch 9/50
2711/2711 [==============================] - 25s 9ms/step - loss: 1.2355 -
accuracy: 0.4910 - val_loss: 1.4298 - val_accuracy: 0.4261
Epoch 10/50
2711/2711 [==============================] - 25s 9ms/step - loss: 1.2057 -
accuracy: 0.5018 - val_loss: 1.4623 - val_accuracy: 0.4131
Epoch 11/50
2711/2711 [==============================] - 25s 9ms/step - loss: 1.1770 -
accuracy: 0.5138 - val_loss: 1.4796 - val_accuracy: 0.4293
Epoch 12/50
2711/2711 [==============================] - 25s 9ms/step - loss: 1.1487 -
accuracy: 0.5235 - val_loss: 1.5140 - val_accuracy: 0.4251
Epoch 13/50
2711/2711 [==============================] - 25s 9ms/step - loss: 1.1205 -
accuracy: 0.5351 - val_loss: 1.5354 - val_accuracy: 0.4227
Epoch 14/50
2711/2711 [==============================] - 25s 9ms/step - loss: 1.0945 -
accuracy: 0.5456 - val_loss: 1.5530 - val_accuracy: 0.4183
Epoch 15/50
2711/2711 [==============================] - 25s 9ms/step - loss: 1.0699 -
accuracy: 0.5551 - val_loss: 1.6631 - val_accuracy: 0.4028
Epoch 16/50
2711/2711 [==============================] - 25s 9ms/step - loss: 1.0413 -
accuracy: 0.5676 - val_loss: 1.6564 - val_accuracy: 0.4108
```

```
Epoch 17/50
2711/2711 [==============================] - 25s 9ms/step - loss: 1.0168 -
accuracy: 0.5764 - val_loss: 1.7044 - val_accuracy: 0.4032
Epoch 18/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.9910 -
accuracy: 0.5898 - val_loss: 1.7265 - val_accuracy: 0.4107
Epoch 19/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.9687 -
accuracy: 0.5996 - val_loss: 1.7810 - val_accuracy: 0.4104
Epoch 20/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.9435 -
accuracy: 0.6077 - val_loss: 1.8366 - val_accuracy: 0.4081
Epoch 21/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.9210 -
accuracy: 0.6168 - val_loss: 1.9400 - val_accuracy: 0.4064
Epoch 22/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.8973 -
accuracy: 0.6276 - val_loss: 1.8951 - val_accuracy: 0.3996
Epoch 23/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.8736 -
accuracy: 0.6370 - val_loss: 1.9624 - val_accuracy: 0.4038
Epoch 24/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.8546 -
accuracy: 0.6453 - val_loss: 2.0222 - val_accuracy: 0.3896
Epoch 25/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.8350 -
accuracy: 0.6532 - val_loss: 2.0770 - val_accuracy: 0.3946
Epoch 26/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.8126 -
accuracy: 0.6623 - val_loss: 2.0956 - val_accuracy: 0.3991
Epoch 27/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.7931 -
accuracy: 0.6702 - val_loss: 2.2186 - val_accuracy: 0.3755
Epoch 28/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.7752 -
accuracy: 0.6776 - val_loss: 2.2707 - val_accuracy: 0.3868
Epoch 29/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.7571 -
accuracy: 0.6874 - val_loss: 2.3105 - val_accuracy: 0.3900
Epoch 30/50
2711/2711 [==============================] - 26s 9ms/step - loss: 0.7403 -
accuracy: 0.6959 - val_loss: 2.4436 - val_accuracy: 0.3876
Epoch 31/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.7207 -
accuracy: 0.7024 - val_loss: 2.4123 - val_accuracy: 0.3775
Epoch 32/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.7067 -
accuracy: 0.7087 - val_loss: 2.5469 - val_accuracy: 0.3842
```

```
Epoch 33/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.6901 -
accuracy: 0.7153 - val_loss: 2.5922 - val_accuracy: 0.3767
Epoch 34/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.6715 -
accuracy: 0.7245 - val_loss: 2.7012 - val_accuracy: 0.3912
Epoch 35/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.6544 -
accuracy: 0.7304 - val_loss: 2.7467 - val_accuracy: 0.3906
Epoch 36/50
2711/2711 [==============================] - 25s 9ms/step - loss: 0.6429 -
accuracy: 0.7362 - val_loss: 2.8205 - val_accuracy: 0.3932
Epoch 37/50
2711/2711 [==============================] - 26s 10ms/step - loss: 0.6261 -
accuracy: 0.7448 - val_loss: 2.8983 - val_accuracy: 0.3718
Epoch 38/50
2711/2711 [==============================] - 22s 8ms/step - loss: 0.6126 -
accuracy: 0.7482 - val_loss: 3.0543 - val_accuracy: 0.3938
Epoch 39/50
2711/2711 [==============================] - 22s 8ms/step - loss: 0.5971 -
accuracy: 0.7557 - val_loss: 3.0940 - val_accuracy: 0.3793
Epoch 40/50
2711/2711 [==============================] - 27s 10ms/step - loss: 0.5856 -
accuracy: 0.7603 - val_loss: 3.1540 - val_accuracy: 0.3740
Epoch 41/50
2711/2711 [==============================] - 22s 8ms/step - loss: 0.5707 -
accuracy: 0.7660 - val_loss: 3.1742 - val_accuracy: 0.3772
Epoch 42/50
2711/2711 [==============================] - 21s 8ms/step - loss: 0.5613 -
accuracy: 0.7715 - val_loss: 3.3334 - val_accuracy: 0.3842
Epoch 43/50
2711/2711 [==============================] - 21s 8ms/step - loss: 0.5493 -
accuracy: 0.7751 - val_loss: 3.4903 - val_accuracy: 0.3875
Epoch 44/50
2711/2711 [==============================] - 21s 8ms/step - loss: 0.5324 -
accuracy: 0.7826 - val_loss: 3.3746 - val_accuracy: 0.3794
Epoch 45/50
2711/2711 [==============================] - 21s 8ms/step - loss: 0.5257 -
accuracy: 0.7865 - val_loss: 3.6265 - val_accuracy: 0.3669
Epoch 46/50
2711/2711 [==============================] - 21s 8ms/step - loss: 0.5090 -
accuracy: 0.7941 - val_loss: 3.7000 - val_accuracy: 0.3773
Epoch 47/50
2711/2711 [==============================] - 21s 8ms/step - loss: 0.5023 -
accuracy: 0.7956 - val_loss: 3.7243 - val_accuracy: 0.3653
Epoch 48/50
2711/2711 [==============================] - 21s 8ms/step - loss: 0.4880 -
accuracy: 0.8022 - val_loss: 3.7980 - val_accuracy: 0.3739
```

```
Epoch 49/50
2711/2711 [==============================] - 21s 8ms/step - loss: 0.4758 -
accuracy: 0.8088 - val_loss: 3.9453 - val_accuracy: 0.3726
Epoch 50/50
2711/2711 [==============================] - 21s 8ms/step - loss: 0.4703 -
accuracy: 0.8096 - val_loss: 4.0616 - val_accuracy: 0.3730
343/343 [==============================] - 1s 3ms/step
```

Model Architecture

[ ]:
```
age_model.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_3 (Conv2D)           (None, 28, 28, 40)        1040

 max_pooling2d_3 (MaxPooling  (None, 14, 14, 40)       0
 2D)

 flatten_3 (Flatten)         (None, 7840)              0

 dense_14 (Dense)            (None, 100)               784100

 dense_15 (Dense)            (None, 9)                 909

=================================================================
Total params: 786,049
Trainable params: 786,049
Non-trainable params: 0
_________________________________________________________________
```


```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_3 (Conv2D)           (None, 28, 28, 40)        1040

 max_pooling2d_3 (MaxPooling  (None, 14, 14, 40)       0
 2D)

 flatten_3 (Flatten)         (None, 7840)              0

 dense_14 (Dense)            (None, 100)               784100

 dense_15 (Dense)            (None, 9)                 909

=================================================================
Total params: 786,049
Trainable params: 786,049
```

```
Non-trainable params: 0
_________________________________________________________________
```

5.3.1 Validation and Training Loss and Accuracy

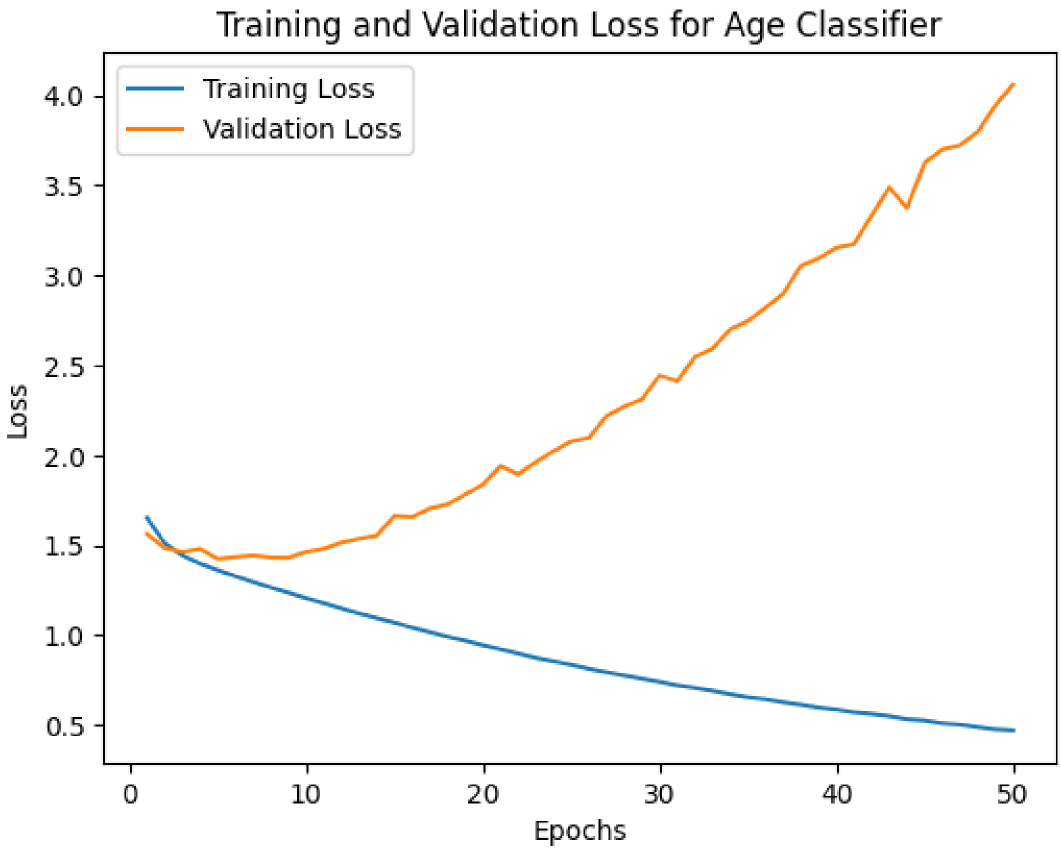
[ ]:
```
# creating a data frame for the loss and accuracy
df_task2_age = pd.DataFrame({'epoch': np.arange(1,epochs+1), 'loss': loss,␣
↪'val_loss': val_loss, 'acc': acc, 'val_acc': val_acc})
df_task2_age
```

[ ]:

	epoch	loss	val_loss	acc	val_acc
0	1	1.651408	1.561587	0.355114	0.394924
1	2	1.510754	1.483411	0.399082	0.405605
2	3	1.443007	1.462286	0.419084	0.418295
3	4	1.396935	1.478939	0.433955	0.406153
4	5	1.360695	1.423431	0.445910	0.424776
5	6	1.327412	1.433758	0.456354	0.421764
6	7	1.295669	1.442516	0.467006	0.425963
7	8	1.264960	1.431561	0.478615	0.421490
8	9	1.235524	1.429776	0.491008	0.426146
9	10	1.205697	1.462324	0.501775	0.413091
10	11	1.176955	1.479636	0.513753	0.429341
11	12	1.148733	1.513994	0.523529	0.425050
12	13	1.120453	1.535427	0.535103	0.422677
13	14	1.094461	1.553004	0.545605	0.418295
14	15	1.069870	1.663106	0.555105	0.402775
15	16	1.041349	1.656356	0.567567	0.410809
16	17	1.016754	1.704441	0.576409	0.403232
17	18	0.991033	1.726502	0.589804	0.410718
18	19	0.968732	1.781040	0.599615	0.410444
19	20	0.943534	1.836561	0.607708	0.408070
20	21	0.921019	1.940000	0.616850	0.406427
21	22	0.897273	1.895083	0.627628	0.399580
22	23	0.873644	1.962445	0.636955	0.403779
23	24	0.854597	2.022209	0.645290	0.389629
24	25	0.834974	2.077036	0.653198	0.394559
25	26	0.812641	2.095571	0.662305	0.399124
26	27	0.793129	2.218619	0.670156	0.375479
27	28	0.775153	2.270673	0.677580	0.386799
28	29	0.757122	2.310491	0.687448	0.389995
29	30	0.740328	2.443589	0.695852	0.387621
30	31	0.720661	2.412298	0.702446	0.377488
31	32	0.706686	2.546851	0.708695	0.384152
32	33	0.690056	2.592166	0.715312	0.376666
33	34	0.671484	2.701168	0.724500	0.391181
34	35	0.654382	2.746678	0.730391	0.390634
35	36	0.642940	2.820501	0.736189	0.393190

36	37	0.626092	2.898335	0.744789	0.371828
37	38	0.612628	3.054280	0.748167	0.393829
38	39	0.597071	3.093968	0.755672	0.379313
39	40	0.585588	3.154002	0.760272	0.374019
40	41	0.570650	3.174158	0.766013	0.377214
41	42	0.561299	3.333449	0.771465	0.384243
42	43	0.549288	3.490256	0.775074	0.387530
43	44	0.532388	3.374559	0.782613	0.379405
44	45	0.525735	3.626542	0.786464	0.366898
45	46	0.508990	3.700003	0.794095	0.377305
46	47	0.502285	3.724308	0.795594	0.365346
47	48	0.488023	3.797988	0.802153	0.373927
48	49	0.475770	3.945289	0.808771	0.372558
49	50	0.470336	4.061615	0.809578	0.373014

[ ]:
```
# plotting validation and training loss
plt.plot(df_task2_age['epoch'], df_task2_age['loss'], label='Training Loss')
plt.plot(df_task2_age['epoch'], df_task2_age['val_loss'], label='Validation␣
↪Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training and Validation Loss for Age Classifier')
plt.legend()
plt.show()
```



[ ]:
```
# Output the results for age classification
print(matrix)
print("Accuracy: ", (matrix[0][0] + matrix[1][1]) / (matrix[0][0] +
 ↪matrix[0][1] + matrix[1][0] + matrix[1][1]))
print("Precision: ", matrix[0][0] / (matrix[0][0] + matrix[0][1]))
```

```
[[  99   77    5   11    4    1    1    0    1]
 [  57  792  218  142   79   46   14    7    1]
 [   6  195  299  402  182   56   24   12    5]
 [  11  152  376 1574  826  256   69   29    7]
 [   7   79  146  850  798  291  112   39    8]
 [   2   37   68  302  438  299  156   45    6]
 [   0   25   31  112  185  199  153   72   19]
 [   1    9    9   40   42   71   80   58   11]
 [   0    5    1   14   13   15   23   33   14]]
Accuracy:  0.8692682926829268
Precision:  0.5625
```

Accuracy The accuracy of the model is 86.92%, which is the percentage of correct predictions made by the model.

Precision The precision of the model is 56.25%, a metric that measures the accuracy of positive predictions.

Confusion Matrix This confusion matrix represents the performance of a model that predicts people's age from face images. From the output, we can see that this model performs better when it predicts the elder people.

6 Task 3: Your own Convolutional Neural Network

1. Build another convolutional neural network, where you choose all the parameters to see if you can get a higher accuracy.
2. Using Min-Max scaling to scale the training dataset and using the same Min and Max values from the training set scale the test dataset.

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

3. Using mini-batch gradient descent to optimize the loss function: "categorical cross-entropy" on the training dataset. Please record the loss value for each of the epochs and create an epoch-loss plot and an accuracy-loss plot for both the training and validation set.
4. Report the following:
   - Final classification accuracy.
   - n-class confusion matrix.

6.1 Model Architecture

1. Three Conv2D layers:
   - First layer: 32 filters, kernel size 3x3, stride 1x1, padding 'same', and ReLU activation.
   - Second layer: 64 filters, kernel size 3x3, stride 1x1, padding 'same', and ReLU activation.
   - Third layer: 128 filters, kernel size 3x3, stride 1x1, padding 'same', and ReLU activation.
2. BatchNormalization layers after each Conv2D layer for improved convergence and training stability.
3. MaxPooling2D layers after each Conv2D layer with pool size 2x2 and padding 'valid'.
4. Flatten layer to convert the 3D feature maps into a 1D vector.
5. Three Dense (fully connected) layers:
   - First Dense layer: 256 neurons with ReLU activation.
   - Second Dense layer: 128 neurons with ReLU activation.
   - Third Dense layer: 'output_dim' neurons with Softmax activation for classification.
6. Dropout layers after the first and second Dense layers with a dropout rate of 0.5 to reduce overfitting.

[ ]:
```
# modelling gender classification
def get_model_3(output_dim):
    model = Sequential()
    model.add(Conv2D(filters=32, kernel_size=3, strides=(1, 1), padding="same",␣
↪input_shape=(32, 32, 1), activation='relu'))
```

```
    model.add(BatchNormalization())
    model.add(MaxPooling2D(pool_size=(2, 2), strides=None, padding="valid"))
    model.add(Conv2D(filters=64, kernel_size=3, strides=(1, 1), padding="same",␣
↪activation='relu'))
    model.add(BatchNormalization())
    model.add(MaxPooling2D(pool_size=(2, 2), strides=None, padding="valid"))
    model.add(Conv2D(filters=128, kernel_size=3, strides=(1, 1),␣
↪padding="same", activation='relu'))
    model.add(BatchNormalization())
    model.add(MaxPooling2D(pool_size=(2, 2), strides=None, padding="valid"))
    model.add(Flatten())
    model.add(Dense(256, activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(128, activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(output_dim, activation='softmax'))
    return model
```

6.2 Gender Classification

[ ]:
```
# classifying gender
gender_model = get_model_3(2)
```

[ ]:
```
gender_model.summary()
```

```
Model: "sequential_8"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_10 (Conv2D)          (None, 32, 32, 32)        320

 batch_normalization_6 (Batc  (None, 32, 32, 32)       128
 hNormalization)

 max_pooling2d_10 (MaxPoolin  (None, 16, 16, 32)       0
 g2D)

 conv2d_11 (Conv2D)          (None, 16, 16, 64)        18496

 batch_normalization_7 (Batc  (None, 16, 16, 64)       256
 hNormalization)

 max_pooling2d_11 (MaxPoolin  (None, 8, 8, 64)         0
 g2D)


_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
```

```
 conv2d_10 (Conv2D)          (None, 32, 32, 32)        320

 batch_normalization_6 (Batc  (None, 32, 32, 32)       128
 hNormalization)

 max_pooling2d_10 (MaxPoolin  (None, 16, 16, 32)       0
 g2D)

 conv2d_11 (Conv2D)          (None, 16, 16, 64)        18496

 batch_normalization_7 (Batc  (None, 16, 16, 64)       256
 hNormalization)

 max_pooling2d_11 (MaxPoolin  (None, 8, 8, 64)         0
 g2D)

 conv2d_12 (Conv2D)          (None, 8, 8, 128)         73856

 batch_normalization_8 (Batc  (None, 8, 8, 128)        512
 hNormalization)

 max_pooling2d_12 (MaxPoolin  (None, 4, 4, 128)        0
 g2D)

 flatten_6 (Flatten)         (None, 2048)              0

 dense_22 (Dense)            (None, 256)               524544

 dropout_4 (Dropout)         (None, 256)               0

 dense_23 (Dense)            (None, 128)               32896

 dropout_5 (Dropout)         (None, 128)               0

 dense_24 (Dense)            (None, 2)                 258

=================================================================
Total params: 651,266
Trainable params: 650,818
Non-trainable params: 448
_________________________________________________________________
```

[ ]:
```
scaled_train_img = [img.reshape(32,32,1) for img in scaled_train_img]
scaled_val_img = [img.reshape(32,32,1) for img in scaled_val_img]
```

[ ]:
```
lr = 0.001
opt = keras.optimizers.Adam(learning_rate=lr)
```

```
bs = 32
epochs = 10
```

[ ]:
```
gender_model.compile(loss='categorical_crossentropy', optimizer=opt,␣
 ↪metrics=['accuracy'])
train_history = gender_model.fit(np.array(scaled_train_img), np.
 ↪array(train_gender),
                    batch_size=bs, epochs=epochs,
                    verbose=1, shuffle=True, validation_data=(np.
 ↪array(scaled_val_img), np.array(val_gender)))
loss = train_history.history['loss']
val_loss = train_history.history['val_loss']
acc = train_history.history['accuracy']
val_acc = train_history.history['val_accuracy']
```

```
Epoch 1/10
2711/2711 [==============================] - 87s 32ms/step - loss: 0.3910 -
accuracy: 0.8194 - val_loss: 0.4081 - val_accuracy: 0.8031
Epoch 2/10
2711/2711 [==============================] - 99s 36ms/step - loss: 0.3740 -
accuracy: 0.8294 - val_loss: 0.4034 - val_accuracy: 0.8120
Epoch 3/10
2711/2711 [==============================] - 96s 35ms/step - loss: 0.3551 -
accuracy: 0.8378 - val_loss: 0.4084 - val_accuracy: 0.8042
Epoch 4/10
2711/2711 [==============================] - 91s 34ms/step - loss: 0.3382 -
accuracy: 0.8460 - val_loss: 0.3960 - val_accuracy: 0.8029
Epoch 5/10
2711/2711 [==============================] - 93s 34ms/step - loss: 0.3211 -
accuracy: 0.8568 - val_loss: 0.3838 - val_accuracy: 0.8167
Epoch 6/10
2711/2711 [==============================] - 99s 36ms/step - loss: 0.3058 -
accuracy: 0.8643 - val_loss: 0.3919 - val_accuracy: 0.8150
Epoch 7/10
2711/2711 [==============================] - 94s 35ms/step - loss: 0.2880 -
accuracy: 0.8711 - val_loss: 0.3773 - val_accuracy: 0.8221
Epoch 8/10
2711/2711 [==============================] - 96s 35ms/step - loss: 0.2720 -
accuracy: 0.8808 - val_loss: 0.4011 - val_accuracy: 0.8077
Epoch 9/10
2711/2711 [==============================] - 98s 36ms/step - loss: 0.2586 -
accuracy: 0.8851 - val_loss: 0.4100 - val_accuracy: 0.8107
Epoch 10/10
2711/2711 [==============================] - 101s 37ms/step - loss: 0.2474 -
accuracy: 0.8921 - val_loss: 0.4167 - val_accuracy: 0.8124
```

6.2.1 Validation and Training Loss and Accuracy

```
[ ]: # creating a data frame for the loss and accuracy
df = pd.DataFrame({'epoch': np.arange(1,epochs+1), 'loss': loss, 'val_loss':␣
↪val_loss, 'acc': acc, 'val_acc': val_acc})
```

```
[ ]: df
```

[ ]:

	epoch	loss	val_loss	acc	val_acc
0	1	0.391001	0.408089	0.819365	0.803086
1	2	0.373978	0.403391	0.829441	0.812032
2	3	0.355143	0.408370	0.837833	0.804181
3	4	0.338193	0.396032	0.846007	0.802903
4	5	0.321145	0.383835	0.856751	0.816688
5	6	0.305822	0.391905	0.864290	0.814953
6	7	0.288019	0.377308	0.871150	0.822074
7	8	0.272013	0.401121	0.880764	0.807741
8	9	0.258644	0.409973	0.885099	0.810663
9	10	0.247393	0.416738	0.892073	0.812397

```
[ ]: # plotting validation and training loss
plt.plot(df['epoch'], df['loss'], label='Training Loss')
plt.plot(df['epoch'], df['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training and Validation Loss for Gender Classifier')
plt.legend()
plt.show()
```

6.3 Confusion Matrix

[ ]:
```
# Concatenate images into a single tensor
val_img_tensor = np.concatenate([np.expand_dims(img, axis=0) for img in␣
↪scaled_val_img], axis=0)

# Make a prediction
gender_pred = gender_model.predict(val_img_tensor)

val_gender = np.array(val_gender)
matrix = confusion_matrix(y_true=val_gender.argmax(axis=1), y_pred=gender_pred.
↪argmax(axis=1))
matrix
```

```
343/343 [==============================] - 4s 11ms/step
```

[ ]:
```
array([[4509, 1283],
       [ 772, 4390]])
```

```
[ ]: Accuracy = (matrix[0][0] + matrix[1][1]) / (matrix[0][0] + matrix[0][1] +␣
     ↪matrix[1][0] + matrix[1][1])
     print("Accuracy: ", Accuracy)
```

```
Accuracy:  0.8123972977907614
```

Discussion We see that the model has an accuracy of 81.23%. The model is better at classifying than the models in previous tasks. However, the model is still not balanced between different classes as it can be observed from the confusion matrix.

6.4 Age Classification

```
[ ]: #min-max scaling
     flattened_train_img = [img.reshape(32*32) for img in train_img]
     flattened_val_img = [img.reshape(32*32) for img in val_img]

     scaler = MinMaxScaler()
     scaler.fit(flattened_train_img)
     print(len(scaler.data_max_), len(scaler.data_min_))# 255 and 0, len=1024

     scaled_train_img = scaler.transform(flattened_train_img)
     scaled_val_img = scaler.transform(flattened_val_img)

     scaled_train_img = [img.reshape(32,32,1) for img in scaled_train_img]
     scaled_val_img = [img.reshape(32,32,1) for img in scaled_val_img]
```

```
1024 1024
```

```
[ ]: # classifying age group
     age_model = get_model_3(9)
```

```
[ ]: age_model.summary()
```

```
Model: "sequential_9"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_13 (Conv2D)          (None, 32, 32, 32)        320

 batch_normalization_9 (Batc  (None, 32, 32, 32)       128
 hNormalization)

 max_pooling2d_13 (MaxPoolin  (None, 16, 16, 32)       0
 g2D)

 conv2d_14 (Conv2D)          (None, 16, 16, 64)        18496

 batch_normalization_10 (Bat  (None, 16, 16, 64)       256
 chNormalization)
```

```
 max_pooling2d_14 (MaxPoolin  (None, 8, 8, 64)         0
 g2D)

 conv2d_15 (Conv2D)          (None, 8, 8, 128)         73856

 batch_normalization_11 (Bat  (None, 8, 8, 128)        512
 chNormalization)

 max_pooling2d_15 (MaxPoolin  (None, 4, 4, 128)        0
 g2D)

 flatten_7 (Flatten)         (None, 2048)              0

 dense_25 (Dense)            (None, 256)               524544

 dropout_6 (Dropout)         (None, 256)               0

 dense_26 (Dense)            (None, 128)               32896

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_13 (Conv2D)          (None, 32, 32, 32)        320

 batch_normalization_9 (Batc  (None, 32, 32, 32)       128
 hNormalization)

 max_pooling2d_13 (MaxPoolin  (None, 16, 16, 32)       0
 g2D)

 conv2d_14 (Conv2D)          (None, 16, 16, 64)        18496

 batch_normalization_10 (Bat  (None, 16, 16, 64)       256
 chNormalization)

 max_pooling2d_14 (MaxPoolin  (None, 8, 8, 64)         0
 g2D)

 conv2d_15 (Conv2D)          (None, 8, 8, 128)         73856

 batch_normalization_11 (Bat  (None, 8, 8, 128)        512
 chNormalization)

 max_pooling2d_15 (MaxPoolin  (None, 4, 4, 128)        0
 g2D)

 flatten_7 (Flatten)         (None, 2048)              0
```

```
 dense_25 (Dense)            (None, 256)               524544

 dropout_6 (Dropout)         (None, 256)               0

 dense_26 (Dense)            (None, 128)               32896

 dropout_7 (Dropout)         (None, 128)               0

 dense_27 (Dense)            (None, 9)                 1161

=================================================================
Total params: 652,169
Trainable params: 651,721
Non-trainable params: 448
_________________________________________________________________
```

[ ]:
```
lr = 0.001
opt = keras.optimizers.Adam(learning_rate=lr)
bs = 32
epochs = 10
```

[ ]:
```
from keras.utils import to_categorical

# # Convert labels to one-hot encoding
# train_age_onehot = to_categorical(train_age, num_classes=9)
# val_age_onehot = to_categorical(val_age, num_classes=9)

# Compile the model
age_model.compile(loss='categorical_crossentropy', optimizer=opt,␣
 ↪metrics=['accuracy'])

train_history = age_model.fit(np.array(scaled_train_img), np.array(train_age),
                    batch_size=bs, epochs=epochs,
                    verbose=1, shuffle=True, validation_data=(np.
 ↪array(scaled_val_img), np.array(val_age)))
loss = train_history.history['loss']
val_loss = train_history.history['val_loss']
acc = train_history.history['accuracy']
val_acc = train_history.history['val_accuracy']
```

```
Epoch 1/10
2711/2711 [==============================] - 96s 35ms/step - loss: 1.8723 -
accuracy: 0.2915 - val_loss: 1.7393 - val_accuracy: 0.3551
Epoch 2/10
2711/2711 [==============================] - 97s 36ms/step - loss: 1.7308 -
accuracy: 0.3265 - val_loss: 1.6360 - val_accuracy: 0.3686
Epoch 3/10
```

```
2711/2711 [==============================] - 91s 33ms/step - loss: 1.6522 -
accuracy: 0.3497 - val_loss: 1.5976 - val_accuracy: 0.3701
Epoch 4/10
2711/2711 [==============================] - 94s 35ms/step - loss: 1.5930 -
accuracy: 0.3679 - val_loss: 1.6240 - val_accuracy: 0.3767
Epoch 5/10
2711/2711 [==============================] - 93s 34ms/step - loss: 1.5391 -
accuracy: 0.3848 - val_loss: 1.5108 - val_accuracy: 0.3992
Epoch 6/10
2711/2711 [==============================] - 97s 36ms/step - loss: 1.4861 -
accuracy: 0.4005 - val_loss: 1.4968 - val_accuracy: 0.3927
Epoch 7/10
2711/2711 [==============================] - 100s 37ms/step - loss: 1.4461 -
accuracy: 0.4127 - val_loss: 1.4645 - val_accuracy: 0.4092
Epoch 8/10
2711/2711 [==============================] - 99s 37ms/step - loss: 1.4145 -
accuracy: 0.4217 - val_loss: 1.4484 - val_accuracy: 0.4096
Epoch 9/10
2711/2711 [==============================] - 92s 34ms/step - loss: 1.3854 -
accuracy: 0.4317 - val_loss: 1.4452 - val_accuracy: 0.4034
Epoch 10/10
2711/2711 [==============================] - 90s 33ms/step - loss: 1.3622 -
accuracy: 0.4394 - val_loss: 1.4557 - val_accuracy: 0.4057
```

6.4.1 Validation and Training Loss and Accuracy

[ ]:
```
# creating a data frame for the loss and accuracy
df = pd.DataFrame({'epoch': np.arange(1,epochs+1), 'loss': loss, 'val_loss':
 ↪val_loss, 'acc': acc, 'val_acc': val_acc})
```

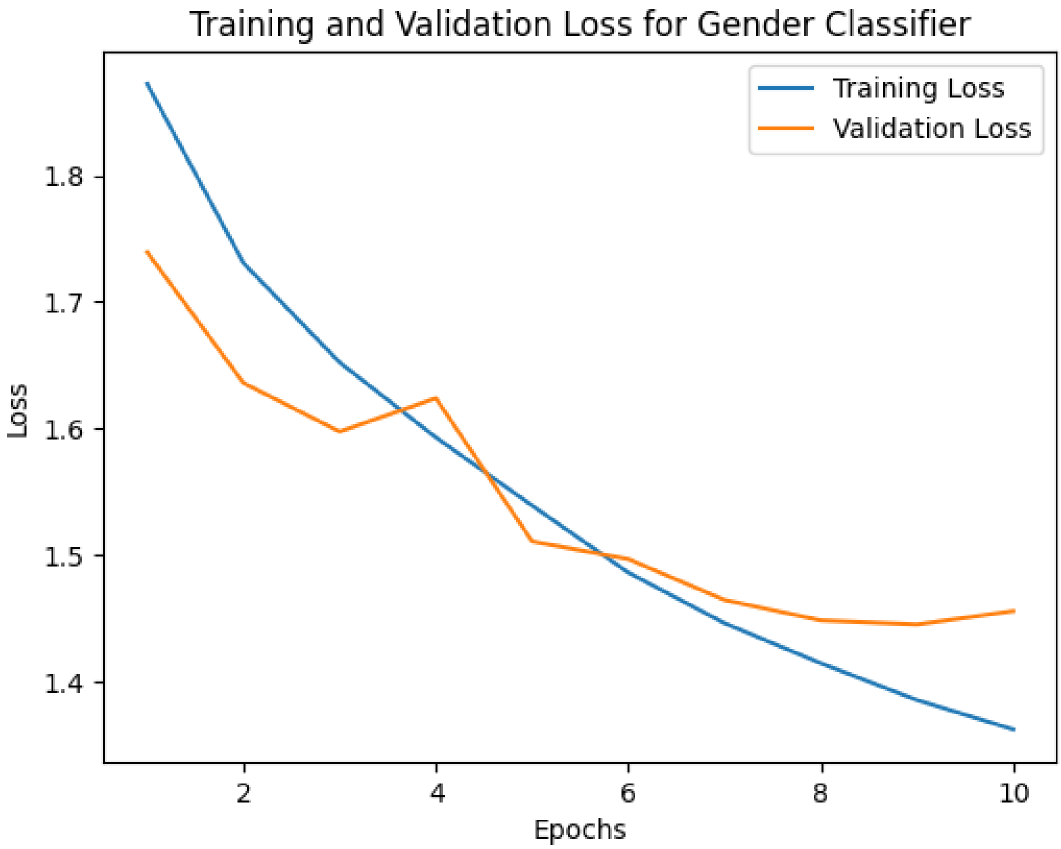
[ ]:
```
df
```

[ ]:

	epoch	loss	val_loss	acc	val_acc
0	1	1.872339	1.739347	0.291478	0.355121
1	2	1.730788	1.636005	0.326489	0.368632
2	3	1.652238	1.597590	0.349742	0.370093
3	4	1.592968	1.623966	0.367853	0.376666
4	5	1.539133	1.510781	0.384764	0.399215
5	6	1.486146	1.496791	0.400500	0.392733
6	7	1.446140	1.464491	0.412743	0.409166
7	8	1.414507	1.448412	0.421724	0.409622
8	9	1.385394	1.445195	0.431719	0.403414
9	10	1.362223	1.455695	0.439362	0.405697

[ ]:
```
# plotting validation and training loss
plt.plot(df['epoch'], df['loss'], label='Training Loss')
plt.plot(df['epoch'], df['val_loss'], label='Validation Loss')
```

```python
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training and Validation Loss for Gender Classifier')
plt.legend()
plt.show()
```



[ ]:
```python
# Concatenate images into a single tensor
val_img_tensor = np.concatenate([np.expand_dims(img, axis=0) for img in␣
 ↪scaled_val_img], axis=0)

# Make a prediction
age_pred = age_model.predict(val_img_tensor)

val_age = np.array(val_age)
matrix = confusion_matrix(y_true=val_age.argmax(axis=1), y_pred=age_pred.
 ↪argmax(axis=1))
```

```
343/343 [==============================] - 4s 11ms/step
```

[ ]:
```python
matrix
```

```
[ ]: array([[   4,  171,    0,   19,    3,    1,    1,    0,    0],
       [   0,  810,    5,  506,   32,    3,    0,    0,    0],
       [   0,  152,   13,  906,  100,   10,    0,    0,    0],
       [   0,   36,    7, 2392,  837,   25,    3,    0,    0],
       [   0,   12,    0, 1239,  979,   93,    7,    0,    0],
       [   0,    4,    0,  427,  727,  167,   28,    0,    0],
       [   0,    1,    0,  157,  352,  208,   78,    0,    0],
       [   0,    2,    0,   41,  104,  100,   73,    1,    0],
       [   0,    1,    0,    9,   39,   27,   40,    2,    0]])
```

```
[ ]: Accuracy = (matrix[0][0] + matrix[1][1]) / (matrix[0][0] + matrix[0][1] +
     ↪matrix[1][0] + matrix[1][1])
     print("Accuracy: ", Accuracy)
```

```
Accuracy:  0.8263959390862944
```

6.4.2 Discussion

The model has an accuracy of 82.6%. The model is better at classifying than the models in previous tasks. However, the model is still not balanced between different classes as it can be observed from the confusion matrix. Like the previous models, it is better at predicting middle age groups than young babies or old adults.

7 Task 4: Your own Convolutional Neural Network on both Tasks Simultaneously

1. Build another convolutional neural network, where you try and classify both tasks with a single network. After your flatten layer have two more fully connected layers for each "branch". Note that in order to do so you will not be able to use the Sequential model.
2. Using Min-Max scaling to scale the training dataset and using the same Min and Max values from the training set scale the test dataset

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

   .

3. Using mini-batch gradient descent to optimize the loss function: "categorical cross-entropy" on the training dataset. Please record the loss value for each of the epochs and create an epoch-loss plot and an accuracy-loss plot for both the training and validation set.
4. Report the following:
   - Final classification accuracy.
   - n-class confusion matrix.

```
[ ]: from tensorflow.keras.models import Model
     from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, Dense, Flatten
```

[ ]:
```
# Define output dimensions for each attribute
output_dim = {'gender': 2, 'age': 9, 'race': 7}
```

[ ]:
```
# Define function to get label arrays for attributes
def get_labels(attr_list):
    train_labels, val_labels = [], []
    for attr in attr_list:
        if attr == 'gender':
            train_labels.append(np.array(train_gender))
            val_labels.append(np.array(val_gender))
        elif attr == 'age':
            train_labels.append(np.array(train_age))
            val_labels.append(np.array(val_age))
        elif attr == 'race':
            train_labels.append(np.array(train_race))
            val_labels.append(np.array(val_race))
        else:
            raise ValueError(f"Invalid attribute: {attr}")
    return train_labels, val_labels
```

[ ]:
```
# Define function to create model
def get_model_4():
    # Define input layer
    input_layer = Input(shape=(32, 32, 1))

    # Define convolutional and pooling layers
    x = Conv2D(filters=16, kernel_size=3, strides=(1, 1), padding="valid",␣
 ↪activation='relu')(input_layer)
    x = MaxPooling2D(pool_size=(2, 2), strides=None, padding="valid")(x)
    x = Conv2D(filters=32, kernel_size=3, strides=(1, 1), padding='valid',␣
 ↪activation='relu')(x)
    x = MaxPooling2D(pool_size=(2, 2), strides=None, padding="valid")(x)
    x = Conv2D(filters=64, kernel_size=3, strides=(1, 1), padding='valid',␣
 ↪activation='relu')(x)
    x = MaxPooling2D(pool_size=(2, 2), strides=None, padding="valid")(x)

    # Define output layers for each attribute
    x = Flatten()(x)
    output_layers = []
    for attr in attr_list:
        output = Dense(128, activation='relu')(x)
        output = Dense(64, activation='relu')(output)
        output = Dense(output_dim[attr], activation='softmax',␣
 ↪name=attr)(output)
        output_layers.append(output)

    # Define model with input and output layers
```

```
    model = Model(inputs=input_layer, outputs=output_layers)

    return model
```

[ ]:
```
# Set attributes as a list
attr_list = ['gender', 'age']

# Get attribute labels for training and validation sets
train_labels, val_labels = get_labels(attr_list)

# Create model
model = get_model_4()
```

[ ]:
```
model.summary()

# Compile model with loss and optimizer
model.compile(loss=['categorical_crossentropy'] * len(attr_list),
                optimizer='adam', metrics='accuracy')
```

```
Model: "model"
________________________________________________________________________________
__________________
 Layer (type)                   Output Shape         Param #     Connected to
================================================================================
==================
 input_1 (InputLayer)           [(None, 32, 32, 1)]  0           []

 conv2d_16 (Conv2D)             (None, 30, 30, 16)   160
['input_1[0][0]']

 max_pooling2d_16 (MaxPooling2D  (None, 15, 15, 16)  0
['conv2d_16[0][0]']
 )

 conv2d_17 (Conv2D)             (None, 13, 13, 32)   4640
['max_pooling2d_16[0][0]']

 max_pooling2d_17 (MaxPooling2D  (None, 6, 6, 32)    0
['conv2d_17[0][0]']
 )

 conv2d_18 (Conv2D)             (None, 4, 4, 64)     18496
['max_pooling2d_17[0][0]']

 max_pooling2d_18 (MaxPooling2D  (None, 2, 2, 64)    0
['conv2d_18[0][0]']
 )
```

```
 flatten_8 (Flatten)            (None, 256)          0
['max_pooling2d_18[0][0]']

 dense_28 (Dense)               (None, 128)          32896
['flatten_8[0][0]']

 dense_30 (Dense)               (None, 128)          32896
['flatten_8[0][0]']

 dense_29 (Dense)               (None, 64)           8256
['dense_28[0][0]']

 dense_31 (Dense)               (None, 64)           8256
['dense_30[0][0]']

 gender (Dense)                 (None, 2)            130
['dense_29[0][0]']

-------------------------------------------------------------------------------
------------------
 Layer (type)                   Output Shape         Param #     Connected to
===============================================================================
==================
 input_1 (InputLayer)           [(None, 32, 32, 1)]  0           []

 conv2d_16 (Conv2D)             (None, 30, 30, 16)   160
['input_1[0][0]']

 max_pooling2d_16 (MaxPooling2D  (None, 15, 15, 16)  0
['conv2d_16[0][0]']
 )

 conv2d_17 (Conv2D)             (None, 13, 13, 32)   4640
['max_pooling2d_16[0][0]']

 max_pooling2d_17 (MaxPooling2D  (None, 6, 6, 32)    0
['conv2d_17[0][0]']
 )

 conv2d_18 (Conv2D)             (None, 4, 4, 64)     18496
['max_pooling2d_17[0][0]']

 max_pooling2d_18 (MaxPooling2D  (None, 2, 2, 64)    0
['conv2d_18[0][0]']
 )

 flatten_8 (Flatten)            (None, 256)          0
['max_pooling2d_18[0][0]']
```

```
 dense_28 (Dense)               (None, 128)          32896
['flatten_8[0][0]']

 dense_30 (Dense)               (None, 128)          32896
['flatten_8[0][0]']

 dense_29 (Dense)               (None, 64)           8256
['dense_28[0][0]']

 dense_31 (Dense)               (None, 64)           8256
['dense_30[0][0]']

 gender (Dense)                 (None, 2)            130
['dense_29[0][0]']

 age (Dense)                    (None, 9)            585
['dense_31[0][0]']

================================================================================
==================
Total params: 106,315
Trainable params: 106,315
Non-trainable params: 0
--------------------------------------------------------------------------------
------------------
```

[ ]:
```python
bs = 32
epochs = 10
```

[ ]:
```python
# Train model
history = model.fit(np.array(scaled_train_img), train_labels,
                    validation_data=(np.array(scaled_val_img), val_labels),
                    batch_size=bs,
                    epochs=epochs,
                    verbose=True,
                    shuffle=True)
```

```
Epoch 1/10
2711/2711 [==============================] - 23s 8ms/step - loss: 2.2749 -
gender_loss: 0.5749 - age_loss: 1.6999 - gender_accuracy: 0.6826 - age_accuracy:
0.3405 - val_loss: 2.0928 - val_gender_loss: 0.5159 - val_age_loss: 1.5769 -
val_gender_accuracy: 0.7332 - val_age_accuracy: 0.3837
Epoch 2/10
2711/2711 [==============================] - 24s 9ms/step - loss: 2.0177 -
gender_loss: 0.4825 - age_loss: 1.5352 - gender_accuracy: 0.7545 - age_accuracy:
0.3889 - val_loss: 1.9790 - val_gender_loss: 0.4724 - val_age_loss: 1.5066 -
val_gender_accuracy: 0.7610 - val_age_accuracy: 0.4012
Epoch 3/10
```

```
2711/2711 [==============================] - 22s 8ms/step - loss: 1.9228 -
gender_loss: 0.4506 - age_loss: 1.4722 - gender_accuracy: 0.7743 - age_accuracy:
0.4077 - val_loss: 1.9313 - val_gender_loss: 0.4667 - val_age_loss: 1.4646 -
val_gender_accuracy: 0.7637 - val_age_accuracy: 0.4159
Epoch 4/10
2711/2711 [==============================] - 22s 8ms/step - loss: 1.8658 -
gender_loss: 0.4311 - age_loss: 1.4347 - gender_accuracy: 0.7880 - age_accuracy:
0.4168 - val_loss: 1.8675 - val_gender_loss: 0.4338 - val_age_loss: 1.4337 -
val_gender_accuracy: 0.7818 - val_age_accuracy: 0.4200
Epoch 5/10
2711/2711 [==============================] - 21s 8ms/step - loss: 1.8252 -
gender_loss: 0.4172 - age_loss: 1.4080 - gender_accuracy: 0.7955 - age_accuracy:
0.4254 - val_loss: 1.8437 - val_gender_loss: 0.4258 - val_age_loss: 1.4179 -
val_gender_accuracy: 0.7853 - val_age_accuracy: 0.4311
Epoch 6/10
2711/2711 [==============================] - 21s 8ms/step - loss: 1.7950 -
gender_loss: 0.4058 - age_loss: 1.3892 - gender_accuracy: 0.8022 - age_accuracy:
0.4326 - val_loss: 1.8598 - val_gender_loss: 0.4245 - val_age_loss: 1.4353 -
val_gender_accuracy: 0.7896 - val_age_accuracy: 0.4208
Epoch 7/10
2711/2711 [==============================] - 23s 8ms/step - loss: 1.7673 -
gender_loss: 0.3954 - age_loss: 1.3719 - gender_accuracy: 0.8072 - age_accuracy:
0.4398 - val_loss: 1.8321 - val_gender_loss: 0.4179 - val_age_loss: 1.4143 -
val_gender_accuracy: 0.7927 - val_age_accuracy: 0.4251
Epoch 8/10
2711/2711 [==============================] - 22s 8ms/step - loss: 1.7464 -
gender_loss: 0.3868 - age_loss: 1.3596 - gender_accuracy: 0.8131 - age_accuracy:
0.4434 - val_loss: 1.8508 - val_gender_loss: 0.4211 - val_age_loss: 1.4297 -
val_gender_accuracy: 0.7917 - val_age_accuracy: 0.4192
Epoch 9/10
2711/2711 [==============================] - 24s 9ms/step - loss: 1.7270 -
gender_loss: 0.3809 - age_loss: 1.3462 - gender_accuracy: 0.8176 - age_accuracy:
0.4468 - val_loss: 1.8493 - val_gender_loss: 0.4388 - val_age_loss: 1.4105 -
val_gender_accuracy: 0.7901 - val_age_accuracy: 0.4320
Epoch 10/10
2711/2711 [==============================] - 23s 9ms/step - loss: 1.7100 -
gender_loss: 0.3740 - age_loss: 1.3360 - gender_accuracy: 0.8206 - age_accuracy:
0.4497 - val_loss: 1.8431 - val_gender_loss: 0.4162 - val_age_loss: 1.4269 -
val_gender_accuracy: 0.7934 - val_age_accuracy: 0.4121
```

[ ]:
```python
# Get training history metrics
total_train_loss = history.history['loss']
total_val_loss = history.history['val_loss']

attr_train_loss = {}
attr_train_acc = {}
attr_val_loss = {}
```

```python
attr_val_acc = {}

for attr in attr_list:
    attr_train_loss[attr] = history.history[f"{attr}_loss"]
    attr_train_acc[attr] = history.history[f"{attr}_accuracy"]
    attr_val_loss[attr] = history.history[f"val_{attr}_loss"]
    attr_val_acc[attr] = history.history[f"val_{attr}_accuracy"]

# Print training history metrics
print("\nTotal training loss:", total_train_loss)
print("\nTotal validation loss:", total_val_loss)
```

```
Total training loss: [2.274850368499756, 2.0176801681518555, 1.9228259325027466,
1.8658283948898315, 1.8251802921295166, 1.7950416803359985, 1.7673461437225342,
1.7463908195495605, 1.7270270586013794, 1.7099673748016357]

Total validation loss: [2.0927507877349854, 1.9789972305297852,
1.9313405752182007, 1.8675098419189453, 1.8437237739562988, 1.8598159551620483,
1.832127571105957, 1.8508437871932983, 1.8493467569351196, 1.8430756330490112]
```

[ ]:
```python
for attr in attr_list:
    print(f"Training loss for {attr}: {attr_train_loss[attr]}")
    print(f"Training accuracy for {attr}: {attr_train_acc[attr]}")
    print(f"Validation loss for {attr}: {attr_val_loss[attr]}")
    print(f"Validation accuracy for {attr}: {attr_val_acc[attr]}")
```

```
Training loss for gender: [0.5749205946922302, 0.4825230538845062,
0.45058807730674744, 0.4310881793498993, 0.41719427704811096, 0.405813992023468,
0.39540764689445496, 0.38678961992263794, 0.38086965680122375,
0.3740086257457733]
Training accuracy for gender: [0.6826408505439758, 0.7545190453529358,
0.7742552757263184, 0.7879507541656494, 0.7955132126808167, 0.8021996021270752,
0.8072373867034912, 0.8130590915679932, 0.8176473379135132, 0.8206331133842468]
Validation loss for gender: [0.5158711075782776, 0.47244375944137573,
0.4667123556137085, 0.4338483512401581, 0.4258001446723938, 0.424514502286911,
0.41786128282546997, 0.42111629247665405, 0.43884989619255066,
0.4162079691886902]
Validation accuracy for gender: [0.7331568598747253, 0.7610005736351013,
0.763739287853241, 0.7818148732185364, 0.7852839231491089, 0.7895745635032654,
0.7926784753799438, 0.7916742563247681, 0.7901223301887512, 0.7934088110923767]
Training loss for age: [1.6999318599700928, 1.535156011581421,
1.4722360372543335, 1.4347398281097412, 1.4079848527908325, 1.3892277479171753,
1.371940016746521, 1.3595969676971436, 1.3461560010910034, 1.3359572887420654]
Training accuracy for age: [0.34053075313568115, 0.38886839151382446,
0.40769389271736145, 0.4168011546134949, 0.42535507678985596,
0.4325717091560364, 0.4398459792137146, 0.44337359070777893, 0.4467974603176117,
0.4497140944004059]
```

```
Validation loss for age: [1.5768795013427734, 1.5065529346466064,
1.464627742767334, 1.4336614608764648, 1.4179234504699707, 1.4353002309799194,
1.4142669439315796, 1.42972731590271, 1.4104970693588257, 1.4268673658370972]
Validation accuracy for age: [0.38369545340538025, 0.4012233018875122,
0.4159211218357086, 0.4200292229652405, 0.43107539415359497,
0.42075952887535095, 0.42514151334762573, 0.4192076027393341,
0.43198832869529724, 0.4120869040489197]
```

[ ]:
```python
# Validation loss and accuracy for each attribute in a dataframe
# Create dataframe with loss and accuracy for each attribute
df = pd.DataFrame({
    'epoch': range(1, epochs+1),
    'total_loss': total_train_loss,
    'total_val_loss': total_val_loss,
})
for attr in attr_list:
    df[f"{attr}_loss"] = attr_train_loss[attr]
    df[f"val_{attr}_loss"] = attr_val_loss[attr]
    df[f"{attr}_acc"] = attr_train_acc[attr]
    df[f"val_{attr}_acc"] = attr_val_acc[attr]

df
```

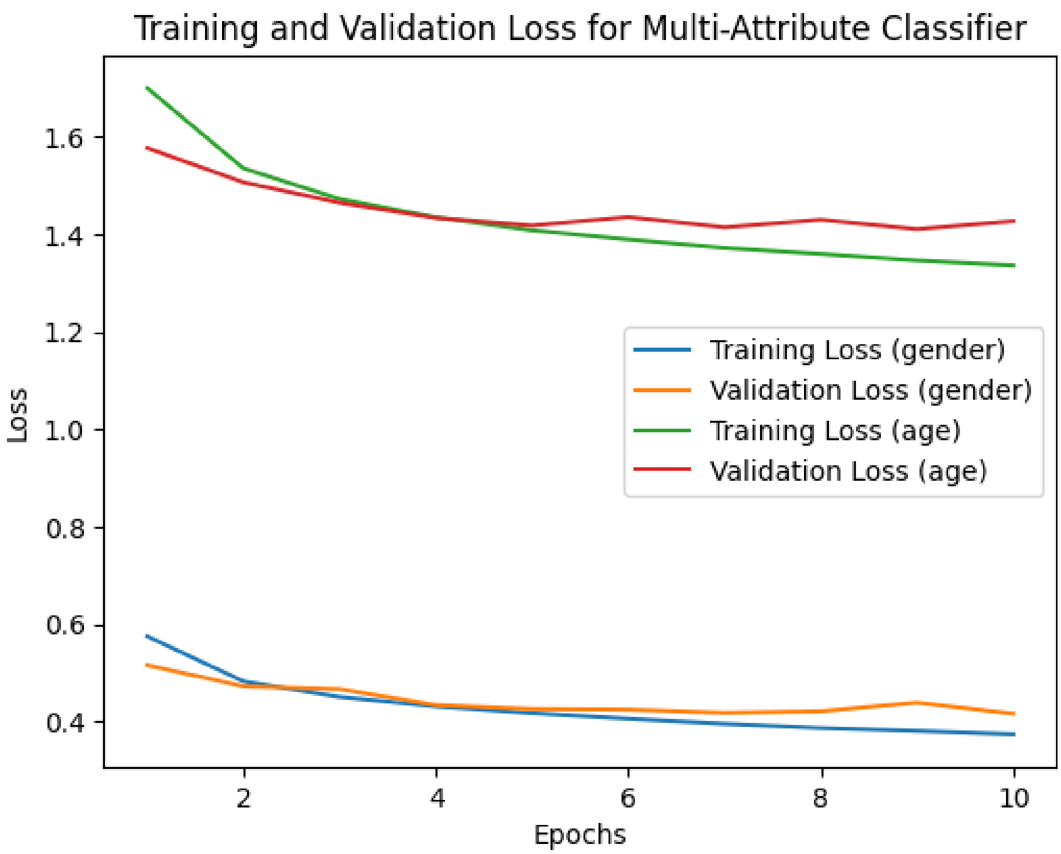
[ ]:

	epoch	total_loss	total_val_loss	gender_loss	val_gender_loss	\
0	1	2.274850	2.092751	0.574921	0.515871	
1	2	2.017680	1.978997	0.482523	0.472444	
2	3	1.922826	1.931341	0.450588	0.466712	
3	4	1.865828	1.867510	0.431088	0.433848	
4	5	1.825180	1.843724	0.417194	0.425800	
5	6	1.795042	1.859816	0.405814	0.424515	
6	7	1.767346	1.832128	0.395408	0.417861	
7	8	1.746391	1.850844	0.386790	0.421116	
8	9	1.727027	1.849347	0.380870	0.438850	
9	10	1.709967	1.843076	0.374009	0.416208	

	gender_acc	val_gender_acc	age_loss	val_age_loss	age_acc	val_age_acc
0	0.682641	0.733157	1.699932	1.576880	0.340531	0.383695
1	0.754519	0.761001	1.535156	1.506553	0.388868	0.401223
2	0.774255	0.763739	1.472236	1.464628	0.407694	0.415921
3	0.787951	0.781815	1.434740	1.433661	0.416801	0.420029
4	0.795513	0.785284	1.407985	1.417923	0.425355	0.431075
5	0.802200	0.789575	1.389228	1.435300	0.432572	0.420760
6	0.807237	0.792678	1.371940	1.414267	0.439846	0.425142
7	0.813059	0.791674	1.359597	1.429727	0.443374	0.419208
8	0.817647	0.790122	1.346156	1.410497	0.446797	0.431988
9	0.820633	0.793409	1.335957	1.426867	0.449714	0.412087

```
[ ]: # Plot training and validation loss for each attribute
for attr in attr_list:
    plt.plot(df['epoch'], df[f"{attr}_loss"], label=f"Training Loss ({attr})")
    plt.plot(df['epoch'], df[f"val_{attr}_loss"], label=f"Validation Loss␣
 ↪({attr})")

plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training and Validation Loss for Multi-Attribute Classifier')
plt.legend()
plt.show()
```



Discussions It is clear from the results that making judgements about age is a lot harder than gender. Let's see the confusion matrix for both the tasks.

7.1 Confusion Matrix and Accuracy

[ ]:
```
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.preprocessing import label_binarize

# Get predicted labels for validation set
val_pred = model.predict(np.array(scaled_val_img))

# Get true labels for each attribute
true_labels = {}
for attr in attr_list:
    if attr == 'gender':
        true_labels[attr] = label_binarize(val_gender, classes=[0,1])
    elif attr == 'age':
        true_labels[attr] = label_binarize(val_age,␣
↪classes=list(range(output_dim[attr])))
    elif attr == 'race':
        true_labels[attr] = label_binarize(val_race,␣
↪classes=list(range(output_dim[attr])))

# Generate confusion matrix for each attribute and calculate accuracy
for i, attr in enumerate(attr_list):
    true = true_labels[attr]
    pred = np.argmax(val_pred[i], axis=1)
    labels = range(output_dim[attr])
    cm = confusion_matrix(true.argmax(axis=1), pred, labels=labels)
    accuracy = accuracy_score(true.argmax(axis=1), pred)
    print(f"Confusion matrix for {attr}:")
    print(cm)
    print(f"Accuracy for {attr}: {accuracy:.4f}\n")
```

```
343/343 [==============================] - 1s 4ms/step
Confusion matrix for gender:
[[4858  934]
 [1329 3833]]
Accuracy for gender: 0.7934

Confusion matrix for age:
[[ 130   56    1    6    5    1    0    0    0]
 [ 110  874  102  192   47   17    5    9    0]
 [   3  253  187  514  178   28    5   13    0]
 [   6  147  132 1746 1036  149   43   41    0]
 [   3   62   42  785 1043  281   64   49    1]
 [   3   40   25  262  523  291  129   78    2]
 [   0   19    3   93  211  191  135  142    2]
 [   0    3    2   38   44   72   55  104    3]
 [   0    3    0   11   15   13   17   55    4]]
Accuracy for age: 0.4121
```

7.1.1 Comments

The accuracy for gender is higher than the accuracy for age. It ties up to the fact of what we saw before. Loss values are higher for training age than gender.

8 Task 5: Variational Auto Encoder

1. Build a variational autoencoder with the following specifications (in this one you have a little more flexibility):
   - Should have at least two convolution layers in the encoder and 2 deconvolution layers in the decoder
   - Latent dimension should be at least 5.
   - Loss should be either MSE or binary cross entropy.
2. Using Min-Max scaling to scale the training dataset and using the same Min and Max values from the training set scale the test dataset

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

.

3. Using mini-batch gradient descent to optimize the loss function on the training dataset. Please record the loss value for each of the epochs and create an epoch-loss plot and an accuracy-loss plot for both the training and validation set.
4. Qualitatively evaluate your model by generating a set of faces by randomly choosing 10 latent vectors and presenting the resulting images.

[ ]:
```
import numpy as np
from sklearn.preprocessing import MinMaxScaler
import keras
from keras.models import Sequential
from keras.layers import Dense,Conv2D,MaxPooling2D,Flatten
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
import argparse
import os
import seaborn as sns
from tensorflow.keras.layers import Lambda, Input, Dense,Conv2DTranspose,Reshape
from tensorflow.keras.models import Model
from tensorflow.keras.datasets import mnist
from tensorflow.keras.losses import mse, binary_crossentropy
from tensorflow.keras.utils import plot_model
from tensorflow.keras import backend as K
import matplotlib.gridspec as gridspec
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, Dense,
 ↪Flatten, Lambda, Reshape, Conv2DTranspose
```

8.0.1 Get Dataset

[ ]:
```
train_img, train_age, train_gender, train_race =␣
 ↪get_dataset(DATA_DIR,'train')#, sample=True)
val_img, val_age, val_gender, val_race = get_dataset(DATA_DIR,'val')#,␣
 ↪sample=True)

# min-max scaling
flattened_train_img = [img.reshape(32*32) for img in train_img]
flattened_val_img = [img.reshape(32*32) for img in val_img]

scaler = MinMaxScaler()
scaler.fit(flattened_train_img)
print(len(scaler.data_max_), len(scaler.data_min_))# 255 and 0, len=1024

scaled_train_img = scaler.transform(flattened_train_img)
scaled_val_img = scaler.transform(flattened_val_img)

scaled_train_img = np.array([img.reshape(32,32,1) for img in scaled_train_img])
scaled_val_img = np.array([img.reshape(32,32,1) for img in scaled_val_img])
```

```
1024 1024
```

[ ]:
```
def sampling(args):
    """Reparameterization trick by sampling from an isotropic unit Gaussian.

    # Arguments
        args (tensor): mean and log of variance of Q(z|X)

    # Returns
        z (tensor): sampled latent vector
    """
    #Extract mean and log of variance
    z_mean, z_log_var = args
    #get batch size and length of vector (size of latent space)
    batch = K.shape(z_mean)[0]
    dim = K.int_shape(z_mean)[1]

    # by default, random_normal has mean = 0 and std = 1.0
    epsilon = K.random_normal(shape=(batch, dim))
    #Return sampled number (need to raise var to correct power)
    return z_mean + K.exp(z_log_var) * epsilon
```

8.1 Encoder Model

[ ]:
```
latent_dim = 10
```

[ ]:
```
inputs = Input(shape=(32,32,1),name = 'encoder_input')
x = Conv2D(filters=16, kernel_size=3, strides=(1, 1), padding="valid",␣
 ↪activation='relu')(inputs)
x = MaxPooling2D(pool_size=(2, 2), strides=None, padding="valid")(x)
x = Conv2D(filters=32,kernel_size=3,strides=(1,1),padding='valid',␣
 ↪activation='relu')(x)
x = MaxPooling2D(pool_size=(2, 2), strides=None, padding="valid")(x)
x = Conv2D(filters=64,kernel_size=3,strides=(1,1),padding='valid',␣
 ↪activation='relu')(x)
x = MaxPooling2D(pool_size=(2, 2), strides=None, padding="valid")(x)
x = Flatten()(x)
x = Dense(128,activation='relu')(x)
z_mean = Dense(latent_dim, name='z_mean')(x)
z_log_var = Dense(latent_dim, name='z_log_var')(x)
```

[ ]:
```
# use reparameterization trick to push the sampling out as input
z = Lambda(sampling, name='z')([z_mean, z_log_var])

# instantiate encoder model
encoder = Model(inputs, z, name='encoder_output')
encoder.summary()
```

```
Model: "encoder_output"
________________________________________________________________________________
__________________
 Layer (type)                   Output Shape         Param #     Connected to
================================================================================
==================
 encoder_input (InputLayer)     [(None, 32, 32, 1)]  0           []

 conv2d_19 (Conv2D)             (None, 30, 30, 16)   160
['encoder_input[0][0]']

 max_pooling2d_19 (MaxPooling2D  (None, 15, 15, 16)  0
['conv2d_19[0][0]']
 )

 conv2d_20 (Conv2D)             (None, 13, 13, 32)   4640
['max_pooling2d_19[0][0]']

 max_pooling2d_20 (MaxPooling2D  (None, 6, 6, 32)    0
['conv2d_20[0][0]']
 )

 conv2d_21 (Conv2D)             (None, 4, 4, 64)     18496
['max_pooling2d_20[0][0]']

 max_pooling2d_21 (MaxPooling2D  (None, 2, 2, 64)    0
```

```
['conv2d_21[0][0]']
 )

 flatten_9 (Flatten)           (None, 256)          0
['max_pooling2d_21[0][0]']

 dense_32 (Dense)              (None, 128)          32896
['flatten_9[0][0]']


--------------------------------------------------------------------------------
------------------
 Layer (type)                  Output Shape         Param #     Connected to
================================================================================
==================
 encoder_input (InputLayer)    [(None, 32, 32, 1)]  0           []

 conv2d_19 (Conv2D)            (None, 30, 30, 16)   160
['encoder_input[0][0]']

 max_pooling2d_19 (MaxPooling2D  (None, 15, 15, 16)  0
['conv2d_19[0][0]']
 )

 conv2d_20 (Conv2D)            (None, 13, 13, 32)   4640
['max_pooling2d_19[0][0]']

 max_pooling2d_20 (MaxPooling2D  (None, 6, 6, 32)    0
['conv2d_20[0][0]']
 )

 conv2d_21 (Conv2D)            (None, 4, 4, 64)     18496
['max_pooling2d_20[0][0]']

 max_pooling2d_21 (MaxPooling2D  (None, 2, 2, 64)    0
['conv2d_21[0][0]']
 )

 flatten_9 (Flatten)           (None, 256)          0
['max_pooling2d_21[0][0]']

 dense_32 (Dense)              (None, 128)          32896
['flatten_9[0][0]']

 z_mean (Dense)                (None, 10)           1290
['dense_32[0][0]']

 z_log_var (Dense)             (None, 10)           1290
['dense_32[0][0]']
```

```
 z (Lambda)                    (None, 10)          0
['z_mean[0][0]',
'z_log_var[0][0]']

================================================================================
==================
Total params: 58,772
Trainable params: 58,772
Non-trainable params: 0
--------------------------------------------------------------------------------
------------------
```

9 Decoder Model

[ ]:
```
latent_inputs = Input(shape=(latent_dim,), name='z_sampling')

x = Dense(128, activation='relu', name="decoder_hidden_layer")(latent_inputs)
x= Reshape((2,2,32))(x)
x = Conv2DTranspose(filters = 64, kernel_size = (3,3), strides = 2, padding =␣
 ↪'same',activation = 'relu')(x)
x = Conv2DTranspose(filters=32,kernel_size=3,strides=2,padding='valid',␣
 ↪activation='relu')(x)
x = Conv2D(filters=16,kernel_size=3,strides=1,padding='valid',␣
 ↪activation='relu')(x)
x = Conv2DTranspose(filters=16,kernel_size=3,strides=2,padding='valid',␣
 ↪activation='relu')(x)
x = Conv2DTranspose(filters=1,kernel_size=4,strides=2,padding='valid',␣
 ↪activation='relu')(x)
```

[ ]:
```
# instantiate decoder model
decoder = Model(latent_inputs, outputs=x, name='decoder_output')
decoder.summary()
```

```
Model: "decoder_output"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 z_sampling (InputLayer)     [(None, 10)]              0

 decoder_hidden_layer (Dense  (None, 128)              1408
 )

 reshape (Reshape)           (None, 2, 2, 32)          0

 conv2d_transpose (Conv2DTra  (None, 4, 4, 64)         18496
 nspose)
```

```
 conv2d_transpose_1 (Conv2DT  (None, 9, 9, 32)         18464
 ranspose)

 conv2d_22 (Conv2D)          (None, 7, 7, 16)          4624

 conv2d_transpose_2 (Conv2DT  (None, 15, 15, 16)       2320
 ranspose)

 conv2d_transpose_3 (Conv2DT  (None, 32, 32, 1)        257
 ranspose)

=================================================================
Total params: 45,569
Trainable params: 45,569
Non-trainable params: 0
_________________________________________________________________
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 z_sampling (InputLayer)     [(None, 10)]              0

 decoder_hidden_layer (Dense  (None, 128)              1408
 )

 reshape (Reshape)           (None, 2, 2, 32)          0

 conv2d_transpose (Conv2DTra  (None, 4, 4, 64)         18496
 nspose)

 conv2d_transpose_1 (Conv2DT  (None, 9, 9, 32)         18464
 ranspose)

 conv2d_22 (Conv2D)          (None, 7, 7, 16)          4624

 conv2d_transpose_2 (Conv2DT  (None, 15, 15, 16)       2320
 ranspose)

 conv2d_transpose_3 (Conv2DT  (None, 32, 32, 1)        257
 ranspose)

=================================================================
Total params: 45,569
Trainable params: 45,569
Non-trainable params: 0
_________________________________________________________________
```

[ ]:
```python
outputs = decoder(encoder(inputs))
vae = Model(inputs = inputs, outputs = outputs)
vae.summary()
```

```
Model: "model_1"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 encoder_input (InputLayer)  [(None, 32, 32, 1)]       0

 encoder_output (Functional)  (None, 10)               58772

 decoder_output (Functional)  (None, 32, 32, 1)        45569

=================================================================
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 encoder_input (InputLayer)  [(None, 32, 32, 1)]       0

 encoder_output (Functional)  (None, 10)               58772

 decoder_output (Functional)  (None, 32, 32, 1)        45569

=================================================================
Total params: 104,341
Trainable params: 104,341
Non-trainable params: 0
_________________________________________________________________
```

9.0.1 Setting up the VAE Loss

We will need to set up the VAE model. We will use the encoder and decoder models we created above. We will also need to define the loss function and the optimizer. - Reconstruction loss: This is the loss between the original image and the reconstructed image. We will use the binary cross-entropy loss for this.

[ ]:
```python
# setting loss
reconstruction_loss = mse(K.flatten(inputs), K.flatten(outputs))
reconstruction_loss *= (32*32) #image_width*image_height

kl_loss = K.exp(z_log_var) + K.square(z_mean) - z_log_var - 1
print(kl_loss.shape)
kl_loss = K.sum(kl_loss, axis=-1)
kl_loss *= 0.05

vae_loss = K.mean(reconstruction_loss + kl_loss)
vae.add_loss(vae_loss)
```

```
vae.compile(optimizer='adam')
```

```
(None, 10)
```

9.1 Training

[ ]:
```
bs = 32
epochs = 10
```

[ ]:
```
train_history = vae.fit(scaled_train_img, scaled_train_img, batch_size=bs,␣
↪epochs=epochs, verbose=1)
```

```
Epoch 1/10
2711/2711 [==============================] - 49s 18ms/step - loss: 21.4176
Epoch 2/10
2711/2711 [==============================] - 45s 17ms/step - loss: 14.6902
Epoch 3/10
2711/2711 [==============================] - 45s 17ms/step - loss: 14.2247
Epoch 4/10
2711/2711 [==============================] - 52s 19ms/step - loss: 14.0073
Epoch 5/10
2711/2711 [==============================] - 50s 18ms/step - loss: 13.8549
Epoch 6/10
2711/2711 [==============================] - 50s 18ms/step - loss: 13.7504
Epoch 7/10
2711/2711 [==============================] - 49s 18ms/step - loss: 13.6533
Epoch 8/10
2711/2711 [==============================] - 47s 17ms/step - loss: 13.5787
Epoch 9/10
2711/2711 [==============================] - 44s 16ms/step - loss: 13.5111
Epoch 10/10
2711/2711 [==============================] - 47s 17ms/step - loss: 13.4604
```

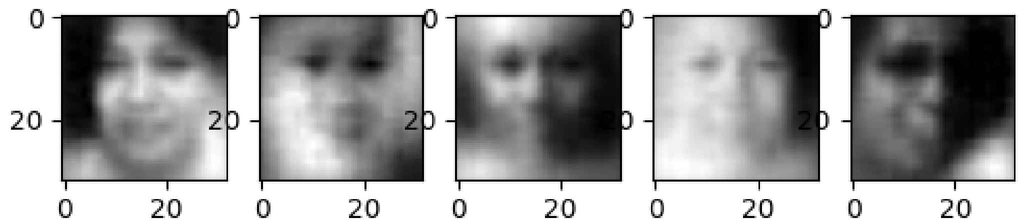
9.2 Comparing the original and reconstructed images

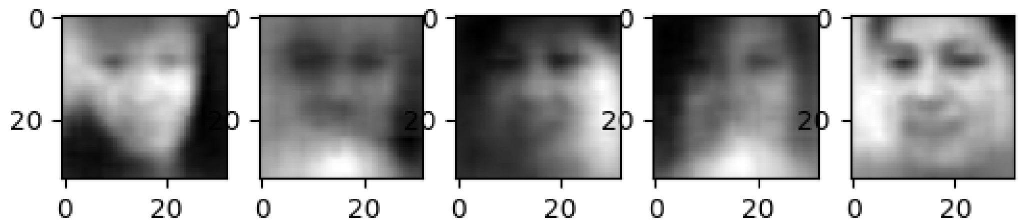
[ ]:
```
out_list = []
for i in range(10):
    plt.subplot(2,5,i+1)
    latent_vectors = np.random.randn(latent_dim).reshape(1, latent_dim)
    img = decoder.predict(latent_vectors)
    img = img.reshape(32,32)
    out_list.append(img)
    plt.imshow(img, cmap=plt.cm.gray)

plt.savefig('vae_output.png')
```

```
1/1 [==============================] - 0s 107ms/step
1/1 [==============================] - 0s 20ms/step
```

```
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 19ms/step
1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 19ms/step
```





Discussion The model reduces the face images to 10-dimensional latent vector. Then, reconstructs the images from the latent vector. The model is able to reconstruct the images as seen in the last output. However, the reconstructed images are not as good as the original images.