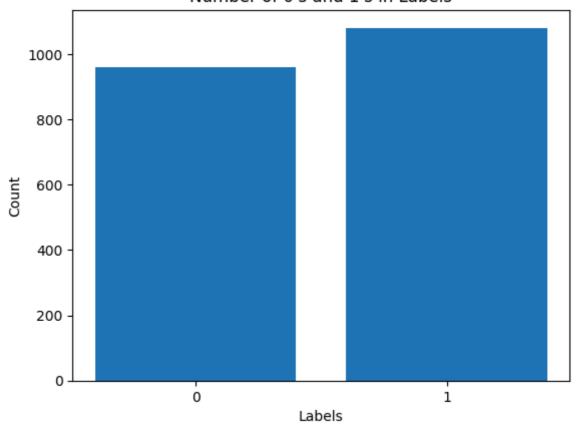
```
In [1]:
        from google.colab import drive
        drive.mount('/content/drive')
        Drive already mounted at /content/drive; to attempt to forcibly remount, call driv
        e.mount("/content/drive", force_remount=True).
In [ ]: import os
         import pickle
        from skimage.io import imread
        from skimage.transform import resize
         import numpy as np
         from sklearn.model_selection import train_test_split
        from sklearn.preprocessing import StandardScaler, LabelEncoder
        from sklearn.svm import SVC
        from sklearn.neighbors import KNeighborsClassifier
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.metrics import classification report, accuracy score
        from sklearn.model selection import GridSearchCV
       input_dir ="/content/drive/MyDrive/Dataset"
In [ ]:
        categories = ['training_fake','training_real']
In [ ]: data = []
        labels =[]
In [ ]: for category_idx,category in enumerate(categories):
            for file in os.listdir(os.path.join(input_dir, category)):
                 img_path = os.path.join(input_dir, category, file)
                 img = imread(img_path)
                 img = resize(img, (15,15))
                 data.append(img.flatten())
                 labels.append(category_idx)
         data = np.asarray(data)
        labels = np.asarray(labels)
In [ ]: x_train, x_test , y_train, y_test = train_test_split(data, labels, test_size = 0.2,
In [ ]:
        data
        array([[0.21686637, 0.26607724, 0.12056783, ..., 0.43321461, 0.39738475,
Out[ ]:
                0.28061314],
                [0.59848347, 0.58460734, 0.41847801, ..., 0.63072004, 0.58678159,
                0.44366264],
               [0.7456379, 0.30116916, 0.40968557, ..., 0.30615458, 0.23674222,
                0.18954393],
                [0.26574721, 0.36874194, 0.37025733, ..., 0.10381542, 0.02566318,
                0.10717465],
               [0.44435289, 0.34354007, 0.24239725, ..., 0.32116241, 0.26774909,
                0.16193692],
               [0.79065056, 0.90475585, 0.91075612, ..., 0.59132982, 0.42368649,
                0.44422604]])
        labels
In [ ]:
        array([0, 0, 0, ..., 1, 1, 1])
Out[ ]:
        count_0 = np.sum(labels == 0)
         count_1 = np.sum(labels == 1)
```

Number of 0's and 1's in Labels



```
In [ ]: classifier = SVC()
        parameters = [{'gamma':[0.01, 0.001, 0.0001], 'C':[1,10,100,1000]}]
         grid_search = GridSearchCV(classifier, parameters)
        grid_search.fit(x_train, y_train)
        best_estimator = grid_search.best_estimator_
        y_prediction = best_estimator.predict(x_test)
         svm_accuracy = accuracy_score(y_test, y_prediction)
        print("SVM Accuracy:", svm_accuracy)
         svm classification report = classification report(y test,y prediction)
         print("\nSVM Classification Report:\n", svm_classification_report)
        #KNN
         knn_model = KNeighborsClassifier()
         knn_model.fit(x_train, y_train)
         knn_predictions = knn_model.predict(x_test)
         knn_accuracy = accuracy_score(y_test, knn_predictions)
         print("KNN Accuracy:", knn_accuracy)
        knn_classification_report = classification_report(y_test, knn_predictions)
```

```
print("\nKNN Classification Report:\n", knn_classification_report)
        #DECISION TREE
        dt model = DecisionTreeClassifier()
        dt_model.fit(x_train, y_train)
        dt_predictions = dt_model.predict(x_test)
        dt_accuracy = accuracy_score(y_test, dt_predictions)
        print("\nDecision Tree Accuracy:", dt accuracy)
        dt_classification_report = classification_report(y_test, dt_predictions)
        print("Decision Tree Classification Report:\n", dt_classification_report)
        SVM Accuracy: 0.5843520782396088
        SVM Classification Report:
                       precision
                                    recall f1-score
                                                       support
                           0.56
                                     0.51
                                               0.54
                                                          192
                   0
                   1
                           0.60
                                     0.65
                                               0.62
                                                          217
                                               0.58
                                                          409
            accuracy
                           0.58
                                     0.58
                                               0.58
                                                          409
           macro avg
        weighted avg
                           0.58
                                     0.58
                                               0.58
                                                          409
        KNN Accuracy: 0.5232273838630807
        KNN Classification Report:
                       precision
                                    recall f1-score
                                                       support
                   0
                           0.49
                                     0.54
                                               0.51
                                                          192
                   1
                           0.56
                                     0.51
                                               0.53
                                                          217
                                                          409
            accuracy
                                               0.52
                           0.52
                                     0.52
                                               0.52
                                                          409
           macro avg
                           0.53
                                     0.52
                                               0.52
                                                          409
        weighted avg
        Decision Tree Accuracy: 0.5330073349633252
        Decision Tree Classification Report:
                       precision
                                    recall f1-score
                                                       support
                           0.50
                                               0.51
                   0
                                     0.52
                                                          192
                   1
                           0.56
                                     0.55
                                               0.55
                                                          217
            accuracy
                                               0.53
                                                          409
                           0.53
                                     0.53
                                               0.53
                                                          409
           macro avg
                                               0.53
        weighted avg
                           0.53
                                     0.53
                                                          409
In [ ]:
        import os
        import pickle
        import numpy as np
        from skimage.io import imread
        from skimage.transform import resize
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import classification_report, accuracy_score
        import tensorflow as tf
        from tensorflow.keras import layers, models
        from sklearn.preprocessing import LabelEncoder
        from tensorflow.keras.preprocessing.image import ImageDataGenerator
In [ ]: data = []
        labels = []
```

```
for category_idx, category in enumerate(categories):
    for file in os.listdir(os.path.join(input_dir, category)):
        img_path = os.path.join(input_dir, category, file)
        img = imread(img_path)
        img = resize(img, (64, 64))
        data.append(img)
        labels.append(category_idx)
data = np.asarray(data)
labels = np.asarray(labels)
# Perform train/test split
x_train, x_test, y_train, y_test = train_test_split(data, labels, test_size=0.2, sk
# Encode Labels
label encoder = LabelEncoder()
y_train_encoded = label_encoder.fit_transform(y_train)
y_test_encoded = label_encoder.transform(y_test)
# Data Augmentation
datagen = ImageDataGenerator(
    rotation_range=20,
   width shift range=0.1,
   height shift range=0.1,
   horizontal_flip=True,
   vertical_flip=True,
    zoom_range=0.1,
   fill_mode='nearest')
# CNN Model
model = models.Sequential([
   layers.Conv2D(32, (3, 3), activation='relu', input shape=(64, 64, 3)),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Flatten(),
    layers.Dropout(0.5),
    layers.Dense(128, activation='relu'),
    layers.Dense(2, activation='softmax')
1)
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
history = model.fit(datagen.flow(x_train, y_train_encoded, batch_size=32),
                    steps per epoch=len(x train) / 32, epochs=100,
                    validation_data=(x_test, y_test_encoded))
test_loss, test_accuracy = model.evaluate(x_test, y_test_encoded)
print("CNN Accuracy:", test_accuracy)
y_pred = np.argmax(model.predict(x_test), axis=-1)
y pred decoded = label encoder.inverse transform(y pred)
cnn_classification_report = classification_report(y_test, y_pred_decoded)
print("\nCNN Classification Report:\n", cnn_classification_report)
```

```
Epoch 1/100
51/51 [============] - 18s 306ms/step - loss: 0.7005 - accuracy:
0.4945 - val loss: 0.6926 - val accuracy: 0.5306
Epoch 2/100
0.5294 - val loss: 0.6918 - val accuracy: 0.5306
Epoch 3/100
0.5227 - val loss: 0.7085 - val accuracy: 0.5306
Epoch 4/100
0.5276 - val_loss: 0.6919 - val_accuracy: 0.5306
Epoch 5/100
0.5294 - val loss: 0.6912 - val accuracy: 0.5306
Epoch 6/100
0.5294 - val loss: 0.6910 - val accuracy: 0.5306
Epoch 7/100
0.5276 - val_loss: 0.6910 - val_accuracy: 0.5306
Epoch 8/100
51/51 [============== ] - 13s 251ms/step - loss: 0.6909 - accuracy:
0.5294 - val loss: 0.6895 - val accuracy: 0.5355
Epoch 9/100
0.5411 - val loss: 0.6865 - val accuracy: 0.5379
Epoch 10/100
0.5453 - val_loss: 0.6897 - val_accuracy: 0.5330
Epoch 11/100
0.5319 - val_loss: 0.6886 - val_accuracy: 0.5281
Epoch 12/100
51/51 [============ ] - 13s 250ms/step - loss: 0.6906 - accuracy:
0.5386 - val_loss: 0.6861 - val_accuracy: 0.5477
Epoch 13/100
0.5429 - val_loss: 0.6846 - val_accuracy: 0.5550
Epoch 14/100
0.5613 - val loss: 0.6866 - val accuracy: 0.5232
Epoch 15/100
0.5527 - val_loss: 0.6839 - val_accuracy: 0.5648
Epoch 16/100
0.5668 - val_loss: 0.6723 - val_accuracy: 0.5819
Epoch 17/100
0.5613 - val_loss: 0.6727 - val_accuracy: 0.5697
Epoch 18/100
0.5496 - val_loss: 0.6860 - val_accuracy: 0.5575
Epoch 19/100
0.5680 - val_loss: 0.6828 - val_accuracy: 0.5770
Epoch 20/100
0.5821 - val_loss: 0.6742 - val_accuracy: 0.5746
Epoch 21/100
0.5754 - val_loss: 0.6718 - val_accuracy: 0.5917
Epoch 22/100
```

```
0.5784 - val_loss: 0.6790 - val_accuracy: 0.6039
Epoch 23/100
51/51 [=========== ] - 17s 335ms/step - loss: 0.6799 - accuracy:
0.5686 - val loss: 0.6758 - val accuracy: 0.5795
Epoch 24/100
0.5723 - val_loss: 0.6769 - val_accuracy: 0.5746
Epoch 25/100
0.5925 - val_loss: 0.6726 - val_accuracy: 0.6088
Epoch 26/100
0.5778 - val loss: 0.6728 - val accuracy: 0.5966
Epoch 27/100
0.5864 - val loss: 0.6695 - val accuracy: 0.6137
Epoch 28/100
0.5600 - val_loss: 0.6748 - val_accuracy: 0.6210
Epoch 29/100
0.5760 - val loss: 0.6695 - val accuracy: 0.5917
Epoch 30/100
0.5705 - val loss: 0.6754 - val accuracy: 0.5819
Epoch 31/100
0.5748 - val_loss: 0.6669 - val_accuracy: 0.5917
Epoch 32/100
0.5870 - val loss: 0.6718 - val accuracy: 0.5966
Epoch 33/100
0.5888 - val_loss: 0.6809 - val_accuracy: 0.5770
Epoch 34/100
0.5876 - val_loss: 0.6701 - val_accuracy: 0.5966
Epoch 35/100
0.6066 - val loss: 0.6814 - val accuracy: 0.6015
Epoch 36/100
0.5876 - val_loss: 0.6747 - val_accuracy: 0.5721
Epoch 37/100
0.6005 - val_loss: 0.6785 - val_accuracy: 0.5623
Epoch 38/100
0.5907 - val loss: 0.6675 - val accuracy: 0.5941
Epoch 39/100
0.6115 - val_loss: 0.6702 - val_accuracy: 0.5892
Epoch 40/100
0.6195 - val_loss: 0.6623 - val_accuracy: 0.6015
Epoch 41/100
0.5993 - val_loss: 0.6663 - val_accuracy: 0.5917
Epoch 42/100
0.5968 - val loss: 0.6739 - val accuracy: 0.5892
Epoch 43/100
51/51 [============= ] - 13s 249ms/step - loss: 0.6655 - accuracy:
```

```
0.5913 - val_loss: 0.6678 - val_accuracy: 0.6186
Epoch 44/100
51/51 [============ ] - 13s 250ms/step - loss: 0.6529 - accuracy:
0.6085 - val loss: 0.6744 - val accuracy: 0.5844
Epoch 45/100
0.5938 - val_loss: 0.6675 - val_accuracy: 0.5966
Epoch 46/100
0.6152 - val_loss: 0.6656 - val_accuracy: 0.6064
Epoch 47/100
0.6091 - val_loss: 0.6667 - val_accuracy: 0.5746
Epoch 48/100
0.5839 - val_loss: 0.6540 - val_accuracy: 0.6333
Epoch 49/100
0.6078 - val_loss: 0.6646 - val_accuracy: 0.5892
Epoch 50/100
0.6023 - val_loss: 0.6711 - val_accuracy: 0.5917
Epoch 51/100
0.6060 - val_loss: 0.6619 - val_accuracy: 0.5917
Epoch 52/100
0.6029 - val_loss: 0.6738 - val_accuracy: 0.6064
Epoch 53/100
51/51 [============ ] - 12s 241ms/step - loss: 0.6564 - accuracy:
0.6036 - val loss: 0.6672 - val accuracy: 0.5917
Epoch 54/100
0.6201 - val_loss: 0.6713 - val_accuracy: 0.6015
Epoch 55/100
0.6170 - val_loss: 0.6783 - val_accuracy: 0.6259
Epoch 56/100
0.6134 - val loss: 0.6676 - val accuracy: 0.5941
Epoch 57/100
0.6225 - val_loss: 0.6648 - val_accuracy: 0.5941
Epoch 58/100
0.6256 - val_loss: 0.6606 - val_accuracy: 0.5966
Epoch 59/100
0.5931 - val loss: 0.6664 - val accuracy: 0.6161
Epoch 60/100
0.6097 - val loss: 0.6642 - val accuracy: 0.5917
0.6299 - val_loss: 0.6680 - val_accuracy: 0.6088
Epoch 62/100
0.6189 - val_loss: 0.6622 - val_accuracy: 0.6015
Epoch 63/100
0.6262 - val_loss: 0.6611 - val_accuracy: 0.6112
Epoch 64/100
0.6103 - val_loss: 0.6692 - val_accuracy: 0.6137
```

```
Epoch 65/100
51/51 [============] - 13s 247ms/step - loss: 0.6501 - accuracy:
0.6164 - val loss: 0.6672 - val accuracy: 0.5819
Epoch 66/100
0.6036 - val loss: 0.6579 - val accuracy: 0.6039
Epoch 67/100
0.6201 - val loss: 0.6649 - val accuracy: 0.5868
Epoch 68/100
0.6244 - val_loss: 0.6695 - val_accuracy: 0.5990
Epoch 69/100
0.6072 - val loss: 0.6607 - val accuracy: 0.6112
Epoch 70/100
0.6385 - val loss: 0.6588 - val accuracy: 0.6235
Epoch 71/100
0.6360 - val_loss: 0.6677 - val_accuracy: 0.6112
Epoch 72/100
0.6140 - val loss: 0.6677 - val accuracy: 0.5941
Epoch 73/100
0.6434 - val loss: 0.6626 - val accuracy: 0.6112
Epoch 74/100
0.6244 - val_loss: 0.6592 - val_accuracy: 0.6015
Epoch 75/100
0.6232 - val_loss: 0.6614 - val_accuracy: 0.6259
Epoch 76/100
51/51 [============ ] - 13s 247ms/step - loss: 0.6328 - accuracy:
0.6373 - val_loss: 0.6583 - val_accuracy: 0.6284
Epoch 77/100
0.6176 - val_loss: 0.6514 - val_accuracy: 0.6015
Epoch 78/100
0.6164 - val_loss: 0.6577 - val_accuracy: 0.6186
Epoch 79/100
0.6342 - val_loss: 0.6667 - val_accuracy: 0.6137
Epoch 80/100
0.6219 - val_loss: 0.6577 - val_accuracy: 0.6210
Epoch 81/100
0.6268 - val_loss: 0.6551 - val_accuracy: 0.6039
Epoch 82/100
0.6489 - val_loss: 0.6696 - val_accuracy: 0.6112
Epoch 83/100
0.6385 - val_loss: 0.6640 - val_accuracy: 0.6064
Epoch 84/100
0.6311 - val_loss: 0.6673 - val_accuracy: 0.5941
Epoch 85/100
0.6385 - val_loss: 0.6588 - val_accuracy: 0.6088
Epoch 86/100
```

```
0.6538 - val_loss: 0.6617 - val_accuracy: 0.6161
Epoch 87/100
0.6225 - val loss: 0.6508 - val accuracy: 0.6357
Epoch 88/100
0.6330 - val loss: 0.6629 - val accuracy: 0.6039
Epoch 89/100
0.6526 - val_loss: 0.6574 - val_accuracy: 0.5966
Epoch 90/100
0.6281 - val loss: 0.6530 - val accuracy: 0.6015
Epoch 91/100
0.6409 - val loss: 0.6475 - val accuracy: 0.6088
0.6464 - val_loss: 0.6640 - val_accuracy: 0.5721
Epoch 93/100
0.6238 - val loss: 0.6560 - val accuracy: 0.6137
Epoch 94/100
0.6483 - val loss: 0.6528 - val accuracy: 0.5990
Epoch 95/100
0.6336 - val_loss: 0.6498 - val_accuracy: 0.6235
Epoch 96/100
0.6324 - val loss: 0.6506 - val accuracy: 0.6015
Epoch 97/100
0.6501 - val_loss: 0.6607 - val_accuracy: 0.6161
Epoch 98/100
0.6385 - val_loss: 0.6851 - val_accuracy: 0.5819
Epoch 99/100
0.6538 - val loss: 0.6638 - val accuracy: 0.6235
Epoch 100/100
0.6452 - val loss: 0.6575 - val accuracy: 0.6210
0.6210
CNN Accuracy: 0.621026873588562
13/13 [======== ] - 1s 52ms/step
CNN Classification Report:
      precision recall f1-score support
     0
        0.60
            0.58
                  0.59
                       192
        0.64
             0.66
                  0.65
                       217
 accuracy
                 0.62
                      409
        0.62
             0.62
                 0.62
                       409
 macro avg
                 0.62
weighted avg
        0.62
             0.62
                       409
```

```
y_test_encoded = label_encoder.transform(y_test)
datagen = ImageDataGenerator(
    rotation range=20,
   width_shift_range=0.1,
   height_shift_range=0.1,
   horizontal_flip=True,
   vertical flip=True,
    zoom_range=0.1,
   fill_mode='nearest')
model = models.Sequential([
   layers.Conv2D(32, (3, 3), activation='relu', input_shape=(64, 64, 3)),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Flatten(),
    layers.Dropout(0.5),
    layers.Dense(128, activation='relu'),
    layers.Dense(2, activation='softmax')
1)
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
history = model.fit(datagen.flow(x_train, y_train_encoded, batch_size=16),
                    steps_per_epoch=len(x_train) / 32, epochs=200,
                    validation_data=(x_test, y_test_encoded))
test_loss, test_accuracy = model.evaluate(x_test, y_test_encoded)
print("CNN Accuracy:", test_accuracy)
y_pred = np.argmax(model.predict(x_test), axis=-1)
y_pred_decoded = label_encoder.inverse_transform(y_pred)
cnn classification report = classification report(y test, y pred decoded)
print("\nCNN Classification Report:\n", cnn_classification_report)
```

```
Epoch 1/200
51/51 [============] - 11s 190ms/step - loss: 0.7007 - accuracy:
0.5037 - val loss: 0.6963 - val accuracy: 0.4694
Epoch 2/200
0.5086 - val loss: 0.6915 - val accuracy: 0.5232
Epoch 3/200
0.5245 - val loss: 0.6918 - val accuracy: 0.5306
Epoch 4/200
0.5282 - val_loss: 0.6914 - val_accuracy: 0.5306
Epoch 5/200
0.5245 - val loss: 0.6915 - val accuracy: 0.5306
Epoch 6/200
0.5551 - val loss: 0.6917 - val accuracy: 0.5306
Epoch 7/200
0.5233 - val_loss: 0.6900 - val_accuracy: 0.5306
Epoch 8/200
0.5282 - val loss: 0.6911 - val accuracy: 0.5306
Epoch 9/200
0.5233 - val loss: 0.6895 - val accuracy: 0.5306
Epoch 10/200
0.5490 - val loss: 0.6905 - val accuracy: 0.5306
Epoch 11/200
0.5355 - val loss: 0.6916 - val accuracy: 0.5306
Epoch 12/200
0.5221 - val_loss: 0.6901 - val_accuracy: 0.5306
Epoch 13/200
0.5282 - val_loss: 0.6903 - val_accuracy: 0.5306
Epoch 14/200
0.5417 - val loss: 0.6882 - val accuracy: 0.5281
Epoch 15/200
0.5306 - val_loss: 0.6893 - val_accuracy: 0.5306
Epoch 16/200
0.5159 - val_loss: 0.6890 - val_accuracy: 0.5452
Epoch 17/200
0.5012 - val_loss: 0.6907 - val_accuracy: 0.5281
Epoch 18/200
0.5331 - val_loss: 0.6883 - val_accuracy: 0.5306
Epoch 19/200
0.5368 - val_loss: 0.6852 - val_accuracy: 0.5403
Epoch 20/200
0.5466 - val_loss: 0.6876 - val_accuracy: 0.5306
Epoch 21/200
0.5453 - val_loss: 0.6901 - val_accuracy: 0.5672
Epoch 22/200
```

```
0.5135 - val_loss: 0.6887 - val_accuracy: 0.5306
Epoch 23/200
0.5478 - val loss: 0.6868 - val accuracy: 0.5746
Epoch 24/200
0.5404 - val loss: 0.6855 - val accuracy: 0.5330
Epoch 25/200
0.5282 - val_loss: 0.6800 - val_accuracy: 0.5452
Epoch 26/200
0.5392 - val loss: 0.6835 - val accuracy: 0.5917
Epoch 27/200
0.5368 - val loss: 0.6819 - val accuracy: 0.5232
Epoch 28/200
0.5723 - val_loss: 0.6837 - val_accuracy: 0.5526
Epoch 29/200
0.5613 - val loss: 0.6788 - val accuracy: 0.5819
Epoch 30/200
0.5833 - val loss: 0.6756 - val accuracy: 0.5892
Epoch 31/200
0.5404 - val_loss: 0.6811 - val_accuracy: 0.5966
Epoch 32/200
0.5355 - val loss: 0.6775 - val accuracy: 0.5550
Epoch 33/200
0.5502 - val_loss: 0.6769 - val_accuracy: 0.5501
Epoch 34/200
0.5404 - val_loss: 0.6828 - val_accuracy: 0.5770
Epoch 35/200
0.5551 - val loss: 0.6740 - val accuracy: 0.5941
Epoch 36/200
0.5809 - val_loss: 0.6885 - val_accuracy: 0.5330
Epoch 37/200
0.5221 - val_loss: 0.6942 - val_accuracy: 0.5306
Epoch 38/200
0.5625 - val loss: 0.6840 - val accuracy: 0.5721
Epoch 39/200
0.5674 - val_loss: 0.6801 - val_accuracy: 0.5477
Epoch 40/200
0.5650 - val_loss: 0.6770 - val_accuracy: 0.5795
Epoch 41/200
0.5551 - val loss: 0.6822 - val accuracy: 0.5844
Epoch 42/200
0.5539 - val loss: 0.6814 - val accuracy: 0.5721
Epoch 43/200
```

```
0.5490 - val_loss: 0.6784 - val_accuracy: 0.5672
Epoch 44/200
0.5686 - val loss: 0.6778 - val accuracy: 0.5697
Epoch 45/200
0.5858 - val_loss: 0.6789 - val_accuracy: 0.5721
Epoch 46/200
0.5858 - val_loss: 0.6817 - val_accuracy: 0.5672
Epoch 47/200
0.5625 - val_loss: 0.6765 - val_accuracy: 0.5721
Epoch 48/200
0.6115 - val_loss: 0.6845 - val_accuracy: 0.5477
Epoch 49/200
0.5674 - val_loss: 0.6840 - val_accuracy: 0.5330
Epoch 50/200
0.5588 - val_loss: 0.6833 - val_accuracy: 0.5819
Epoch 51/200
0.5956 - val_loss: 0.6778 - val_accuracy: 0.5721
Epoch 52/200
0.5748 - val_loss: 0.6804 - val_accuracy: 0.5746
Epoch 53/200
0.5699 - val loss: 0.6752 - val accuracy: 0.6064
Epoch 54/200
0.5600 - val_loss: 0.6715 - val_accuracy: 0.5966
Epoch 55/200
0.5735 - val_loss: 0.6705 - val_accuracy: 0.6161
Epoch 56/200
0.5858 - val loss: 0.6729 - val accuracy: 0.6161
Epoch 57/200
0.5686 - val_loss: 0.6743 - val_accuracy: 0.6088
Epoch 58/200
0.5723 - val_loss: 0.6774 - val_accuracy: 0.5452
Epoch 59/200
0.5748 - val loss: 0.6750 - val accuracy: 0.5990
Epoch 60/200
0.5588 - val loss: 0.6760 - val accuracy: 0.5501
0.5539 - val_loss: 0.6825 - val_accuracy: 0.5355
Epoch 62/200
0.5429 - val_loss: 0.6744 - val_accuracy: 0.5648
Epoch 63/200
0.5748 - val_loss: 0.6761 - val_accuracy: 0.5795
Epoch 64/200
0.5711 - val_loss: 0.6776 - val_accuracy: 0.5892
```

```
Epoch 65/200
0.5993 - val loss: 0.6812 - val accuracy: 0.5917
Epoch 66/200
0.5735 - val loss: 0.6812 - val accuracy: 0.5844
Epoch 67/200
0.5784 - val loss: 0.6796 - val accuracy: 0.5892
Epoch 68/200
0.5907 - val_loss: 0.6743 - val_accuracy: 0.5844
Epoch 69/200
0.5784 - val loss: 0.6840 - val accuracy: 0.5648
Epoch 70/200
0.5711 - val loss: 0.6750 - val accuracy: 0.5966
Epoch 71/200
0.5858 - val_loss: 0.6737 - val_accuracy: 0.5819
Epoch 72/200
0.5956 - val loss: 0.6786 - val accuracy: 0.5844
Epoch 73/200
0.5833 - val loss: 0.6698 - val accuracy: 0.5941
Epoch 74/200
0.5784 - val_loss: 0.6767 - val_accuracy: 0.6039
Epoch 75/200
0.5980 - val loss: 0.6750 - val accuracy: 0.5844
Epoch 76/200
0.5833 - val_loss: 0.6725 - val_accuracy: 0.5966
Epoch 77/200
0.5797 - val loss: 0.6669 - val accuracy: 0.5941
Epoch 78/200
0.5870 - val loss: 0.6687 - val accuracy: 0.5966
Epoch 79/200
0.5723 - val_loss: 0.6700 - val_accuracy: 0.5697
Epoch 80/200
0.6189 - val_loss: 0.6736 - val_accuracy: 0.5819
Epoch 81/200
0.6127 - val_loss: 0.6686 - val_accuracy: 0.5770
Epoch 82/200
0.5956 - val_loss: 0.6697 - val_accuracy: 0.5648
Epoch 83/200
0.5699 - val_loss: 0.6730 - val_accuracy: 0.6064
Epoch 84/200
0.5882 - val_loss: 0.6689 - val_accuracy: 0.6015
Epoch 85/200
0.6029 - val_loss: 0.6670 - val_accuracy: 0.5868
Epoch 86/200
```

```
0.5895 - val_loss: 0.6645 - val_accuracy: 0.5868
Epoch 87/200
0.6054 - val loss: 0.6733 - val accuracy: 0.5746
Epoch 88/200
0.5907 - val loss: 0.6807 - val accuracy: 0.5941
Epoch 89/200
0.5699 - val_loss: 0.6715 - val_accuracy: 0.6088
Epoch 90/200
0.6078 - val loss: 0.6686 - val accuracy: 0.5795
Epoch 91/200
0.5968 - val loss: 0.6653 - val accuracy: 0.5917
Epoch 92/200
0.5833 - val_loss: 0.6649 - val_accuracy: 0.6015
Epoch 93/200
0.6127 - val loss: 0.6670 - val accuracy: 0.6064
Epoch 94/200
0.5993 - val loss: 0.6647 - val accuracy: 0.5844
Epoch 95/200
0.5919 - val_loss: 0.6676 - val_accuracy: 0.5917
Epoch 96/200
0.6042 - val loss: 0.6727 - val accuracy: 0.5868
Epoch 97/200
0.5748 - val_loss: 0.6672 - val_accuracy: 0.5819
Epoch 98/200
0.5907 - val_loss: 0.6709 - val_accuracy: 0.5844
Epoch 99/200
0.6115 - val loss: 0.6652 - val accuracy: 0.5941
Epoch 100/200
0.5760 - val loss: 0.6655 - val accuracy: 0.5868
Epoch 101/200
0.5760 - val_loss: 0.6648 - val_accuracy: 0.6088
Epoch 102/200
0.5956 - val loss: 0.6602 - val accuracy: 0.5917
Epoch 103/200
0.5870 - val_loss: 0.6582 - val_accuracy: 0.5868
Epoch 104/200
0.6189 - val_loss: 0.6596 - val_accuracy: 0.6137
Epoch 105/200
0.6152 - val_loss: 0.6727 - val_accuracy: 0.5746
Epoch 106/200
0.5980 - val loss: 0.6679 - val accuracy: 0.5990
Epoch 107/200
```

```
0.6103 - val loss: 0.6492 - val accuracy: 0.6308
Epoch 108/200
0.6189 - val_loss: 0.6576 - val_accuracy: 0.6039
Epoch 109/200
0.5846 - val_loss: 0.6622 - val_accuracy: 0.6039
Epoch 110/200
51/51 [============ ] - 10s 192ms/step - loss: 0.6507 - accuracy:
0.6213 - val_loss: 0.6483 - val_accuracy: 0.6333
Epoch 111/200
0.5968 - val_loss: 0.6574 - val_accuracy: 0.6039
Epoch 112/200
0.6078 - val_loss: 0.6585 - val_accuracy: 0.6161
Epoch 113/200
0.5674 - val_loss: 0.6568 - val_accuracy: 0.6064
Epoch 114/200
0.5980 - val_loss: 0.6600 - val_accuracy: 0.5844
Epoch 115/200
0.6103 - val_loss: 0.6515 - val_accuracy: 0.6088
Epoch 116/200
0.5944 - val_loss: 0.6553 - val_accuracy: 0.6235
Epoch 117/200
0.5515 - val loss: 0.6682 - val accuracy: 0.5844
Epoch 118/200
0.5846 - val_loss: 0.6601 - val_accuracy: 0.6015
Epoch 119/200
0.6029 - val_loss: 0.6595 - val_accuracy: 0.6112
Epoch 120/200
0.5809 - val loss: 0.6722 - val accuracy: 0.6088
Epoch 121/200
0.6091 - val_loss: 0.6607 - val_accuracy: 0.5990
Epoch 122/200
0.6324 - val_loss: 0.6563 - val_accuracy: 0.5941
Epoch 123/200
0.6189 - val loss: 0.6580 - val accuracy: 0.6210
Epoch 124/200
0.5699 - val_loss: 0.6589 - val_accuracy: 0.6210
Epoch 125/200
0.6225 - val_loss: 0.6512 - val_accuracy: 0.6137
Epoch 126/200
0.5772 - val_loss: 0.6587 - val_accuracy: 0.6161
Epoch 127/200
0.6029 - val_loss: 0.6580 - val_accuracy: 0.6015
Epoch 128/200
0.6152 - val_loss: 0.6535 - val_accuracy: 0.6039
```

```
Epoch 129/200
0.6189 - val loss: 0.6565 - val accuracy: 0.6112
Epoch 130/200
0.6189 - val loss: 0.6606 - val accuracy: 0.6137
Epoch 131/200
0.6042 - val loss: 0.6750 - val accuracy: 0.5868
Epoch 132/200
0.6348 - val_loss: 0.6641 - val_accuracy: 0.6039
Epoch 133/200
0.5993 - val loss: 0.6705 - val accuracy: 0.5917
Epoch 134/200
0.6262 - val loss: 0.6608 - val accuracy: 0.5795
Epoch 135/200
0.5931 - val_loss: 0.6685 - val_accuracy: 0.5746
Epoch 136/200
51/51 [============ ] - 10s 196ms/step - loss: 0.6495 - accuracy:
0.6275 - val loss: 0.6542 - val accuracy: 0.6112
Epoch 137/200
0.6176 - val loss: 0.6720 - val accuracy: 0.6259
Epoch 138/200
0.6005 - val_loss: 0.6587 - val_accuracy: 0.5941
Epoch 139/200
0.6213 - val loss: 0.6594 - val accuracy: 0.6039
Epoch 140/200
0.5944 - val_loss: 0.6568 - val_accuracy: 0.6064
Epoch 141/200
0.6005 - val_loss: 0.6723 - val_accuracy: 0.6210
Epoch 142/200
0.5833 - val_loss: 0.6574 - val_accuracy: 0.6161
Epoch 143/200
0.6115 - val_loss: 0.6522 - val_accuracy: 0.5990
Epoch 144/200
0.6201 - val_loss: 0.6599 - val_accuracy: 0.5941
Epoch 145/200
0.5944 - val_loss: 0.6599 - val_accuracy: 0.6039
Epoch 146/200
0.6189 - val_loss: 0.6433 - val_accuracy: 0.5941
Epoch 147/200
0.6238 - val_loss: 0.6530 - val_accuracy: 0.6015
Epoch 148/200
0.6275 - val_loss: 0.6639 - val_accuracy: 0.6235
Epoch 149/200
0.6029 - val_loss: 0.6478 - val_accuracy: 0.6039
Epoch 150/200
```

```
0.6127 - val_loss: 0.6613 - val_accuracy: 0.6210
Epoch 151/200
0.6103 - val loss: 0.6573 - val accuracy: 0.6088
Epoch 152/200
0.6078 - val_loss: 0.6588 - val_accuracy: 0.5892
Epoch 153/200
0.6275 - val_loss: 0.6527 - val_accuracy: 0.6235
Epoch 154/200
0.6287 - val loss: 0.6608 - val accuracy: 0.5892
Epoch 155/200
0.6336 - val loss: 0.6597 - val accuracy: 0.6064
Epoch 156/200
0.6078 - val_loss: 0.6588 - val_accuracy: 0.5966
Epoch 157/200
0.6324 - val loss: 0.6594 - val accuracy: 0.5917
Epoch 158/200
0.6262 - val loss: 0.6588 - val accuracy: 0.6064
Epoch 159/200
0.5907 - val_loss: 0.6667 - val_accuracy: 0.5917
Epoch 160/200
0.6115 - val loss: 0.6593 - val accuracy: 0.6064
Epoch 161/200
0.6250 - val_loss: 0.6586 - val_accuracy: 0.6137
Epoch 162/200
0.5760 - val_loss: 0.6561 - val_accuracy: 0.6015
Epoch 163/200
0.6324 - val loss: 0.6587 - val accuracy: 0.6088
Epoch 164/200
0.5895 - val_loss: 0.6516 - val_accuracy: 0.6137
Epoch 165/200
0.6348 - val_loss: 0.6521 - val_accuracy: 0.5917
Epoch 166/200
0.6201 - val loss: 0.6552 - val accuracy: 0.6039
Epoch 167/200
0.5956 - val_loss: 0.6519 - val_accuracy: 0.6210
Epoch 168/200
0.6446 - val_loss: 0.6471 - val_accuracy: 0.6284
Epoch 169/200
0.6042 - val_loss: 0.6535 - val_accuracy: 0.6210
Epoch 170/200
0.6164 - val loss: 0.6390 - val accuracy: 0.6161
Epoch 171/200
```

```
0.5956 - val_loss: 0.6538 - val_accuracy: 0.6112
Epoch 172/200
0.6397 - val_loss: 0.6473 - val_accuracy: 0.6186
Epoch 173/200
0.6287 - val_loss: 0.6515 - val_accuracy: 0.6186
Epoch 174/200
0.6336 - val_loss: 0.6626 - val_accuracy: 0.5844
Epoch 175/200
0.6091 - val_loss: 0.6491 - val_accuracy: 0.5966
Epoch 176/200
0.6483 - val_loss: 0.6479 - val_accuracy: 0.5966
Epoch 177/200
0.6348 - val_loss: 0.6520 - val_accuracy: 0.6284
Epoch 178/200
0.6225 - val_loss: 0.6531 - val_accuracy: 0.6137
Epoch 179/200
0.5980 - val_loss: 0.6481 - val_accuracy: 0.5917
Epoch 180/200
0.6483 - val_loss: 0.6505 - val_accuracy: 0.6137
Epoch 181/200
0.6066 - val loss: 0.6496 - val accuracy: 0.6137
Epoch 182/200
0.6054 - val_loss: 0.6656 - val_accuracy: 0.6235
Epoch 183/200
0.6213 - val_loss: 0.6681 - val_accuracy: 0.6210
Epoch 184/200
0.6446 - val loss: 0.6536 - val accuracy: 0.6284
Epoch 185/200
0.6127 - val_loss: 0.6763 - val_accuracy: 0.5941
Epoch 186/200
0.6275 - val_loss: 0.6786 - val_accuracy: 0.5917
Epoch 187/200
0.6287 - val loss: 0.6611 - val accuracy: 0.6210
Epoch 188/200
0.6176 - val_loss: 0.6568 - val_accuracy: 0.6112
Epoch 189/200
0.6422 - val_loss: 0.6640 - val_accuracy: 0.5941
Epoch 190/200
0.6091 - val_loss: 0.6725 - val_accuracy: 0.6308
Epoch 191/200
0.6176 - val_loss: 0.6544 - val_accuracy: 0.6357
Epoch 192/200
0.6238 - val_loss: 0.6427 - val_accuracy: 0.6430
```

```
0.6176 - val loss: 0.6598 - val accuracy: 0.5892
     Epoch 194/200
     0.5956 - val loss: 0.6613 - val accuracy: 0.6015
     Epoch 195/200
     0.6434 - val_loss: 0.6592 - val_accuracy: 0.6235
     Epoch 196/200
     0.6422 - val_loss: 0.6475 - val_accuracy: 0.6186
     Epoch 197/200
     0.6556 - val loss: 0.6713 - val accuracy: 0.6381
     Epoch 198/200
     0.6409 - val loss: 0.6477 - val accuracy: 0.6357
     Epoch 199/200
     0.6042 - val_loss: 0.6481 - val_accuracy: 0.6284
     Epoch 200/200
     0.6458 - val_loss: 0.6525 - val_accuracy: 0.6333
     0.6333
     CNN Accuracy: 0.6332518458366394
     13/13 [========= ] - 1s 51ms/step
     CNN Classification Report:
                precision recall f1-score
                                      support
                   0.60
                        0.65
                                0.62
             0
                                        192
                   0.67
                         0.62
                                0.64
                                        217
             1
                                0.63
                                        409
        accuracy
                         0.63
                  0.63
                                0.63
                                        409
       macro avg
     weighted avg
                   0.64
                         0.63
                                0.63
                                        409
      input dir ="/content/drive/MyDrive/imge classification"
In [2]:
      categories = ['Fake', 'Real']
In [3]: import os
      import numpy as np
      import tensorflow as tf
      from tensorflow.keras.layers import Input, Conv2D, Flatten, Dense, Dropout, BatchNc
      from tensorflow.keras.models import Model
      from tensorflow.keras.optimizers import Adam
      from tensorflow.keras.applications import MobileNetV2
      from tensorflow.keras.preprocessing.image import ImageDataGenerator
      from sklearn.model_selection import train_test_split
      def load and preprocess image(image path, target size=(224, 224)):
        img = tf.keras.preprocessing.image.load_img(image_path, target_size=target_size
        img_array = tf.keras.preprocessing.image.img_to_array(img) / 255.0
        return img array
      def load_and_preprocess_images(image_paths, target_size=(224, 224)):
        images = [load_and_preprocess_image(image_path, target_size) for image_path in
        return np.array(images)
      def create_siamese_network(input_shape):
```

Epoch 193/200

```
base_model = MobileNetV2(weights='imagenet', include_top=False, input_shape=ing
    for layer in base model.layers:
        layer.trainable = False
   x = GlobalAveragePooling2D()(base model.output)
   x = Dense(128, activation='relu')(x)
   x = Dropout(0.5)(x)
    return Model(inputs=base_model.input, outputs=x)
def create_comparison_model(input_shape):
    input_image1 = Input(shape=input_shape)
    input_image2 = Input(shape=input_shape)
    siamese network = create siamese network(input shape)
    output1 = siamese_network(input_image1)
   output2 = siamese_network(input_image2)
   concatenated = Concatenate()([output1, output2])
   x = Dense(256, activation='relu')(concatenated)
   x = Dropout(0.5)(x)
    output = Dense(1, activation='sigmoid')(x)
    return Model(inputs=[input_image1, input_image2], outputs=output)
input_dir = "/content/drive/MyDrive/imge_classification"
categories = ['Fake', 'Real']
image_paths1 = [os.path.join(input_dir, categories[0], filename) for filename in os
image paths2 = [os.path.join(input dir, categories[1], filename) for filename in os
X1 = load and preprocess images(image paths1)
X2 = load_and_preprocess_images(image_paths2)
y = np.zeros(len(X1))
y[:len(X1)] = 1
X1_train, X1_test, X2_train, X2_test, y_train, y_test = train_test_split(X1, X2, y)
input shape = X1 train[0].shape
model = create comparison model(input shape)
model.compile(optimizer=Adam(learning_rate=0.001), loss='binary_crossentropy', metr
datagen = ImageDataGenerator(rotation_range=20, width_shift_range=0.1, height_shift
history = model.fit(datagen.flow([X1_train, X2_train], y_train, batch_size=32), epc
loss, accuracy = model.evaluate([X1_test, X2_test], y_test)
print("Test Loss:", loss)
print("Test Accuracy:", accuracy)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-application
s/mobilenet_v2/mobilenet_v2_weights_tf_dim_ordering_tf_kernels_1.0_224_no_top.h5
9406464/9406464 [=========== ] - 0s Ous/step
Epoch 1/20
000e+00 - val loss: 0.2343 - val accuracy: 1.0000
8333 - val_loss: 0.0515 - val_accuracy: 1.0000
Epoch 3/20
0000 - val_loss: 0.0103 - val_accuracy: 1.0000
Epoch 4/20
0000 - val loss: 0.0019 - val accuracy: 1.0000
Epoch 5/20
0000 - val_loss: 3.3849e-04 - val_accuracy: 1.0000
Epoch 6/20
1/1 [============== ] - 1s 555ms/step - loss: 0.0747 - accuracy: 1.
0000 - val_loss: 5.3728e-05 - val_accuracy: 1.0000
Epoch 7/20
1/1 [========== - - 1s 634ms/step - loss: 1.6080e-04 - accurac
y: 1.0000 - val_loss: 9.4501e-06 - val_accuracy: 1.0000
Epoch 8/20
1/1 [========== - - 1s 565ms/step - loss: 2.9646e-04 - accurac
y: 1.0000 - val loss: 1.7848e-06 - val accuracy: 1.0000
Epoch 9/20
y: 1.0000 - val_loss: 3.6817e-07 - val_accuracy: 1.0000
Epoch 10/20
1/1 [=========== - - 1s 862ms/step - loss: 3.8469e-04 - accurac
y: 1.0000 - val_loss: 8.1724e-08 - val_accuracy: 1.0000
Epoch 11/20
1/1 [==========] - 1s 1s/step - loss: 2.5338e-06 - accuracy:
1.0000 - val_loss: 2.0318e-08 - val_accuracy: 1.0000
Epoch 12/20
y: 1.0000 - val_loss: 5.5303e-09 - val_accuracy: 1.0000
Epoch 13/20
1/1 [==========] - 1s 1s/step - loss: 2.7834e-07 - accuracy:
1.0000 - val_loss: 1.6310e-09 - val_accuracy: 1.0000
Epoch 14/20
1.0000 - val_loss: 5.2387e-10 - val_accuracy: 1.0000
Epoch 15/20
y: 1.0000 - val_loss: 1.8365e-10 - val_accuracy: 1.0000
Epoch 16/20
1/1 [==========] - 1s 609ms/step - loss: 5.3129e-08 - accurac
y: 1.0000 - val_loss: 6.9630e-11 - val_accuracy: 1.0000
Epoch 17/20
y: 1.0000 - val_loss: 2.8371e-11 - val_accuracy: 1.0000
1/1 [=========== - 1s 559ms/step - loss: 2.6764e-08 - accurac
y: 1.0000 - val_loss: 1.2347e-11 - val_accuracy: 1.0000
Epoch 19/20
1/1 [=========== - - 1s 587ms/step - loss: 4.1817e-08 - accurac
y: 1.0000 - val_loss: 5.7160e-12 - val_accuracy: 1.0000
Epoch 20/20
1/1 [============= - 1s 562ms/step - loss: 5.6534e-07 - accurac
y: 1.0000 - val_loss: 2.8104e-12 - val_accuracy: 1.0000
```

Test Loss: 2.810352645044034e-12 Test Accuracy: 0.94678546364353335 import tensorflow as tf In [17]: import numpy as np image_path1 = "/content/hxmg6Mja.jpg" image_path2 = "/content/real_00001.jpg" img1 = tf.io.read_file(image_path1) img2 = tf.io.read_file(image_path2) img1 = tf.image.decode_jpeg(img1, channels=3) img2 = tf.image.decode_jpeg(img2, channels=3) img1_resized = tf.image.resize(img1, (224, 224)) img2_resized = tf.image.resize(img2, (224, 224)) img1_resized = np.expand_dims(img1_resized, axis=0) img2_resized = np.expand_dims(img2_resized, axis=0) prediction = model.predict([img1_resized, img2_resized]) if prediction < 0.98:</pre> print("The images are the same (Fake).") else: print("The images are different (Real)") 1/1 [=======] - 0s 123ms/step

y: 0.927737577386

The images are different (Fake)

In []: