FacialEmotionRecognition

June 5, 2022

[1]:
```python
# Basics
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from pandas.core.common import random_state

# Sklearn
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.decomposition import PCA
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.cluster import KMeans
from sklearn.pipeline import Pipeline
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay


# Tensorflow
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
import tensorflow.keras.layers as layers
from tensorflow.keras.utils import to_categorical


# Graphing Style
%matplotlib inline
```

[2]:
```python
from google.colab import drive
drive.mount('/content/drive')
```

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

1 Data Cleaning and Exploratory Data Analysis

[3]:
```python
face = pd.read_csv("/content/drive/MyDrive/Colab Notebooks/face.csv")
```

[4]:
```python
face.shape
```

[4]:
```
(28709, 2)
```

[5]:
```python
face["pixels"] = face.pixels.apply(lambda x: np.array(tuple(map(int, x.
 ↪split()))))
```

[6]:
```python
face.head()
```

[6]:

	emotion	pixels
0	0	[70, 80, 82, 72, 58, 58, 60, 63, 54, 58, 60, 4…
1	0	[151, 150, 147, 155, 148, 133, 111, 140, 170, …
2	2	[231, 212, 156, 164, 174, 138, 161, 173, 182, …
3	4	[24, 32, 36, 30, 32, 23, 19, 20, 30, 41, 21, 2…
4	6	[4, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3, 15, 23…

[7]:
```python
emo_di = {0: "Angry", 1:"Disgust", 2: "Fear", 3: "Happy", 4: "Sad", 5:␣
 ↪"Surprise", 6: "Neutral"}
```

[8]:
```python
plt.figure(figsize = (20,20))
start_index = 0
for i in range(7):
    plt.subplot(1,7,i+1)
    plt.grid(False)
    plt.xticks([])
    plt.yticks([])
    plt.imshow(face[face.emotion == i].pixels.iloc[20].reshape(48,48),␣
 ↪cmap="gray")
    plt.xlabel("{} = {}".format(i, emo_di[i]))
```

[9]:
```python
face.emotion.value_counts()
```

[9]:
```
3    7215
6    4965
4    4830
```

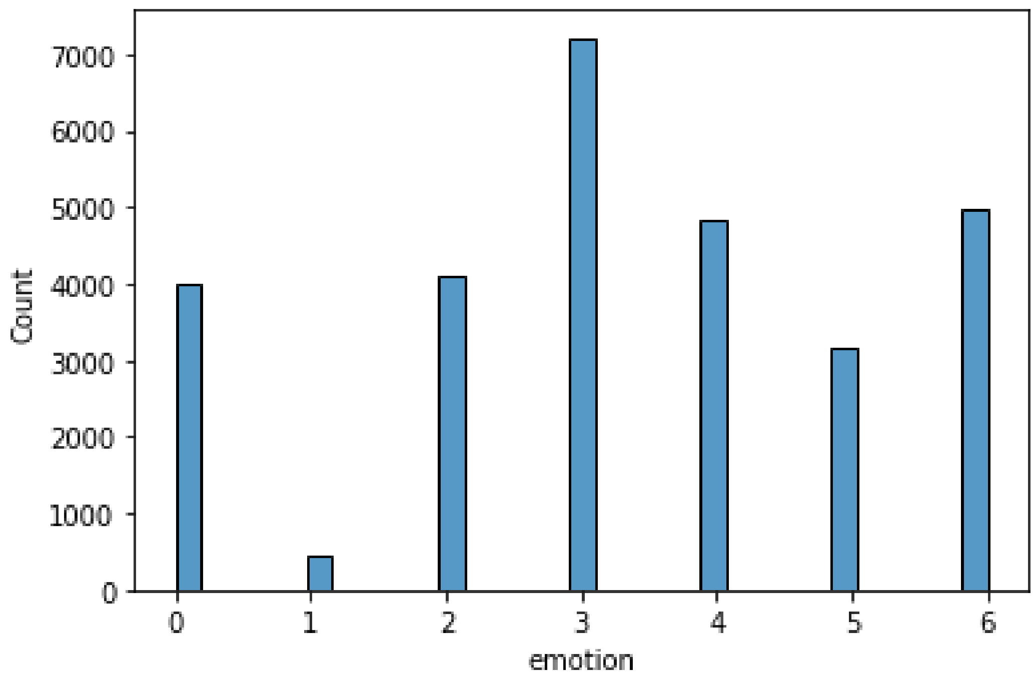
```
2    4097
0    3995
5    3171
1     436
Name: emotion, dtype: int64
```

[10]:

```python
sns.histplot(face.emotion)
```

[10]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f43872e6ed0>
```



[11]:

```python
train, test = train_test_split(face, train_size=0.6, random_state=1)
val, test = train_test_split(test, test_size=0.5, random_state=1)

# Oversample and subsample
faces_balanced = None
for i in range(7):
    if faces_balanced is None:
        faces_balanced = train[train.emotion == i].sample(n=3000, replace=True,␣
 ↪random_state=100)
    else:
        faces_balanced = pd.concat([faces_balanced, train[train.emotion == i].
 ↪sample(n=3000, replace=True, random_state=100)], sort = False)
faces_balanced = faces_balanced.sample(frac=1, random_state=49)
```

```
train_x = np.concatenate(np.asarray(faces_balanced["pixels"])).reshape(-1, 48 *␣
↪48)
val_x = np.concatenate(np.asarray(val["pixels"])).reshape(-1, 48 * 48)
test_x = np.concatenate(np.asarray(test["pixels"])).reshape(-1, 48 * 48)
train_y = faces_balanced.emotion
val_y = val.emotion
test_y = test.emotion

x_mean = np.mean(train_x)
x_std = np.std(train_x) + 1e-10
train_x = (train_x - x_mean) / x_std
val_x = (val_x - x_mean) / x_std
test_x = (test_x - x_mean) / x_std
```

[12]:

```
train_y.value_counts()
```

[12]:

```
4    3000
5    3000
2    3000
0    3000
1    3000
3    3000
6    3000
Name: emotion, dtype: int64
```

[13]:

```
val_y.value_counts()
```

[13]:

```
3    1420
6    1035
4     963
0     811
2     796
5     625
1      92
Name: emotion, dtype: int64
```

[14]:

```
test_y.value_counts()
```

[14]:

```
3    1494
6     976
4     946
2     833
0     792
5     627
1      74
Name: emotion, dtype: int64
```

2 Modeling

2.1 Naive Bayes

[15]:
```
nb = GaussianNB()
nb.fit(train_x, train_y)
```

[15]:
```
GaussianNB()
```

[16]:
```
nb.score(train_x, train_y)
```

[16]:
```
0.23157142857142857
```

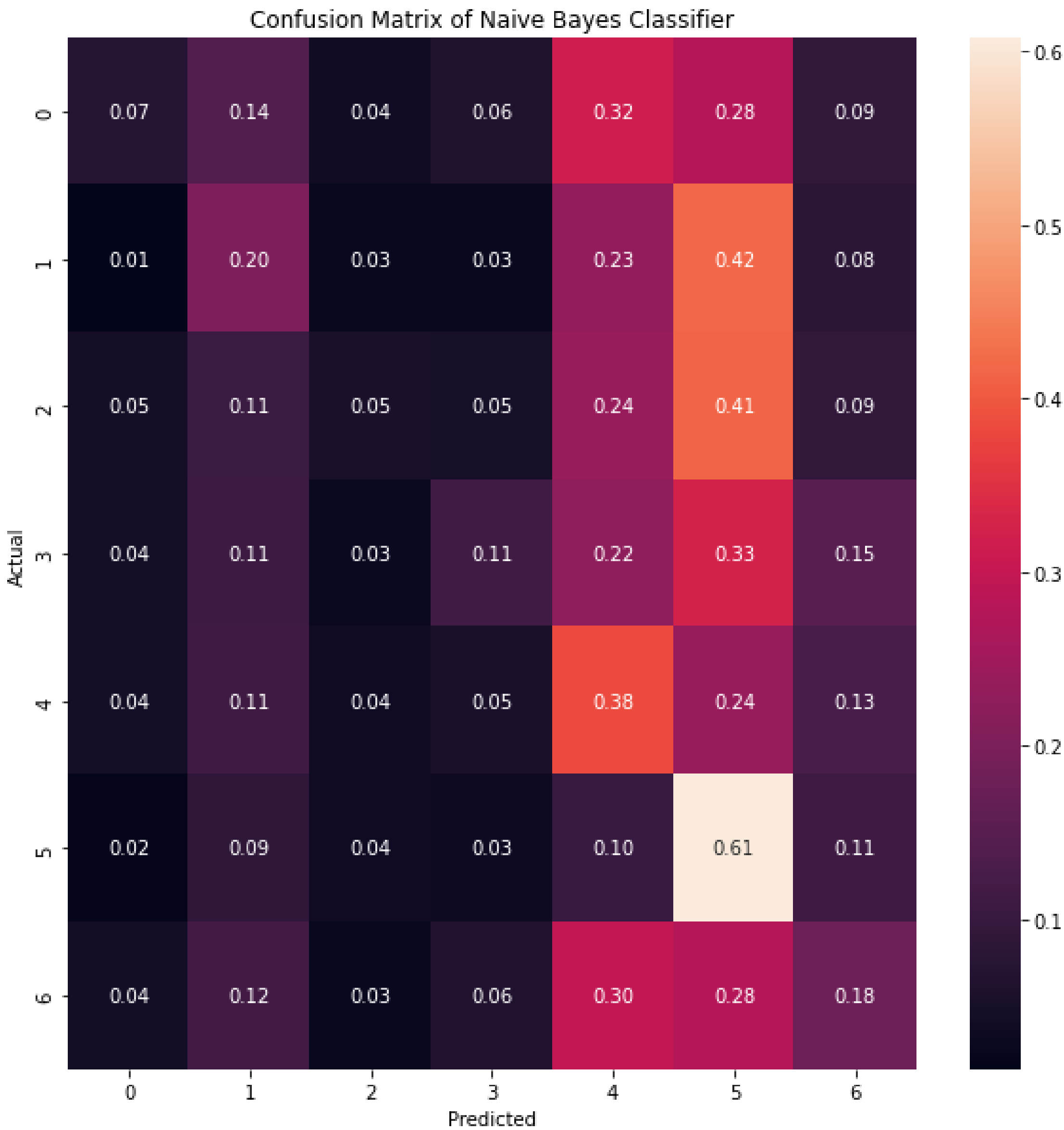
[17]:
```
nb.score(val_x, val_y)
```

[17]:
```
0.20358760013932428
```

[18]:
```
nb.score(test_x, test_y)
```

[18]:
```
0.20968303726924417
```

[19]:
```
cm = confusion_matrix(test_y, nb.predict(test_x))
cmn = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(cmn, annot=True, fmt='.2f', xticklabels=nb.classes_, yticklabels=nb.
  ↪classes_)
plt.title('Confusion Matrix of Naive Bayes Classifier')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show(block=False)
```



2.2 Logistic Regression

[20]:
```
lr = LogisticRegression(penalty='l2', tol=0.1, solver='saga')
lr.fit(train_x, train_y)
```

[20]:
```
LogisticRegression(solver='saga', tol=0.1)
```

[21]:
```
lr.score(train_x, train_y)
```

[21]:
```
0.4888571428571429
```

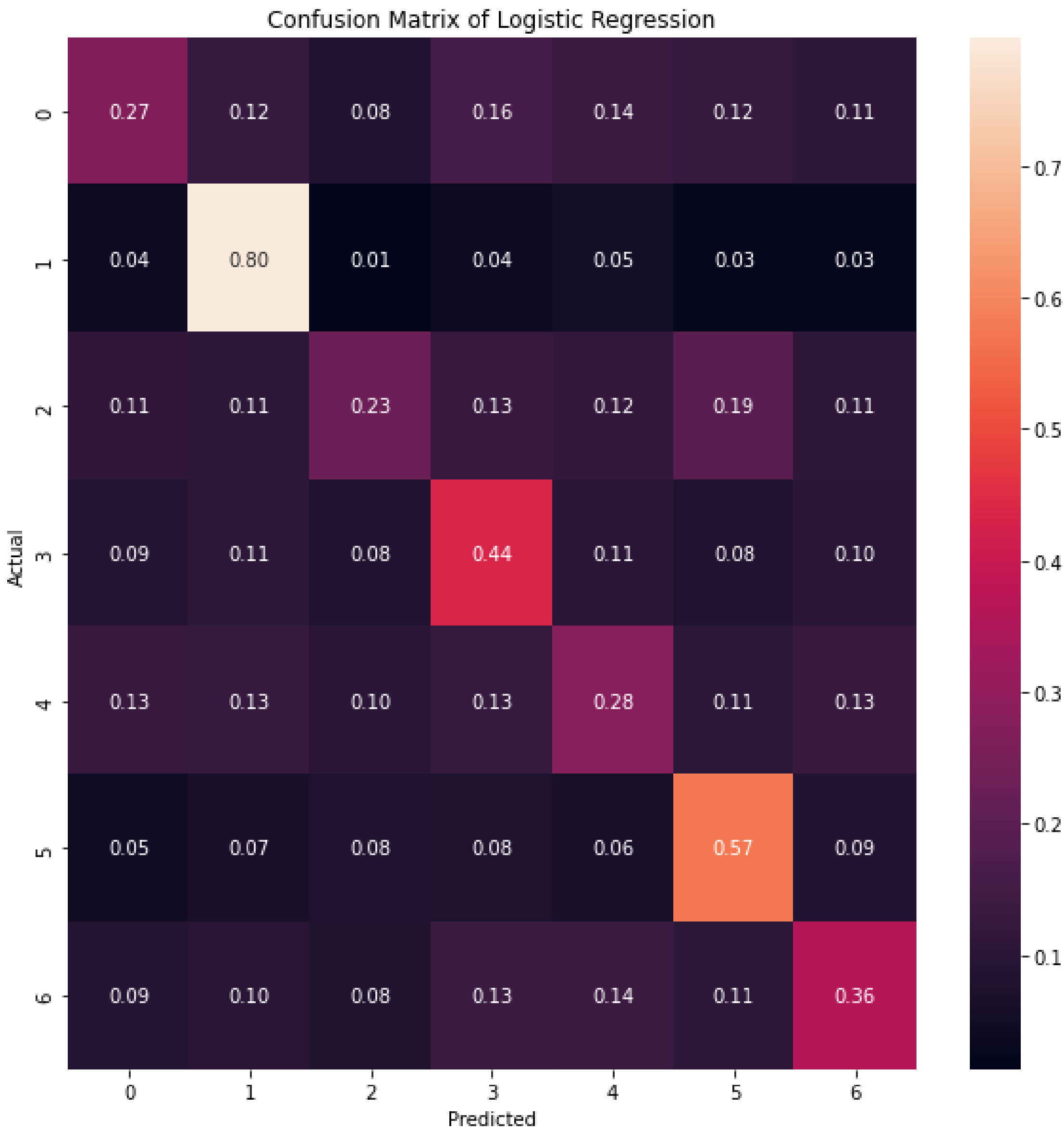
[22]:
```
lr.score(val_x, val_y)
```

[22]: 0.36363636363636365

[23]:
```
lr.score(test_x, test_y)
```

[23]: 0.36450714036920934

[24]:
```
cm = confusion_matrix(test_y, lr.predict(test_x))
cmn = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(cmn, annot=True, fmt='.2f', xticklabels=nb.classes_, yticklabels=nb.
 ↪classes_)
plt.title('Confusion Matrix of Logistic Regression')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show(block=False)
```



2.3 K-Means + Logistic Regression

[25]:
```
pl = Pipeline([
    ("kmeans", KMeans(n_clusters=35)),
    ("logisreg", LogisticRegression(penalty='none', tol=0.1, solver='saga'))
])
```

[26]:
```
pl.fit(train_x, train_y)
```

[26]: Pipeline(steps=[('kmeans', KMeans(n_clusters=35)),
                ('logisreg',
                 LogisticRegression(penalty='none', solver='saga', tol=0.1))])

[27]:
```
pl.score(train_x, train_y)
```

[27]: 0.2277142857142857

[28]:
```
pl.score(val_x, val_y)
```

[28]: 0.19696969696969696

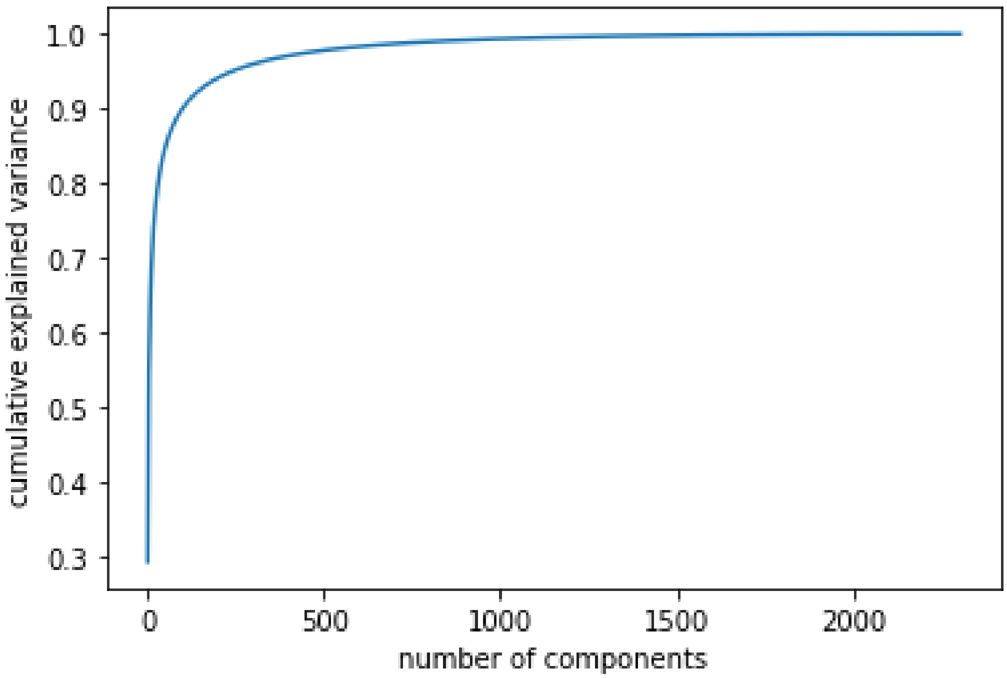
[29]:
```
pl.score(test_x, test_y)
```

[29]: 0.1966213862765587

[30]:
```
cm = confusion_matrix(test_y, pl.predict(test_x))
cmn = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(cmn, annot=True, fmt='.2f', xticklabels=nb.classes_, yticklabels=nb.
 ↪classes_)
plt.title('Confusion Matrix of K-Means + Logistic Regression')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show(block=False)
```

2.4 KNN with PCA + CV

[31]:
```
pca = PCA().fit(train_x)
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');
```



[32]:
```
pl1 = Pipeline([
    ("PCA", PCA(n_components=100)),
    ("knn", KNeighborsClassifier())
])
params = {"knn__n_neighbors": [1, 3, 5, 7, 12, 15, 20]}
grids = GridSearchCV(pl1, params, cv=5)
grids.fit(train_x, train_y)
```

[32]:
```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('PCA', PCA(n_components=100)),
                                       ('knn', KNeighborsClassifier())]),
             param_grid={'knn__n_neighbors': [1, 3, 5, 7, 12, 15, 20]})
```

[33]:
```
grids.best_params_
```

[33]:
```
{'knn__n_neighbors': 1}
```

[34]:
```
grids.best_score_
```

[34]:
```
0.6629047619047619
```

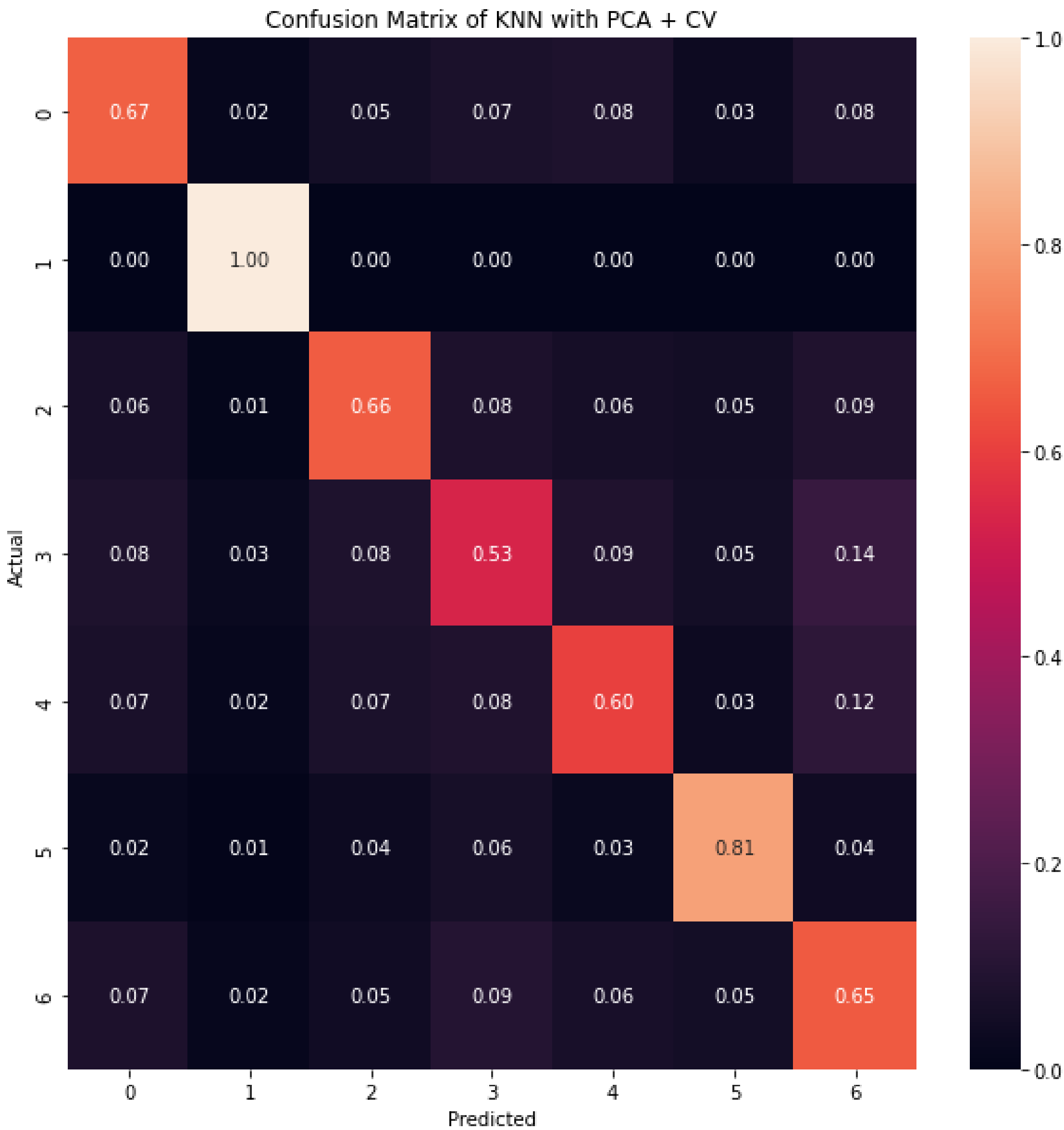
[35]:
```
grids.best_estimator_.score(val_x, val_y)
```

[35]:
```
0.6461163357715082
```

[36]:
```
grids.best_estimator_.score(test_x, test_y)
```

[36]: 0.6379310344827587

[37]:
```
cm = confusion_matrix(test_y, grids.best_estimator_.predict(test_x))
cmn = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(cmn, annot=True, fmt='.2f', xticklabels=nb.classes_, yticklabels=nb.
↪classes_)
plt.title('Confusion Matrix of KNN with PCA + CV')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show(block=False)
```



2.5 Random Forest

[38]:
```
rfc = RandomForestClassifier(max_depth=5)
rfc.fit(train_x, train_y)
```

[38]:
```
RandomForestClassifier(max_depth=5)
```

[39]:
```
rfc.score(train_x, train_y)
```

[39]:
```
0.4005714285714286
```

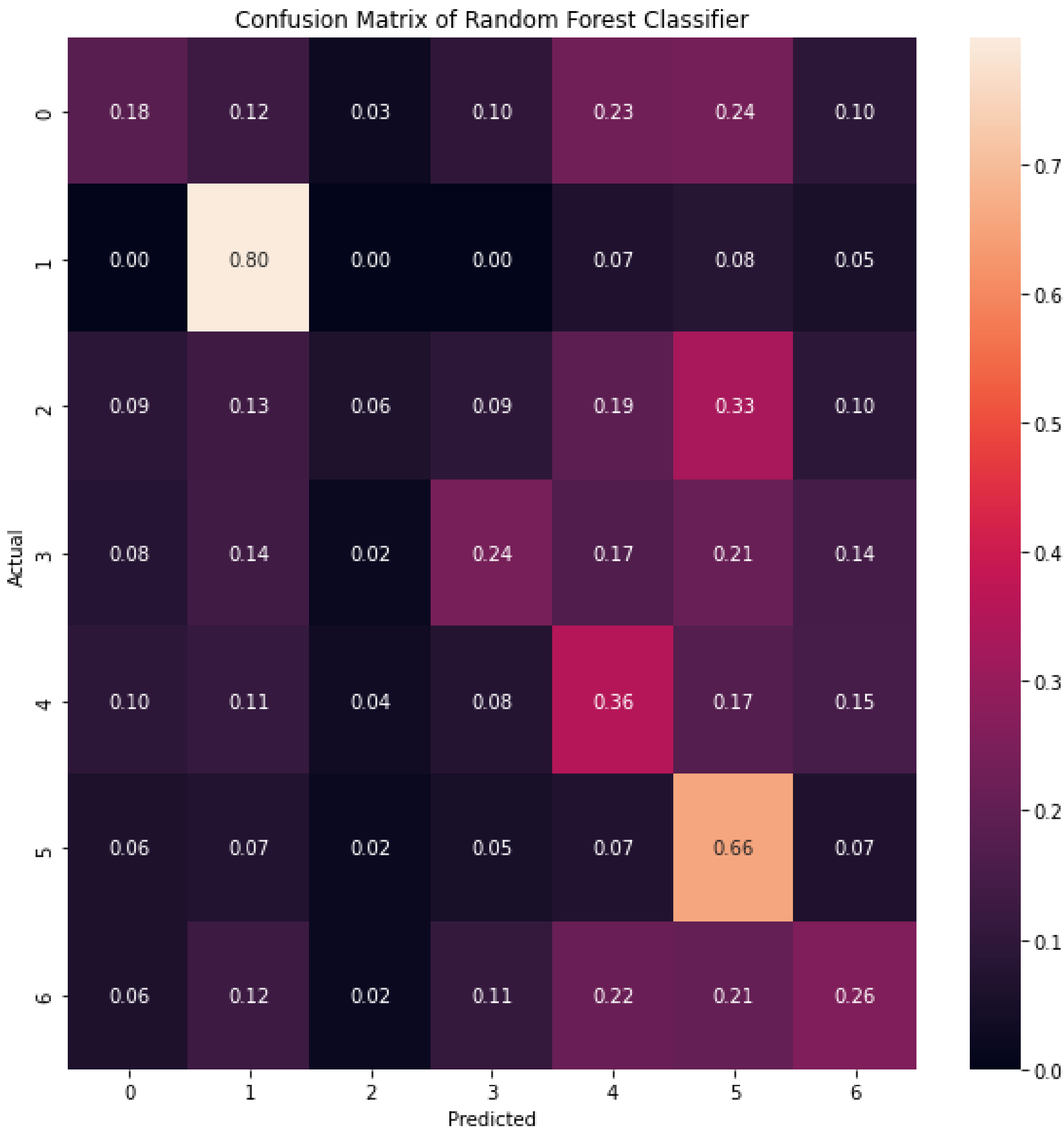
[40]:
```
rfc.score(val_x, val_y)
```

[40]:
```
0.2871821664925113
```

[41]:
```
rfc.score(test_x, test_y)
```

[41]:
```
0.28126088470916055
```

[42]:
```
cm = confusion_matrix(test_y, rfc.predict(test_x))
cmn = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(cmn, annot=True, fmt='.2f', xticklabels=nb.classes_, yticklabels=nb.
 ↪classes_)
plt.title('Confusion Matrix of Random Forest Classifier')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show(block=False)
```



2.6 Support Vector Machine with PCA

[43]:
```
pl2 = Pipeline([
              ("PCA", PCA(n_components=50)),
              ("svm", SVC())
])
pl2.fit(train_x, train_y)
```

[43]:
```
Pipeline(steps=[('PCA', PCA(n_components=50)), ('svm', SVC())])
```

[44]:
```
pl2.score(train_x, train_y)
```

[44]: 0.6312857142857143

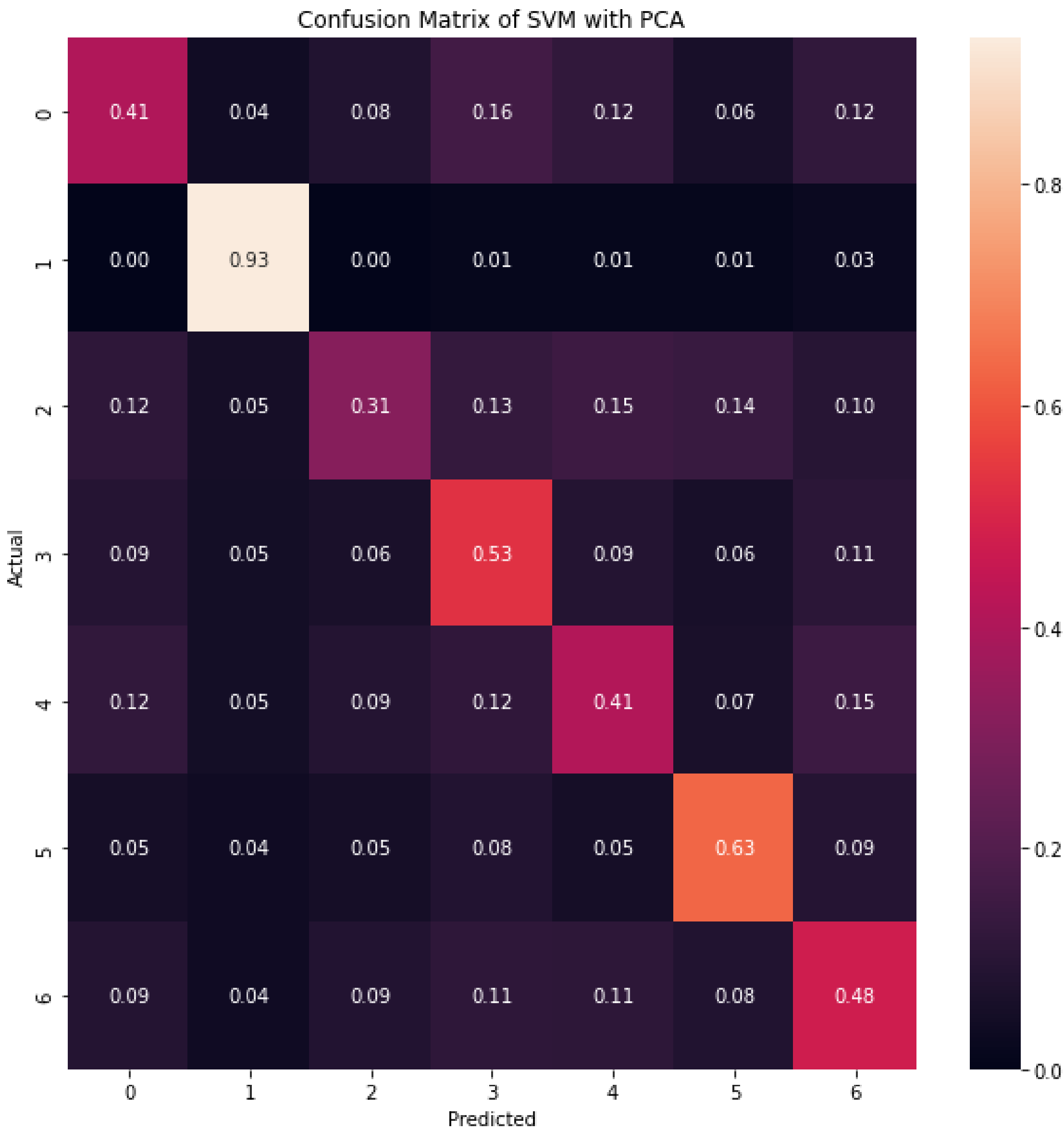
[45]:
```
pl2.score(val_x, val_y)
```

[45]: 0.45942180424939044

[46]:
```
pl2.score(test_x, test_y)
```

[46]: 0.46900034831069315

[47]:
```
cm = confusion_matrix(test_y, pl2.predict(test_x))
cmn = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(cmn, annot=True, fmt='.2f', xticklabels=nb.classes_, yticklabels=nb.
 ↪classes_)
plt.title('Confusion Matrix of SVM with PCA')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show(block=False)
```



2.7 Artificial Neural Network

[99]:
```
train_y_cat = to_categorical(train_y)
val_y_cat = to_categorical(val_y)
test_y_cat = to_categorical(test_y)
```

[100]:
```
model = Sequential()
model.add(Dense(256, activation = 'relu', input_shape = (48 * 48,)))
model.add(Dense(256, activation = 'relu'))
model.add(Dense(256, activation = 'relu')),
model.add(Dense(256, activation = 'relu')),
```

```
model.add(Dense(7, activation = 'softmax'))

model.compile(optimizer = 'adam', loss = 'categorical_crossentropy', metrics =
 ['accuracy'])
model.summary()
```

```
Model: "sequential_9"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_22 (Dense)            (None, 256)               590080

 dense_23 (Dense)            (None, 256)               65792

 dense_24 (Dense)            (None, 256)               65792

 dense_25 (Dense)            (None, 256)               65792

 dense_26 (Dense)            (None, 7)                 1799

=================================================================
Total params: 789,255
Trainable params: 789,255
Non-trainable params: 0
_________________________________________________________________
```

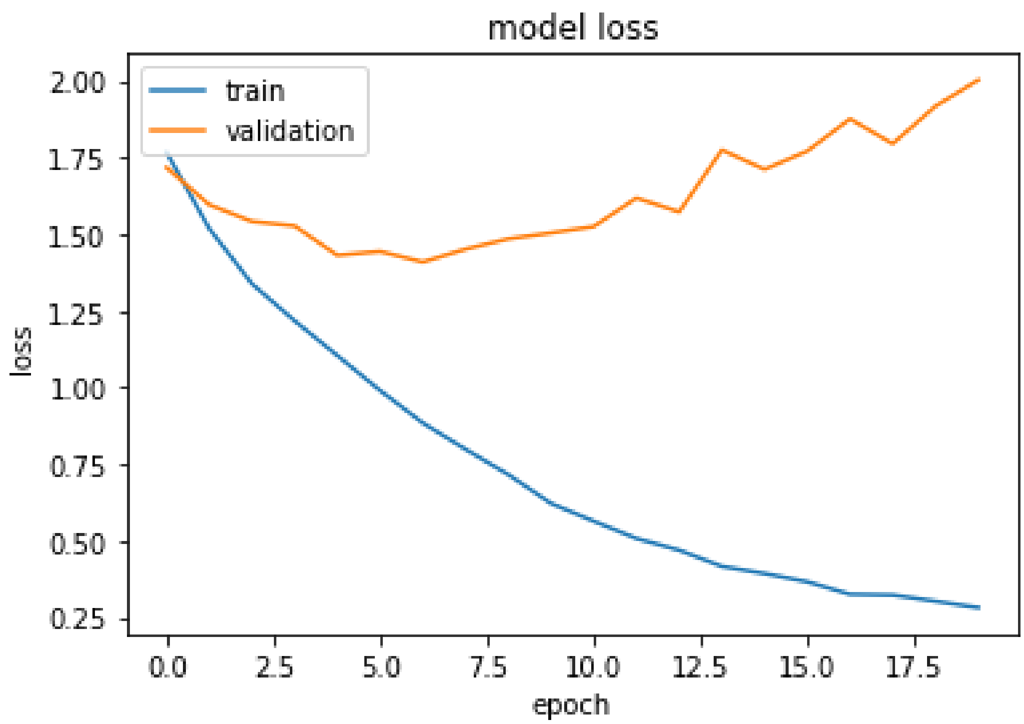
[101]:
```
history = model.fit(train_x, train_y_cat, epochs = 20, validation_data =
 (val_x, val_y_cat))
```

```
Epoch 1/20
657/657 [==============================] - 4s 5ms/step - loss: 1.7671 -
accuracy: 0.3019 - val_loss: 1.7173 - val_accuracy: 0.3022
Epoch 2/20
657/657 [==============================] - 3s 5ms/step - loss: 1.5181 -
accuracy: 0.4083 - val_loss: 1.5960 - val_accuracy: 0.3661
Epoch 3/20
657/657 [==============================] - 3s 5ms/step - loss: 1.3385 -
accuracy: 0.4810 - val_loss: 1.5412 - val_accuracy: 0.3931
Epoch 4/20
657/657 [==============================] - 3s 5ms/step - loss: 1.2176 -
accuracy: 0.5320 - val_loss: 1.5267 - val_accuracy: 0.4072
Epoch 5/20
657/657 [==============================] - 3s 4ms/step - loss: 1.1043 -
accuracy: 0.5774 - val_loss: 1.4307 - val_accuracy: 0.4702
Epoch 6/20
657/657 [==============================] - 3s 5ms/step - loss: 0.9904 -
accuracy: 0.6308 - val_loss: 1.4433 - val_accuracy: 0.4805
```

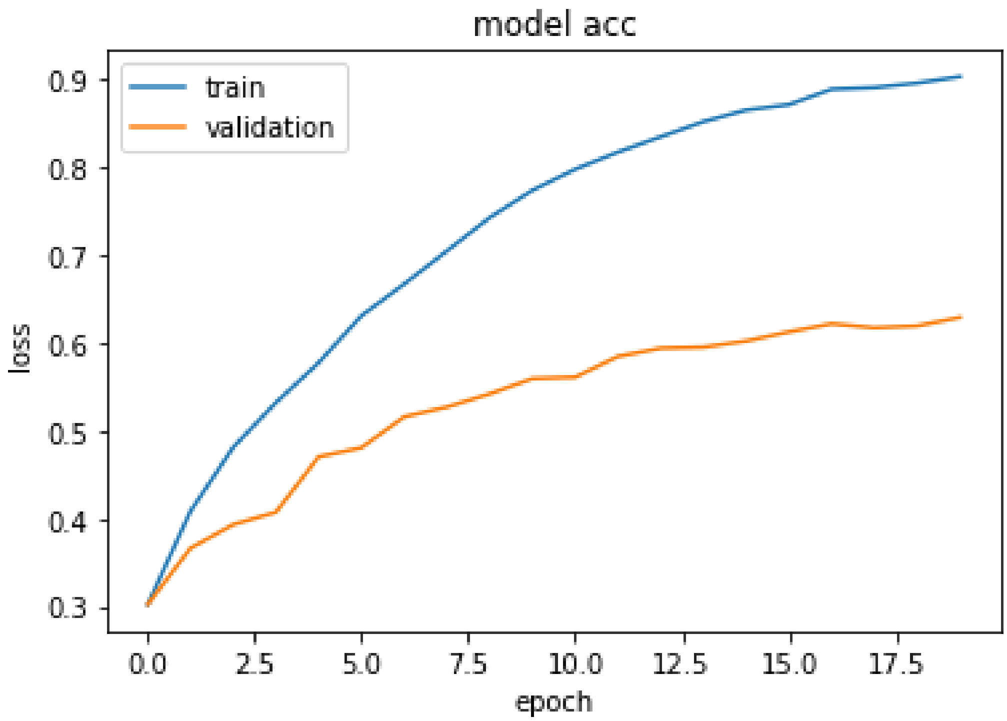
```
Epoch 7/20
657/657 [==============================] - 3s 5ms/step - loss: 0.8841 -
accuracy: 0.6672 - val_loss: 1.4089 - val_accuracy: 0.5158
Epoch 8/20
657/657 [==============================] - 3s 5ms/step - loss: 0.7984 -
accuracy: 0.7047 - val_loss: 1.4509 - val_accuracy: 0.5270
Epoch 9/20
657/657 [==============================] - 3s 5ms/step - loss: 0.7165 -
accuracy: 0.7427 - val_loss: 1.4845 - val_accuracy: 0.5420
Epoch 10/20
657/657 [==============================] - 3s 5ms/step - loss: 0.6224 -
accuracy: 0.7739 - val_loss: 1.5038 - val_accuracy: 0.5594
Epoch 11/20
657/657 [==============================] - 3s 5ms/step - loss: 0.5644 -
accuracy: 0.7979 - val_loss: 1.5244 - val_accuracy: 0.5610
Epoch 12/20
657/657 [==============================] - 3s 5ms/step - loss: 0.5080 -
accuracy: 0.8174 - val_loss: 1.6178 - val_accuracy: 0.5845
Epoch 13/20
657/657 [==============================] - 3s 5ms/step - loss: 0.4697 -
accuracy: 0.8347 - val_loss: 1.5725 - val_accuracy: 0.5939
Epoch 14/20
657/657 [==============================] - 3s 5ms/step - loss: 0.4167 -
accuracy: 0.8520 - val_loss: 1.7744 - val_accuracy: 0.5951
Epoch 15/20
657/657 [==============================] - 3s 5ms/step - loss: 0.3934 -
accuracy: 0.8652 - val_loss: 1.7112 - val_accuracy: 0.6021
Epoch 16/20
657/657 [==============================] - 3s 5ms/step - loss: 0.3665 -
accuracy: 0.8714 - val_loss: 1.7708 - val_accuracy: 0.6125
Epoch 17/20
657/657 [==============================] - 3s 5ms/step - loss: 0.3258 -
accuracy: 0.8890 - val_loss: 1.8759 - val_accuracy: 0.6217
Epoch 18/20
657/657 [==============================] - 3s 5ms/step - loss: 0.3235 -
accuracy: 0.8909 - val_loss: 1.7949 - val_accuracy: 0.6172
Epoch 19/20
657/657 [==============================] - 3s 5ms/step - loss: 0.3030 -
accuracy: 0.8960 - val_loss: 1.9177 - val_accuracy: 0.6193
Epoch 20/20
657/657 [==============================] - 3s 5ms/step - loss: 0.2823 -
accuracy: 0.9033 - val_loss: 2.0023 - val_accuracy: 0.6290
```

[102]:
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
```

```
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```



[103]:
```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model acc')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```

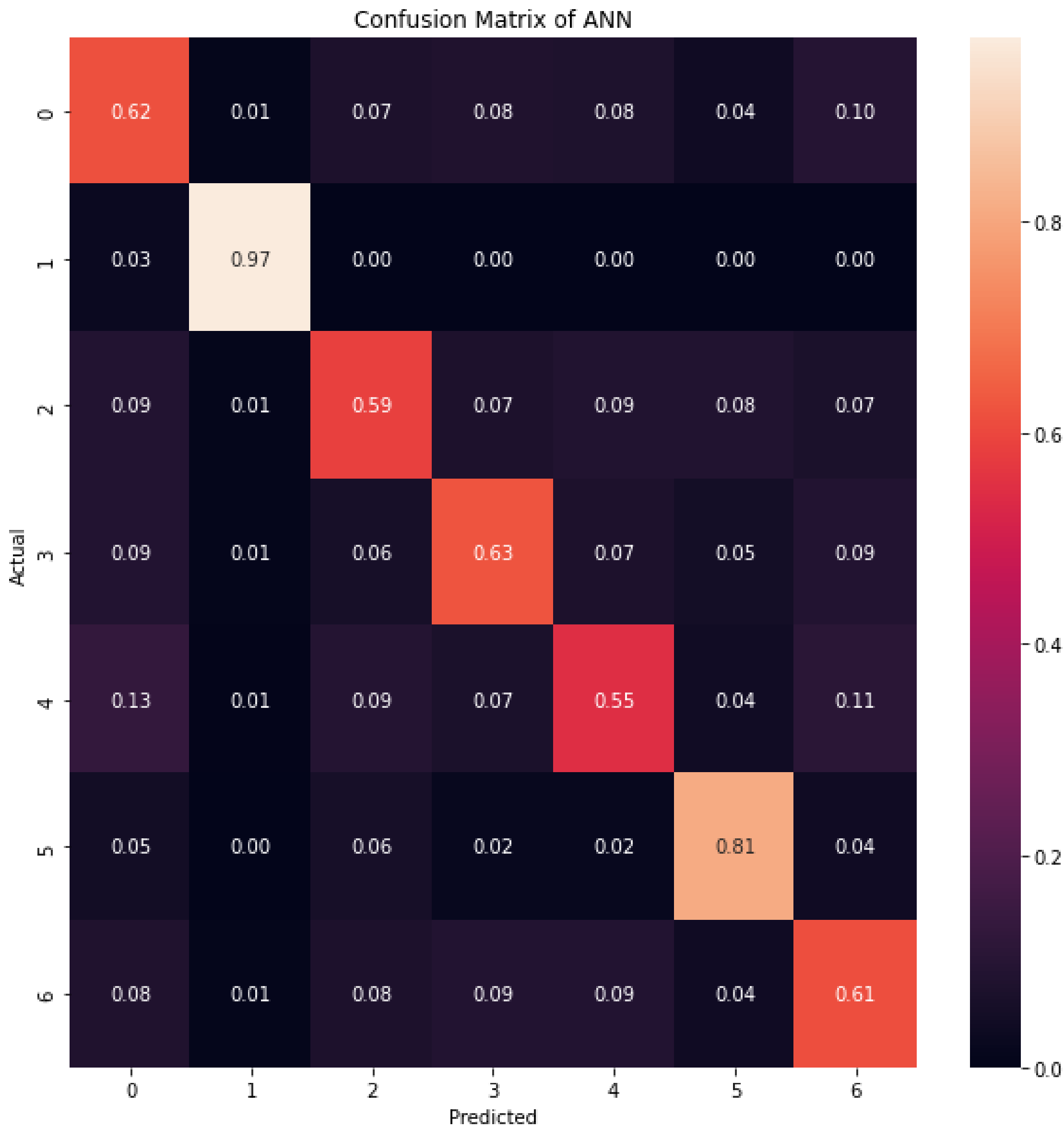


[104]:
```
model.evaluate(test_x, test_y_cat)
```

```
180/180 [==============================] - 0s 2ms/step - loss: 1.9723 -
accuracy: 0.6287
```

[104]:
```
[1.972302794456482, 0.6287007927894592]
```

[105]:
```
cm = confusion_matrix(test_y, np.apply_along_axis(np.argmax, 1, model.
 ↪predict(test_x)))
cmn = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(cmn, annot=True, fmt='.2f', xticklabels=nb.classes_, yticklabels=nb.
 ↪classes_)
plt.title('Confusion Matrix of ANN')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show(block=False)
```



2.8 Convolutional Neural Network

[86]:
```
train_x_cnn = train_x.reshape(-1, 48, 48, 1)
val_x_cnn = val_x.reshape(-1, 48, 48, 1)
test_x_cnn = test_x.reshape(-1, 48, 48, 1)
```

[93]:
```
model3 = Sequential([
  layers.Conv2D(32, (3, 3), activation='relu', input_shape=(48, 48, 1)),
  layers.Conv2D(16, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
```

```
    layers.MaxPooling2D(),
    layers.Conv2D(64, 3, padding='same', activation='relu'),
    layers.MaxPooling2D(),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dense(7)
])
```

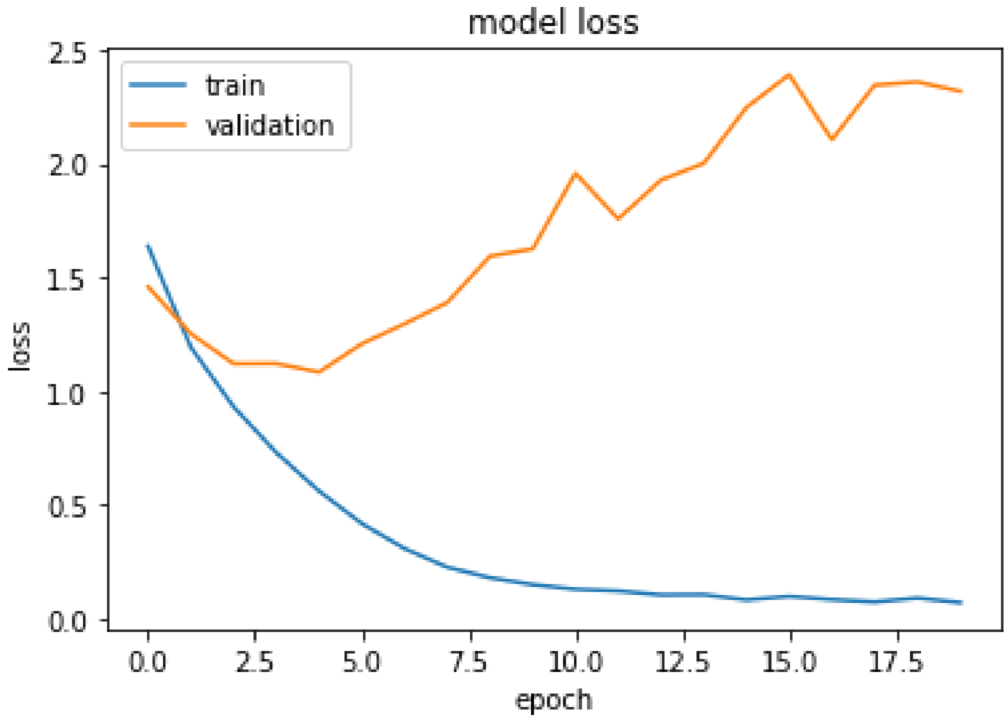
[94]:
```
model3.compile(optimizer='adam',
              loss=tf.keras.losses.
 ↪SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

[95]:
```
history3 = model3.fit(train_x_cnn, train_y, epochs = 20, validation_data =␣
 ↪(val_x_cnn, val_y))
```

```
Epoch 1/20
657/657 [==============================] - 16s 24ms/step - loss: 1.6371 -
accuracy: 0.3590 - val_loss: 1.4592 - val_accuracy: 0.4352
Epoch 2/20
657/657 [==============================] - 16s 24ms/step - loss: 1.1933 -
accuracy: 0.5517 - val_loss: 1.2526 - val_accuracy: 0.5219
Epoch 3/20
657/657 [==============================] - 16s 24ms/step - loss: 0.9327 -
accuracy: 0.6554 - val_loss: 1.1211 - val_accuracy: 0.5920
Epoch 4/20
657/657 [==============================] - 16s 24ms/step - loss: 0.7309 -
accuracy: 0.7345 - val_loss: 1.1220 - val_accuracy: 0.6172
Epoch 5/20
657/657 [==============================] - 16s 24ms/step - loss: 0.5627 -
accuracy: 0.8034 - val_loss: 1.0846 - val_accuracy: 0.6641
Epoch 6/20
657/657 [==============================] - 16s 24ms/step - loss: 0.4200 -
accuracy: 0.8506 - val_loss: 1.2082 - val_accuracy: 0.6628
Epoch 7/20
657/657 [==============================] - 16s 24ms/step - loss: 0.3095 -
accuracy: 0.8928 - val_loss: 1.2962 - val_accuracy: 0.6886
Epoch 8/20
657/657 [==============================] - 16s 24ms/step - loss: 0.2275 -
accuracy: 0.9235 - val_loss: 1.3900 - val_accuracy: 0.7055
Epoch 9/20
657/657 [==============================] - 16s 24ms/step - loss: 0.1819 -
accuracy: 0.9378 - val_loss: 1.5935 - val_accuracy: 0.6998
Epoch 10/20
657/657 [==============================] - 16s 24ms/step - loss: 0.1518 -
accuracy: 0.9492 - val_loss: 1.6249 - val_accuracy: 0.7062
Epoch 11/20
```

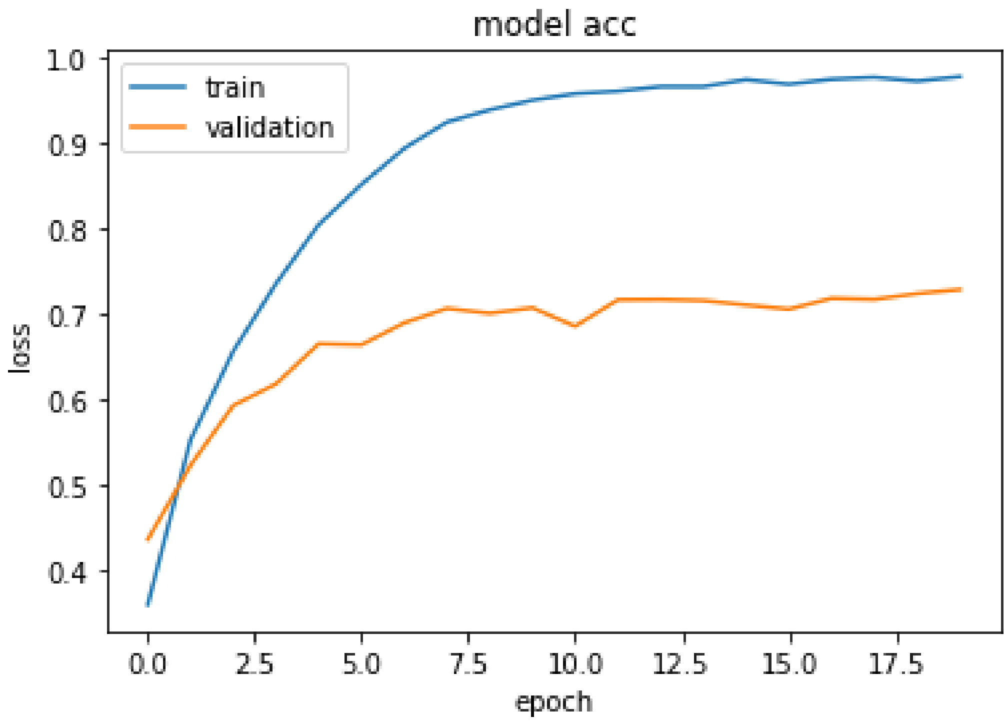
```
657/657 [==============================] - 16s 24ms/step - loss: 0.1315 -
accuracy: 0.9568 - val_loss: 1.9570 - val_accuracy: 0.6846
Epoch 12/20
657/657 [==============================] - 16s 24ms/step - loss: 0.1240 -
accuracy: 0.9598 - val_loss: 1.7568 - val_accuracy: 0.7156
Epoch 13/20
657/657 [==============================] - 16s 24ms/step - loss: 0.1064 -
accuracy: 0.9652 - val_loss: 1.9280 - val_accuracy: 0.7160
Epoch 14/20
657/657 [==============================] - 16s 24ms/step - loss: 0.1075 -
accuracy: 0.9651 - val_loss: 2.0010 - val_accuracy: 0.7147
Epoch 15/20
657/657 [==============================] - 16s 24ms/step - loss: 0.0847 -
accuracy: 0.9733 - val_loss: 2.2462 - val_accuracy: 0.7095
Epoch 16/20
657/657 [==============================] - 16s 24ms/step - loss: 0.1002 -
accuracy: 0.9679 - val_loss: 2.3902 - val_accuracy: 0.7046
Epoch 17/20
657/657 [==============================] - 16s 24ms/step - loss: 0.0861 -
accuracy: 0.9738 - val_loss: 2.1045 - val_accuracy: 0.7173
Epoch 18/20
657/657 [==============================] - 16s 24ms/step - loss: 0.0756 -
accuracy: 0.9760 - val_loss: 2.3444 - val_accuracy: 0.7161
Epoch 19/20
657/657 [==============================] - 16s 24ms/step - loss: 0.0930 -
accuracy: 0.9715 - val_loss: 2.3581 - val_accuracy: 0.7229
Epoch 20/20
657/657 [==============================] - 16s 24ms/step - loss: 0.0727 -
accuracy: 0.9768 - val_loss: 2.3171 - val_accuracy: 0.7276
```

[106]:
```
plt.plot(history3.history['loss'])
plt.plot(history3.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```



[107]:

```
plt.plot(history3.history['accuracy'])
plt.plot(history3.history['val_accuracy'])
plt.title('model acc')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```

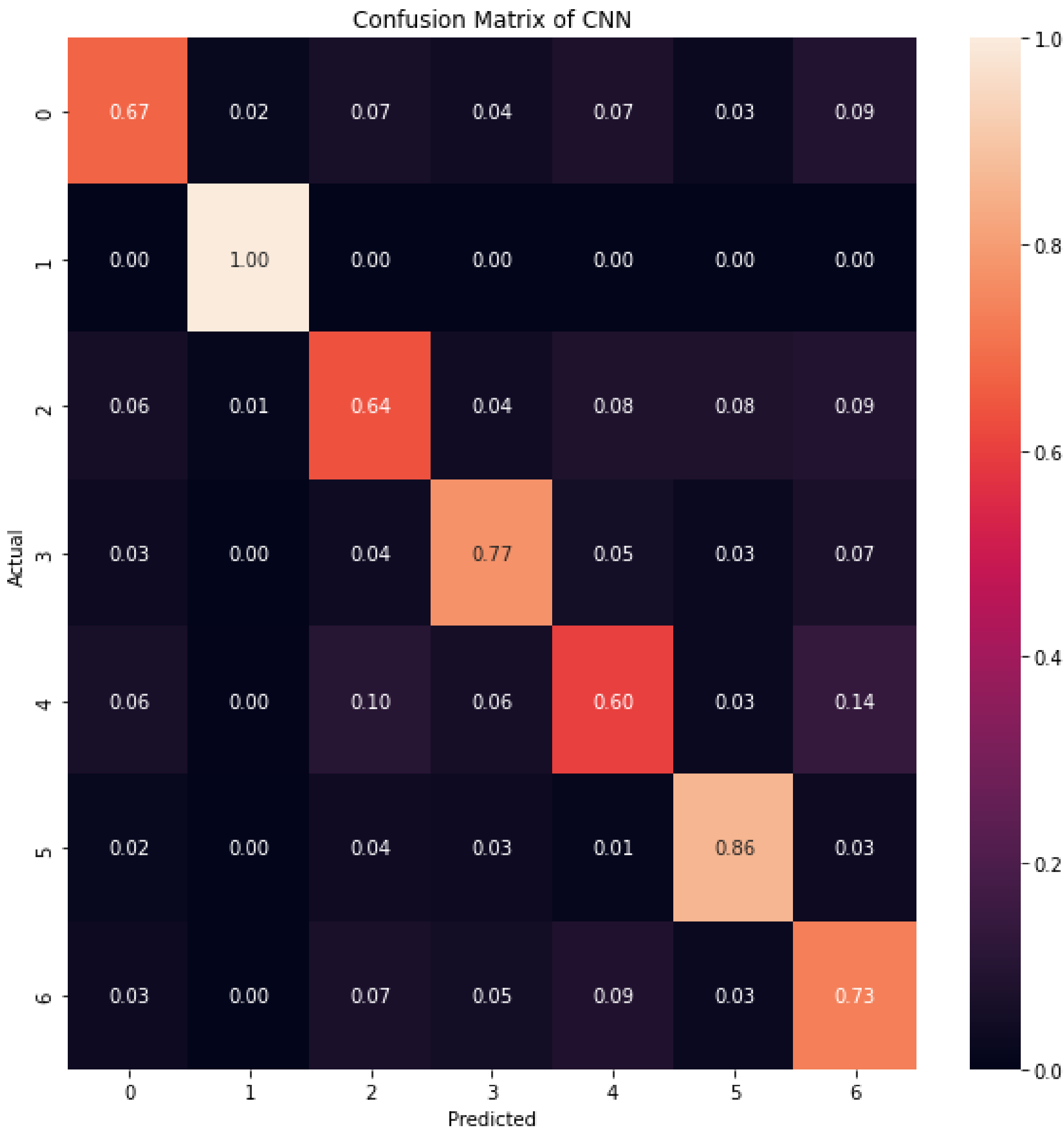


[96]:
```
model3.evaluate(test_x_cnn, test_y)
```

```
180/180 [==============================] - 1s 7ms/step - loss: 2.3736 -
accuracy: 0.7177
```

[96]: [2.3736231327056885, 0.7176941633224487]

[97]:
```
cm = confusion_matrix(test_y, np.apply_along_axis(np.argmax, 1, model3.
 ↪predict(test_x_cnn)))
cmn = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(cmn, annot=True, fmt='.2f', xticklabels=nb.classes_, yticklabels=nb.
 ↪classes_)
plt.title('Confusion Matrix of CNN')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show(block=False)
```



[108]:
```
model.save('saved_model/ann.h5')
model3.save('saved_model/cnn.h5')
```