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

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

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

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

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

[8]:
```
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]))
```

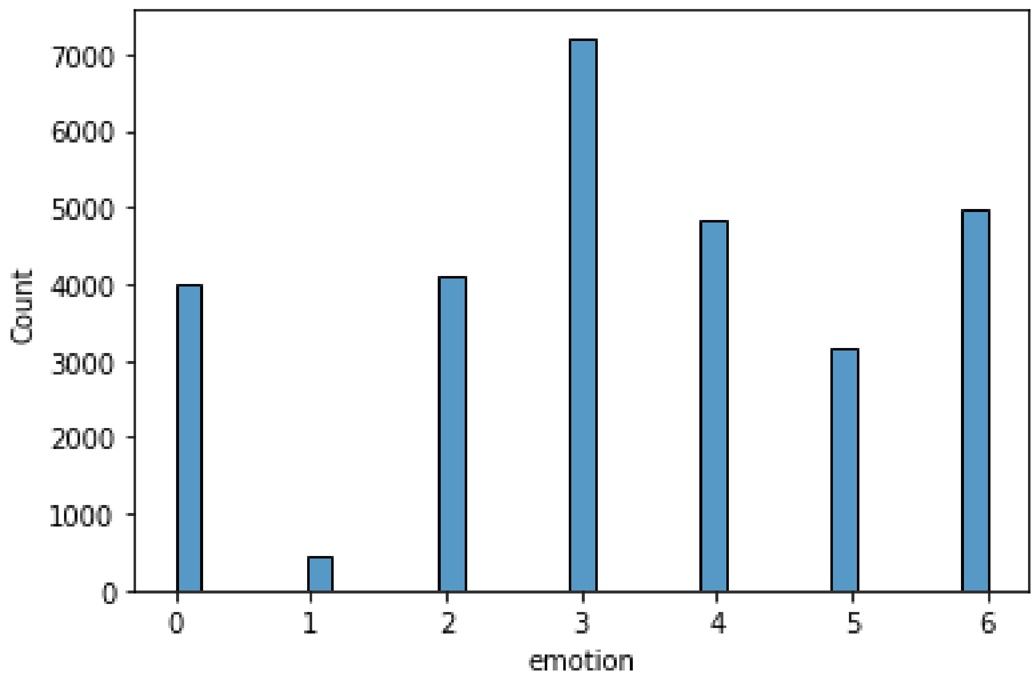
[9]:
```
face.emotion.value_counts()
```

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

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

[10]:
```
sns.histplot(face.emotion)
```

[10]: <matplotlib.axes._subplots.AxesSubplot at 0x7f43872e6ed0>



[11]:
```
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 = face[face.emotion == i].sample(n=3000, replace=True,␣
 ↪random_state=100)
    else:
        faces_balanced = pd.concat([faces_balanced, face[face.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
```

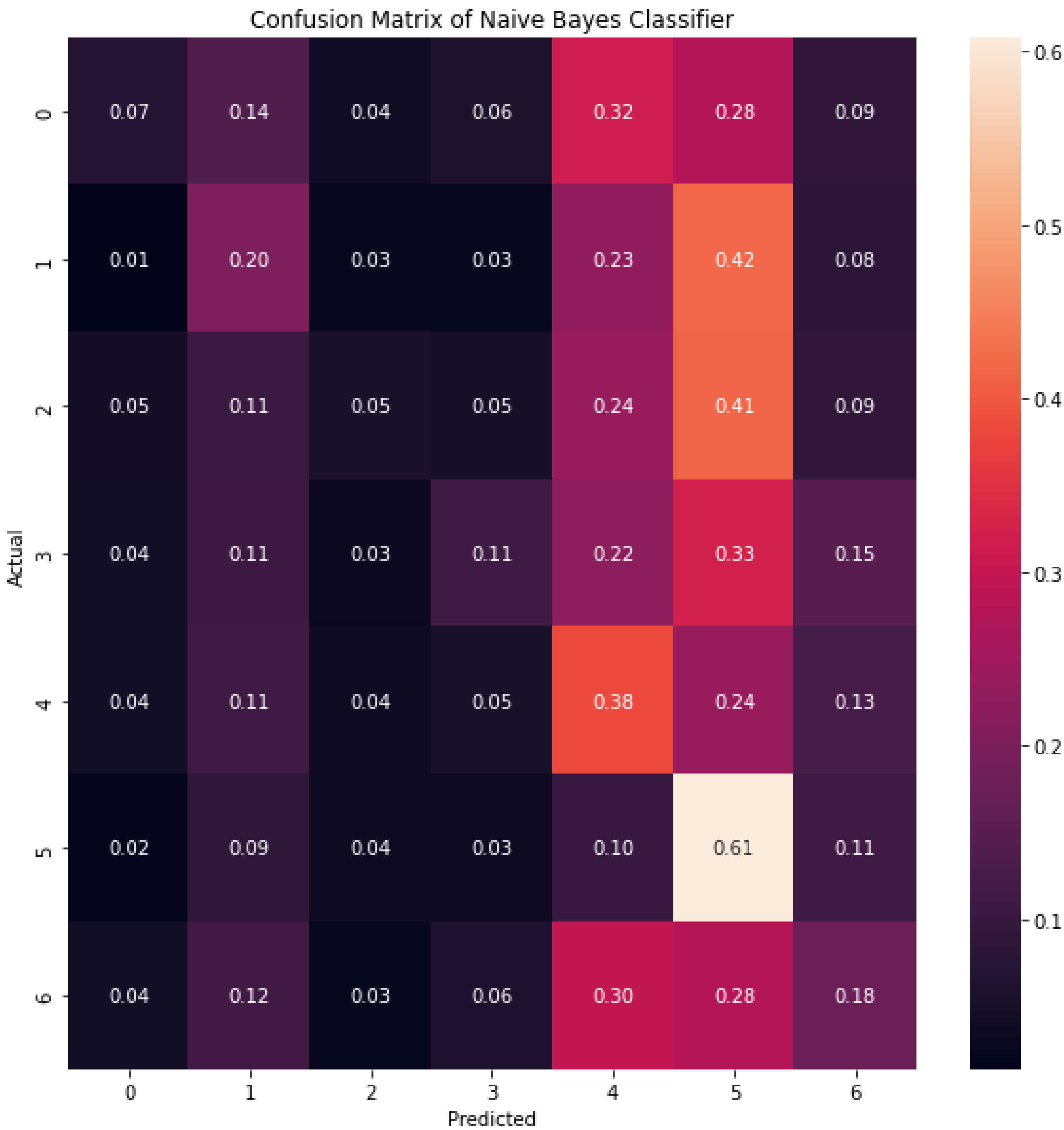
[17]:
```
nb.score(val_x, val_y)
```

[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
```

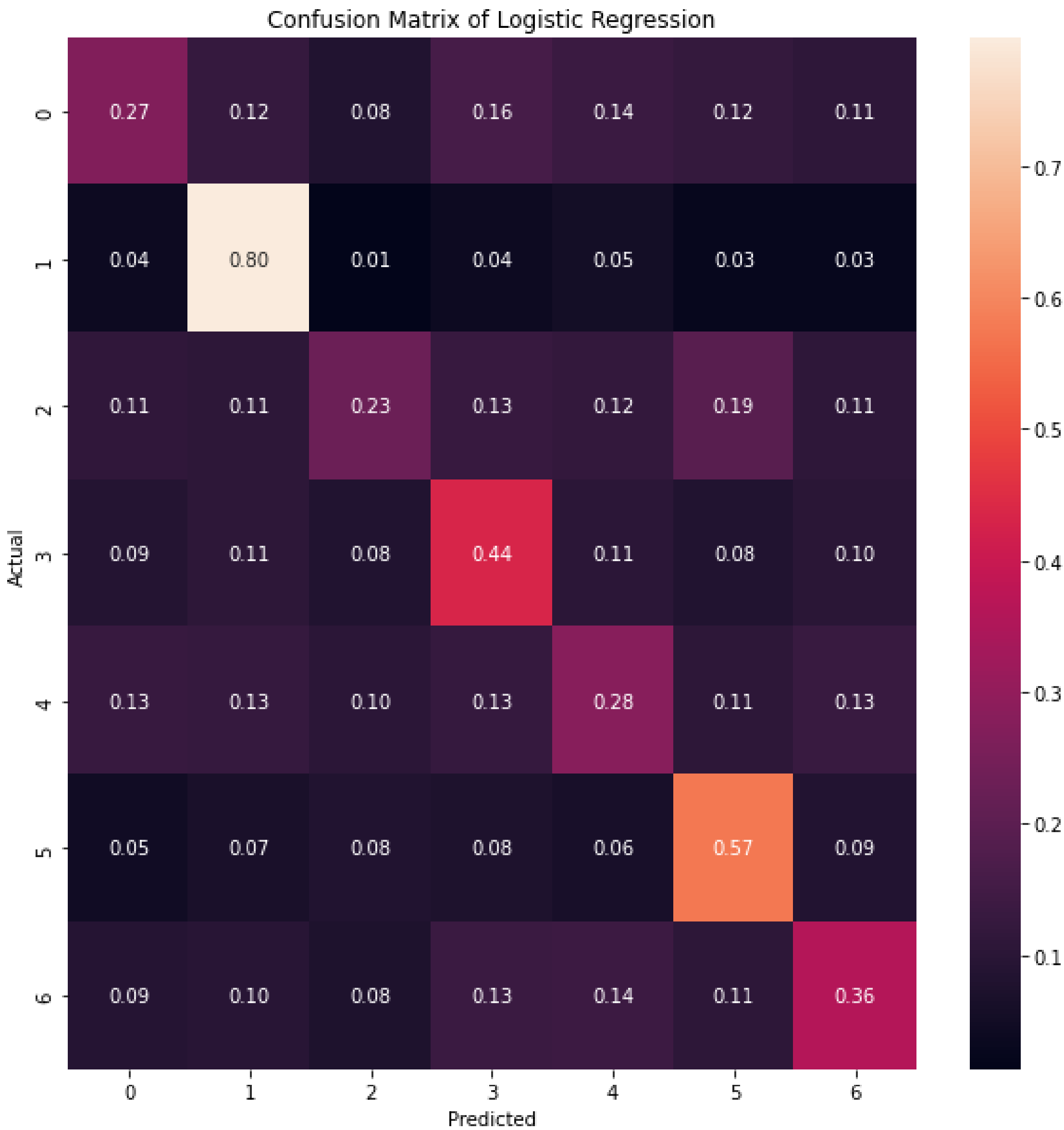
[22]:
```
lr.score(val_x, val_y)
```

[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
```

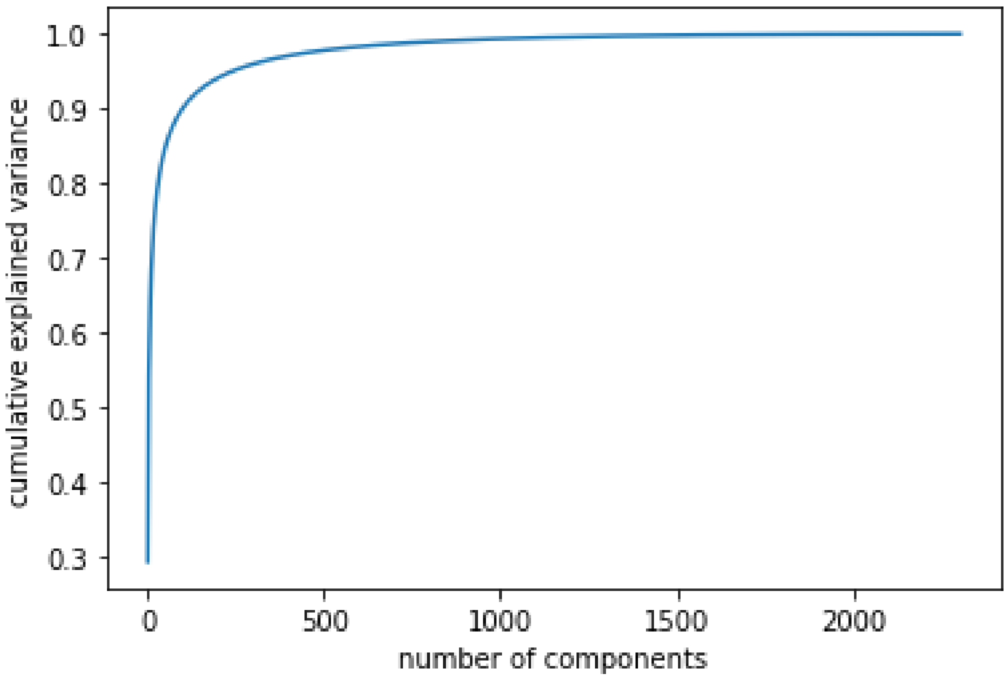
[29]:
```
pl.score(test_x, test_y)
```

[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
```

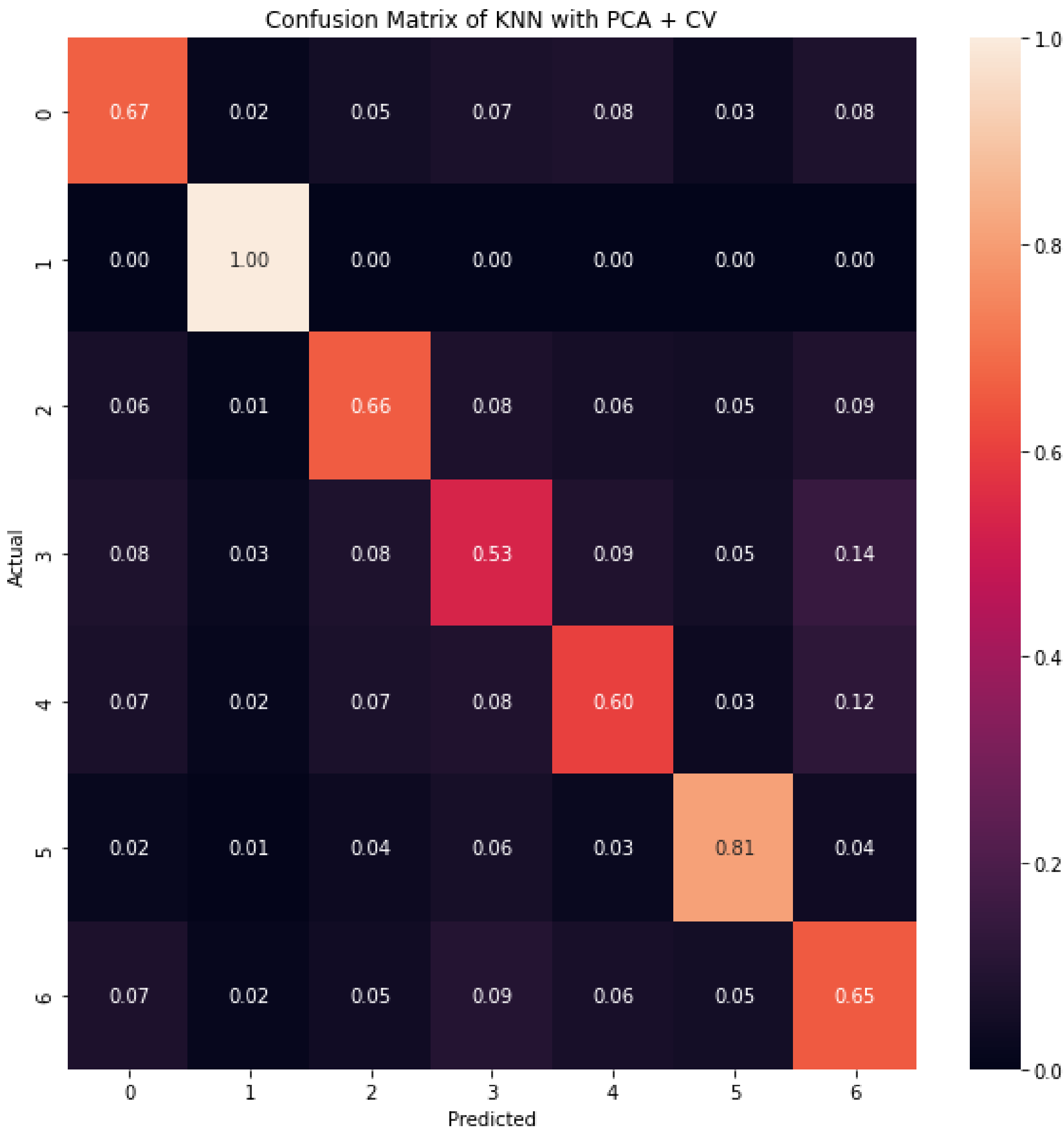
[36]:

```
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

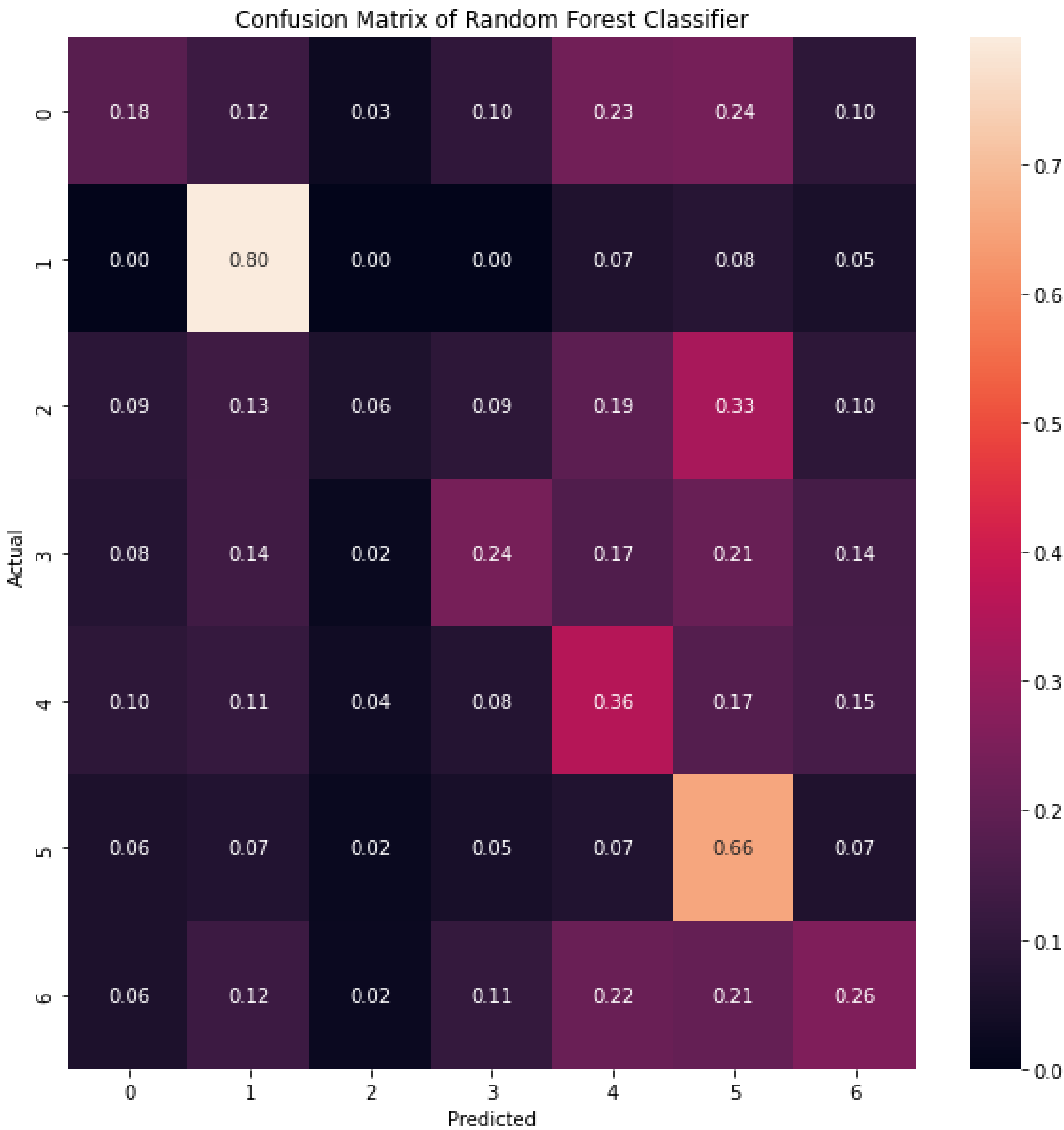
[40]:
```
rfc.score(val_x, val_y)
```

[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

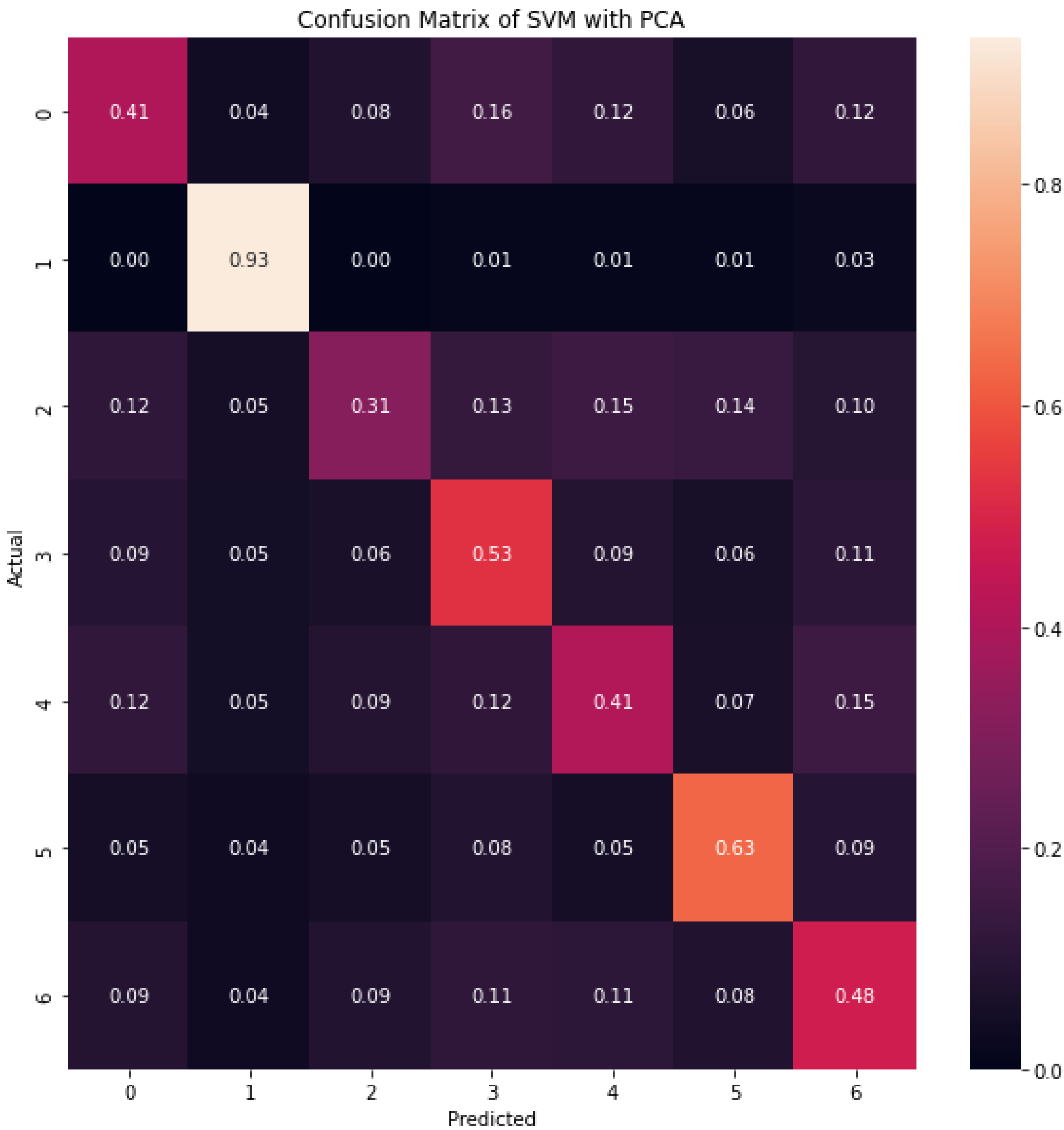
[45]:
```
pl2.score(val_x, val_y)
```

[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

[48]:
```
train_y_cat = to_categorical(train_y)
val_y_cat = to_categorical(val_y)
test_y_cat = to_categorical(test_y)
```

[49]:
```
model = Sequential()
model.add(Dense(256, activation = 'relu', input_shape = (48 * 48,)))
model.add(layers.Dropout(0.2))
model.add(Dense(256, activation = 'relu'))
model.add(layers.Dropout(0.5))
```

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

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

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

 dropout (Dropout)           (None, 256)               0

 dense_1 (Dense)             (None, 256)               65792

 dropout_1 (Dropout)         (None, 256)               0

 dense_2 (Dense)             (None, 7)                 1799

=================================================================
Total params: 657,671
Trainable params: 657,671
Non-trainable params: 0
_________________________________________________________________
```

[50]:
```
history = model.fit(train_x, train_y_cat, epochs = 20, validation_data =
    (val_x, val_y_cat))
```

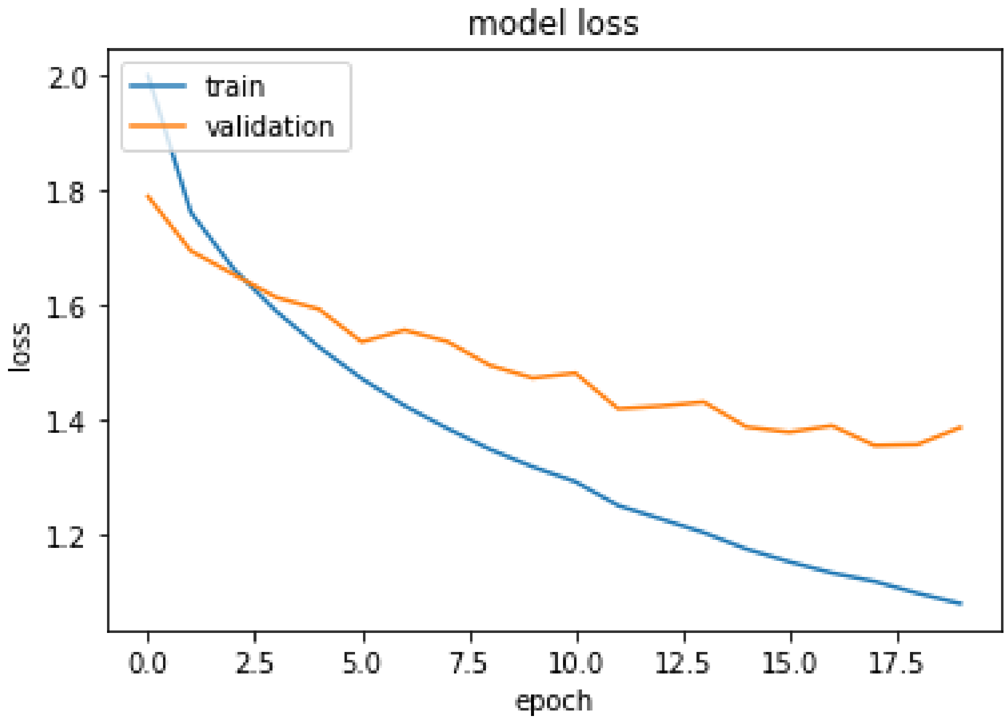
```
Epoch 1/20
657/657 [==============================] - 3s 4ms/step - loss: 1.9979 -
accuracy: 0.2342 - val_loss: 1.7877 - val_accuracy: 0.2896
Epoch 2/20
657/657 [==============================] - 2s 3ms/step - loss: 1.7601 -
accuracy: 0.3051 - val_loss: 1.6930 - val_accuracy: 0.3260
Epoch 3/20
657/657 [==============================] - 2s 3ms/step - loss: 1.6622 -
accuracy: 0.3450 - val_loss: 1.6524 - val_accuracy: 0.3419
Epoch 4/20
657/657 [==============================] - 2s 3ms/step - loss: 1.5882 -
accuracy: 0.3782 - val_loss: 1.6124 - val_accuracy: 0.3476
Epoch 5/20
657/657 [==============================] - 2s 3ms/step - loss: 1.5259 -
accuracy: 0.3974 - val_loss: 1.5918 - val_accuracy: 0.3640
Epoch 6/20
657/657 [==============================] - 2s 3ms/step - loss: 1.4710 -
accuracy: 0.4197 - val_loss: 1.5349 - val_accuracy: 0.3824
```

```
Epoch 7/20
657/657 [==============================] - 2s 3ms/step - loss: 1.4237 -
accuracy: 0.4397 - val_loss: 1.5554 - val_accuracy: 0.3821
Epoch 8/20
657/657 [==============================] - 2s 3ms/step - loss: 1.3842 -
accuracy: 0.4523 - val_loss: 1.5355 - val_accuracy: 0.3997
Epoch 9/20
657/657 [==============================] - 2s 3ms/step - loss: 1.3478 -
accuracy: 0.4737 - val_loss: 1.4938 - val_accuracy: 0.4141
Epoch 10/20
657/657 [==============================] - 2s 3ms/step - loss: 1.3177 -
accuracy: 0.4853 - val_loss: 1.4720 - val_accuracy: 0.4223
Epoch 11/20
657/657 [==============================] - 2s 3ms/step - loss: 1.2917 -
accuracy: 0.4943 - val_loss: 1.4804 - val_accuracy: 0.4211
Epoch 12/20
657/657 [==============================] - 2s 3ms/step - loss: 1.2503 -
accuracy: 0.5108 - val_loss: 1.4184 - val_accuracy: 0.4392
Epoch 13/20
657/657 [==============================] - 2s 3ms/step - loss: 1.2268 -
accuracy: 0.5206 - val_loss: 1.4231 - val_accuracy: 0.4523
Epoch 14/20
657/657 [==============================] - 2s 3ms/step - loss: 1.2032 -
accuracy: 0.5339 - val_loss: 1.4302 - val_accuracy: 0.4471
Epoch 15/20
657/657 [==============================] - 2s 3ms/step - loss: 1.1745 -
accuracy: 0.5481 - val_loss: 1.3867 - val_accuracy: 0.4639
Epoch 16/20
657/657 [==============================] - 2s 3ms/step - loss: 1.1525 -
accuracy: 0.5531 - val_loss: 1.3777 - val_accuracy: 0.4692
Epoch 17/20
657/657 [==============================] - 2s 3ms/step - loss: 1.1330 -
accuracy: 0.5601 - val_loss: 1.3889 - val_accuracy: 0.4742
Epoch 18/20
657/657 [==============================] - 2s 3ms/step - loss: 1.1182 -
accuracy: 0.5707 - val_loss: 1.3544 - val_accuracy: 0.4913
Epoch 19/20
657/657 [==============================] - 2s 3ms/step - loss: 1.0975 -
accuracy: 0.5771 - val_loss: 1.3563 - val_accuracy: 0.4908
Epoch 20/20
657/657 [==============================] - 2s 3ms/step - loss: 1.0797 -
accuracy: 0.5885 - val_loss: 1.3858 - val_accuracy: 0.4798
```

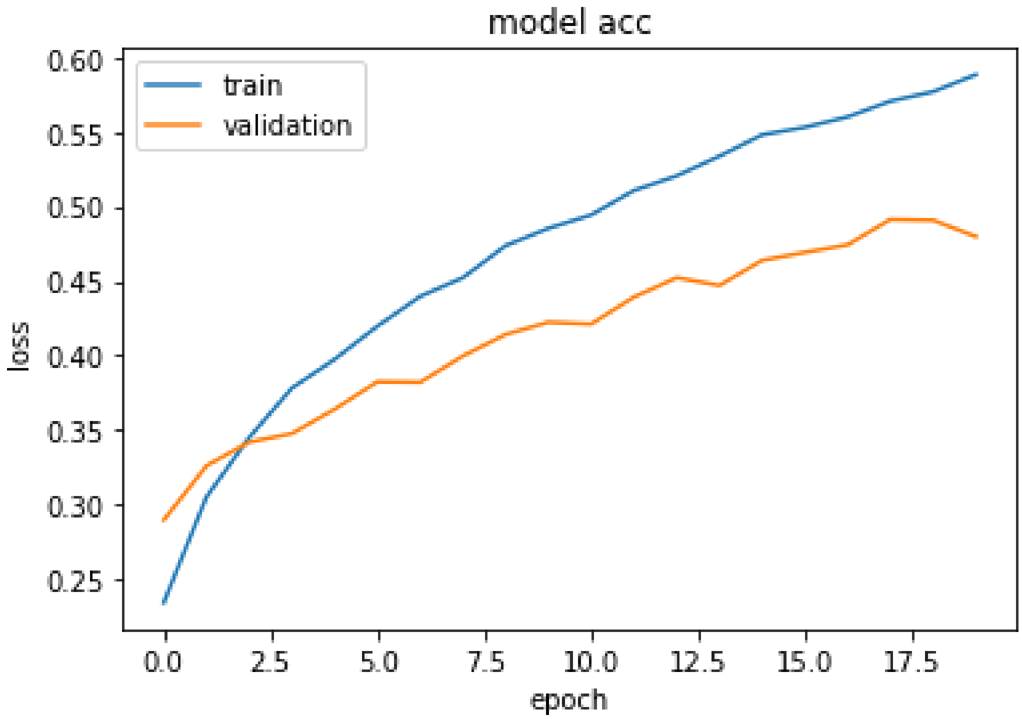
[51]:

```
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()
```



[52]:
```
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()
```

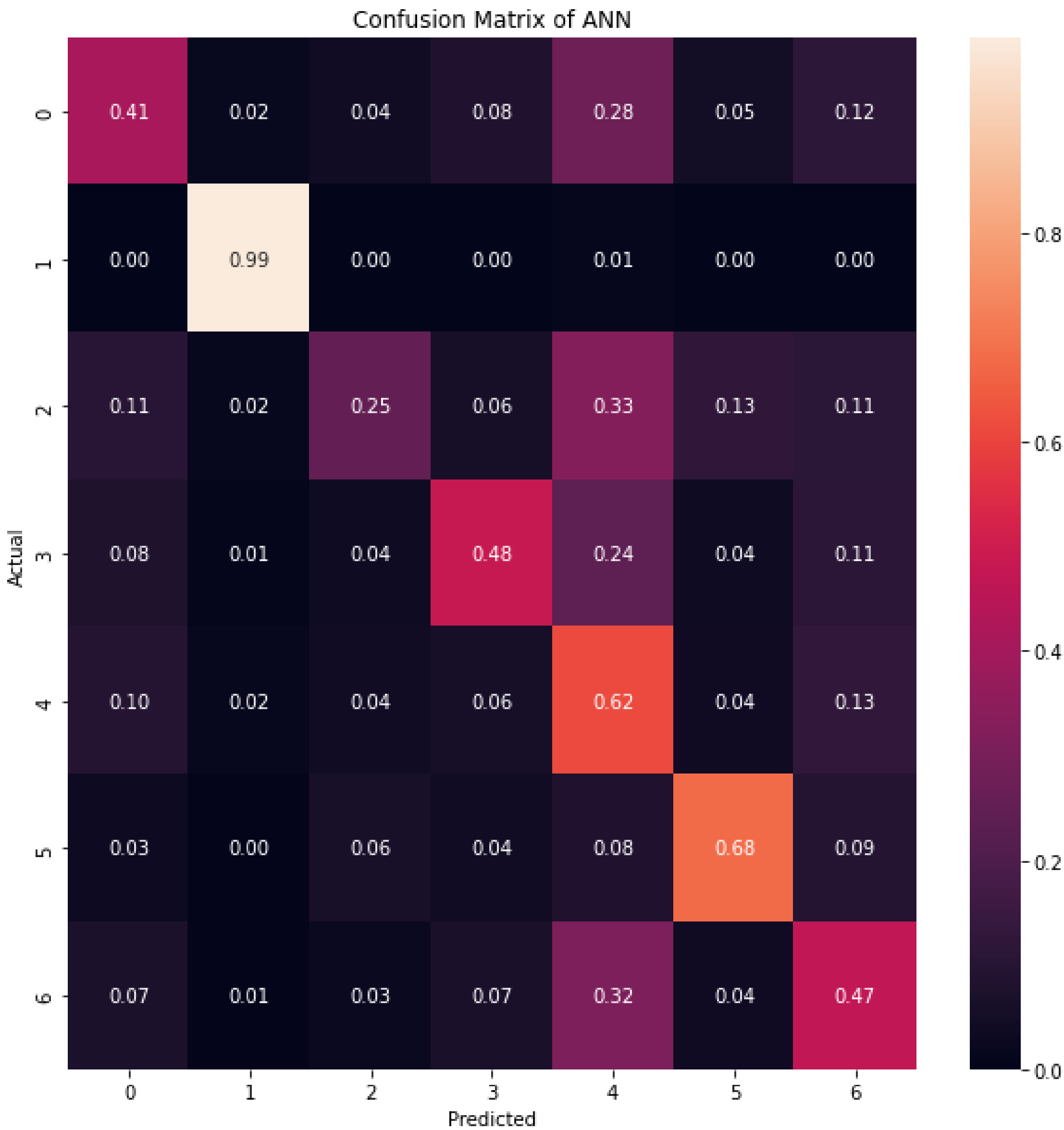


[53]:
```
model.evaluate(test_x, test_y_cat)
```

```
180/180 [==============================] - 0s 2ms/step - loss: 1.3736 -
accuracy: 0.4866
```

[53]: [1.3736388683319092, 0.48659002780914307]

[54]:
```
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

[55]:
```
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)
```

[56]:
```
model2 = Sequential()
model2.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(48, 48,␣
↪1)))
model2.add(layers.MaxPooling2D((2, 2)))
model2.add(layers.Conv2D(64, (3, 3), activation='relu'))
```

```
model2.add(layers.Dropout(0.5))
model2.add(layers.MaxPooling2D((2, 2)))
model2.add(layers.Dropout(0.5))
model2.add(layers.Conv2D(64, (3, 3), activation='relu'))
model2.add(layers.Flatten())
model2.add(layers.Dropout(0.2))
model2.add(layers.Dense(64, activation='relu'))
model2.add(layers.Dropout(0.5))
model2.add(layers.Dense(7))
```

[57]:
```
model2.compile(optimizer='adam',
              loss=tf.keras.losses.
 ↪SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
model2.summary()
```

```
Model: "sequential_1"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 46, 46, 32)        320

 max_pooling2d (MaxPooling2D  (None, 23, 23, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 21, 21, 64)        18496

 dropout_2 (Dropout)         (None, 21, 21, 64)        0

 max_pooling2d_1 (MaxPooling  (None, 10, 10, 64)       0
 2D)

 dropout_3 (Dropout)         (None, 10, 10, 64)        0

 conv2d_2 (Conv2D)           (None, 8, 8, 64)          36928

 flatten (Flatten)           (None, 4096)              0

 dropout_4 (Dropout)         (None, 4096)              0

 dense_3 (Dense)             (None, 64)                262208

 dropout_5 (Dropout)         (None, 64)                0

 dense_4 (Dense)             (None, 7)                 455

=================================================================
```

```
Total params: 318,407
Trainable params: 318,407
Non-trainable params: 0
_________________________________________________________________
```

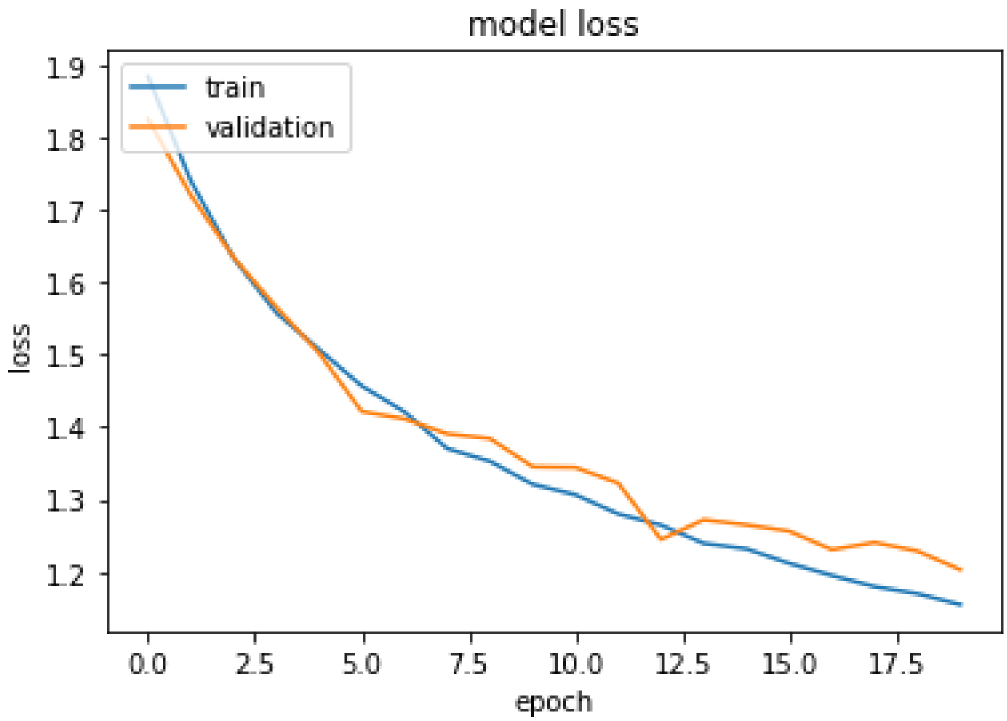
[58]:
```
history2 = model2.fit(train_x_cnn, train_y, epochs = 20, validation_data =
    ↪(val_x_cnn, val_y))
```

```
Epoch 1/20
657/657 [==============================] - 13s 19ms/step - loss: 1.8835 -
accuracy: 0.2175 - val_loss: 1.8248 - val_accuracy: 0.3095
Epoch 2/20
657/657 [==============================] - 14s 22ms/step - loss: 1.7397 -
accuracy: 0.3118 - val_loss: 1.7198 - val_accuracy: 0.3459
Epoch 3/20
657/657 [==============================] - 14s 22ms/step - loss: 1.6333 -
accuracy: 0.3683 - val_loss: 1.6342 - val_accuracy: 0.3865
Epoch 4/20
657/657 [==============================] - 14s 22ms/step - loss: 1.5578 -
accuracy: 0.3953 - val_loss: 1.5656 - val_accuracy: 0.4112
Epoch 5/20
657/657 [==============================] - 14s 22ms/step - loss: 1.5071 -
accuracy: 0.4158 - val_loss: 1.5021 - val_accuracy: 0.4613
Epoch 6/20
657/657 [==============================] - 14s 22ms/step - loss: 1.4568 -
accuracy: 0.4378 - val_loss: 1.4215 - val_accuracy: 0.4767
Epoch 7/20
657/657 [==============================] - 14s 22ms/step - loss: 1.4209 -
accuracy: 0.4530 - val_loss: 1.4112 - val_accuracy: 0.4812
Epoch 8/20
657/657 [==============================] - 14s 22ms/step - loss: 1.3702 -
accuracy: 0.4678 - val_loss: 1.3905 - val_accuracy: 0.5012
Epoch 9/20
657/657 [==============================] - 14s 22ms/step - loss: 1.3526 -
accuracy: 0.4790 - val_loss: 1.3841 - val_accuracy: 0.4976
Epoch 10/20
657/657 [==============================] - 15s 22ms/step - loss: 1.3210 -
accuracy: 0.4891 - val_loss: 1.3451 - val_accuracy: 0.5237
Epoch 11/20
657/657 [==============================] - 15s 22ms/step - loss: 1.3066 -
accuracy: 0.4932 - val_loss: 1.3442 - val_accuracy: 0.5169
Epoch 12/20
657/657 [==============================] - 15s 22ms/step - loss: 1.2801 -
accuracy: 0.5069 - val_loss: 1.3227 - val_accuracy: 0.5371
Epoch 13/20
657/657 [==============================] - 15s 22ms/step - loss: 1.2647 -
accuracy: 0.5121 - val_loss: 1.2448 - val_accuracy: 0.5455
Epoch 14/20
```

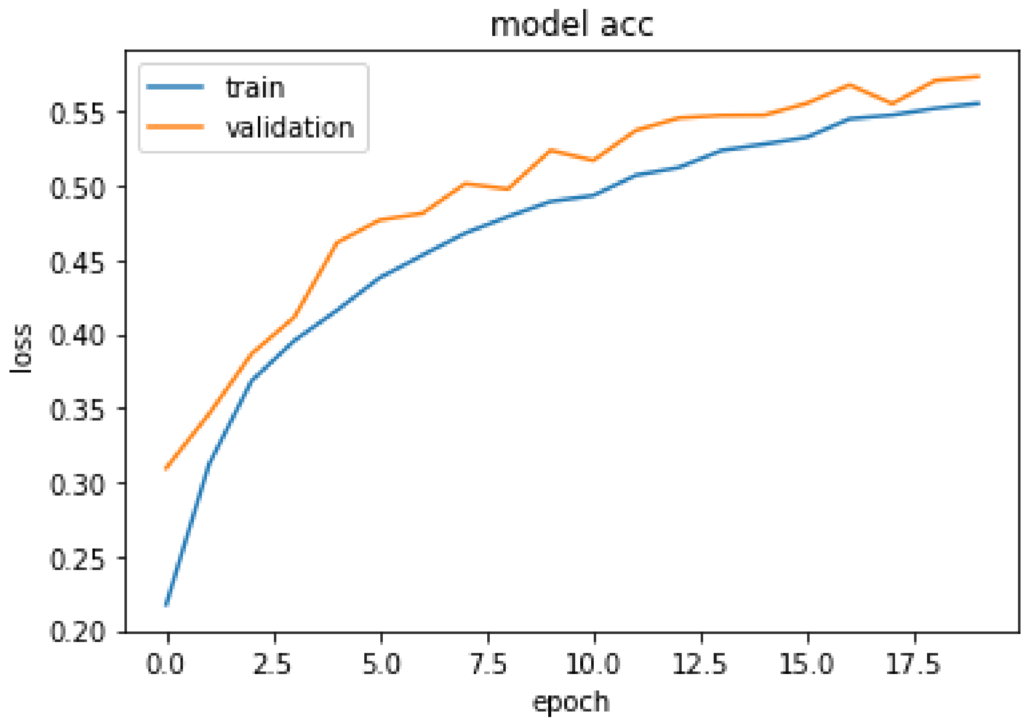
```
657/657 [==============================] - 15s 22ms/step - loss: 1.2394 -
accuracy: 0.5236 - val_loss: 1.2720 - val_accuracy: 0.5472
Epoch 15/20
657/657 [==============================] - 15s 22ms/step - loss: 1.2318 -
accuracy: 0.5278 - val_loss: 1.2650 - val_accuracy: 0.5474
Epoch 16/20
657/657 [==============================] - 15s 22ms/step - loss: 1.2119 -
accuracy: 0.5324 - val_loss: 1.2563 - val_accuracy: 0.5554
Epoch 17/20
657/657 [==============================] - 15s 22ms/step - loss: 1.1951 -
accuracy: 0.5449 - val_loss: 1.2307 - val_accuracy: 0.5677
Epoch 18/20
657/657 [==============================] - 15s 22ms/step - loss: 1.1799 -
accuracy: 0.5474 - val_loss: 1.2406 - val_accuracy: 0.5550
Epoch 19/20
657/657 [==============================] - 15s 22ms/step - loss: 1.1701 -
accuracy: 0.5519 - val_loss: 1.2287 - val_accuracy: 0.5707
Epoch 20/20
657/657 [==============================] - 15s 22ms/step - loss: 1.1550 -
accuracy: 0.5552 - val_loss: 1.2032 - val_accuracy: 0.5733
```

[59]:

```
plt.plot(history2.history['loss'])
plt.plot(history2.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```



[60]:
```
plt.plot(history2.history['accuracy'])
plt.plot(history2.history['val_accuracy'])
plt.title('model acc')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```

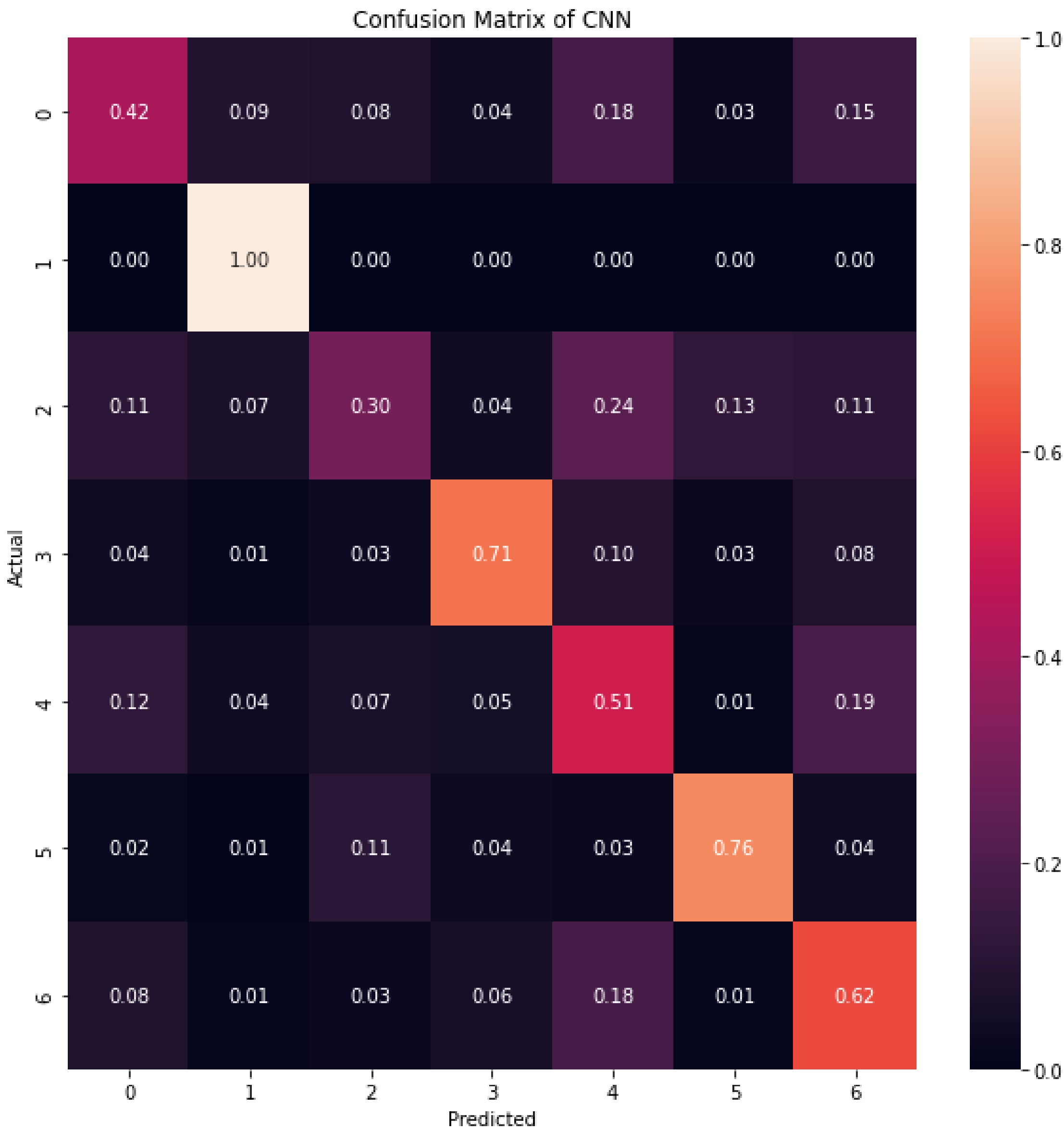


[61]:
```
model2.evaluate(test_x_cnn, test_y)
```

```
180/180 [==============================] - 1s 4ms/step - loss: 1.2005 -
accuracy: 0.5705
```

[61]:
```
[1.2005456686019897, 0.5705329179763794]
```

[62]:
```
cm = confusion_matrix(test_y, np.apply_along_axis(np.argmax, 1, model2.
 ↪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)
```



[63]:
```
model.save('saved_model/ann.h5')
model2.save('saved_model/cnn.h5')
```