Facial_Emotion_Recognition

June 2, 2022

[ ]:
```
# Basics
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt


# 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


# 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
```

1 Data Cleaning and Exploratory Data Analysis

[ ]:
```
face = pd.read_csv("face.csv")
```

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

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

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

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

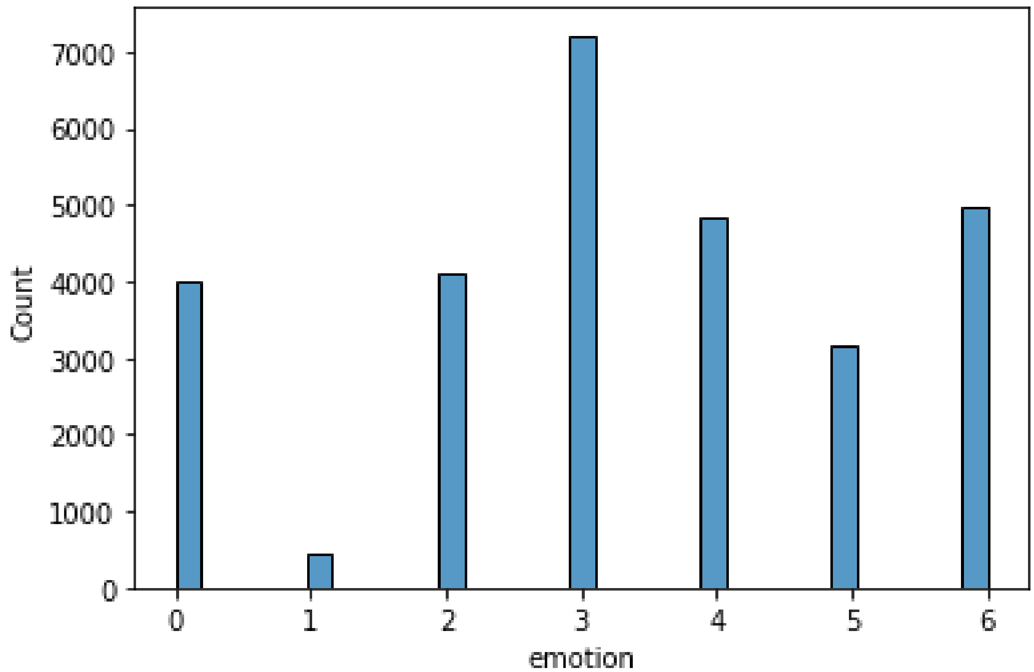
[ ]:
```
   emotion                                             pixels
0        0  [70, 80, 82, 72, 58, 58, 60, 63, 54, 58, 60, 4…
1        0  [151, 150, 147, 155, 148, 133, 111, 140, 170, …
2        2  [231, 212, 156, 164, 174, 138, 161, 173, 182, …
3        4  [24, 32, 36, 30, 32, 23, 19, 20, 30, 41,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

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

[ ]:
```
3    7215
6    4965
4    4830
2    4097
0    3995
5    3171
1     436
Name: emotion, dtype: int64
```

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

[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f09712b7710>
```



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

[ ]:
```
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))
    plt.xlabel("{} = {}".format(i, emo_di[i]))
```

For each one, consider using Cross Validation and/or PCA

[ ]:
```
train_x, test_x, train_y, test_y = train_test_split(np.concatenate(np.
↪asarray(face["pixels"])).reshape(-1, 48 * 48),
```

```
                                                    face.emotion,
                                                    train_size=0.7,
                                                    random_state=1)
val_x, test_x, val_y, test_y = train_test_split(test_x, test_y, test_size=0.5,␣
 ↪random_state=1)


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
```

2 Naive Bayes

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

[ ]: GaussianNB()

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

[ ]: 0.2174562101910828

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

[ ]: 0.2173206408172742

3 K-Means + Logistic Regression

[ ]:
```
pl = Pipeline([
    ("kmeans", KMeans(n_clusters=35)),
    ("logisreg", LogisticRegression(max_iter=10000))
])
```

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

[ ]:
```
Pipeline(steps=[('kmeans', KMeans(n_clusters=35)),
                ('logisreg', LogisticRegression(max_iter=10000))])
```

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

[ ]: 0.2907046178343949

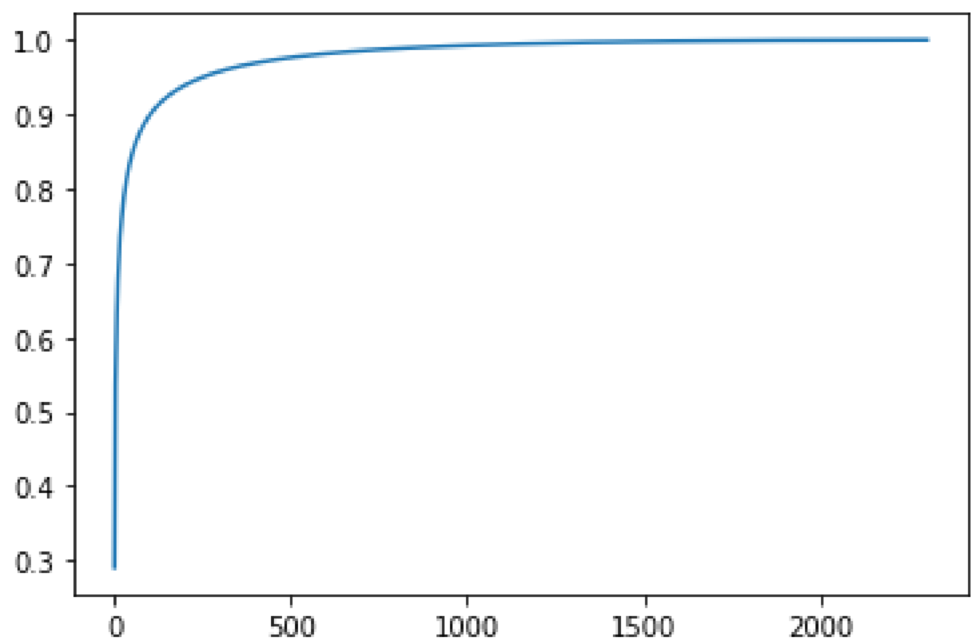
[ ]:
```
pl.score(test_x, test_y)
```

[ ]: 0.300208962154632

4 KNN with PCA + CV

[105]:
```
pca = PCA().fit(train_x)
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');
```

[105]: [<matplotlib.lines.Line2D at 0x7f096ea127d0>]



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

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

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

[ ]: {'SVM__n_neighbors': 1}

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

[ ]: 0.3501692953495771

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

[ ]: 0.3824007429765498

5 Random Forest

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

[ ]: RandomForestClassifier(max_depth=5)

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

[ ]: 0.33947054140127386

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

[ ]: 0.325748781054098

6 Support Vector Machine with PCA

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

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

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

[ ]: 0.529110270700637

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

[ ]: 0.4202461109821221

7 Artificial Neural Network

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

```
[ ]: 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_9"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_24 (Dense)            (None, 256)               590080

 dropout_24 (Dropout)        (None, 256)               0

 dense_25 (Dense)            (None, 256)               65792

 dropout_25 (Dropout)        (None, 256)               0

 dense_26 (Dense)            (None, 7)                 1799

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

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

```
Epoch 1/20
628/628 [==============================] - 3s 4ms/step - loss: 1.9194 -
accuracy: 0.2578 - val_loss: 1.6879 - val_accuracy: 0.3240
Epoch 2/20
628/628 [==============================] - 2s 4ms/step - loss: 1.7295 -
accuracy: 0.3127 - val_loss: 1.6489 - val_accuracy: 0.3430
Epoch 3/20
628/628 [==============================] - 2s 4ms/step - loss: 1.6975 -
```

```
accuracy: 0.3255 - val_loss: 1.6416 - val_accuracy: 0.3525
Epoch 4/20
628/628 [==============================] - 2s 4ms/step - loss: 1.6646 -
accuracy: 0.3395 - val_loss: 1.6127 - val_accuracy: 0.3725
Epoch 5/20
628/628 [==============================] - 2s 4ms/step - loss: 1.6375 -
accuracy: 0.3522 - val_loss: 1.5856 - val_accuracy: 0.3760
Epoch 6/20
628/628 [==============================] - 2s 4ms/step - loss: 1.6230 -
accuracy: 0.3581 - val_loss: 1.5936 - val_accuracy: 0.3695
Epoch 7/20
628/628 [==============================] - 2s 4ms/step - loss: 1.6047 -
accuracy: 0.3643 - val_loss: 1.5770 - val_accuracy: 0.3804
Epoch 8/20
628/628 [==============================] - 2s 4ms/step - loss: 1.5815 -
accuracy: 0.3740 - val_loss: 1.5767 - val_accuracy: 0.3758
Epoch 9/20
628/628 [==============================] - 2s 4ms/step - loss: 1.5687 -
accuracy: 0.3763 - val_loss: 1.5728 - val_accuracy: 0.3883
Epoch 10/20
628/628 [==============================] - 2s 4ms/step - loss: 1.5510 -
accuracy: 0.3781 - val_loss: 1.5647 - val_accuracy: 0.3888
Epoch 11/20
628/628 [==============================] - 2s 4ms/step - loss: 1.5299 -
accuracy: 0.3926 - val_loss: 1.5620 - val_accuracy: 0.3969
Epoch 12/20
628/628 [==============================] - 2s 4ms/step - loss: 1.5212 -
accuracy: 0.3997 - val_loss: 1.5500 - val_accuracy: 0.3878
Epoch 13/20
628/628 [==============================] - 2s 4ms/step - loss: 1.4995 -
accuracy: 0.4034 - val_loss: 1.5435 - val_accuracy: 0.3929
Epoch 14/20
628/628 [==============================] - 2s 4ms/step - loss: 1.4866 -
accuracy: 0.4118 - val_loss: 1.5528 - val_accuracy: 0.3902
Epoch 15/20
628/628 [==============================] - 2s 4ms/step - loss: 1.4737 -
accuracy: 0.4163 - val_loss: 1.5392 - val_accuracy: 0.4008
Epoch 16/20
628/628 [==============================] - 2s 4ms/step - loss: 1.4602 -
accuracy: 0.4252 - val_loss: 1.5423 - val_accuracy: 0.3908
Epoch 17/20
628/628 [==============================] - 2s 4ms/step - loss: 1.4438 -
accuracy: 0.4303 - val_loss: 1.5306 - val_accuracy: 0.3978
Epoch 18/20
628/628 [==============================] - 2s 4ms/step - loss: 1.4253 -
accuracy: 0.4346 - val_loss: 1.5410 - val_accuracy: 0.3934
Epoch 19/20
628/628 [==============================] - 2s 4ms/step - loss: 1.4208 -
```

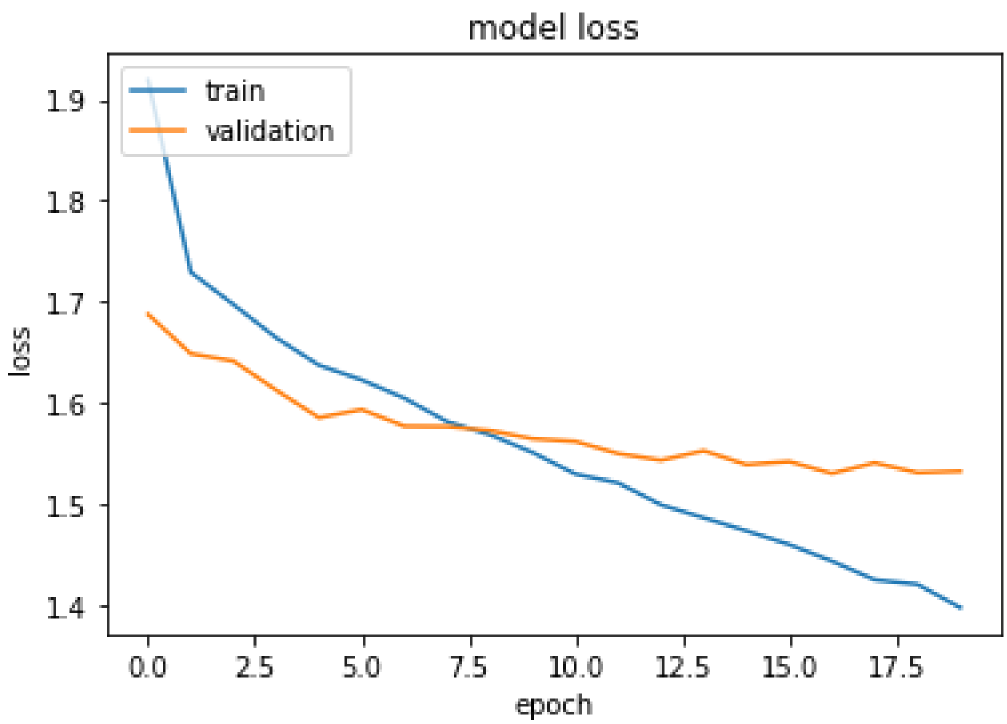
```
accuracy: 0.4397 - val_loss: 1.5313 - val_accuracy: 0.4043
Epoch 20/20
628/628 [==============================] - 2s 4ms/step - loss: 1.3977 -
accuracy: 0.4453 - val_loss: 1.5326 - val_accuracy: 0.4094
```

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

```
135/135 [==============================] - 0s 2ms/step - loss: 1.5339 -
accuracy: 0.4165
```

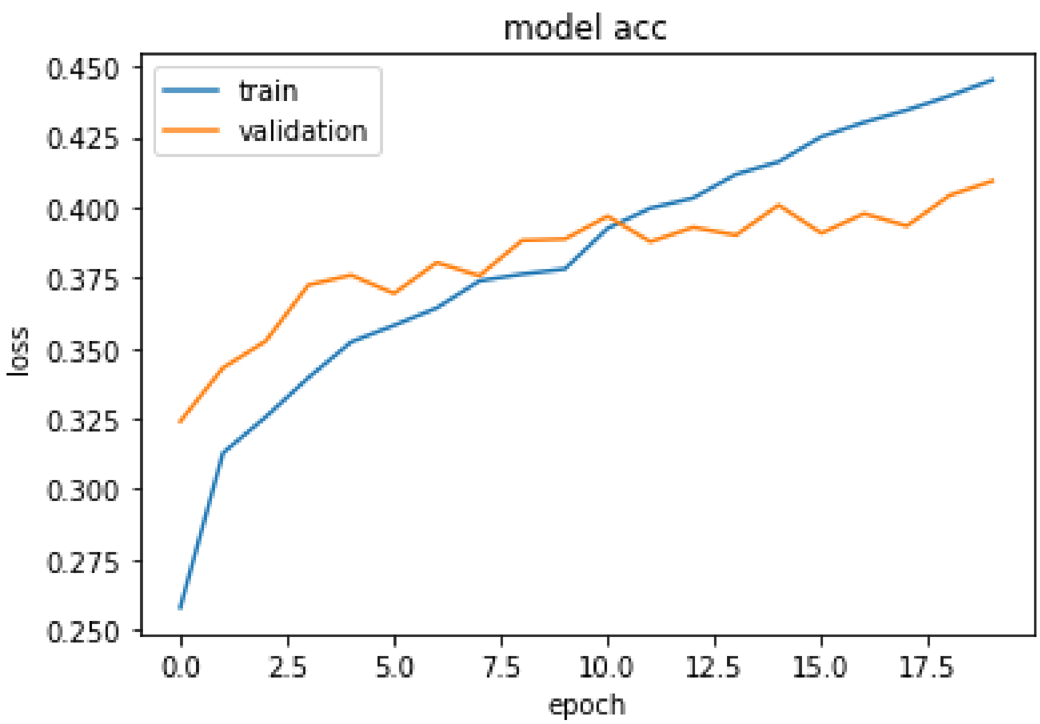
[ ]: [1.5338551998138428, 0.4165312349796295]

[ ]:
```
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()
```



[ ]:
```
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()
```



8 Convolutional Neural Network

[ ]:
```
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)
```

[ ]:
```
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))
```

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

```
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_6 (Conv2D)           (None, 46, 46, 32)        320

 max_pooling2d_4 (MaxPooling  (None, 23, 23, 32)       0
 2D)

 conv2d_7 (Conv2D)           (None, 21, 21, 64)        18496

 dropout_20 (Dropout)        (None, 21, 21, 64)        0

 max_pooling2d_5 (MaxPooling  (None, 10, 10, 64)       0
 2D)

 dropout_21 (Dropout)        (None, 10, 10, 64)        0

 conv2d_8 (Conv2D)           (None, 8, 8, 64)          36928

 flatten_2 (Flatten)         (None, 4096)              0

 dropout_22 (Dropout)        (None, 4096)              0

 dense_22 (Dense)            (None, 64)                262208

 dropout_23 (Dropout)        (None, 64)                0

 dense_23 (Dense)            (None, 7)                 455

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

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

```
Epoch 1/20
628/628 [==============================] - 11s 17ms/step - loss: 1.3236 -
accuracy: 0.4935 - val_loss: 1.2828 - val_accuracy: 0.5288
Epoch 2/20
628/628 [==============================] - 11s 17ms/step - loss: 1.2908 -
accuracy: 0.5005 - val_loss: 1.2522 - val_accuracy: 0.5362
Epoch 3/20
628/628 [==============================] - 11s 17ms/step - loss: 1.2902 -
accuracy: 0.5046 - val_loss: 1.2851 - val_accuracy: 0.5369
Epoch 4/20
628/628 [==============================] - 10s 16ms/step - loss: 1.2828 -
accuracy: 0.5089 - val_loss: 1.2514 - val_accuracy: 0.5367
Epoch 5/20
628/628 [==============================] - 11s 17ms/step - loss: 1.2763 -
accuracy: 0.5104 - val_loss: 1.2417 - val_accuracy: 0.5460
Epoch 6/20
628/628 [==============================] - 11s 17ms/step - loss: 1.2686 -
accuracy: 0.5152 - val_loss: 1.2644 - val_accuracy: 0.5344
Epoch 7/20
628/628 [==============================] - 10s 17ms/step - loss: 1.2630 -
accuracy: 0.5131 - val_loss: 1.2503 - val_accuracy: 0.5327
Epoch 8/20
628/628 [==============================] - 11s 18ms/step - loss: 1.2396 -
accuracy: 0.5226 - val_loss: 1.2336 - val_accuracy: 0.5504
Epoch 9/20
628/628 [==============================] - 11s 17ms/step - loss: 1.2385 -
accuracy: 0.5263 - val_loss: 1.2258 - val_accuracy: 0.5464
Epoch 10/20
628/628 [==============================] - 10s 16ms/step - loss: 1.2373 -
accuracy: 0.5246 - val_loss: 1.2111 - val_accuracy: 0.5601
Epoch 11/20
628/628 [==============================] - 11s 17ms/step - loss: 1.2300 -
accuracy: 0.5261 - val_loss: 1.2415 - val_accuracy: 0.5404
Epoch 12/20
628/628 [==============================] - 11s 17ms/step - loss: 1.2291 -
accuracy: 0.5303 - val_loss: 1.2201 - val_accuracy: 0.5555
Epoch 13/20
628/628 [==============================] - 10s 17ms/step - loss: 1.2211 -
accuracy: 0.5269 - val_loss: 1.2300 - val_accuracy: 0.5523
Epoch 14/20
628/628 [==============================] - 11s 17ms/step - loss: 1.2184 -
accuracy: 0.5353 - val_loss: 1.1994 - val_accuracy: 0.5546
Epoch 15/20
628/628 [==============================] - 11s 17ms/step - loss: 1.1957 -
accuracy: 0.5423 - val_loss: 1.2166 - val_accuracy: 0.5497
Epoch 16/20
628/628 [==============================] - 11s 17ms/step - loss: 1.2046 -
accuracy: 0.5376 - val_loss: 1.2463 - val_accuracy: 0.5416
```

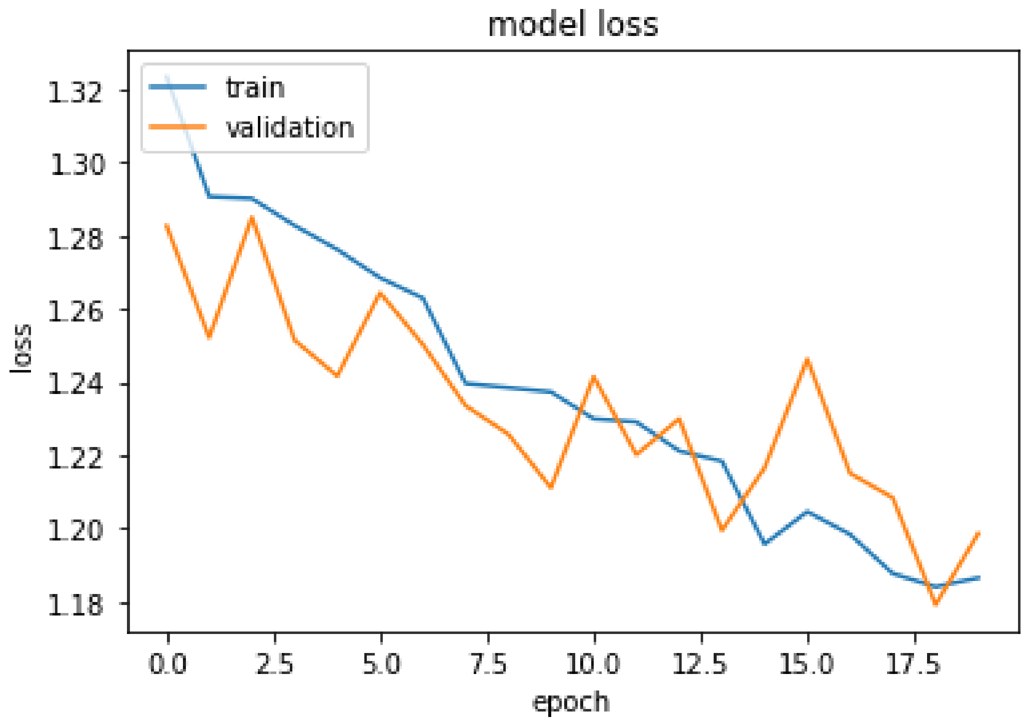
```
Epoch 17/20
628/628 [==============================] - 10s 16ms/step - loss: 1.1984 -
accuracy: 0.5403 - val_loss: 1.2151 - val_accuracy: 0.5632
Epoch 18/20
628/628 [==============================] - 11s 17ms/step - loss: 1.1876 -
accuracy: 0.5438 - val_loss: 1.2084 - val_accuracy: 0.5469
Epoch 19/20
628/628 [==============================] - 11s 17ms/step - loss: 1.1841 -
accuracy: 0.5469 - val_loss: 1.1792 - val_accuracy: 0.5683
Epoch 20/20
628/628 [==============================] - 11s 17ms/step - loss: 1.1865 -
accuracy: 0.5445 - val_loss: 1.1986 - val_accuracy: 0.5557
```

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

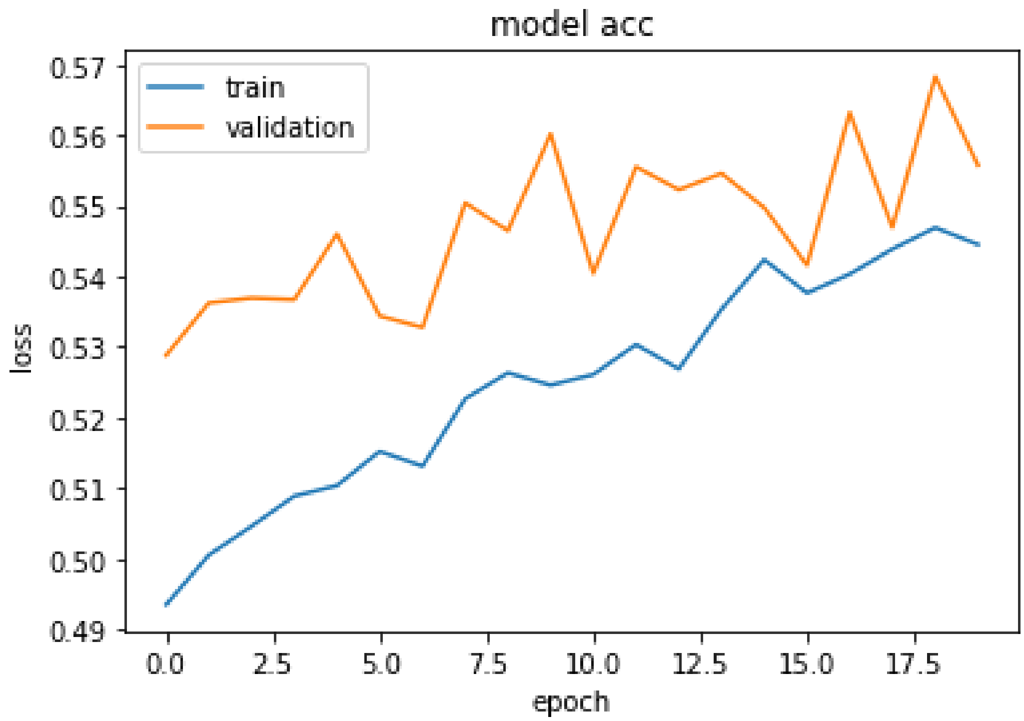
```
135/135 [==============================] - 1s 5ms/step - loss: 1.2030 -
accuracy: 0.5544
```

[ ]:
```
[1.202962040901184, 0.554446280002594]
```

[ ]:
```
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()
```



[ ]:
```
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()
```



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