

Final Model - Group4

October 31, 2019

0.0.1 Importing required packages

```
[1]: import os,sys
import pandas as pd
from sklearn.model_selection import train_test_split
import scipy.io
import numpy as np
from scipy.spatial.distance import pdist
import time
import math
import xgboost as xgb
from xgboost.sklearn import XGBClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
import keras
from keras.utils import to_categorical
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
```

Using TensorFlow backend.

/Users/Qiqi/opt/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:516: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.

```
_np_qint8 = np.dtype [("qint8", np.int8, 1)]
```

/Users/Qiqi/opt/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:517: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.

```
_np_quint8 = np.dtype [("quint8", np.uint8, 1)]
```

/Users/Qiqi/opt/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:518: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.

```
_np_qint16 = np.dtype [("qint16", np.int16, 1)]
```

/Users/Qiqi/opt/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:519: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of

```

numpy, it will be understood as (type, (1,)) / '(1,)type'.
_np_quint16 = np.dtype(["quint16", np.uint16, 1])
/Users/Qiqi/opt/anaconda3/lib/python3.7/site-
packages/tensorflow/python/framework/dtypes.py:520: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
_np_qint32 = np.dtype(["qint32", np.int32, 1])
/Users/Qiqi/opt/anaconda3/lib/python3.7/site-
packages/tensorflow/python/framework/dtypes.py:525: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
_np_resource = np.dtype(["resource", np.ubyte, 1])
/Users/Qiqi/opt/anaconda3/lib/python3.7/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:541: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
_np_qint8 = np.dtype(["qint8", np.int8, 1])
/Users/Qiqi/opt/anaconda3/lib/python3.7/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:542: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
_np_quint8 = np.dtype(["quint8", np.uint8, 1])
/Users/Qiqi/opt/anaconda3/lib/python3.7/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:543: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
_np_qint16 = np.dtype(["qint16", np.int16, 1])
/Users/Qiqi/opt/anaconda3/lib/python3.7/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:544: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
_np_quint16 = np.dtype(["quint16", np.uint16, 1])
/Users/Qiqi/opt/anaconda3/lib/python3.7/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:545: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
_np_qint32 = np.dtype(["qint32", np.int32, 1])
/Users/Qiqi/opt/anaconda3/lib/python3.7/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:550: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
_np_resource = np.dtype(["resource", np.ubyte, 1])

```

```

[2]: from keras.layers import Dense, Activation, Flatten, Input, Dropout
      from keras.layers import BatchNormalization
      from keras.models import Model
      from keras import initializers

```

```
from keras.optimizers import Adam
```

0.0.2 loading data

```
[3]: # change the root to your own path
root = sys.path[0]
train_dir = os.path.join(root, '../data/train_set')
train_image_dir = os.path.join(train_dir, 'images')
train_pt_dir = os.path.join(train_dir, 'points' )
train_label_path = os.path.join(train_dir, "label.csv")

[4]: info = pd.read_csv(train_label_path)
train_idx, test_idx = train_test_split(info['Index'], test_size=0.2,
    ↪random_state=123)

# read mat file and store coordinates in mat
m = []
for idx in info['Index']:
    file = "%04d.mat"%(idx)
    m.append( scipy.io.loadmat( os.path.join( train_pt_dir, file ) ))

mat = [x[[i for i in x.keys() if not i in ['__header__', '__version__',
    ↪'__globals__']][0]] for x in m]
```

0.0.3 train test split

```
[5]: train_idx, test_idx = train_test_split(info['Index'], test_size=0.2,
    ↪random_state=123)

[6]: train_mat = [ mat[i-1] for i in train_idx ]
test_mat = [ mat[i-1] for i in test_idx ]

[7]: train_labels = info.emotion_idx[train_idx-1]
test_labels = info.emotion_idx[test_idx-1]

[8]: train_label_cat = to_categorical(train_labels)
train_label_cat= train_label_cat[:,1:]
test_label_cat = to_categorical(test_labels)
test_label_cat= test_label_cat[:,1:]
```

0.0.4 feature extraction

```
[9]: # method 1 pairwise_dist_cal
#def pairwise_dist_cal(xy_cord):
#    p_dist = []
#    for i in range(xy_cord.shape[0]):
#        for j in range(i+1,xy_cord.shape[0]):
#            p_dist.append( abs(round(xy_cord[i,0]) - round(xy_cord[j,0] )) )
#            p_dist.append( abs(round(xy_cord[i,1]) - round(xy_cord[j,1] )) )
#    return p_dist

#### updated methods with selected fiducial points; this reduce 78 points to 50
'''
feature selection : 1. remove points P64 - 70 and P72 - 78
                    2. remove P51,53,55,57,58,60, 61, 63
                    3. calculate midpoints between upper and lower eyebrow lines
→and replace P20-22,P24-16 with midpoints
So there is in total 50 points left, which gives 50*49 pairwise distance
'''

def pairwise_dist_cal_updt(mt):
    t0 = time.time()
    p_dist_updt = np.zeros([len(mt),1225,2])
    n = len(mt)
    for k in range(n):
        xy_cord = mt[k]

        xy_cord_cpy = xy_cord

        # eye_brow midpoint
        to_add_brl = (xy_cord_cpy[19:22]+ xy_cord_cpy[23:26])/2
        to_add_brr = (xy_cord_cpy[27:30]+ xy_cord_cpy[31:34])/2

        # index to remove
        rm_idx = np.append(np.arange(63,70), np.arange(71,78))
        rm_idx = np.append(rm_idx,np.arange(50,57,2) )
        rm_idx = np.append(rm_idx, [57,59,60,62])
        rm_idx = np.append(rm_idx, np.arange(19,22))
        rm_idx = np.append(rm_idx, np.arange(23,26))
        rm_idx = np.append(rm_idx, np.arange(27,30))
        rm_idx = np.append(rm_idx, np.arange(31,34))
        xy_cord = np.delete(xy_cord, rm_idx, axis = 0)
        xy_cord = np.concatenate((xy_cord,to_add_brl,to_add_brr))
```

```

dist_h = []
dist_v = []
for i in range(xy_cord.shape[0]):
    for j in range(i+1,xy_cord.shape[0]):
        dist_h.append( abs(round(xy_cord[i,0]) - round(xy_cord[j,0] )) )
        dist_v.append( abs(round(xy_cord[i,1]) - round(xy_cord[j,1] )) )
    ↪)

p_dist_updt[k,:,0]= dist_h
p_dist_updt[k,:,1]= dist_v

print("feature constructions takes %s seconds" % (time.time() - t0))
return p_dist_updt.reshape([n,2450])

```

```

[10]: print("training: ")
train_data = pairwise_dist_cal_updt(train_mat[0:])

```

training:
feature constructions takes 19.490326166152954 seconds

```

[11]: print("testing: ")
test_data = pairwise_dist_cal_updt(test_mat[0:])

```

testing:
feature constructions takes 4.743052959442139 seconds

0.0.5 XGB

```

[12]: from xgboost.sklearn import XGBClassifier

```

```

[13]: train_labels_xgb = [ x - 1 for x in train_labels ]
test_labels_xgb = [ x - 1 for x in test_labels ]

```

```

[30]: xgb = XGBClassifier(
    learning_rate=0.1,
    n_estimators= 200,
    max_depth=5,
    min_child_weight=1,
    gamma=0,
    subsample=0.8,
    colsample_bytree=0.8,
    objective= 'multi:softmax', # for multi-labels classification
    num_class = 22,
    scale_pos_weight=1,

```

```

seed=123)
start_time=time.time()
xgb.fit(train_data, train_labels_xgb ,eval_metric='auc')
print("training model takes %s seconds" % round((time.time() - start_time),3))

```

training model takes 1156.417 seconds

```

[31]: start_time = time.time()
pred_xgb = xgb.predict(test_data)
print("testing model takes %s seconds" % round((time.time() - start_time),3))

```

testing model takes 1.199 seconds

```

[32]: acc_xgb = accuracy_score(pred_xgb,test_labels_xgb )
print("Test accuracy is %s percent" %(acc_xgb*100))

```

Test accuracy is 47.4 percent

Try other learner rate and n_trees

```

[33]: xgb_2 = XGBClassifier(
    learning_rate =0.01,
    n_estimators= 500,
    max_depth= 3 ,
    min_child_weight=1,
    gamma=0,
    subsample=0.8,
    colsample_bytree=0.8,
    objective= 'multi:softmax',  # for multi-labels classification
    num_class = 22,
    scale_pos_weight=1,
    seed=123)

```

```

[34]: start_time = time.time()
xgb_2.fit(train_data, train_labels_xgb ,eval_metric='auc')
print("training model takes %s seconds" % round((time.time() - start_time),3))

```

training model takes 2236.248 seconds

```

[40]: pred_xgb_2_train = xgb_2.predict(train_data)
acc_2_train = accuracy_score(pred_xgb_2_train,train_labels_xgb )
print("Train accuracy is %s percent" %(acc_2_train *100))

```

Train accuracy is 98.15 percent

```

[41]: start_time = time.time()
pred_xgb_2 = xgb_2.predict(test_data)
print("Testing model takes %s seconds" % round((time.time() - start_time),3))

```

Testing model takes 2.033 seconds

```
[42]: acc_2_test = accuracy_score(pred_xgb_2,test_labels_xgb )
      print("Test accuracy is %s percent" %(acc_2_test *100))
```

Test accuracy is 49.2 percent

Since XGB doesn't improve that much. We decided to try other models, like Neural Network

0.0.6 Neural Network

```
[14]: X = train_data
      Y = train_label_cat
```

first model

```
[15]: input_shape = [2450]
      input_layer = Input(input_shape)
      x = BatchNormalization()(input_layer)
      x = Dense(22*20,activation='relu',kernel_initializer=initializers.
        ↳glorot_normal(seed=4))(x)
      x = Dropout(0.25)(x)
      x = BatchNormalization()(x)
      x = Dense(22*10,activation='relu',kernel_initializer=initializers.
        ↳glorot_normal(seed=4))(x)
      x = Dropout(0.25)(x)
      x = Dense(22*6,activation='relu',kernel_initializer=initializers.
        ↳glorot_normal(seed=4))(x)
      x = Dropout(0.25)(x)
      x = Dense(22*2,activation='relu',kernel_initializer=initializers.
        ↳glorot_normal(seed=4))(x)
      output_layer = Dense(22,activation='softmax',kernel_initializer=initializers.
        ↳glorot_normal(seed=4))(x)
      model = Model(input_layer,output_layer)
```

```
[16]: start_time = time.time()
      model.compile(loss='categorical_crossentropy',optimizer = Adam(lr=0.
        ↳001),metrics=['accuracy'])
      model_hist = model.fit(X,Y,epochs=100)
      plt.figure(figsize=[8,6])
      plt.plot(model_hist.history['accuracy'],'r',linewidth=1.0)
      plt.legend(['Training Accuracy'],fontsize=18)
      plt.xlabel('Epochs ',fontsize=16)
      plt.ylabel('Accuracy',fontsize=16)
      plt.title('Accuracy Curves',fontsize=16)
      print("training model takes %s seconds" % round((time.time() - start_time),3))
```

WARNING:tensorflow:From /Users/Qiqi/opt/anaconda3/lib/python3.7/site-packages/keras/backend/tensorflow_backend.py:422: The name tf.global_variables is deprecated. Please use tf.compat.v1.global_variables instead.

```
Epoch 1/100
2000/2000 [=====] - 3s 1ms/step - loss: 3.0098 -
accuracy: 0.1100
Epoch 2/100
2000/2000 [=====] - 2s 1ms/step - loss: 2.6026 -
accuracy: 0.1940
Epoch 3/100
2000/2000 [=====] - 2s 1ms/step - loss: 2.3021 -
accuracy: 0.2700
Epoch 4/100
2000/2000 [=====] - 2s 1ms/step - loss: 2.1436 -
accuracy: 0.2975
Epoch 5/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.9974 -
accuracy: 0.3440
Epoch 6/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.8468 -
accuracy: 0.3920
Epoch 7/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.8075 -
accuracy: 0.4035
Epoch 8/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.6632 -
accuracy: 0.4440
Epoch 9/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.6180 -
accuracy: 0.4590
Epoch 10/100
2000/2000 [=====] - 2s 981us/step - loss: 1.5304 -
accuracy: 0.4800
Epoch 11/100
2000/2000 [=====] - 2s 987us/step - loss: 1.4909 -
accuracy: 0.5015
Epoch 12/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.4268 -
accuracy: 0.5180
Epoch 13/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.3894 -
accuracy: 0.5365
Epoch 14/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.3802 -
accuracy: 0.5255
Epoch 15/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.3244 -
```



```

accuracy: 0.5605
Epoch 16/100
2000/2000 [=====] - 3s 1ms/step - loss: 1.2694 -
accuracy: 0.5745
Epoch 17/100
2000/2000 [=====] - 2s 933us/step - loss: 1.2331 -
accuracy: 0.5825
Epoch 18/100
2000/2000 [=====] - 2s 1000us/step - loss: 1.2198 -
accuracy: 0.5815
Epoch 19/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.1474 -
accuracy: 0.5970
Epoch 20/100
2000/2000 [=====] - 3s 1ms/step - loss: 1.1679 -
accuracy: 0.6030
Epoch 21/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.1470 -
accuracy: 0.6075
Epoch 22/100
2000/2000 [=====] - 2s 965us/step - loss: 1.0993 -
accuracy: 0.6320
Epoch 23/100
2000/2000 [=====] - 2s 967us/step - loss: 1.1024 -
accuracy: 0.6235
Epoch 24/100
2000/2000 [=====] - 2s 956us/step - loss: 1.0572 -
accuracy: 0.6230
Epoch 25/100
2000/2000 [=====] - 2s 907us/step - loss: 1.0434 -
accuracy: 0.6440
Epoch 26/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.0149 -
accuracy: 0.6510
Epoch 27/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.9574 -
accuracy: 0.6670
Epoch 28/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.9542 -
accuracy: 0.6605
Epoch 29/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.9491 -
accuracy: 0.6785
Epoch 30/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.9717 -
accuracy: 0.6615
Epoch 31/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.9332 -

```

```

accuracy: 0.6855
Epoch 32/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.8520 -
accuracy: 0.6990
Epoch 33/100
2000/2000 [=====] - 2s 980us/step - loss: 0.9046 -
accuracy: 0.6970
Epoch 34/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.8415 -
accuracy: 0.7115
Epoch 35/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.8357 -
accuracy: 0.7155
Epoch 36/100
2000/2000 [=====] - 2s 947us/step - loss: 0.8008 -
accuracy: 0.7305
Epoch 37/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.7911 -
accuracy: 0.7240
Epoch 38/100
2000/2000 [=====] - 2s 979us/step - loss: 0.8218 -
accuracy: 0.7190
Epoch 39/100
2000/2000 [=====] - 2s 941us/step - loss: 0.8060 -
accuracy: 0.7160
Epoch 40/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.7463 -
accuracy: 0.7435
Epoch 41/100
2000/2000 [=====] - 2s 912us/step - loss: 0.7460 -
accuracy: 0.7500
Epoch 42/100
2000/2000 [=====] - 2s 869us/step - loss: 0.7506 -
accuracy: 0.7410
Epoch 43/100
2000/2000 [=====] - 2s 878us/step - loss: 0.7058 -
accuracy: 0.7515
Epoch 44/100
2000/2000 [=====] - 2s 886us/step - loss: 0.6827 -
accuracy: 0.7620
Epoch 45/100
2000/2000 [=====] - 2s 885us/step - loss: 0.6540 -
accuracy: 0.7715
Epoch 46/100
2000/2000 [=====] - 2s 886us/step - loss: 0.6767 -
accuracy: 0.7645
Epoch 47/100
2000/2000 [=====] - 2s 883us/step - loss: 0.6161 -

```

```

accuracy: 0.7880
Epoch 48/100
2000/2000 [=====] - 2s 898us/step - loss: 0.6803 -
accuracy: 0.7715
Epoch 49/100
2000/2000 [=====] - 2s 938us/step - loss: 0.6737 -
accuracy: 0.7675
Epoch 50/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.6390 -
accuracy: 0.7830
Epoch 51/100
2000/2000 [=====] - 2s 894us/step - loss: 0.6277 -
accuracy: 0.7915
Epoch 52/100
2000/2000 [=====] - 2s 854us/step - loss: 0.6583 -
accuracy: 0.7755
Epoch 53/100
2000/2000 [=====] - 2s 855us/step - loss: 0.6178 -
accuracy: 0.7880
Epoch 54/100
2000/2000 [=====] - 2s 844us/step - loss: 0.5641 -
accuracy: 0.8095
Epoch 55/100
2000/2000 [=====] - 2s 839us/step - loss: 0.5681 -
accuracy: 0.8045
Epoch 56/100
2000/2000 [=====] - 2s 852us/step - loss: 0.5861 -
accuracy: 0.7980
Epoch 57/100
2000/2000 [=====] - 2s 851us/step - loss: 0.5702 -
accuracy: 0.8055
Epoch 58/100
2000/2000 [=====] - 2s 856us/step - loss: 0.6220 -
accuracy: 0.7885
Epoch 59/100
2000/2000 [=====] - 2s 864us/step - loss: 0.5483 -
accuracy: 0.8085
Epoch 60/100
2000/2000 [=====] - 2s 855us/step - loss: 0.5028 -
accuracy: 0.8235
Epoch 61/100
2000/2000 [=====] - 2s 849us/step - loss: 0.4832 -
accuracy: 0.8315
Epoch 62/100
2000/2000 [=====] - 2s 846us/step - loss: 0.5437 -
accuracy: 0.8120
Epoch 63/100
2000/2000 [=====] - 2s 848us/step - loss: 0.5407 -

```

```

accuracy: 0.8175
Epoch 64/100
2000/2000 [=====] - 2s 860us/step - loss: 0.5417 -
accuracy: 0.8240
Epoch 65/100
2000/2000 [=====] - 2s 863us/step - loss: 0.5588 -
accuracy: 0.8105
Epoch 66/100
2000/2000 [=====] - 2s 861us/step - loss: 0.4595 -
accuracy: 0.8530
Epoch 67/100
2000/2000 [=====] - 2s 852us/step - loss: 0.4676 -
accuracy: 0.8365
Epoch 68/100
2000/2000 [=====] - 2s 848us/step - loss: 0.4443 -
accuracy: 0.8510
Epoch 69/100
2000/2000 [=====] - 2s 855us/step - loss: 0.4556 -
accuracy: 0.8395
Epoch 70/100
2000/2000 [=====] - 2s 902us/step - loss: 0.4938 -
accuracy: 0.8275
Epoch 71/100
2000/2000 [=====] - 2s 868us/step - loss: 0.4749 -
accuracy: 0.8430
Epoch 72/100
2000/2000 [=====] - 2s 867us/step - loss: 0.4462 -
accuracy: 0.8510
Epoch 73/100
2000/2000 [=====] - 2s 870us/step - loss: 0.4206 -
accuracy: 0.8530
Epoch 74/100
2000/2000 [=====] - 2s 884us/step - loss: 0.4645 -
accuracy: 0.8425
Epoch 75/100
2000/2000 [=====] - 2s 874us/step - loss: 0.4099 -
accuracy: 0.8655
Epoch 76/100
2000/2000 [=====] - 2s 840us/step - loss: 0.4463 -
accuracy: 0.8495
Epoch 77/100
2000/2000 [=====] - 2s 832us/step - loss: 0.4053 -
accuracy: 0.8695
Epoch 78/100
2000/2000 [=====] - 2s 850us/step - loss: 0.3804 -
accuracy: 0.8745
Epoch 79/100
2000/2000 [=====] - 2s 845us/step - loss: 0.4179 -

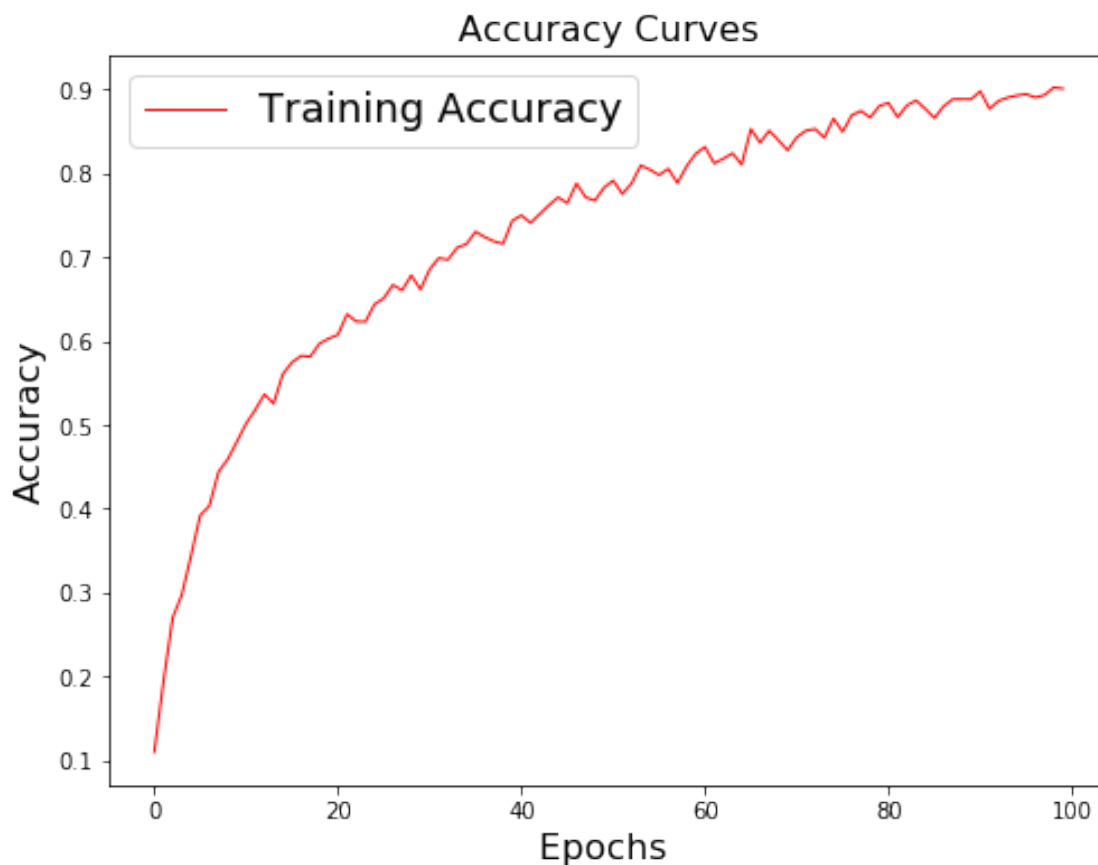
```

```

accuracy: 0.8665
Epoch 80/100
2000/2000 [=====] - 2s 841us/step - loss: 0.3642 -
accuracy: 0.8805
Epoch 81/100
2000/2000 [=====] - 2s 836us/step - loss: 0.3640 -
accuracy: 0.8840
Epoch 82/100
2000/2000 [=====] - 2s 846us/step - loss: 0.3795 -
accuracy: 0.8670
Epoch 83/100
2000/2000 [=====] - 2s 852us/step - loss: 0.3688 -
accuracy: 0.8810
Epoch 84/100
2000/2000 [=====] - 2s 869us/step - loss: 0.3296 -
accuracy: 0.8870
Epoch 85/100
2000/2000 [=====] - 2s 853us/step - loss: 0.3453 -
accuracy: 0.8770
Epoch 86/100
2000/2000 [=====] - 2s 850us/step - loss: 0.4187 -
accuracy: 0.8660
Epoch 87/100
2000/2000 [=====] - 2s 856us/step - loss: 0.3666 -
accuracy: 0.8800
Epoch 88/100
2000/2000 [=====] - 2s 866us/step - loss: 0.3456 -
accuracy: 0.8885
Epoch 89/100
2000/2000 [=====] - 2s 868us/step - loss: 0.3607 -
accuracy: 0.8885
Epoch 90/100
2000/2000 [=====] - 2s 867us/step - loss: 0.3411 -
accuracy: 0.8885
Epoch 91/100
2000/2000 [=====] - 2s 868us/step - loss: 0.3199 -
accuracy: 0.8980
Epoch 92/100
2000/2000 [=====] - 2s 874us/step - loss: 0.3638 -
accuracy: 0.8770
Epoch 93/100
2000/2000 [=====] - 2s 867us/step - loss: 0.3461 -
accuracy: 0.8865
Epoch 94/100
2000/2000 [=====] - 2s 870us/step - loss: 0.3559 -
accuracy: 0.8905
Epoch 95/100
2000/2000 [=====] - 2s 875us/step - loss: 0.3377 -

```

```
accuracy: 0.8930
Epoch 96/100
2000/2000 [=====] - 2s 880us/step - loss: 0.3310 -
accuracy: 0.8945
Epoch 97/100
2000/2000 [=====] - 2s 947us/step - loss: 0.3237 -
accuracy: 0.8905
Epoch 98/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.3168 -
accuracy: 0.8935
Epoch 99/100
2000/2000 [=====] - 2s 904us/step - loss: 0.3273 -
accuracy: 0.9025
Epoch 100/100
2000/2000 [=====] - 2s 866us/step - loss: 0.2955 -
accuracy: 0.9010
training model takes 195.464 seconds
```



```
[45]: t0 = time.time()
      pred = model.predict(test_data)
```

```

pred_lst = []
for i in range(len(pred)):
    arr = pred[i]
    idx = np.argwhere(arr == np.max(arr))
    pred_lst.append(idx[0][0])
tst_labl = np.argmax(test_label_cat, axis=-1)
acc = accuracy_score(pred_lst, tst_labl)
print("Test accuracy is %s percent" % round(acc*100,3))
print("testing model takes %s seconds" % round((time.time() - t0),3))

```

Test accuracy is 53.6 percent
testing model takes 0.144 seconds

second model

```

[18]: input_shape = [2450]
input_layer = Input(input_shape)
x = BatchNormalization(momentum = 0.88)(input_layer)
x = Dense(22*10,activation='relu',kernel_initializer=initializers.
    ↳glorot_normal(seed=4))(x)
x = Dropout(0.25)(x)
x = BatchNormalization()(x)
x = Dense(22*8,activation='relu',kernel_initializer=initializers.
    ↳glorot_normal(seed=4))(x)
x = Dropout(0.25)(x)
x = Dense(22*4,activation='relu',kernel_initializer=initializers.
    ↳glorot_normal(seed=4))(x)
x = Dropout(0.25)(x)
x = Dense(22*2,activation='relu',kernel_initializer=initializers.
    ↳glorot_normal(seed=4))(x)
output_layer = Dense(22,activation='softmax',kernel_initializer=initializers.
    ↳glorot_normal(seed=4))(x)
model2 = Model(input_layer,output_layer)

```

```

[19]: start_time = time.time()
model2.compile(loss='categorical_crossentropy',optimizer = Adam(lr=0.
    ↳001),metrics=['accuracy'])
model_his = model2.fit(X,Y,epochs=100)
plt.figure(figsize=[8,6])
plt.plot(model_his.history['accuracy'],'r',linewidth=1.0)
plt.legend(['Training Accuracy'],fontsize=18)
plt.xlabel('Epochs ',fontsize=16)
plt.ylabel('Accuracy',fontsize=16)
plt.title('Accuracy Curves',fontsize=16)
print("training model takes %s seconds" % round((time.time() - start_time),3))

```

Epoch 1/100

2000/2000 [=====] - 1s 690us/step - loss: 3.0590 -
 accuracy: 0.0815
 Epoch 2/100
 2000/2000 [=====] - 1s 399us/step - loss: 2.7153 -
 accuracy: 0.1690
 Epoch 3/100
 2000/2000 [=====] - 1s 413us/step - loss: 2.3441 -
 accuracy: 0.2405
 Epoch 4/100
 2000/2000 [=====] - 1s 409us/step - loss: 2.1477 -
 accuracy: 0.2965
 Epoch 5/100
 2000/2000 [=====] - 1s 445us/step - loss: 1.9895 -
 accuracy: 0.3360
 Epoch 6/100
 2000/2000 [=====] - 1s 415us/step - loss: 1.8939 -
 accuracy: 0.3710
 Epoch 7/100
 2000/2000 [=====] - 1s 399us/step - loss: 1.8041 -
 accuracy: 0.3915
 Epoch 8/100
 2000/2000 [=====] - 1s 399us/step - loss: 1.7150 -
 accuracy: 0.4380
 Epoch 9/100
 2000/2000 [=====] - 1s 395us/step - loss: 1.6383 -
 accuracy: 0.4565
 Epoch 10/100
 2000/2000 [=====] - 1s 433us/step - loss: 1.6166 -
 accuracy: 0.4625
 Epoch 11/100
 2000/2000 [=====] - 1s 406us/step - loss: 1.5693 -
 accuracy: 0.4705
 Epoch 12/100
 2000/2000 [=====] - 1s 408us/step - loss: 1.5100 -
 accuracy: 0.4810
 Epoch 13/100
 2000/2000 [=====] - 1s 404us/step - loss: 1.4937 -
 accuracy: 0.4740
 Epoch 14/100
 2000/2000 [=====] - 1s 416us/step - loss: 1.4503 -
 accuracy: 0.5055
 Epoch 15/100
 2000/2000 [=====] - 1s 415us/step - loss: 1.3912 -
 accuracy: 0.5140
 Epoch 16/100
 2000/2000 [=====] - 1s 407us/step - loss: 1.3669 -
 accuracy: 0.5355
 Epoch 17/100

2000/2000 [=====] - 1s 424us/step - loss: 1.3558 -
 accuracy: 0.5405
 Epoch 18/100
 2000/2000 [=====] - 1s 396us/step - loss: 1.3229 -
 accuracy: 0.5545
 Epoch 19/100
 2000/2000 [=====] - 1s 408us/step - loss: 1.3107 -
 accuracy: 0.5550
 Epoch 20/100
 2000/2000 [=====] - 1s 432us/step - loss: 1.3305 -
 accuracy: 0.5415
 Epoch 21/100
 2000/2000 [=====] - 1s 462us/step - loss: 1.2595 -
 accuracy: 0.5740
 Epoch 22/100
 2000/2000 [=====] - 1s 408us/step - loss: 1.2346 -
 accuracy: 0.5710
 Epoch 23/100
 2000/2000 [=====] - 1s 409us/step - loss: 1.1947 -
 accuracy: 0.5960
 Epoch 24/100
 2000/2000 [=====] - 1s 423us/step - loss: 1.1987 -
 accuracy: 0.6010
 Epoch 25/100
 2000/2000 [=====] - 1s 438us/step - loss: 1.1820 -
 accuracy: 0.5935
 Epoch 26/100
 2000/2000 [=====] - 1s 432us/step - loss: 1.1559 -
 accuracy: 0.5955
 Epoch 27/100
 2000/2000 [=====] - 1s 418us/step - loss: 1.1476 -
 accuracy: 0.6075
 Epoch 28/100
 2000/2000 [=====] - 1s 420us/step - loss: 1.1151 -
 accuracy: 0.6210
 Epoch 29/100
 2000/2000 [=====] - 1s 408us/step - loss: 1.1068 -
 accuracy: 0.6195
 Epoch 30/100
 2000/2000 [=====] - 1s 420us/step - loss: 1.0692 -
 accuracy: 0.6355
 Epoch 31/100
 2000/2000 [=====] - 1s 421us/step - loss: 1.0720 -
 accuracy: 0.6355
 Epoch 32/100
 2000/2000 [=====] - 1s 413us/step - loss: 1.0374 -
 accuracy: 0.6410
 Epoch 33/100

2000/2000 [=====] - 1s 438us/step - loss: 1.0714 -
 accuracy: 0.6415
 Epoch 34/100
 2000/2000 [=====] - 1s 443us/step - loss: 1.0232 -
 accuracy: 0.6420
 Epoch 35/100
 2000/2000 [=====] - 1s 440us/step - loss: 1.0210 -
 accuracy: 0.6475
 Epoch 36/100
 2000/2000 [=====] - 1s 422us/step - loss: 0.9603 -
 accuracy: 0.6670
 Epoch 37/100
 2000/2000 [=====] - 1s 408us/step - loss: 0.9819 -
 accuracy: 0.6570
 Epoch 38/100
 2000/2000 [=====] - 1s 405us/step - loss: 0.9750 -
 accuracy: 0.6775
 Epoch 39/100
 2000/2000 [=====] - 1s 429us/step - loss: 0.9673 -
 accuracy: 0.6660
 Epoch 40/100
 2000/2000 [=====] - 1s 422us/step - loss: 0.9188 -
 accuracy: 0.6805
 Epoch 41/100
 2000/2000 [=====] - 1s 409us/step - loss: 0.9627 -
 accuracy: 0.6725
 Epoch 42/100
 2000/2000 [=====] - 1s 414us/step - loss: 0.9577 -
 accuracy: 0.6600
 Epoch 43/100
 2000/2000 [=====] - 1s 422us/step - loss: 0.9035 -
 accuracy: 0.6880
 Epoch 44/100
 2000/2000 [=====] - 1s 416us/step - loss: 0.8769 -
 accuracy: 0.7005
 Epoch 45/100
 2000/2000 [=====] - 1s 418us/step - loss: 0.8466 -
 accuracy: 0.7080
 Epoch 46/100
 2000/2000 [=====] - 1s 447us/step - loss: 0.8414 -
 accuracy: 0.7130
 Epoch 47/100
 2000/2000 [=====] - 1s 413us/step - loss: 0.7949 -
 accuracy: 0.7265
 Epoch 48/100
 2000/2000 [=====] - 1s 420us/step - loss: 0.8681 -
 accuracy: 0.7010
 Epoch 49/100

2000/2000 [=====] - 1s 430us/step - loss: 0.8371 -
 accuracy: 0.7085
 Epoch 50/100
 2000/2000 [=====] - 1s 424us/step - loss: 0.8439 -
 accuracy: 0.7135
 Epoch 51/100
 2000/2000 [=====] - 1s 429us/step - loss: 0.7993 -
 accuracy: 0.7280
 Epoch 52/100
 2000/2000 [=====] - 1s 424us/step - loss: 0.7692 -
 accuracy: 0.7305
 Epoch 53/100
 2000/2000 [=====] - 1s 467us/step - loss: 0.7951 -
 accuracy: 0.7260
 Epoch 54/100
 2000/2000 [=====] - 1s 441us/step - loss: 0.8462 -
 accuracy: 0.7055
 Epoch 55/100
 2000/2000 [=====] - 1s 435us/step - loss: 0.8228 -
 accuracy: 0.7230
 Epoch 56/100
 2000/2000 [=====] - 1s 424us/step - loss: 0.7397 -
 accuracy: 0.7460
 Epoch 57/100
 2000/2000 [=====] - 1s 440us/step - loss: 0.7218 -
 accuracy: 0.7495
 Epoch 58/100
 2000/2000 [=====] - 1s 437us/step - loss: 0.6724 -
 accuracy: 0.7770
 Epoch 59/100
 2000/2000 [=====] - 1s 426us/step - loss: 0.7428 -
 accuracy: 0.7425
 Epoch 60/100
 2000/2000 [=====] - 1s 433us/step - loss: 0.7412 -
 accuracy: 0.7470
 Epoch 61/100
 2000/2000 [=====] - 1s 433us/step - loss: 0.6528 -
 accuracy: 0.7785
 Epoch 62/100
 2000/2000 [=====] - 1s 432us/step - loss: 0.7069 -
 accuracy: 0.7575
 Epoch 63/100
 2000/2000 [=====] - 1s 438us/step - loss: 0.6897 -
 accuracy: 0.7610
 Epoch 64/100
 2000/2000 [=====] - 1s 426us/step - loss: 0.7245 -
 accuracy: 0.7550
 Epoch 65/100

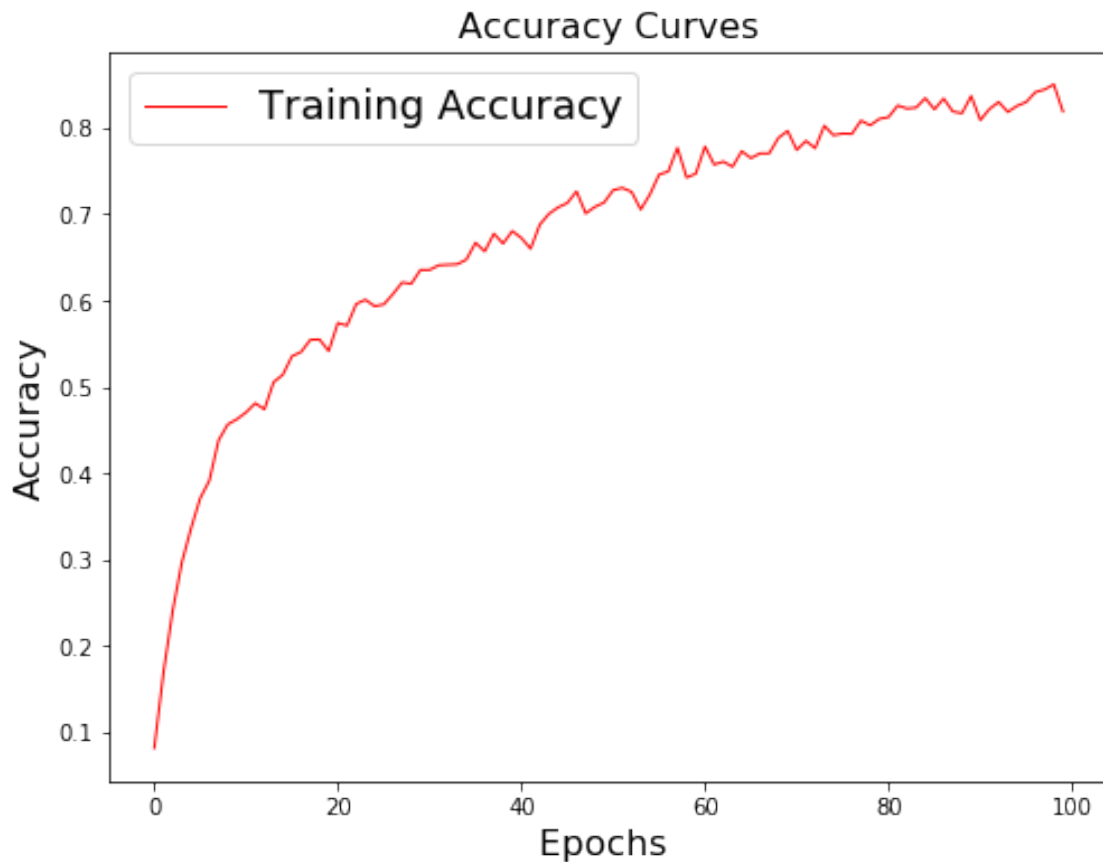
2000/2000 [=====] - 1s 449us/step - loss: 0.6653 -
 accuracy: 0.7730
 Epoch 66/100
 2000/2000 [=====] - 1s 438us/step - loss: 0.6764 -
 accuracy: 0.7650
 Epoch 67/100
 2000/2000 [=====] - 1s 430us/step - loss: 0.6674 -
 accuracy: 0.7705
 Epoch 68/100
 2000/2000 [=====] - 1s 435us/step - loss: 0.6639 -
 accuracy: 0.7705
 Epoch 69/100
 2000/2000 [=====] - 1s 430us/step - loss: 0.6315 -
 accuracy: 0.7885
 Epoch 70/100
 2000/2000 [=====] - 1s 432us/step - loss: 0.6171 -
 accuracy: 0.7965
 Epoch 71/100
 2000/2000 [=====] - 1s 429us/step - loss: 0.6642 -
 accuracy: 0.7745
 Epoch 72/100
 2000/2000 [=====] - 1s 423us/step - loss: 0.6131 -
 accuracy: 0.7850
 Epoch 73/100
 2000/2000 [=====] - 1s 438us/step - loss: 0.6445 -
 accuracy: 0.7765
 Epoch 74/100
 2000/2000 [=====] - 1s 426us/step - loss: 0.5957 -
 accuracy: 0.8025
 Epoch 75/100
 2000/2000 [=====] - 1s 441us/step - loss: 0.6373 -
 accuracy: 0.7915
 Epoch 76/100
 2000/2000 [=====] - 1s 439us/step - loss: 0.6218 -
 accuracy: 0.7935
 Epoch 77/100
 2000/2000 [=====] - 1s 450us/step - loss: 0.6312 -
 accuracy: 0.7930
 Epoch 78/100
 2000/2000 [=====] - 1s 406us/step - loss: 0.5746 -
 accuracy: 0.8085
 Epoch 79/100
 2000/2000 [=====] - 1s 427us/step - loss: 0.5848 -
 accuracy: 0.8030
 Epoch 80/100
 2000/2000 [=====] - 1s 741us/step - loss: 0.5477 -
 accuracy: 0.8105
 Epoch 81/100

2000/2000 [=====] - 1s 741us/step - loss: 0.5349 -
 accuracy: 0.8125
 Epoch 82/100
 2000/2000 [=====] - 1s 651us/step - loss: 0.5381 -
 accuracy: 0.8260
 Epoch 83/100
 2000/2000 [=====] - 1s 605us/step - loss: 0.5320 -
 accuracy: 0.8225
 Epoch 84/100
 2000/2000 [=====] - 1s 707us/step - loss: 0.5029 -
 accuracy: 0.8235
 Epoch 85/100
 2000/2000 [=====] - 1s 669us/step - loss: 0.5050 -
 accuracy: 0.8345
 Epoch 86/100
 2000/2000 [=====] - 1s 599us/step - loss: 0.5244 -
 accuracy: 0.8215
 Epoch 87/100
 2000/2000 [=====] - 1s 549us/step - loss: 0.4986 -
 accuracy: 0.8340
 Epoch 88/100
 2000/2000 [=====] - 1s 527us/step - loss: 0.5296 -
 accuracy: 0.8190
 Epoch 89/100
 2000/2000 [=====] - 1s 601us/step - loss: 0.5135 -
 accuracy: 0.8170
 Epoch 90/100
 2000/2000 [=====] - 1s 638us/step - loss: 0.4818 -
 accuracy: 0.8370
 Epoch 91/100
 2000/2000 [=====] - 1s 510us/step - loss: 0.5363 -
 accuracy: 0.8090
 Epoch 92/100
 2000/2000 [=====] - 1s 639us/step - loss: 0.5282 -
 accuracy: 0.8220
 Epoch 93/100
 2000/2000 [=====] - 1s 656us/step - loss: 0.5103 -
 accuracy: 0.8300
 Epoch 94/100
 2000/2000 [=====] - 1s 645us/step - loss: 0.5158 -
 accuracy: 0.8185
 Epoch 95/100
 2000/2000 [=====] - 1s 507us/step - loss: 0.5069 -
 accuracy: 0.8255
 Epoch 96/100
 2000/2000 [=====] - 1s 604us/step - loss: 0.5065 -
 accuracy: 0.8300
 Epoch 97/100

```

2000/2000 [=====] - 1s 558us/step - loss: 0.4514 -
accuracy: 0.8415
Epoch 98/100
2000/2000 [=====] - 1s 510us/step - loss: 0.4713 -
accuracy: 0.8445
Epoch 99/100
2000/2000 [=====] - 1s 533us/step - loss: 0.4496 -
accuracy: 0.8505
Epoch 100/100
2000/2000 [=====] - 1s 368us/step - loss: 0.5042 -
accuracy: 0.8190
training model takes 94.409 seconds

```



```

[43]: t0 = time.time()
pred2 = model2.predict(test_data)
pred_lst2 = []
for i in range(len(pred2)):
    arr = pred2[i]
    idx = np.argmax(arr)
    pred_lst2.append(idx)

```

```
tst_labl = np.argmax(test_label_cat, axis=-1)
acc = accuracy_score(pred_lst2, tst_labl)
print("Test accuracy is %s percent" % round(acc*100,3))
print("testing model takes %s seconds" % round((time.time() - t0),3))
```

Test accuracy is 56.4 percent
testing model takes 0.179 seconds

third model

```
[21]: input_shape = [2450]
input_layer = Input(input_shape)
x = BatchNormalization(momentum = 0.88)(input_layer)
x = Dense(22*20,activation='relu',kernel_initializer=initializers.
    ↳glorot_normal(seed=4))(x)
x = Dropout(0.25)(x)
x = BatchNormalization()(x)
x = Dense(22*10,activation='relu',kernel_initializer=initializers.
    ↳glorot_normal(seed=4))(x)
x = Dropout(0.25)(x)
x = Dense(22*6,activation='relu',kernel_initializer=initializers.
    ↳glorot_normal(seed=4))(x)
x = Dropout(0.25)(x)
x = Dense(22*2,activation='relu',kernel_initializer=initializers.
    ↳glorot_normal(seed=4))(x)
output_layer = Dense(22,activation='softmax',kernel_initializer=initializers.
    ↳glorot_normal(seed=4))(x)
model3 = Model(input_layer,output_layer)
```

```
[22]: start_time = time.time()
model3.compile(loss='categorical_crossentropy',optimizer = Adam(lr=0.
    ↳001),metrics=['accuracy'])
model_hist = model3.fit(X,Y,epochs=100)
plt.figure(figsize=[8,6])
plt.plot(model_hist.history['accuracy'],'r',linewidth=1.0)
plt.legend(['Training Accuracy'],fontsize=18)
plt.xlabel('Epochs ',fontsize=16)
plt.ylabel('Accuracy',fontsize=16)
plt.title('Accuracy Curves',fontsize=16)
print("training model takes %s seconds" % round((time.time() - start_time),3))
```

Epoch 1/100

2000/2000 [=====] - 2s 1ms/step - loss: 2.9908 -
accuracy: 0.0975

Epoch 2/100

2000/2000 [=====] - 1s 750us/step - loss: 2.6035 -
accuracy: 0.2020

Epoch 3/100
2000/2000 [=====] - 2s 1ms/step - loss: 2.2965 -
accuracy: 0.2825

Epoch 4/100
2000/2000 [=====] - 2s 1ms/step - loss: 2.0985 -
accuracy: 0.3215

Epoch 5/100
2000/2000 [=====] - 3s 1ms/step - loss: 1.9475 -
accuracy: 0.3640

Epoch 6/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.8338 -
accuracy: 0.3995

Epoch 7/100
2000/2000 [=====] - 4s 2ms/step - loss: 1.7790 -
accuracy: 0.4050

Epoch 8/100
2000/2000 [=====] - 3s 1ms/step - loss: 1.6514 -
accuracy: 0.4510

Epoch 9/100
2000/2000 [=====] - 3s 1ms/step - loss: 1.5575 -
accuracy: 0.4695

Epoch 10/100
2000/2000 [=====] - 3s 1ms/step - loss: 1.5226 -
accuracy: 0.4700

Epoch 11/100
2000/2000 [=====] - 3s 2ms/step - loss: 1.4856 -
accuracy: 0.4965

Epoch 12/100
2000/2000 [=====] - 3s 1ms/step - loss: 1.4759 -
accuracy: 0.4970

Epoch 13/100
2000/2000 [=====] - 3s 1ms/step - loss: 1.4046 -
accuracy: 0.5185

Epoch 14/100
2000/2000 [=====] - 3s 2ms/step - loss: 1.2936 -
accuracy: 0.5600

Epoch 15/100
2000/2000 [=====] - 3s 2ms/step - loss: 1.3201 -
accuracy: 0.5510

Epoch 16/100
2000/2000 [=====] - 3s 1ms/step - loss: 1.3237 -
accuracy: 0.5535

Epoch 17/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.1766 -
accuracy: 0.5985

Epoch 18/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.2648 -
accuracy: 0.5560

Epoch 19/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.1955 -
accuracy: 0.5905: 0s - loss: 1.1955 - accuracy: 0.59

Epoch 20/100
2000/2000 [=====] - 3s 1ms/step - loss: 1.1674 -
accuracy: 0.6080

Epoch 21/100
2000/2000 [=====] - 2s 1ms/step - loss: 1.1315 -
accuracy: 0.6115

Epoch 22/100
2000/2000 [=====] - 2s 953us/step - loss: 1.0826 -
accuracy: 0.62051s

Epoch 23/100
2000/2000 [=====] - 2s 787us/step - loss: 1.0949 -
accuracy: 0.6255

Epoch 24/100
2000/2000 [=====] - 1s 734us/step - loss: 1.0493 -
accuracy: 0.6390

Epoch 25/100
2000/2000 [=====] - 1s 728us/step - loss: 1.0591 -
accuracy: 0.6330

Epoch 26/100
2000/2000 [=====] - 1s 730us/step - loss: 1.0335 -
accuracy: 0.6525

Epoch 27/100
2000/2000 [=====] - 1s 746us/step - loss: 1.0075 -
accuracy: 0.6450

Epoch 28/100
2000/2000 [=====] - 1s 730us/step - loss: 0.9678 -
accuracy: 0.6720

Epoch 29/100
2000/2000 [=====] - 2s 918us/step - loss: 1.0129 -
accuracy: 0.6520

Epoch 30/100
2000/2000 [=====] - 2s 901us/step - loss: 0.9687 -
accuracy: 0.6595

Epoch 31/100
2000/2000 [=====] - 2s 955us/step - loss: 0.9172 -
accuracy: 0.6895

Epoch 32/100
2000/2000 [=====] - 2s 832us/step - loss: 0.9052 -
accuracy: 0.6865

Epoch 33/100
2000/2000 [=====] - 2s 913us/step - loss: 0.8806 -
accuracy: 0.6930

Epoch 34/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.8464 -
accuracy: 0.7075

Epoch 35/100
2000/2000 [=====] - 2s 857us/step - loss: 0.8443 -
accuracy: 0.7110

Epoch 36/100
2000/2000 [=====] - 2s 953us/step - loss: 0.7887 -
accuracy: 0.7200

Epoch 37/100
2000/2000 [=====] - 2s 750us/step - loss: 0.8209 -
accuracy: 0.7155

Epoch 38/100
2000/2000 [=====] - 2s 841us/step - loss: 0.8098 -
accuracy: 0.7225

Epoch 39/100
2000/2000 [=====] - 2s 810us/step - loss: 0.7952 -
accuracy: 0.7385

Epoch 40/100
2000/2000 [=====] - 2s 750us/step - loss: 0.7986 -
accuracy: 0.7315

Epoch 41/100
2000/2000 [=====] - 1s 726us/step - loss: 0.7655 -
accuracy: 0.7325

Epoch 42/100
2000/2000 [=====] - 2s 883us/step - loss: 0.7523 -
accuracy: 0.7440

Epoch 43/100
2000/2000 [=====] - 2s 844us/step - loss: 0.7324 -
accuracy: 0.7520

Epoch 44/100
2000/2000 [=====] - 2s 879us/step - loss: 0.7128 -
accuracy: 0.75950s - loss: 0.7036 - accuracy: 0.

Epoch 45/100
2000/2000 [=====] - 2s 847us/step - loss: 0.7191 -
accuracy: 0.7440

Epoch 46/100
2000/2000 [=====] - 2s 851us/step - loss: 0.7354 -
accuracy: 0.7630

Epoch 47/100
2000/2000 [=====] - 2s 865us/step - loss: 0.6836 -
accuracy: 0.7585

Epoch 48/100
2000/2000 [=====] - 2s 833us/step - loss: 0.6988 -
accuracy: 0.7605

Epoch 49/100
2000/2000 [=====] - 2s 881us/step - loss: 0.6303 -
accuracy: 0.7825

Epoch 50/100
2000/2000 [=====] - 2s 892us/step - loss: 0.6538 -
accuracy: 0.7740

Epoch 51/100
2000/2000 [=====] - 2s 827us/step - loss: 0.5883 -
accuracy: 0.7965

Epoch 52/100
2000/2000 [=====] - 2s 849us/step - loss: 0.6166 -
accuracy: 0.7840

Epoch 53/100
2000/2000 [=====] - 2s 981us/step - loss: 0.6008 -
accuracy: 0.7890

Epoch 54/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.6245 -
accuracy: 0.7865

Epoch 55/100
2000/2000 [=====] - 1s 746us/step - loss: 0.6091 -
accuracy: 0.7845

Epoch 56/100
2000/2000 [=====] - 1s 710us/step - loss: 0.6098 -
accuracy: 0.7895

Epoch 57/100
2000/2000 [=====] - 1s 690us/step - loss: 0.6251 -
accuracy: 0.7945

Epoch 58/100
2000/2000 [=====] - 1s 693us/step - loss: 0.6090 -
accuracy: 0.7895

Epoch 59/100
2000/2000 [=====] - 1s 695us/step - loss: 0.5603 -
accuracy: 0.8025

Epoch 60/100
2000/2000 [=====] - 2s 933us/step - loss: 0.5294 -
accuracy: 0.8190

Epoch 61/100
2000/2000 [=====] - 2s 898us/step - loss: 0.5618 -
accuracy: 0.8115

Epoch 62/100
2000/2000 [=====] - 2s 924us/step - loss: 0.5549 -
accuracy: 0.8155

Epoch 63/100
2000/2000 [=====] - 2s 831us/step - loss: 0.5232 -
accuracy: 0.8195

Epoch 64/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.5062 -
accuracy: 0.8235

Epoch 65/100
2000/2000 [=====] - 2s 876us/step - loss: 0.4977 -
accuracy: 0.8350

Epoch 66/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.5203 -
accuracy: 0.8085

Epoch 67/100
2000/2000 [=====] - 2s 755us/step - loss: 0.4724 -
accuracy: 0.8420

Epoch 68/100
2000/2000 [=====] - 2s 907us/step - loss: 0.5018 -
accuracy: 0.8340

Epoch 69/100
2000/2000 [=====] - 2s 912us/step - loss: 0.4772 -
accuracy: 0.8345

Epoch 70/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.4488 -
accuracy: 0.8450

Epoch 71/100
2000/2000 [=====] - 2s 952us/step - loss: 0.4805 -
accuracy: 0.8400

Epoch 72/100
2000/2000 [=====] - 2s 876us/step - loss: 0.4579 -
accuracy: 0.8445

Epoch 73/100
2000/2000 [=====] - 2s 834us/step - loss: 0.4257 -
accuracy: 0.8485

Epoch 74/100
2000/2000 [=====] - 3s 2ms/step - loss: 0.4421 -
accuracy: 0.8625

Epoch 75/100
2000/2000 [=====] - 3s 1ms/step - loss: 0.3868 -
accuracy: 0.8620

Epoch 76/100
2000/2000 [=====] - 3s 1ms/step - loss: 0.4789 -
accuracy: 0.8445

Epoch 77/100
2000/2000 [=====] - 3s 1ms/step - loss: 0.4521 -
accuracy: 0.8500

Epoch 78/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.4047 -
accuracy: 0.8590

Epoch 79/100
2000/2000 [=====] - 3s 1ms/step - loss: 0.4047 -
accuracy: 0.8605

Epoch 80/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.4193 -
accuracy: 0.8660

Epoch 81/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.4102 -
accuracy: 0.8620

Epoch 82/100
2000/2000 [=====] - 3s 2ms/step - loss: 0.3858 -
accuracy: 0.8700

Epoch 83/100
2000/2000 [=====] - 3s 2ms/step - loss: 0.3721 -
accuracy: 0.8720

Epoch 84/100
2000/2000 [=====] - 3s 1ms/step - loss: 0.3919 -
accuracy: 0.8605

Epoch 85/100
2000/2000 [=====] - 3s 1ms/step - loss: 0.3791 -
accuracy: 0.8710

Epoch 86/100
2000/2000 [=====] - 3s 1ms/step - loss: 0.3732 -
accuracy: 0.8710

Epoch 87/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.3738 -
accuracy: 0.8720

Epoch 88/100
2000/2000 [=====] - 3s 1ms/step - loss: 0.3500 -
accuracy: 0.8830

Epoch 89/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.3251 -
accuracy: 0.8945

Epoch 90/100
2000/2000 [=====] - 2s 931us/step - loss: 0.3979 -
accuracy: 0.8670

Epoch 91/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.3487 -
accuracy: 0.8795

Epoch 92/100
2000/2000 [=====] - 2s 890us/step - loss: 0.3731 -
accuracy: 0.8750

Epoch 93/100
2000/2000 [=====] - 3s 1ms/step - loss: 0.4100 -
accuracy: 0.8650

Epoch 94/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.3546 -
accuracy: 0.8755

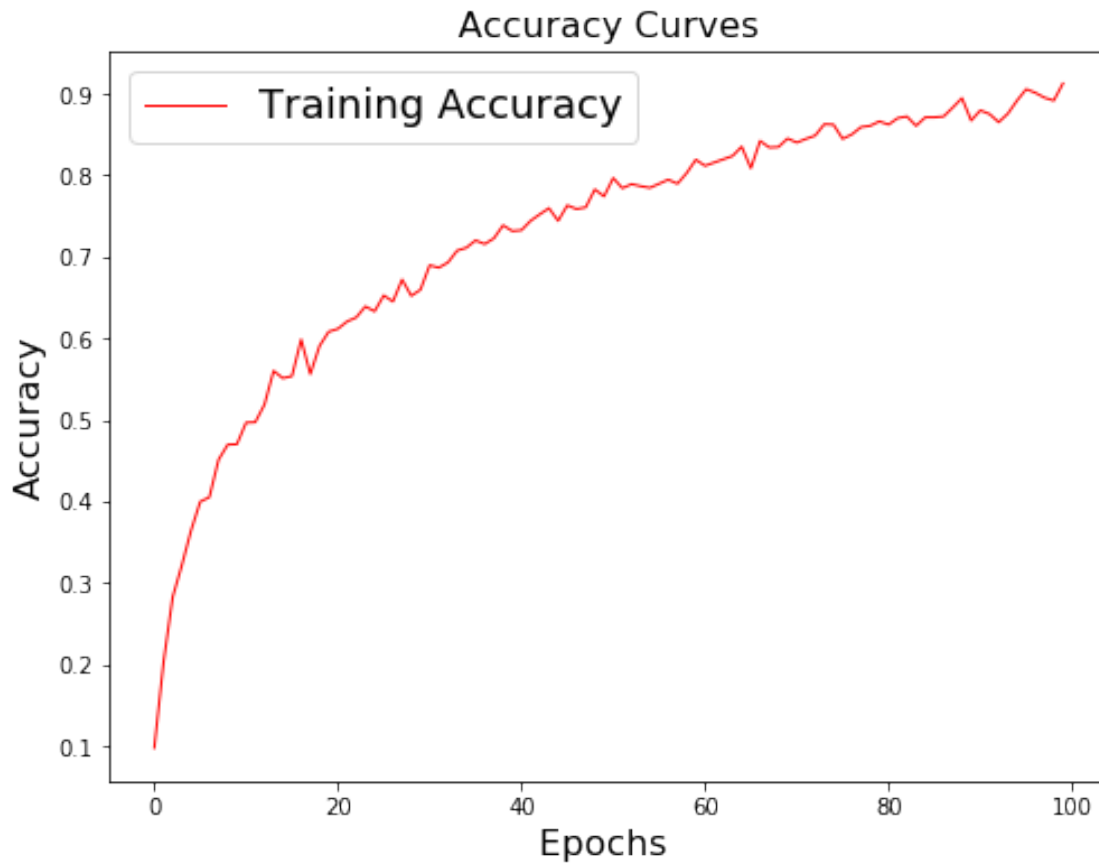
Epoch 95/100
2000/2000 [=====] - 2s 1ms/step - loss: 0.3288 -
accuracy: 0.8915

Epoch 96/100
2000/2000 [=====] - 3s 1ms/step - loss: 0.2954 -
accuracy: 0.9055

Epoch 97/100
2000/2000 [=====] - 3s 2ms/step - loss: 0.2969 -
accuracy: 0.9010

Epoch 98/100
2000/2000 [=====] - 3s 1ms/step - loss: 0.3132 -
accuracy: 0.8950

Epoch 99/100
2000/2000 [=====] - 3s 1ms/step - loss: 0.3239 -
accuracy: 0.8915
Epoch 100/100
2000/2000 [=====] - 2s 960us/step - loss: 0.2765 -
accuracy: 0.9125
training model takes 215.43 seconds



```
[44]: t0 = time.time()
pred3 = model3.predict(test_data)
pred_lst3 = []
for i in range(len(pred3)):
    arr = pred3[i]
    idx = np.argwhere(arr == np.max(arr))
    pred_lst3.append(idx[0][0])
tst_labl = np.argmax(test_label_cat, axis=-1)

acc = accuracy_score(pred_lst3, tst_labl)
print("Test accuracy is %s percent" % round(acc*100,3))
print("testing model takes %s seconds" % round((time.time() - t0),3))
```

Test accuracy is 55.6 percent
testing model takes 0.17 seconds

Since second model gives the highest test accuracy among three, so decides to use this on the presentation day.

0.0.7 Run the testing data - using model2 in NN

```
[24]: tst_root = sys.path[0]
test_dir = os.path.join(tst_root, '../data/test_set_sec2')
test_path = os.path.join(test_dir, "labels_prediction.csv")
test_index = pd.read_csv(test_path)
test_pt_dir = os.path.join(test_dir, 'points' )
```

```
[25]: # read mat file and store coordinates in mat
m_test = []
for idx in test_index['Index']:
    file = "%04d.mat"%(idx)
    m_test.append( scipy.io.loadmat( os.path.join( test_pt_dir, file ) ))
```

```
[26]: mat_test = [x[[i for i in x.keys() if not i in ['__header__', '__version__',
↳ '__globals__']][0]] for x in m_test]
```

```
[27]: to_test_data = pairwise_dist_cal_updt(mat_test)
# choose model2
```

feature constructions takes 30.239994049072266 seconds

```
[28]: t0 = time.time()
pred_test = model2.predict(to_test_data)
pred_test_lst = []
for i in range(len(pred_test)):
    arr = pred_test[i]
    idx = np.argmax(arr == np.max(arr))
    pred_test_lst.append(idx[0][0])
print("testing model takes %s seconds" % round((time.time() - t0),3))
```

testing model takes 0.315 seconds

```
[29]: final_pred = pd.DataFrame([1+x for x in pred_test_lst]).to_csv("../output/
↳ final_model.csv",index=False)
```

```
[ ]:
```