# HW3

# November 19, 2021

```
[1]: import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     import tensorflow as tf
     import cv2
     import statistics as sts
     import warnings
     warnings.filterwarnings('ignore')
     from time import time
[2]: train_df = pd.read_csv('/content/drive/MyDrive/Homework3/Q1_Train_Data.csv')
     test_df = pd.read_csv('/content/drive/MyDrive/Homework3/Q1_Test_Data.csv')
     validation_df = pd.read_csv('/content/drive/MyDrive/Homework3/Q1_Validation_Data.
      ⇔csv')
[3]: emotions = {'angry':0, 'disgust':1, 'fear':2, 'happy':3,
                 'sad':4, 'surprise':5, 'neutral':6}
[4]: | train_angry_df = train_df.loc[train_df['emotion'] == 0]
     train_angry_df = train_angry_df.reset_index(drop = True)
     train_disgust_df = train_df.loc[train_df['emotion'] == 1]
     train_disgust_df = train_disgust_df.reset_index(drop = True)
     train_fear_df = train_df.loc[train_df['emotion'] == 2]
     train_fear_df = train_fear_df.reset_index(drop = True)
     train_happy_df = train_df.loc[train_df['emotion'] == 3]
     train_happy_df = train_happy_df.reset_index(drop = True)
     train_sad_df = train_df.loc[train_df['emotion'] == 4]
     train_sad_df = train_sad_df.reset_index(drop = True)
     train_surprise_df = train_df.loc[train_df['emotion'] == 5]
     train_surprise_df = train_surprise_df.reset_index(drop = True)
```

```
train_neutral_df = train_df.loc[train_df['emotion'] == 6]
     train_neutral_df = train_neutral_df.reset_index(drop = True)
[5]: | images = [train_angry_df['pixels'][0], train_angry_df['pixels'][1],
               train_disgust_df['pixels'][0], train_disgust_df['pixels'][1],
               train_fear_df['pixels'][0], train_fear_df['pixels'][1],
               train_happy_df['pixels'][0], train_happy_df['pixels'][1],
               train_sad_df['pixels'][0], train_sad_df['pixels'][1],
               train_surprise_df['pixels'][0], train_surprise_df['pixels'][1],
               train_neutral_df['pixels'][0], train_neutral_df['pixels'][1]]
[6]: def process_image(image_str):
       img_flat = image_str.split()
       img_flat = list(map(lambda x: float(x), img_flat))
       mean = sts.mean(img_flat)
       stdev = sts.stdev(img_flat)
       img_arr = np.asarray(img_flat)
       img_arr = (img_arr - mean)/ max(stdev, 1/np.sqrt(48*48))
       img = img_arr.reshape(48, 48)
       return img
[7]: # reading images
     images = [process_image(image) for image in images]
[8]: fig = plt.figure(figsize=(6, 24))
     # setting values to rows and column variables
     rows = 7
     columns = 2
     for i, image in enumerate(images):
       fig.add_subplot(rows, columns, i+1)
       plt.imshow(image, cmap = 'gray', aspect = 'auto')
      plt.axis('off')
       if i\%2 == 0:
         emotion = list(emotions.keys())[i//2]
       plt.title('{}'.format(emotion))
```



**a.** Two images per class is displayed above.

```
[9]: print("Number of samples for angry emotion = {}". format(len(train_angry_df)))
      print("Number of samples for disgust emotion = {}".__
       →format(len(train_disgust_df)))
      print("Number of samples for fear emotion = {}". format(len(train_fear_df)))
      print("Number of samples for happy emotion = {}". format(len(train_happy_df)))
      print("Number of samples for sad emotion = {}". format(len(train_sad_df)))
      print("Number of samples for surprise emotion = {}".__
       →format(len(train_surprise_df)))
      print("Number of samples for neutral emotion = {}"._
       →format(len(train_neutral_df)))
     Number of samples for angry emotion = 3995
     Number of samples for disgust emotion = 436
     Number of samples for fear emotion = 4097
     Number of samples for happy emotion = 7215
     Number of samples for sad emotion = 4830
     Number of samples for surprise emotion = 3171
     Number of samples for neutral emotion = 4965
     b. number of samples per emotion is listed below
        • Angry: 3995
        • Disgust: 436
        • Fear: 4097
        • Happy: 7215
        • Sad: 4830
        • Surprise: 3171
        • Neutral: 4965
[10]: | X_train = np.asarray([process_image(X) for X in list(train_df['pixels'])])
      X_train.shape
[10]: (28709, 48, 48)
[11]: |y_train = [tf.keras.utils.to_categorical(y, num_classes = 7, dtype = "float32")__
       →for y in list(train_df['emotion'])]
      y_train = np.asarray(y_train)
      y_train.shape
[11]: (28709, 7)
[12]: X_val = np.asarray([process_image(X) for X in list(validation_df['pixels'])])
      X_val.shape
[12]: (3589, 48, 48)
```

```
[13]: |y_val = [tf.keras.utils.to_categorical(y, num_classes = 7, dtype = "float32")__
       →for y in list(validation_df['emotion'])]
      y_val = np.asarray(y_val)
      y_val.shape
[13]: (3589, 7)
[14]: X_test = np.asarray([process_image(X) for X in list(test_df['pixels'])])
      X_test.shape
[14]: (3589, 48, 48)
[15]: y_test = [tf.keras.utils.to_categorical(y, num_classes = 7, dtype = "float32")_
       →for y in list(test_df['emotion'])]
      y_test = np.asarray(y_test)
      y_test.shape
[15]: (3589, 7)
[16]: X_train_fnn = X_train.reshape(-1, 2304)
      X_{val_fnn} = X_{val.reshape(-1, 2304)}
      X_test_fnn = X_test.reshape(-1, 2304)
[17]: import keras
      from keras.models import Sequential
      from keras.layers import Dense
      from keras.layers import Dropout
      from keras.callbacks import ModelCheckpoint
      from keras import regularizers
[18]: # Neural network
      fnn_model1 = Sequential()
      fnn_model1.add(Dense(128, input_dim = 2304, kernel_regularizer = regularizers.
       \hookrightarrow12(12=0.01), activation = 'relu'))
      fnn_model1.add(Dense(64, kernel_regularizer = regularizers.12(12=0.01),
       →activation= 'relu'))
      fnn_model1.add(Dense(32, kernel_regularizer = regularizers.12(12=0.01),
       →activation = 'relu'))
      fnn_model1.add(Dense(7, activation = 'softmax'))
 []: fnn_checkpoint1 = ModelCheckpoint("best_fnn_model1.hdf5", monitor = 'val_loss',__
       \rightarrowverbose = 1,
                                         save_best_only = True, mode =' min', period =__
       →1)
[20]: optimizer = tf.keras.optimizers.Adam(learning_rate = 0.001)
```

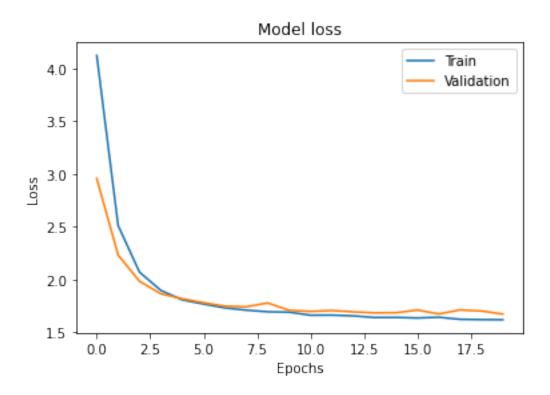
```
→metrics = ['accuracy'])
[21]: start = time()
   history_fnn1 = fnn_model1.fit(X_train_fnn, y_train,
                validation_data = (X_val_fnn, y_val),
                epochs = 20, batch_size = 512,
                validation_batch_size = 512,
                callbacks=[fnn_checkpoint1])
   time_to_run = time() - start
   Epoch 1/20
   0.3170
   Epoch 00001: val_loss improved from inf to 2.95675, saving model to
   best_fnn_model1.hdf5
   0.3170 - val_loss: 2.9567 - val_accuracy: 0.3667
   Epoch 2/20
   Epoch 00002: val_loss improved from 2.95675 to 2.23093, saving model to
   best_fnn_model1.hdf5
   0.3796 - val_loss: 2.2309 - val_accuracy: 0.3656
   Epoch 3/20
   0.3901
   Epoch 00003: val_loss improved from 2.23093 to 1.98270, saving model to
   best_fnn_model1.hdf5
   57/57 [============== ] - Os 5ms/step - loss: 2.0691 - accuracy:
   0.3911 - val_loss: 1.9827 - val_accuracy: 0.3806
   Epoch 4/20
   Epoch 00004: val_loss improved from 1.98270 to 1.86366, saving model to
   best_fnn_model1.hdf5
   57/57 [============= ] - Os 5ms/step - loss: 1.8957 - accuracy:
   0.3994 - val_loss: 1.8637 - val_accuracy: 0.3823
   Epoch 5/20
   Epoch 00005: val_loss improved from 1.86366 to 1.81721, saving model to
   best_fnn_model1.hdf5
   0.4042 - val_loss: 1.8172 - val_accuracy: 0.3734
```

fnn\_model1.compile(loss='categorical\_crossentropy', optimizer = optimizer, u

```
Epoch 6/20
Epoch 00006: val_loss improved from 1.81721 to 1.77925, saving model to
best_fnn_model1.hdf5
0.4046 - val_loss: 1.7793 - val_accuracy: 0.3817
Epoch 7/20
0.4117
Epoch 00007: val_loss improved from 1.77925 to 1.74664, saving model to
best_fnn_model1.hdf5
0.4116 - val_loss: 1.7466 - val_accuracy: 0.3867
Epoch 00008: val_loss improved from 1.74664 to 1.74087, saving model to
best_fnn_model1.hdf5
0.4122 - val_loss: 1.7409 - val_accuracy: 0.3884
Epoch 9/20
0.4155
Epoch 00009: val_loss did not improve from 1.74087
0.4146 - val_loss: 1.7767 - val_accuracy: 0.3689
Epoch 10/20
0.4090
Epoch 00010: val_loss improved from 1.74087 to 1.70722, saving model to
best_fnn_model1.hdf5
0.4089 - val_loss: 1.7072 - val_accuracy: 0.3865
Epoch 11/20
Epoch 00011: val_loss improved from 1.70722 to 1.69714, saving model to
best_fnn_model1.hdf5
0.4219 - val_loss: 1.6971 - val_accuracy: 0.3962
Epoch 12/20
0.4176
Epoch 00012: val_loss did not improve from 1.69714
0.4167 - val_loss: 1.7053 - val_accuracy: 0.3862
Epoch 13/20
```

```
0.4180
Epoch 00013: val_loss improved from 1.69714 to 1.69240, saving model to
best_fnn_model1.hdf5
57/57 [============= ] - Os 5ms/step - loss: 1.6544 - accuracy:
0.4172 - val_loss: 1.6924 - val_accuracy: 0.3979
Epoch 14/20
Epoch 00014: val_loss improved from 1.69240 to 1.68309, saving model to
best_fnn_model1.hdf5
57/57 [============= ] - Os 5ms/step - loss: 1.6390 - accuracy:
0.4275 - val_loss: 1.6831 - val_accuracy: 0.3951
Epoch 15/20
0.4211
Epoch 00015: val_loss did not improve from 1.68309
0.4221 - val_loss: 1.6844 - val_accuracy: 0.4060
Epoch 16/20
0.4274
Epoch 00016: val_loss did not improve from 1.68309
57/57 [============== - Os 5ms/step - loss: 1.6344 - accuracy:
0.4275 - val_loss: 1.7100 - val_accuracy: 0.3962
Epoch 17/20
Epoch 00017: val_loss improved from 1.68309 to 1.67300, saving model to
best_fnn_model1.hdf5
0.4220 - val_loss: 1.6730 - val_accuracy: 0.3959
Epoch 18/20
53/57 [=========>:...] - ETA: Os - loss: 1.6216 - accuracy:
0.4290
Epoch 00018: val_loss did not improve from 1.67300
0.4290 - val_loss: 1.7105 - val_accuracy: 0.3887
Epoch 19/20
0.4284
Epoch 00019: val_loss did not improve from 1.67300
0.4288 - val_loss: 1.7008 - val_accuracy: 0.3923
Epoch 20/20
0.4333
Epoch 00020: val_loss improved from 1.67300 to 1.67140, saving model to
```

```
best_fnn_model1.hdf5
    0.4335 - val_loss: 1.6714 - val_accuracy: 0.3940
[22]: fnn_model1.summary()
    print(time_to_run)
    Model: "sequential"
           ______
    Layer (type)
                          Output Shape
    _____
     dense (Dense)
                          (None, 128)
                                              295040
    dense_1 (Dense)
                          (None, 64)
                                              8256
    dense_2 (Dense)
                          (None, 32)
                                              2080
     dense_3 (Dense)
                          (None, 7)
                                              231
    Total params: 305,607
    Trainable params: 305,607
    Non-trainable params: 0
    8.261720895767212
[23]: plt.plot(history_fnn1.history['loss'])
    plt.plot(history_fnn1.history['val_loss'])
    plt.title('Model loss')
    plt.ylabel('Loss')
    plt.xlabel('Epochs')
    plt.legend(['Train', 'Validation'], loc='upper right')
    plt.show()
```



```
[24]: # Neural network
fnn_model2 = Sequential()
fnn_model2.add(Dense(256, input_dim = 2304, activation = 'relu'))
fnn_model2.add(Dropout(0.5))
fnn_model2.add(Dense(64, activation= 'relu'))
fnn_model2.add(Dropout(0.2))
fnn_model2.add(Dense(7, activation = 'softmax'))
[25]: fnn_checkpoint2 = ModelCheckpoint("best_fnn_model2.hdf5", monitor = 'val_loss', u
everbose = 1,
```

 $\label{lem:warning:tensorflow:`period` argument is deprecated. Please use `save\_freq` to specify the frequency in number of batches seen.$ 

 $\hookrightarrow 1)$ 

save\_best\_only = True, mode =' min', period =\_

WARNING:tensorflow: Model Checkpoint mode min is unknown, fallback to auto mode.

```
[26]: optimizer = tf.keras.optimizers.Adam(learning_rate = 0.002)

fnn_model2.compile(loss='categorical_crossentropy', optimizer = optimizer, 
→metrics = ['accuracy'])
```

```
[27]: start = time()
```

```
history_fnn2 = fnn_model2.fit(X_train_fnn, y_train,
            validation_data = (X_val_fnn, y_val),
            epochs = 20, batch_size = 512,
            validation_batch_size = 512,
            callbacks=[fnn_checkpoint2])
time_to_run = time() - start
Epoch 1/20
Epoch 00001: val_loss improved from inf to 1.72485, saving model to
best_fnn_model2.hdf5
57/57 [============= ] - 1s 8ms/step - loss: 1.9897 - accuracy:
0.2488 - val_loss: 1.7249 - val_accuracy: 0.3232
Epoch 2/20
0.3036
Epoch 00002: val_loss improved from 1.72485 to 1.66313, saving model to
best_fnn_model2.hdf5
0.3037 - val_loss: 1.6631 - val_accuracy: 0.3394
Epoch 3/20
Epoch 00003: val_loss improved from 1.66313 to 1.65258, saving model to
best_fnn_model2.hdf5
0.3294 - val_loss: 1.6526 - val_accuracy: 0.3605
Epoch 4/20
0.3397
Epoch 00004: val_loss improved from 1.65258 to 1.62031, saving model to
best_fnn_model2.hdf5
0.3407 - val_loss: 1.6203 - val_accuracy: 0.3670
Epoch 5/20
0.3520
Epoch 00005: val_loss improved from 1.62031 to 1.59883, saving model to
best_fnn_model2.hdf5
0.3523 - val_loss: 1.5988 - val_accuracy: 0.3748
Epoch 6/20
Epoch 00006: val_loss improved from 1.59883 to 1.59079, saving model to
best_fnn_model2.hdf5
```

```
0.3601 - val_loss: 1.5908 - val_accuracy: 0.3661
Epoch 7/20
0.3667
Epoch 00007: val_loss improved from 1.59079 to 1.57615, saving model to
best_fnn_model2.hdf5
0.3667 - val_loss: 1.5761 - val_accuracy: 0.3828
Epoch 8/20
0.3744
Epoch 00008: val_loss improved from 1.57615 to 1.56677, saving model to
best_fnn_model2.hdf5
0.3745 - val_loss: 1.5668 - val_accuracy: 0.3926
Epoch 9/20
0.3793
Epoch 00009: val_loss improved from 1.56677 to 1.55329, saving model to
best_fnn_model2.hdf5
0.3793 - val_loss: 1.5533 - val_accuracy: 0.3906
Epoch 10/20
Epoch 00010: val_loss improved from 1.55329 to 1.54969, saving model to
best_fnn_model2.hdf5
0.3891 - val_loss: 1.5497 - val_accuracy: 0.4110
Epoch 11/20
0.3970
Epoch 00011: val_loss improved from 1.54969 to 1.52988, saving model to
best_fnn_model2.hdf5
0.3970 - val_loss: 1.5299 - val_accuracy: 0.4015
Epoch 12/20
0.3971
Epoch 00012: val_loss did not improve from 1.52988
57/57 [============= ] - Os 5ms/step - loss: 1.5215 - accuracy:
0.3966 - val_loss: 1.5315 - val_accuracy: 0.3976
Epoch 13/20
Epoch 00013: val_loss improved from 1.52988 to 1.51797, saving model to
best_fnn_model2.hdf5
```

```
0.3992 - val_loss: 1.5180 - val_accuracy: 0.4037
Epoch 14/20
0.4092
Epoch 00014: val_loss did not improve from 1.51797
0.4090 - val_loss: 1.5218 - val_accuracy: 0.4126
Epoch 15/20
0.4095
Epoch 00015: val_loss did not improve from 1.51797
0.4099 - val_loss: 1.5213 - val_accuracy: 0.4026
Epoch 16/20
Epoch 00016: val_loss improved from 1.51797 to 1.51432, saving model to
best_fnn_model2.hdf5
0.4121 - val_loss: 1.5143 - val_accuracy: 0.4085
Epoch 17/20
0.4156
Epoch 00017: val_loss improved from 1.51432 to 1.51024, saving model to
best_fnn_model2.hdf5
0.4156 - val_loss: 1.5102 - val_accuracy: 0.4060
Epoch 18/20
Epoch 00018: val_loss improved from 1.51024 to 1.50626, saving model to
best_fnn_model2.hdf5
57/57 [============= ] - Os 5ms/step - loss: 1.4675 - accuracy:
0.4237 - val_loss: 1.5063 - val_accuracy: 0.3979
Epoch 19/20
Epoch 00019: val_loss improved from 1.50626 to 1.49913, saving model to
best_fnn_model2.hdf5
0.4246 - val_loss: 1.4991 - val_accuracy: 0.4107
Epoch 20/20
0.4292
Epoch 00020: val_loss did not improve from 1.49913
0.4294 - val_loss: 1.5005 - val_accuracy: 0.4140
```

```
[28]: fnn_model2.summary()
print(time_to_run)
```

Model: "sequential\_1"

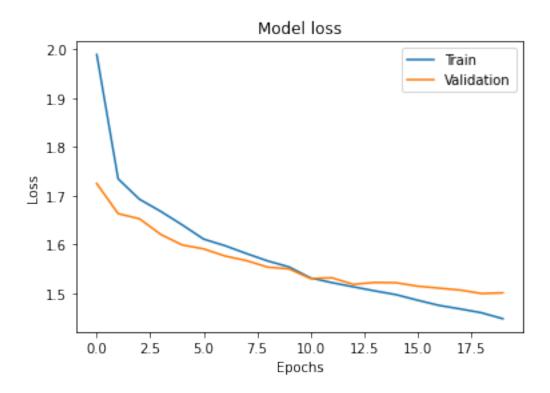
Layer (type)	Output Shape	Param #
dense_4 (Dense)	(None, 256)	590080
dropout (Dropout)	(None, 256)	0
dense_5 (Dense)	(None, 64)	16448
<pre>dropout_1 (Dropout)</pre>	(None, 64)	0
dense_6 (Dense)	(None, 7)	455

\_\_\_\_\_

Total params: 606,983 Trainable params: 606,983 Non-trainable params: 0

\_\_\_\_\_\_

```
[29]: plt.plot(history_fnn2.history['loss'])
   plt.plot(history_fnn2.history['val_loss'])
   plt.title('Model loss')
   plt.ylabel('Loss')
   plt.xlabel('Epochs')
   plt.legend(['Train', 'Validation'], loc='upper right')
   plt.show()
```



 $\label{lem:warning:tensorflow:`period` argument is deprecated. Please use `save\_freq` to specify the frequency in number of batches seen.$ 

**→**1)

WARNING:tensorflow:ModelCheckpoint mode min is unknown, fallback to auto mode.

```
[32]: optimizer = tf.keras.optimizers.Adam(learning_rate = 0.0005)

fnn_model3.compile(loss='categorical_crossentropy', optimizer = optimizer, 
→metrics = ['accuracy'])
```

```
[33]: start = time()
history_fnn3 = fnn_model3.fit(X_train_fnn, y_train,
```

```
epochs = 20, batch_size = 512,
          validation_batch_size = 512,
          callbacks=[fnn_checkpoint3])
time_to_run = time() - start
Epoch 1/20
0.2559
Epoch 00001: val_loss improved from inf to 1.68260, saving model to
best_fnn_model3.hdf5
0.2594 - val_loss: 1.6826 - val_accuracy: 0.3541
Epoch 2/20
0.3314
Epoch 00002: val_loss improved from 1.68260 to 1.63446, saving model to
best_fnn_model3.hdf5
0.3332 - val_loss: 1.6345 - val_accuracy: 0.3717
Epoch 3/20
0.3526
Epoch 00003: val_loss improved from 1.63446 to 1.61218, saving model to
best_fnn_model3.hdf5
0.3538 - val_loss: 1.6122 - val_accuracy: 0.3753
Epoch 4/20
0.3691
Epoch 00004: val_loss improved from 1.61218 to 1.58756, saving model to
best_fnn_model3.hdf5
0.3679 - val_loss: 1.5876 - val_accuracy: 0.3848
Epoch 5/20
0.3782
Epoch 00005: val_loss improved from 1.58756 to 1.57362, saving model to
best_fnn_model3.hdf5
0.3792 - val_loss: 1.5736 - val_accuracy: 0.3951
Epoch 6/20
0.3876
Epoch 00006: val_loss improved from 1.57362 to 1.55999, saving model to
best_fnn_model3.hdf5
```

validation\_data = (X\_val\_fnn, y\_val),

```
0.3882 - val_loss: 1.5600 - val_accuracy: 0.3940
Epoch 7/20
Epoch 00007: val_loss improved from 1.55999 to 1.54675, saving model to
best_fnn_model3.hdf5
0.3951 - val_loss: 1.5467 - val_accuracy: 0.3982
Epoch 8/20
0.4096
Epoch 00008: val_loss improved from 1.54675 to 1.54018, saving model to
best_fnn_model3.hdf5
0.4081 - val_loss: 1.5402 - val_accuracy: 0.4029
Epoch 9/20
51/57 [===========>...] - ETA: Os - loss: 1.5102 - accuracy:
Epoch 00009: val_loss improved from 1.54018 to 1.52771, saving model to
best_fnn_model3.hdf5
0.4212 - val_loss: 1.5277 - val_accuracy: 0.4037
Epoch 10/20
0.4272
Epoch 00010: val_loss improved from 1.52771 to 1.52365, saving model to
best_fnn_model3.hdf5
0.4263 - val_loss: 1.5237 - val_accuracy: 0.4029
Epoch 11/20
Epoch 00011: val_loss improved from 1.52365 to 1.50973, saving model to
best_fnn_model3.hdf5
0.4373 - val_loss: 1.5097 - val_accuracy: 0.4093
Epoch 12/20
Epoch 00012: val_loss improved from 1.50973 to 1.50197, saving model to
best_fnn_model3.hdf5
0.4483 - val_loss: 1.5020 - val_accuracy: 0.4179
Epoch 13/20
Epoch 00013: val_loss improved from 1.50197 to 1.49981, saving model to
best_fnn_model3.hdf5
```

```
0.4560 - val_loss: 1.4998 - val_accuracy: 0.4149
Epoch 14/20
50/57 [============>...] - ETA: Os - loss: 1.3876 - accuracy:
0.4762
Epoch 00014: val_loss improved from 1.49981 to 1.48964, saving model to
best_fnn_model3.hdf5
0.4770 - val_loss: 1.4896 - val_accuracy: 0.4255
Epoch 15/20
49/57 [===========>...] - ETA: Os - loss: 1.3595 - accuracy:
Epoch 00015: val_loss improved from 1.48964 to 1.48674, saving model to
best_fnn_model3.hdf5
0.4870 - val_loss: 1.4867 - val_accuracy: 0.4213
Epoch 16/20
0.5047
Epoch 00016: val_loss improved from 1.48674 to 1.47938, saving model to
best_fnn_model3.hdf5
0.5048 - val_loss: 1.4794 - val_accuracy: 0.4299
Epoch 17/20
0.5183
Epoch 00017: val_loss improved from 1.47938 to 1.46924, saving model to
best_fnn_model3.hdf5
0.5176 - val_loss: 1.4692 - val_accuracy: 0.4391
Epoch 18/20
0.5339
Epoch 00018: val_loss improved from 1.46924 to 1.46370, saving model to
best_fnn_model3.hdf5
0.5348 - val_loss: 1.4637 - val_accuracy: 0.4344
Epoch 19/20
0.5506
Epoch 00019: val_loss did not improve from 1.46370
57/57 [============= ] - Os 5ms/step - loss: 1.2163 - accuracy:
0.5509 - val_loss: 1.4809 - val_accuracy: 0.4285
Epoch 20/20
51/57 [==========>...] - ETA: Os - loss: 1.1869 - accuracy:
Epoch 00020: val_loss did not improve from 1.46370
```

```
0.5653 - val_loss: 1.4731 - val_accuracy: 0.4411
```

```
[34]: fnn_model3.summary() print(time_to_run)
```

Model: "sequential\_2"

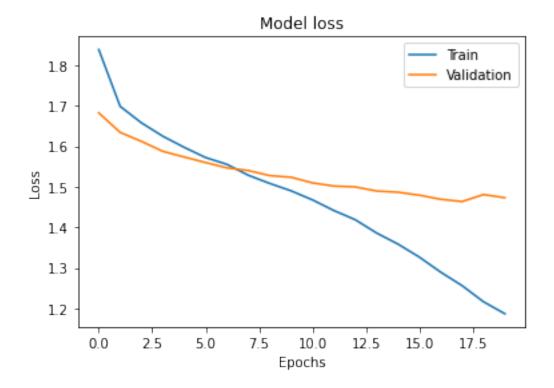
Layer (type)	Output Shape	Param #
dense_7 (Dense)	(None, 512)	1180160
dense_8 (Dense)	(None, 64)	32832
dropout_2 (Dropout)	(None, 64)	0
dense_9 (Dense)	(None, 7)	455

\_\_\_\_\_

Total params: 1,213,447 Trainable params: 1,213,447 Non-trainable params: 0

-----

```
[35]: plt.plot(history_fnn3.history['loss'])
   plt.plot(history_fnn3.history['val_loss'])
   plt.title('Model loss')
   plt.ylabel('Loss')
   plt.xlabel('Epochs')
   plt.legend(['Train', 'Validation'], loc='upper right')
   plt.show()
```



# **c(i).** Details of the 3 different FNN models are listed below:

### **#Details on FNN Model 1:**

Number of hidden layers: 2

Number of neurons in 4 layers: 128, 64, 32, 7

Total parameters: 305607

Optimizer used: Adam with learning rate of 0.001

Regulerizer used: 12

Dropout: N/A

Activation function for input and hidden layers: ReLU

Activation function for output layer: Softmax

Training accuracy (for the best model): 43.35%

Validation accuracy (for the best model): 39.40%

Training time: 8.26 s

#### \_\_\_\_

# **#Details on FNN Model 2:**

Number of hidden layers: 1

Number of neurons in 3 layers: 256, 64, 7

Total parameters: 606983

Optimizer used: Adam with learning rate of 0.002

Regulerizer used: N/A

Dropout: 0.5 after 1st layer, 0.2 after 2nd layer

Activation function for input and hidden layers: ReLU

Activation function for output layer: Softmax

Training accuracy (for the best model): 42.46%

Validation accuracy (for the best model): 41.07%

Training time: 10.95 s

### **#Details on FNN Model 3:**

Number of hidden layers: 1

Number of neurons in 3 layers: 512, 64, 7

Total parameters: 1213447

Optimizer used: Adam with learning rate of 0.0005

Regulerizer used: N/A

Dropout: 0.4 after 2nd layer

Activation function for input and hidden layers: Sigmoid

Activation function for output layer: Softmax

Training accuracy (for the best model): 53.48%

Validation accuracy (for the best model): 43.44%

Training time: 7.61 s

We get a very clear idea about how different models are performing with this training set from the listing above. Even though the model 3 achieves the best training and validation accuracy for the best weights saved during training process, it has an overfitting tendency as per the loss curve. On the other hand model 2 performed similarly on the validation set and has less overfitting tendency overall. So, model 2 can be safely chosen as the best model and used for testing.

```
[36]: best_fnn_model = tf.keras.models.load_model("best_fnn_model3.hdf5")
score = best_fnn_model.evaluate(X_test_fnn, y_test, verbose=0)
print("%s: %.2f%%" % (best_fnn_model.metrics_names[1], score[1]*100))
```

accuracy: 43.69%

**c(ii).** Emotion classification accuracy on the testing set = 43.69%

```
[37]: from keras.layers import Activation, Flatten, Conv2D, MaxPooling2D
      from keras.layers import BatchNormalization
      from keras.utils import np_utils
[38]: cnn_model1 = Sequential()
      cnn_model1.add(Conv2D(filters=96, input_shape=(48, 48, 1), kernel_regularizer = __
       \rightarrowregularizers.12(12=0.01),
                             kernel_size=(11,11), strides=(4,4), padding='same'))
      cnn_model1.add(BatchNormalization())
      cnn_model1.add(Activation('relu'))
      cnn_model1.add(MaxPooling2D(pool_size=(2,2), strides=(2,2), padding='same'))
      cnn_model1.add(Conv2D(filters=256, kernel_size=(5, 5), kernel_regularizer = u
       \rightarrowregularizers.12(12=0.01),
                             strides=(1,1), padding='same'))
      cnn_model1.add(BatchNormalization())
      cnn_model1.add(Activation('relu'))
      cnn_model1.add(MaxPooling2D(pool_size=(2,2), strides=(2,2), padding='same'))
      cnn_model1.add(Conv2D(filters=384, kernel_size=(3,3), kernel_regularizer = 0
       \rightarrowregularizers.12(12=0.01),
                             strides=(1,1), padding='same'))
      cnn_model1.add(BatchNormalization())
      cnn_model1.add(Activation('relu'))
      cnn_model1.add(Flatten())
      cnn_model1.add(Dense(4096, input_shape=(32,32,3,)))
      cnn_model1.add(BatchNormalization())
      cnn_model1.add(Activation('relu'))
      cnn_model1.add(Dropout(0.4))
      cnn_model1.add(Dense(1000))
      cnn_model1.add(BatchNormalization())
      cnn_model1.add(Activation('relu'))
```

Model: "sequential\_3"

cnn\_model1.summary()

cnn\_model1.add(Dropout(0.4))

cnn\_model1.add(BatchNormalization())
cnn\_model1.add(Activation('softmax'))

cnn\_model1.add(Dense(7))

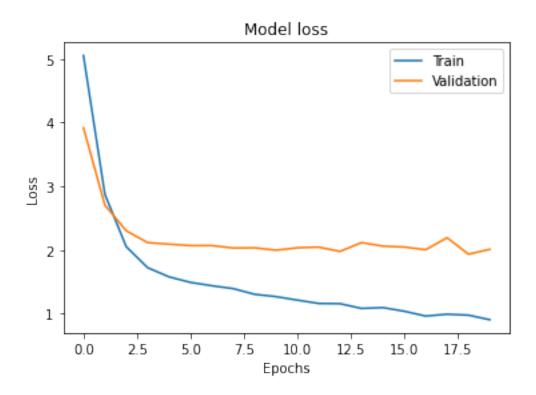
	Output Shape	Param #
conv2d (Conv2D)		
<pre>batch_normalization (BatchN ormalization)</pre>	(None, 12, 12, 96)	384
activation (Activation)	(None, 12, 12, 96)	0
<pre>max_pooling2d (MaxPooling2D )</pre>	(None, 6, 6, 96)	0
conv2d_1 (Conv2D)	(None, 6, 6, 256)	614656
<pre>batch_normalization_1 (Batc hNormalization)</pre>	(None, 6, 6, 256)	1024
activation_1 (Activation)	(None, 6, 6, 256)	0
<pre>max_pooling2d_1 (MaxPooling 2D)</pre>	(None, 3, 3, 256)	0
conv2d_2 (Conv2D)	(None, 3, 3, 384)	885120
<pre>batch_normalization_2 (Batc hNormalization)</pre>	(None, 3, 3, 384)	1536
activation_2 (Activation)	(None, 3, 3, 384)	0
flatten (Flatten)	(None, 3456)	0
dense_10 (Dense)	(None, 4096)	14159872
<pre>batch_normalization_3 (Batc hNormalization)</pre>	(None, 4096)	16384
activation_3 (Activation)	(None, 4096)	0
dropout_3 (Dropout)	(None, 4096)	0
dense_11 (Dense)	(None, 1000)	4097000
batch_normalization_4 (BatchNormalization)	(None, 1000)	4000
activation_4 (Activation)	(None, 1000)	0

```
dropout_4 (Dropout)
                        (None, 1000)
                                                      0
     dense_12 (Dense)
                              (None, 7)
                                                      7007
     batch_normalization_5 (Batc (None, 7)
                                                      28
     hNormalization)
                             (None, 7)
     activation_5 (Activation)
    Total params: 19,798,723
    Trainable params: 19,787,045
    Non-trainable params: 11,678
[39]: cnn_checkpoint1 = ModelCheckpoint("best_cnn_model1.hdf5", monitor = 'val_loss', u
      \rightarrowverbose = 1,
        save_best_only = True, mode = ' min', period = 1)
    WARNING:tensorflow:`period` argument is deprecated. Please use `save_freq` to
    specify the frequency in number of batches seen.
    WARNING:tensorflow: Model Checkpoint mode min is unknown, fallback to auto mode.
[40]: optimizer = tf.keras.optimizers.Adam(learning_rate = 0.0005)
     cnn_model1.compile(loss='categorical_crossentropy', optimizer = optimizer, u
      →metrics = ['accuracy'])
[41]: start = time()
     history_cnn1 = cnn_model1.fit(X_train, y_train,
                       validation_data = (X_val, y_val),
                       epochs = 20, batch_size = 512,
                       validation_batch_size = 512,
                       callbacks=[cnn_checkpoint1])
     time_to_run = time() - start
    Epoch 1/20
    Epoch 00001: val_loss improved from inf to 3.91944, saving model to
    best_cnn_model1.hdf5
    57/57 [============= ] - 18s 44ms/step - loss: 5.0546 -
    accuracy: 0.3671 - val_loss: 3.9194 - val_accuracy: 0.1744
    Epoch 2/20
    0.4586
    Epoch 00002: val_loss improved from 3.91944 to 2.70535, saving model to
```

```
best_cnn_model1.hdf5
0.4583 - val_loss: 2.7053 - val_accuracy: 0.3282
0.4964
Epoch 00003: val_loss improved from 2.70535 to 2.30108, saving model to
best_cnn_model1.hdf5
0.4958 - val_loss: 2.3011 - val_accuracy: 0.2558
Epoch 4/20
0.5410
Epoch 00004: val_loss improved from 2.30108 to 2.11499, saving model to
best_cnn_model1.hdf5
0.5409 - val_loss: 2.1150 - val_accuracy: 0.3706
Epoch 5/20
0.5695
Epoch 00005: val_loss improved from 2.11499 to 2.09084, saving model to
best_cnn_model1.hdf5
0.5688 - val_loss: 2.0908 - val_accuracy: 0.3943
Epoch 6/20
0.6037
Epoch 00006: val_loss improved from 2.09084 to 2.06818, saving model to
best_cnn_model1.hdf5
0.6034 - val_loss: 2.0682 - val_accuracy: 0.3714
Epoch 7/20
0.6302
Epoch 00007: val_loss did not improve from 2.06818
0.6295 - val_loss: 2.0689 - val_accuracy: 0.3658
Epoch 8/20
Epoch 00008: val_loss improved from 2.06818 to 2.03060, saving model to
best_cnn_model1.hdf5
0.6560 - val_loss: 2.0306 - val_accuracy: 0.3892
Epoch 9/20
0.6950
Epoch 00009: val_loss did not improve from 2.03060
```

```
0.6947 - val_loss: 2.0339 - val_accuracy: 0.3717
Epoch 10/20
0.7202
Epoch 00010: val_loss improved from 2.03060 to 1.99577, saving model to
best_cnn_model1.hdf5
0.7196 - val_loss: 1.9958 - val_accuracy: 0.4377
Epoch 11/20
0.7450
Epoch 00011: val_loss did not improve from 1.99577
0.7449 - val_loss: 2.0342 - val_accuracy: 0.3982
Epoch 12/20
0.7686
Epoch 00012: val_loss did not improve from 1.99577
57/57 [===========] - 2s 32ms/step - loss: 1.1590 - accuracy:
0.7683 - val_loss: 2.0444 - val_accuracy: 0.3720
Epoch 13/20
0.7748
Epoch 00013: val_loss improved from 1.99577 to 1.97698, saving model to
best_cnn_model1.hdf5
0.7749 - val_loss: 1.9770 - val_accuracy: 0.4316
Epoch 14/20
0.8058
Epoch 00014: val_loss did not improve from 1.97698
57/57 [============] - 2s 32ms/step - loss: 1.0807 - accuracy:
0.8059 - val_loss: 2.1152 - val_accuracy: 0.3243
Epoch 15/20
Epoch 00015: val_loss did not improve from 1.97698
0.8014 - val_loss: 2.0595 - val_accuracy: 0.4060
Epoch 16/20
Epoch 00016: val_loss did not improve from 1.97698
57/57 [===========] - 2s 32ms/step - loss: 1.0367 - accuracy:
0.8276 - val_loss: 2.0457 - val_accuracy: 0.3848
Epoch 17/20
```

```
0.8545
   Epoch 00017: val_loss did not improve from 1.97698
   0.8542 - val_loss: 2.0032 - val_accuracy: 0.4503
   Epoch 18/20
   0.8447
   Epoch 00018: val_loss did not improve from 1.97698
   0.8446 - val_loss: 2.1920 - val_accuracy: 0.3422
   Epoch 19/20
   55/57 [==============>..] - ETA: Os - loss: 0.9753 - accuracy:
   0.8522
   Epoch 00019: val_loss improved from 1.97698 to 1.93276, saving model to
   best_cnn_model1.hdf5
   0.8523 - val_loss: 1.9328 - val_accuracy: 0.4645
   Epoch 20/20
   0.8762
   Epoch 00020: val_loss did not improve from 1.93276
   0.8766 - val_loss: 2.0102 - val_accuracy: 0.4257
[42]: plt.plot(history_cnn1.history['loss'])
   plt.plot(history_cnn1.history['val_loss'])
   plt.title('Model loss')
   plt.ylabel('Loss')
   plt.xlabel('Epochs')
   plt.legend(['Train', 'Validation'], loc='upper right')
   plt.show()
   print(time_to_run)
```



```
[43]: cnn_model2 = Sequential()
      cnn_model2.add(Conv2D(filters=96, input_shape=(48, 48, 1), kernel_regularizer = __
       \rightarrowregularizers.12(12=0.01),
                             kernel_size=(11,11), strides=(4,4), padding='same'))
      cnn_model2.add(Activation('relu'))
      cnn_model2.add(MaxPooling2D(pool_size=(2,2), strides=(2,2), padding='same'))
      cnn_model2.add(Conv2D(filters=48, kernel_size=(3,3), kernel_regularizer =_
       \rightarrowregularizers.12(12=0.01),
                             strides=(1,1), padding='same'))
      cnn_model2.add(Activation('relu'))
      cnn_model2.add(Flatten())
      cnn_model2.add(Dense(1048, input_shape=(32,32,3,)))
      cnn_model2.add(Activation('sigmoid'))
      cnn_model2.add(Dropout(0.4))
      cnn_model2.add(Dense(128))
      cnn_model2.add(Activation('sigmoid'))
```

```
cnn_model2.add(Dropout(0.4))
cnn_model2.add(Dense(7))
cnn_model2.add(Activation('softmax'))
cnn_model2.summary()
```

Model: "sequential\_4"

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 12, 12, 96)	11712
activation_6 (Activation)	(None, 12, 12, 96)	0
<pre>max_pooling2d_2 (MaxPooling 2D)</pre>	(None, 6, 6, 96)	0
conv2d_4 (Conv2D)	(None, 6, 6, 48)	41520
activation_7 (Activation)	(None, 6, 6, 48)	0
flatten_1 (Flatten)	(None, 1728)	0
dense_13 (Dense)	(None, 1048)	1811992
activation_8 (Activation)	(None, 1048)	0
dropout_5 (Dropout)	(None, 1048)	0
dense_14 (Dense)	(None, 128)	134272
activation_9 (Activation)	(None, 128)	0
dropout_6 (Dropout)	(None, 128)	0
dense_15 (Dense)	(None, 7)	903
activation_10 (Activation)	(None, 7)	0

\_\_\_\_\_

Total params: 2,000,399 Trainable params: 2,000,399 Non-trainable params: 0

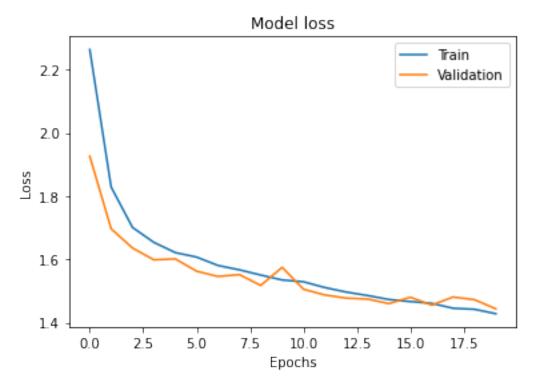
\_\_\_\_\_\_

```
[44]: cnn_checkpoint2 = ModelCheckpoint("best_cnn_model2.hdf5", monitor = 'val_loss', u
     \rightarrowverbose = 1,
       save_best_only = True, mode =' min', period = 1)
    WARNING:tensorflow:`period` argument is deprecated. Please use `save_freq` to
    specify the frequency in number of batches seen.
    WARNING:tensorflow: Model Checkpoint mode min is unknown, fallback to auto mode.
[45]: optimizer = tf.keras.optimizers.Adam(learning_rate = 0.0005)
    cnn_model2.compile(loss='categorical_crossentropy', optimizer = optimizer, u
     →metrics = ['accuracy'])
[46]: start = time()
    history_cnn2 = cnn_model2.fit(X_train, y_train,
                   validation_data = (X_val, y_val),
                   epochs = 20, batch_size = 512,
                   validation_batch_size = 512,
                   callbacks=[cnn_checkpoint2])
    time_to_run = time() - start
    Epoch 1/20
    0.2295
    Epoch 00001: val_loss improved from inf to 1.92585, saving model to
    best_cnn_model2.hdf5
    0.2294 - val_loss: 1.9259 - val_accuracy: 0.3115
    Epoch 2/20
    Epoch 00002: val_loss improved from 1.92585 to 1.69652, saving model to
    best_cnn_model2.hdf5
    57/57 [===========] - 1s 10ms/step - loss: 1.8285 - accuracy:
    0.3187 - val_loss: 1.6965 - val_accuracy: 0.3795
    Epoch 3/20
    0.3550
    Epoch 00003: val_loss improved from 1.69652 to 1.63573, saving model to
    best_cnn_model2.hdf5
    0.3550 - val_loss: 1.6357 - val_accuracy: 0.3982
    Epoch 4/20
    0.3718
    Epoch 00004: val_loss improved from 1.63573 to 1.59834, saving model to
```

```
best_cnn_model2.hdf5
0.3719 - val_loss: 1.5983 - val_accuracy: 0.4035
0.3871
Epoch 00005: val_loss did not improve from 1.59834
0.3872 - val_loss: 1.6014 - val_accuracy: 0.4015
Epoch 6/20
Epoch 00006: val_loss improved from 1.59834 to 1.56238, saving model to
best_cnn_model2.hdf5
57/57 [===========] - 1s 10ms/step - loss: 1.6070 - accuracy:
0.3936 - val_loss: 1.5624 - val_accuracy: 0.4146
Epoch 7/20
0.4080
Epoch 00007: val_loss improved from 1.56238 to 1.54572, saving model to
best_cnn_model2.hdf5
0.4077 - val_loss: 1.5457 - val_accuracy: 0.4257
Epoch 8/20
0.4122
Epoch 00008: val_loss did not improve from 1.54572
57/57 [============= ] - 1s 9ms/step - loss: 1.5668 - accuracy:
0.4123 - val_loss: 1.5517 - val_accuracy: 0.4205
Epoch 9/20
Epoch 00009: val_loss improved from 1.54572 to 1.51739, saving model to
best_cnn_model2.hdf5
0.4244 - val_loss: 1.5174 - val_accuracy: 0.4361
Epoch 10/20
0.4299
Epoch 00010: val_loss did not improve from 1.51739
0.4298 - val_loss: 1.5746 - val_accuracy: 0.4060
Epoch 11/20
Epoch 00011: val_loss improved from 1.51739 to 1.50540, saving model to
best_cnn_model2.hdf5
```

```
0.4327 - val_loss: 1.5054 - val_accuracy: 0.4439
Epoch 12/20
Epoch 00012: val_loss improved from 1.50540 to 1.48726, saving model to
best_cnn_model2.hdf5
0.4409 - val_loss: 1.4873 - val_accuracy: 0.4458
Epoch 13/20
0.4497
Epoch 00013: val_loss improved from 1.48726 to 1.47732, saving model to
best_cnn_model2.hdf5
0.4496 - val_loss: 1.4773 - val_accuracy: 0.4581
Epoch 14/20
51/57 [===========>...] - ETA: Os - loss: 1.4832 - accuracy:
Epoch 00014: val_loss improved from 1.47732 to 1.47441, saving model to
best_cnn_model2.hdf5
57/57 [===========] - 1s 10ms/step - loss: 1.4855 - accuracy:
0.4527 - val_loss: 1.4744 - val_accuracy: 0.4581
Epoch 15/20
0.4605
Epoch 00015: val_loss improved from 1.47441 to 1.45998, saving model to
best_cnn_model2.hdf5
0.4599 - val_loss: 1.4600 - val_accuracy: 0.4695
Epoch 16/20
Epoch 00016: val_loss did not improve from 1.45998
57/57 [============= - 1s 9ms/step - loss: 1.4664 - accuracy:
0.4649 - val_loss: 1.4801 - val_accuracy: 0.4542
Epoch 17/20
Epoch 00017: val_loss improved from 1.45998 to 1.45538, saving model to
best_cnn_model2.hdf5
0.4635 - val_loss: 1.4554 - val_accuracy: 0.4692
Epoch 18/20
53/57 [===========>...] - ETA: Os - loss: 1.4450 - accuracy:
0.4740
Epoch 00018: val_loss did not improve from 1.45538
0.4735 - val_loss: 1.4808 - val_accuracy: 0.4595
```

```
Epoch 19/20
   51/57 [============>...] - ETA: Os - loss: 1.4402 - accuracy:
   0.4741
   Epoch 00019: val_loss did not improve from 1.45538
   0.4733 - val_loss: 1.4723 - val_accuracy: 0.4578
   Epoch 20/20
   0.4845
   Epoch 00020: val_loss improved from 1.45538 to 1.44347, saving model to
   best_cnn_model2.hdf5
   0.4821 - val_loss: 1.4435 - val_accuracy: 0.4734
[47]: plt.plot(history_cnn2.history['loss'])
    plt.plot(history_cnn2.history['val_loss'])
    plt.title('Model loss')
    plt.ylabel('Loss')
    plt.xlabel('Epochs')
    plt.legend(['Train', 'Validation'], loc='upper right')
    plt.show()
    print(time_to_run)
```



```
[48]: cnn_model3 = Sequential()
      cnn_model3.add(Conv2D(filters=48, input_shape=(48, 48, 1), kernel_regularizer = ___
       \rightarrowregularizers.12(12=0.01),
                             kernel_size=(5,5), strides=(2,2), padding='same'))
      cnn_model3.add(Activation('relu'))
      cnn_model3.add(MaxPooling2D(pool_size=(2,2), strides=(2,2), padding='same'))
      cnn_model3.add(Conv2D(filters=16, kernel_size=(3,3), kernel_regularizer =__
       \rightarrowregularizers.12(12=0.01),
                             strides=(1,1), padding='same'))
      cnn_model3.add(Activation('relu'))
      cnn_model3.add(Dropout(0.4))
      cnn_model3.add(Flatten())
      cnn_model3.add(Dense(256))
      cnn_model3.add(Activation('relu'))
      cnn_model3.add(Dropout(0.2))
      cnn_model3.add(Dense(64))
      cnn_model3.add(Activation('relu'))
      cnn_model3.add(Dropout(0.2))
      cnn_model3.add(Dense(7))
      cnn_model3.add(Activation('softmax'))
      cnn_model3.summary()
```

Model: "sequential\_5"

Layer (type)	Output Shape	Param #
conv2d_5 (Conv2D)	(None, 24, 24, 48)	1248
activation_11 (Activation)	(None, 24, 24, 48)	0
<pre>max_pooling2d_3 (MaxPooling 2D)</pre>	(None, 12, 12, 48)	0
conv2d_6 (Conv2D)	(None, 12, 12, 16)	6928
activation_12 (Activation)	(None, 12, 12, 16)	0
dropout_7 (Dropout)	(None, 12, 12, 16)	0

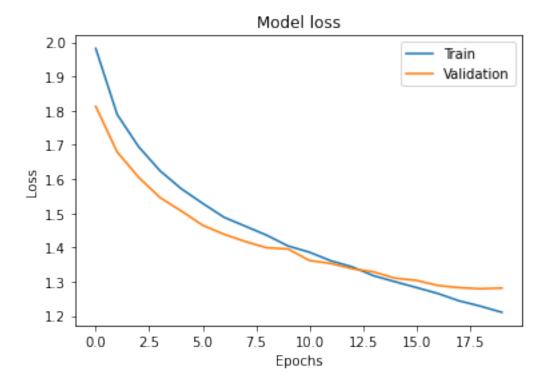
```
flatten_2 (Flatten)
                                  (None, 2304)
      dense_16 (Dense)
                                   (None, 256)
                                                             590080
      activation_13 (Activation) (None, 256)
                                                             0
      dropout_8 (Dropout)
                                   (None, 256)
                                                             0
      dense_17 (Dense)
                                   (None, 64)
                                                             16448
      activation_14 (Activation) (None, 64)
                                   (None, 64)
      dropout_9 (Dropout)
      dense_18 (Dense)
                                   (None, 7)
                                                             455
      activation_15 (Activation)
                                  (None, 7)
     Total params: 615,159
     Trainable params: 615,159
     Non-trainable params: 0
[49]: cnn_checkpoint3 = ModelCheckpoint("best_cnn_model3.hdf5", monitor = 'val_loss',
       \rightarrowverbose = 1,
          save_best_only = True, mode =' min', period = 1)
     WARNING:tensorflow:`period` argument is deprecated. Please use `save_freq` to
     specify the frequency in number of batches seen.
     WARNING:tensorflow:ModelCheckpoint mode min is unknown, fallback to auto mode.
[50]: optimizer = tf.keras.optimizers.Adam(learning_rate = 0.0005)
      cnn_model3.compile(loss='categorical_crossentropy', optimizer = optimizer, __
       →metrics = ['accuracy'])
[51]: start = time()
      history_cnn3 = cnn_model3.fit(X_train, y_train,
                          validation_data = (X_val, y_val),
                          epochs = 20, batch_size = 512,
                          validation_batch_size = 512,
                          callbacks=[cnn_checkpoint3])
      time_to_run = time() - start
     Epoch 1/20
```

```
0.2802
Epoch 00001: val_loss improved from inf to 1.81245, saving model to
best_cnn_model3.hdf5
0.2803 - val_loss: 1.8124 - val_accuracy: 0.3658
Epoch 2/20
Epoch 00002: val_loss improved from 1.81245 to 1.67925, saving model to
best_cnn_model3.hdf5
0.3581 - val_loss: 1.6792 - val_accuracy: 0.4009
Epoch 3/20
Epoch 00003: val_loss improved from 1.67925 to 1.60565, saving model to
best_cnn_model3.hdf5
0.3852 - val_loss: 1.6057 - val_accuracy: 0.4163
Epoch 4/20
57/57 [============== ] - ETA: Os - loss: 1.6246 - accuracy:
0.4069
Epoch 00004: val_loss improved from 1.60565 to 1.54609, saving model to
best_cnn_model3.hdf5
57/57 [============= ] - 1s 9ms/step - loss: 1.6246 - accuracy:
0.4069 - val_loss: 1.5461 - val_accuracy: 0.4363
Epoch 5/20
Epoch 00005: val_loss improved from 1.54609 to 1.50678, saving model to
best_cnn_model3.hdf5
0.4266 - val_loss: 1.5068 - val_accuracy: 0.4570
Epoch 6/20
0.4420
Epoch 00006: val_loss improved from 1.50678 to 1.46498, saving model to
best_cnn_model3.hdf5
0.4409 - val_loss: 1.4650 - val_accuracy: 0.4639
Epoch 7/20
Epoch 00007: val_loss improved from 1.46498 to 1.43873, saving model to
best_cnn_model3.hdf5
0.4577 - val_loss: 1.4387 - val_accuracy: 0.4820
Epoch 8/20
```

```
0.4677
Epoch 00008: val_loss improved from 1.43873 to 1.41734, saving model to
best_cnn_model3.hdf5
0.4676 - val_loss: 1.4173 - val_accuracy: 0.4756
Epoch 9/20
57/57 [============= ] - ETA: Os - loss: 1.4358 - accuracy:
0.4759
Epoch 00009: val_loss improved from 1.41734 to 1.39918, saving model to
best_cnn_model3.hdf5
57/57 [============= ] - 1s 9ms/step - loss: 1.4358 - accuracy:
0.4759 - val_loss: 1.3992 - val_accuracy: 0.4921
Epoch 10/20
0.4881
Epoch 00010: val_loss improved from 1.39918 to 1.39554, saving model to
best_cnn_model3.hdf5
57/57 [============= ] - 1s 9ms/step - loss: 1.4043 - accuracy:
0.4882 - val_loss: 1.3955 - val_accuracy: 0.4859
Epoch 11/20
57/57 [============== ] - ETA: Os - loss: 1.3861 - accuracy:
Epoch 00011: val_loss improved from 1.39554 to 1.36196, saving model to
best_cnn_model3.hdf5
0.4956 - val_loss: 1.3620 - val_accuracy: 0.4976
Epoch 12/20
57/57 [============= - ETA: Os - loss: 1.3611 - accuracy:
0.5041
Epoch 00012: val_loss improved from 1.36196 to 1.35316, saving model to
best_cnn_model3.hdf5
0.5041 - val_loss: 1.3532 - val_accuracy: 0.5035
Epoch 13/20
Epoch 00013: val_loss improved from 1.35316 to 1.33796, saving model to
best_cnn_model3.hdf5
57/57 [============= ] - 1s 9ms/step - loss: 1.3433 - accuracy:
0.5116 - val_loss: 1.3380 - val_accuracy: 0.5071
Epoch 14/20
0.5206
Epoch 00014: val_loss improved from 1.33796 to 1.32859, saving model to
best_cnn_model3.hdf5
0.5205 - val_loss: 1.3286 - val_accuracy: 0.5046
```

```
Epoch 15/20
   0.5305
   Epoch 00015: val_loss improved from 1.32859 to 1.31030, saving model to
   best_cnn_model3.hdf5
   57/57 [============== ] - 1s 9ms/step - loss: 1.3000 - accuracy:
   0.5305 - val_loss: 1.3103 - val_accuracy: 0.5247
   Epoch 16/20
   0.5368
   Epoch 00016: val_loss improved from 1.31030 to 1.30378, saving model to
   best_cnn_model3.hdf5
   0.5368 - val_loss: 1.3038 - val_accuracy: 0.5274
   Epoch 17/20
   Epoch 00017: val_loss improved from 1.30378 to 1.28909, saving model to
   best_cnn_model3.hdf5
   0.5428 - val_loss: 1.2891 - val_accuracy: 0.5274
   Epoch 18/20
   Epoch 00018: val_loss improved from 1.28909 to 1.28253, saving model to
   best_cnn_model3.hdf5
   0.5547 - val_loss: 1.2825 - val_accuracy: 0.5369
   Epoch 19/20
   Epoch 00019: val_loss improved from 1.28253 to 1.27936, saving model to
   best_cnn_model3.hdf5
   57/57 [============== ] - 1s 9ms/step - loss: 1.2285 - accuracy:
   0.5625 - val_loss: 1.2794 - val_accuracy: 0.5366
   Epoch 20/20
   0.5698
   Epoch 00020: val_loss did not improve from 1.27936
   0.5696 - val_loss: 1.2813 - val_accuracy: 0.5339
[52]: plt.plot(history_cnn3.history['loss'])
   plt.plot(history_cnn3.history['val_loss'])
   plt.title('Model loss')
   plt.ylabel('Loss')
   plt.xlabel('Epochs')
```

```
plt.legend(['Train', 'Validation'], loc='upper right')
plt.show()
print(time_to_run)
```



## 11.894754886627197

**d(i).** Details of the 3 different CNN models are listed below:

## **#Details on CNN Model 1:**

Number of conv layers: 3

Number of pooling layers: 2

Total parameters: 19798723

Optimizer used: Adam with learning rate of 0.0005

Regulerizer used: 12 regulerizer used with conv layers

Dropout: 0.4 after dense layers

Activation function for input and hidden layers: ReLU

Activation function for output layer: Softmax

Training accuracy (for the best model): 85.23%

Validation accuracy (for the best model): 46.45%

Training time: 83.49 s

**#Details on CNN Model 2:** 

Number of conv layers: 2

Number of pooling layers: 1

Total parameters: 20003999

Optimizer used: Adam with learning rate of 0.0005

Regulerizer used: 12 regulerizer used with conv layers

Dropout: 0.4 after dense layers

Activation function for input and hidden layers: ReLU for conv layers & Sigmoid for dense layers

Activation function for output layer: Softmax

Training accuracy (for the best model): 48.21%

Validation accuracy (for the best model): 47.34%

Training time: 12.48 s

**#Details on FNN Model 3:** 

Number of conv layers: 2

Number of pooling layers: 1

Total parameters: 615159

Optimizer used: Adam with learning rate of 0.0005

Regulerizer used: 12 regulerizer used with conv layers

Dropout: 0.4 after 2nd conv layers, 0.2 after dense layers

Activation function for input and hidden layers: ReLU

Activation function for output layer: Softmax

Training accuracy (for the best model): 56.25%

Validation accuracy (for the best model): 53.66%

Training time: 11.89 s

Analayzing the performance of the 3 models on train and validation sets, it can be concluded that the 3rd model performs well and we should use it for testing. One notable thing about the CNN models are they have higher number of parameters and runtime compared to the FNN model and their results are improved by roughly 10%.

```
[53]: best_cnn_model = tf.keras.models.load_model("best_cnn_model3.hdf5")
      score = best_cnn_model.evaluate(X_test, y_test, verbose=0)
      print("%s: %.2f%%" % (best_cnn_model.metrics_names[1], score[1]*100))
     accuracy: 54.00%
     d(ii). Emotion classification accuracy on the testing set = 54.00%
[54]: !pip install -q -U keras-tuner
          || 98 kB 5.1 MB/s eta 0:00:011
[55]: def build_model(hp):
          model = keras.Sequential([
          keras.layers.Conv2D(
              filters = hp.Int('conv_1_filter', min_value=32, max_value=128, step=16),
              kernel_size = hp.Choice('conv_1_kernel', values = [3,5]),
              activation = hp.Choice('conv_1_activition', values = ['relu', 'sigmoid']),
              input_shape = (48, 48, 1),
              padding = 'same'),
          keras.layers.MaxPooling2D(
              pool_size = hp.Choice('pool_1_kernel', values = [2,4]),
              strides = (2,2),
              padding ='same'),
          keras.layers.Conv2D(
              filters = hp.Int('conv_2_filter', min_value=32, max_value=64, step=16),
              kernel_size = hp.Choice('conv_2_kernel', values = [3,5]),
              activation = 'relu',
              padding = 'same'),
          keras.layers.MaxPooling2D(
              pool_size = hp.Choice('pool_2_kernel', values = [2,4]),
              strides = (2,2),
              padding = 'same'),
          keras.layers.Flatten(),
          keras.layers.Dense(
              units = hp.Int('dense_1_units', min_value=64, max_value=512, step=16),
              activation = hp.Choice('dense_1_activition', values =_
       →['relu','sigmoid'])),
          keras.layers.Dense(7, activation='softmax')
```

```
])
         model.compile(optimizer=tf.keras.optimizers.Adam(hp.Choice('learning_rate',_
       \rightarrowvalues=[1e-2, 1e-3])),
                   loss='categorical_crossentropy',
                   metrics=['accuracy'])
         return model
[56]: #importing random search
     from keras_tuner import BayesianOptimization
      #creating randomsearch object
     tuner = BayesianOptimization(build_model,
                         objective='val_loss',
                         max_trials = 5,
                         overwrite = True)
      # search best parameter
     tuner.search(X_train, y_train, epochs=10, batch_size = 512,__
       →validation_data=(X_val, y_val))
     Trial 5 Complete [00h 00m 28s]
     val_loss: 1.2554805278778076
     Best val_loss So Far: 1.2032557725906372
     Total elapsed time: 00h 01m 47s
     INFO:tensorflow:Oracle triggered exit
[57]: model = tuner.get_best_models(num_models=1)[0]
     print (model.summary())
     # Evaluate the best model.
     loss, accuracy = model.evaluate(X_test, y_test)
     print('loss:', loss)
     print('accuracy:', accuracy*100)
     Model: "sequential"
     Layer (type)
                                 Output Shape
                                                          Param #
     ______
                                 (None, 48, 48, 32)
      conv2d (Conv2D)
                                                          832
      max_pooling2d (MaxPooling2D (None, 24, 24, 32)
      )
      conv2d_1 (Conv2D)
                                 (None, 24, 24, 64)
                                                          18496
      max_pooling2d_1 (MaxPooling (None, 12, 12, 64)
      2D)
```

```
dense (Dense)
                                 (None, 64)
                                                          589888
       dense_1 (Dense)
                                 (None, 7)
                                                          455
      Total params: 609,671
      Trainable params: 609,671
      Non-trainable params: 0
      None
      accuracy: 0.5573
      loss: 1.1789838075637817
      accuracy: 55.72583079338074
      e. Emotion classification accuracy on the testing set = 55.73%
[149]: from tensorflow.keras.applications import VGG16
      vgg_model = VGG16(weights = 'imagenet', include_top = False, input_shape = (48, __
       48, 3)
[151]: # Freeze bottom layers
      for layer in vgg_model.layers[:17]:
          layer.trainable = False
      for i, layer in enumerate(vgg_model.layers):
          print(i, layer.name, layer.trainable)
      0 input_10 False
      1 block1_conv1 False
      2 block1_conv2 False
      3 block1_pool False
      4 block2_conv1 False
      5 block2_conv2 False
      6 block2_pool False
      7 block3_conv1 False
      8 block3_conv2 False
      9 block3_conv3 False
      10 block3_pool False
      11 block4_conv1 False
      12 block4_conv2 False
      13 block4_conv3 False
      14 block4_pool False
      15 block5_conv1 False
      16 block5_conv2 False
      17 block5_conv3 True
```

(None, 9216)

flatten (Flatten)

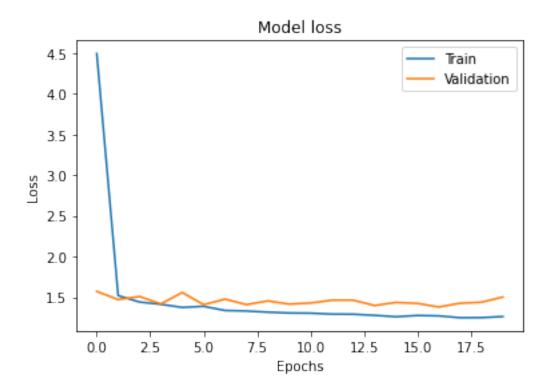
```
18 block5_pool True
```

```
[152]: x = vgg_model.output
      x = Flatten()(x)
      x = Dense(1024, activation='relu')(x)
      x = Dropout(0.5)(x)
      x = Dense(7, activation='softmax')(x)
      transfer_model = tf.keras.Model(inputs = vgg_model.input, outputs = x)
[154]: checkpoint3 = ModelCheckpoint('vgg16_finetune.h15',
                                 monitor= 'val_loss',
                                 mode= 'min',
                                 save_best_only = True,
                                 verbose= 1)
[155]: from tensorflow.keras.optimizers import Adam
      learning_rate= 0.005
      transfer_model.compile(loss="categorical_crossentropy", __
       →optimizer=Adam(lr=learning_rate), metrics=["accuracy"])
[148]: X_train_trn = np.stack((X_train, X_train, X_train), axis = 3)
      X_test_trn = np.stack((X_test, X_test, X_test), axis = 3)
      X_val_trn = np.stack((X_val, X_val, X_val), axis = 3)
[156]: transfer_history = transfer_model.fit(
         X_train_trn, y_train,
         batch_size = 512,
         epochs=20,
         validation_data=(X_val_trn, y_val),
         callbacks = [checkpoint3])
     Epoch 1/20
     0.2909
     Epoch 00001: val_loss improved from inf to 1.57159, saving model to
     vgg16_finetune.h15
     INFO:tensorflow:Assets written to: vgg16_finetune.h15/assets
     57/57 [=========== ] - 38s 667ms/step - loss: 4.4926 -
     accuracy: 0.2910 - val_loss: 1.5716 - val_accuracy: 0.3756
     Epoch 2/20
     0.4092
     Epoch 00002: val_loss improved from 1.57159 to 1.47074, saving model to
     vgg16_finetune.h15
     INFO:tensorflow:Assets written to: vgg16_finetune.h15/assets
     57/57 [=========== ] - 6s 105ms/step - loss: 1.5196 -
     accuracy: 0.4094 - val_loss: 1.4707 - val_accuracy: 0.4416
```

```
Epoch 3/20
0.4490
Epoch 00003: val_loss did not improve from 1.47074
0.4490 - val_loss: 1.5088 - val_accuracy: 0.4269
Epoch 4/20
Epoch 00004: val_loss improved from 1.47074 to 1.41811, saving model to
vgg16_finetune.h15
INFO:tensorflow:Assets written to: vgg16_finetune.h15/assets
accuracy: 0.4649 - val_loss: 1.4181 - val_accuracy: 0.4561
0.4818
Epoch 00005: val_loss did not improve from 1.41811
0.4817 - val_loss: 1.5577 - val_accuracy: 0.3965
Epoch 6/20
Epoch 00006: val_loss improved from 1.41811 to 1.40841, saving model to
vgg16_finetune.h15
INFO:tensorflow:Assets written to: vgg16_finetune.h15/assets
57/57 [=========== ] - 6s 110ms/step - loss: 1.3881 -
accuracy: 0.4762 - val_loss: 1.4084 - val_accuracy: 0.4617
0.4948
Epoch 00007: val_loss did not improve from 1.40841
0.4949 - val_loss: 1.4766 - val_accuracy: 0.4466
Epoch 8/20
0.4985
Epoch 00008: val_loss did not improve from 1.40841
0.4985 - val_loss: 1.4085 - val_accuracy: 0.4597
Epoch 9/20
0.5055
Epoch 00009: val_loss did not improve from 1.40841
57/57 [============] - 4s 68ms/step - loss: 1.3161 - accuracy:
0.5053 - val_loss: 1.4546 - val_accuracy: 0.4380
Epoch 10/20
```

```
0.5071
Epoch 00010: val_loss did not improve from 1.40841
0.5073 - val_loss: 1.4152 - val_accuracy: 0.4734
Epoch 11/20
Epoch 00011: val_loss did not improve from 1.40841
57/57 [============] - 4s 68ms/step - loss: 1.3040 - accuracy:
0.5108 - val_loss: 1.4287 - val_accuracy: 0.4556
Epoch 12/20
0.5149
Epoch 00012: val_loss did not improve from 1.40841
0.5149 - val_loss: 1.4634 - val_accuracy: 0.4427
Epoch 13/20
0.5166
Epoch 00013: val_loss did not improve from 1.40841
57/57 [===========] - 4s 68ms/step - loss: 1.2908 - accuracy:
0.5166 - val_loss: 1.4630 - val_accuracy: 0.4508
Epoch 14/20
0.5227
Epoch 00014: val_loss improved from 1.40841 to 1.39755, saving model to
vgg16_finetune.h15
INFO:tensorflow:Assets written to: vgg16_finetune.h15/assets
accuracy: 0.5228 - val_loss: 1.3975 - val_accuracy: 0.4706
Epoch 15/20
0.5300
Epoch 00015: val_loss did not improve from 1.39755
57/57 [===========] - 4s 68ms/step - loss: 1.2602 - accuracy:
0.5299 - val_loss: 1.4362 - val_accuracy: 0.4542
Epoch 16/20
0.5264
Epoch 00016: val_loss did not improve from 1.39755
0.5265 - val_loss: 1.4241 - val_accuracy: 0.4544
Epoch 17/20
Epoch 00017: val_loss improved from 1.39755 to 1.37925, saving model to
vgg16_finetune.h15
INFO:tensorflow:Assets written to: vgg16_finetune.h15/assets
```

```
57/57 [=========== ] - 6s 112ms/step - loss: 1.2708 -
   accuracy: 0.5255 - val_loss: 1.3792 - val_accuracy: 0.4806
   Epoch 18/20
   0.5375
   Epoch 00018: val_loss did not improve from 1.37925
   0.5375 - val_loss: 1.4262 - val_accuracy: 0.4653
   Epoch 19/20
   56/57 [==========>.] - ETA: Os - loss: 1.2486 - accuracy:
   0.5344
   Epoch 00019: val_loss did not improve from 1.37925
   0.5342 - val_loss: 1.4384 - val_accuracy: 0.4542
   Epoch 20/20
   0.5299
   Epoch 00020: val_loss did not improve from 1.37925
   0.5300 - val_loss: 1.5022 - val_accuracy: 0.4363
[157]: plt.plot(transfer_history.history['loss'])
    plt.plot(transfer_history.history['val_loss'])
    plt.title('Model loss')
    plt.ylabel('Loss')
    plt.xlabel('Epochs')
    plt.legend(['Train', 'Validation'], loc='upper right')
    plt.show()
```



```
[158]: best_trn_model = tf.keras.models.load_model("vgg16_finetune.h15")
score = best_trn_model.evaluate(X_test_trn, y_test, verbose=0)
print("%s: %.2f%%" % (model.metrics_names[1], score[1]*100))
```

accuracy: 48.59%

(f). I have used VGG-16 pretrained model and fine-tuned it with the training data. I started with pretrained imagenet weights for training and froze all the conv blocks except the last conv and pool layers and fine tuned the weights for those layers and the dense layers at the top. The accuracy of the best model is 48.59% on the test set.

```
[159]: X_train_aug = np.expand_dims(X_train, axis=-1)
X_val_aug = np.expand_dims(X_val, axis=-1)
X_test_aug = np.expand_dims(X_test, axis=-1)
```

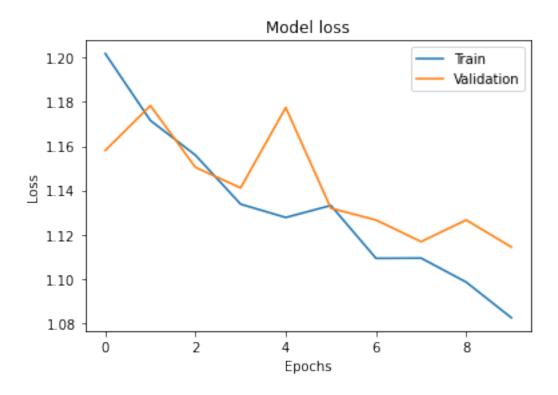
```
[204]: from keras.preprocessing.image import ImageDataGenerator
train_datagen = ImageDataGenerator(
    fill_mode='nearest',
    rotation_range=20,
    shear_range=20,
    zoom_range=0.1,
    horizontal_flip = True)

valid_datagen = ImageDataGenerator()
```

```
train_generator = train_datagen.flow(
           X_train_aug, y_train,
           batch_size = 512)
       validation_generator = valid_datagen.flow(
           X_val_aug, y_val,
           batch_size = 256)
[205]: n_rows=3
       n_cols=5
       n_{images} = n_{rows} * n_{cols}
       plt.figure(figsize=(n_cols*4, n_rows*3))
       for image_index in range(n_images):
           image, label = next(train_generator)
           img = image[0].squeeze()
           plt.subplot(n_rows, n_cols, image_index+1)
           plt.axis('off')
           plt.imshow(img, cmap = 'gray')
 []: checkpoint_4 = ModelCheckpoint("best_cnn_aug_model.hdf5", monitor = 'val_loss',__
        \rightarrowverbose = 1,
           save_best_only = True, mode =' min', period = 1)
[207]: history = model.fit_generator(train_generator,
                                      validation_data=validation_generator,
                                      epochs = 10,
                                      callbacks=[checkpoint_4])
```

```
Epoch 1/10
0.5464
Epoch 00001: val_loss improved from inf to 1.15808, saving model to
best_cnn_aug_model.hdf5
57/57 [=========== ] - 8s 141ms/step - loss: 1.2019 -
accuracy: 0.5464 - val_loss: 1.1581 - val_accuracy: 0.5620
Epoch 2/10
0.5588
Epoch 00002: val_loss did not improve from 1.15808
accuracy: 0.5588 - val_loss: 1.1784 - val_accuracy: 0.5556
Epoch 3/10
57/57 [============= ] - ETA: Os - loss: 1.1559 - accuracy:
0.5671
Epoch 00003: val_loss improved from 1.15808 to 1.15041, saving model to
best_cnn_aug_model.hdf5
57/57 [=========== ] - 8s 139ms/step - loss: 1.1559 -
accuracy: 0.5671 - val_loss: 1.1504 - val_accuracy: 0.5662
57/57 [============= ] - ETA: Os - loss: 1.1338 - accuracy:
Epoch 00004: val_loss improved from 1.15041 to 1.14113, saving model to
best_cnn_aug_model.hdf5
accuracy: 0.5732 - val_loss: 1.1411 - val_accuracy: 0.5717
Epoch 5/10
57/57 [============ - ETA: Os - loss: 1.1277 - accuracy:
0.5782
Epoch 00005: val_loss did not improve from 1.14113
accuracy: 0.5782 - val_loss: 1.1775 - val_accuracy: 0.5637
Epoch 6/10
57/57 [============= ] - ETA: Os - loss: 1.1332 - accuracy:
0.5722
Epoch 00006: val_loss improved from 1.14113 to 1.13193, saving model to
best_cnn_aug_model.hdf5
accuracy: 0.5722 - val_loss: 1.1319 - val_accuracy: 0.5759
Epoch 7/10
57/57 [============= ] - ETA: Os - loss: 1.1093 - accuracy:
Epoch 00007: val_loss improved from 1.13193 to 1.12660, saving model to
best_cnn_aug_model.hdf5
57/57 [=========== ] - 8s 138ms/step - loss: 1.1093 -
accuracy: 0.5811 - val_loss: 1.1266 - val_accuracy: 0.5748
Epoch 8/10
```

```
0.5833
    Epoch 00008: val_loss improved from 1.12660 to 1.11680, saving model to
    best_cnn_aug_model.hdf5
    accuracy: 0.5833 - val_loss: 1.1168 - val_accuracy: 0.5768
    0.5890
    Epoch 00009: val_loss did not improve from 1.11680
    57/57 [============ ] - 8s 137ms/step - loss: 1.0985 -
    accuracy: 0.5890 - val_loss: 1.1266 - val_accuracy: 0.5823
    Epoch 10/10
    57/57 [============ ] - ETA: Os - loss: 1.0824 - accuracy:
    Epoch 00010: val_loss improved from 1.11680 to 1.11436, saving model to
    best_cnn_aug_model.hdf5
    accuracy: 0.5934 - val_loss: 1.1144 - val_accuracy: 0.5885
[208]: plt.plot(history.history['loss'])
    plt.plot(history.history['val_loss'])
    plt.title('Model loss')
    plt.ylabel('Loss')
    plt.xlabel('Epochs')
    plt.legend(['Train', 'Validation'], loc='upper right')
    plt.show()
```



```
[209]: model = tf.keras.models.load_model("best_cnn_aug_model.hdf5")
score = model.evaluate(X_test, y_test, verbose=0)
print("%s: %.2f%%" % (model.metrics_names[1], score[1]*100))
```

accuracy: 58.26%

**g.** I have augmented the model using image data generator. For data augmentation, I have used rotation, shear, zoom and horizontal flip. Some of the augmented images are also displayed in a cell above. I have also trained a cnn model (model obtained from previous Bayesian optimization step) using augmented data. The accuracy on the test set is 58.26%.