

# Exercises5

November 27, 2020

## 1 Exercise set 5

### 1.1 Answered to all questions (1-5).

## 2 Question 1

Number of parameters in:

### First layer:

49152 inputs connected to each neuron in first layer. Therefore  $49152 \cdot 100 = 4915200$  learnable weights. Also each neuron in first layer has a bias value. Therefore total number of parameters in this layer is  $4915200 + 100 = 4915300$

### Second layer:

100 inputs connected to each neuron in second layer. Therefore  $100 \cdot 100 = 10000$  learnable weights. Also each neuron in second layer has a bias value. Therefore total number of parameters in this layer is  $10000 + 100 = 10100$

### Third layer:

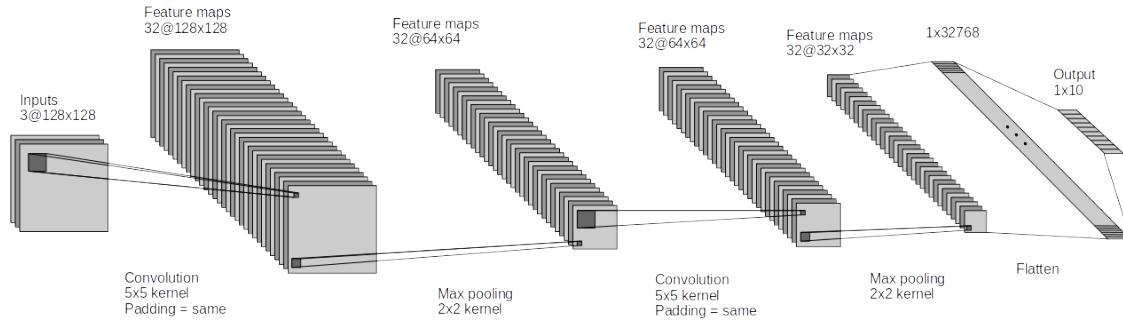
100 inputs connected to each neuron in third layer. Therefore  $100 \cdot 10 = 1000$  learnable weights. Also each neuron in third layer has a bias value. Therefore total number of parameters in this layer is  $1000 + 10 = 1010$

### Total number of parameters in network

$$4915300 + 10100 + 1010 = 4926410$$

## 3 Question 2

a)



b)

Number of parameters in:

### First convolutional layer:

Each convolution kernel has  $5 * 5$  parameters and we have 3 input layers. Therefore a single convolutional kernel “cube” has a  $5 * 5 * 3 = 75$  learnable weight parameters. Also, you need to learn unique one for each output feature map. Therefore  $75 * 32 = 2400$  learnable weight parameters. Last thing is to add bias values for each output feature map, which increases the total number of parameters to  $2400 + 32 = 2432$

### Pooling layer:

Pooling layer takes no parameters. It just shrinks the size of each feature map.

### Second convolutional layer:

Each convolution kernel has  $5 * 5$  parameters and we have 32 input layers. Therefore a single convolutional kernel “cube” has a  $5 * 5 * 32 = 800$  learnable weight parameters. Also, you need to learn unique one for each output feature map. Therefore  $800 * 32 = 25600$  learnable weight parameters. Last thing is to add bias values for each output feature map, which increases the total number of parameters to  $25600 + 32 = 25632$

### Pooling layer:

Takes no parameters.

### Flatten

No learnable parameters. Just reduces the dimensionality of the input.

### Output layer

Each neuron in the input is connected to each neuron in the output with learnable weight parameter. Therefore  $32768 * 10 = 327680$  learnable weight parameters. Also each neuron in the output layer has a learnable bias value. Therefore learnable parameters in this layer adds up to  $327680 + 10 = 327690$

### Total number of parameters in the network

$$2432 + 25632 + 327690 = 355754$$

c)

On first layer, the convolution window slides over all possible locations in the 3 input channels and multiplies the corresponding pixel values intersecting with the window. This procedure has to be done for each output feature map. In numbers, convolution window has a size of  $5 \times 5$  so 25 multiplications is done in single location. Also, convolution window of given size can move to 124 different positions horizontally, and 124 different positions vertically in the feature map of size of  $128 \times 128$ . Therefore,  $5 \times 5$  window has  $124 * 124 = 15376$  possible locations in the single input channel, so  $15376 * 25 = 384400$  multiplications. We have 3 input channels, so multiplications needed to calculate values for a single output channel equals to  $3 * 384400 = 1153200$ . Finally, we have 32 output channels, so total number of scalar multiplications on the first convolutional layer equals to  $32 * 1153200 = 36902400$ .

## 4 Question 3

```
[1]: import os
import numpy as np
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
# Load the data
os.chdir('/home/tuomas/Python/DATA.ML.200/Ex5')
trainX = np.load('X_train.npy')
trainY = np.load('y_train.npy')
testX = np.load('X_test.npy')
testY = np.load('y_test.npy')
# Vectorize
trainX_vec = trainX.reshape(-1, trainX.shape[1]*trainX.shape[2])
testX_vec = testX.reshape(-1, testX.shape[1]*testX.shape[2])
```

```
[2]: models = [RandomForestClassifier(n_estimators=10,n_jobs=-1),
                RandomForestClassifier(n_estimators=50,n_jobs=-1),
                RandomForestClassifier(n_estimators=100,n_jobs=-1)]

names = ['RF10','RF50','RF100']
accuracy = []
for i in range(len(models)):
    print('Training {}'.format(names[i]))
    models[i].fit(trainX_vec, trainY)
    print('Testing {}'.format(names[i]))
    predY = models[i].predict(testX_vec)
    print('Evaluating {}'.format(names[i]))
    accuracy.append(accuracy_score(testY, predY))
```

```
Training RF10...
Testing RF10...
Evaluating RF10...
Training RF50...
Testing RF50...
Evaluating RF50...
```

Training RF100...  
Testing RF100...  
Evaluating RF100...

```
[3]: # a, b & c
for i in range(len(accuracy)):
    print('{} accuracy = {}'.format(names[i], accuracy[i]))
```

RF10 accuracy = 0.5153333333333333  
RF50 accuracy = 0.5833333333333334  
RF100 accuracy = 0.5946666666666667

## 5 Question 4

```
[3]: from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, BatchNormalization, Dropout, Flatten, Dense, MaxPool2D
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.callbacks import EarlyStopping
# Add dummy dimensions & categorize labels
trainX = trainX[..., np.newaxis]
trainY_cat = to_categorical(trainY, 15)
testX = testX[..., np.newaxis]
testY_cat = to_categorical(testY, 15)
```

```
[3]: # Build the CNN
layers=[Conv2D(32, kernel_size=5, activation='relu', input_shape=(40,501,1)),
        MaxPool2D(pool_size=(2,2)),
        Conv2D(32, kernel_size=5, activation='relu', padding='same'),
        MaxPool2D(pool_size=(2,2)),
        Flatten(),
        Dense(15, activation='softmax')]

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

```
[5]: # Train the CNN
callback = EarlyStopping(monitor='val_accuracy', patience=10,
                        restore_best_weights=True, mode="max")

epochs = 50
batch_size = 64
history = model.fit(trainX, trainY_cat,
                    validation_data=(testX, testY_cat),
                    batch_size=batch_size,
                    epochs=epochs,
```

```
use_multiprocessing=True,  
callbacks=[callback],  
verbose=1  
)
```

Epoch 1/50

71/71 [=====] - 6s 84ms/step - loss: 3.1328 - accuracy:  
0.1016 - val\_loss: 2.3994 - val\_accuracy: 0.1580

Epoch 2/50

71/71 [=====] - 3s 39ms/step - loss: 2.5945 - accuracy:  
0.1187 - val\_loss: 2.6976 - val\_accuracy: 0.1493

Epoch 3/50

71/71 [=====] - 3s 39ms/step - loss: 2.5573 - accuracy:  
0.1102 - val\_loss: 2.3555 - val\_accuracy: 0.1533

Epoch 4/50

71/71 [=====] - 3s 39ms/step - loss: 2.2633 - accuracy:  
0.1660 - val\_loss: 2.1841 - val\_accuracy: 0.1700

Epoch 5/50

71/71 [=====] - 3s 40ms/step - loss: 2.1549 - accuracy:  
0.2078 - val\_loss: 2.1832 - val\_accuracy: 0.1653

Epoch 6/50

71/71 [=====] - 3s 39ms/step - loss: 2.1116 - accuracy:  
0.2249 - val\_loss: 2.1855 - val\_accuracy: 0.1907

Epoch 7/50

71/71 [=====] - 3s 39ms/step - loss: 2.0582 - accuracy:  
0.2589 - val\_loss: 2.1002 - val\_accuracy: 0.2693

Epoch 8/50

71/71 [=====] - 3s 39ms/step - loss: 2.0374 - accuracy:  
0.2771 - val\_loss: 2.0809 - val\_accuracy: 0.2820

Epoch 9/50

71/71 [=====] - 3s 39ms/step - loss: 2.0016 - accuracy:  
0.2993 - val\_loss: 2.1304 - val\_accuracy: 0.3167

Epoch 10/50

71/71 [=====] - 3s 39ms/step - loss: 2.1852 - accuracy:  
0.2664 - val\_loss: 2.1242 - val\_accuracy: 0.2660

Epoch 11/50

71/71 [=====] - 3s 39ms/step - loss: 2.0052 - accuracy:  
0.3136 - val\_loss: 2.0605 - val\_accuracy: 0.2933

Epoch 12/50

71/71 [=====] - 3s 39ms/step - loss: 1.9471 - accuracy:  
0.3451 - val\_loss: 2.0276 - val\_accuracy: 0.2907

Epoch 13/50

71/71 [=====] - 3s 39ms/step - loss: 1.9099 - accuracy:  
0.3300 - val\_loss: 2.0049 - val\_accuracy: 0.3160

Epoch 14/50

71/71 [=====] - 3s 39ms/step - loss: 1.8808 - accuracy:  
0.3436 - val\_loss: 1.9618 - val\_accuracy: 0.2900

Epoch 15/50  
71/71 [=====] - 3s 39ms/step - loss: 1.8345 - accuracy:  
0.3664 - val\_loss: 1.9271 - val\_accuracy: 0.3447  
Epoch 16/50  
71/71 [=====] - 3s 39ms/step - loss: 1.8350 - accuracy:  
0.3696 - val\_loss: 1.9270 - val\_accuracy: 0.3080  
Epoch 17/50  
71/71 [=====] - 3s 39ms/step - loss: 1.7908 - accuracy:  
0.3793 - val\_loss: 1.8866 - val\_accuracy: 0.3633  
Epoch 18/50  
71/71 [=====] - 3s 39ms/step - loss: 1.7455 - accuracy:  
0.3951 - val\_loss: 2.0116 - val\_accuracy: 0.3353  
Epoch 19/50  
71/71 [=====] - 3s 39ms/step - loss: 1.7645 - accuracy:  
0.3924 - val\_loss: 1.8413 - val\_accuracy: 0.3307  
Epoch 20/50  
71/71 [=====] - 3s 39ms/step - loss: 1.6786 - accuracy:  
0.4218 - val\_loss: 1.9011 - val\_accuracy: 0.3053  
Epoch 21/50  
71/71 [=====] - 3s 40ms/step - loss: 1.6249 - accuracy:  
0.4358 - val\_loss: 1.8084 - val\_accuracy: 0.3480  
Epoch 22/50  
71/71 [=====] - 3s 39ms/step - loss: 1.6020 - accuracy:  
0.4480 - val\_loss: 1.7787 - val\_accuracy: 0.3727  
Epoch 23/50  
71/71 [=====] - 3s 39ms/step - loss: 1.5198 - accuracy:  
0.4749 - val\_loss: 1.8750 - val\_accuracy: 0.3540  
Epoch 24/50  
71/71 [=====] - 3s 39ms/step - loss: 1.5056 - accuracy:  
0.4731 - val\_loss: 1.7611 - val\_accuracy: 0.4113  
Epoch 25/50  
71/71 [=====] - 3s 39ms/step - loss: 1.4192 - accuracy:  
0.5093 - val\_loss: 1.7532 - val\_accuracy: 0.3853  
Epoch 26/50  
71/71 [=====] - 3s 39ms/step - loss: 1.3364 - accuracy:  
0.5427 - val\_loss: 1.6745 - val\_accuracy: 0.4140  
Epoch 27/50  
71/71 [=====] - 3s 39ms/step - loss: 1.2526 - accuracy:  
0.5618 - val\_loss: 1.7301 - val\_accuracy: 0.4360  
Epoch 28/50  
71/71 [=====] - 3s 39ms/step - loss: 1.1888 - accuracy:  
0.5929 - val\_loss: 1.7342 - val\_accuracy: 0.4327  
Epoch 29/50  
71/71 [=====] - 3s 40ms/step - loss: 1.0604 - accuracy:  
0.6353 - val\_loss: 1.7289 - val\_accuracy: 0.4327  
Epoch 30/50  
71/71 [=====] - 3s 39ms/step - loss: 1.0344 - accuracy:  
0.6482 - val\_loss: 1.6827 - val\_accuracy: 0.4387

```

Epoch 31/50
71/71 [=====] - 3s 39ms/step - loss: 0.9364 - accuracy:
0.6827 - val_loss: 1.8933 - val_accuracy: 0.4373
Epoch 32/50
71/71 [=====] - 3s 39ms/step - loss: 0.9105 - accuracy:
0.6918 - val_loss: 1.9479 - val_accuracy: 0.4493
Epoch 33/50
71/71 [=====] - 3s 39ms/step - loss: 0.8713 - accuracy:
0.7082 - val_loss: 1.8138 - val_accuracy: 0.4127
Epoch 34/50
71/71 [=====] - 3s 39ms/step - loss: 0.8252 - accuracy:
0.7238 - val_loss: 1.8386 - val_accuracy: 0.4347
Epoch 35/50
71/71 [=====] - 3s 39ms/step - loss: 0.7992 - accuracy:
0.7267 - val_loss: 1.8279 - val_accuracy: 0.4400
Epoch 36/50
71/71 [=====] - 3s 39ms/step - loss: 0.7525 - accuracy:
0.7518 - val_loss: 1.9589 - val_accuracy: 0.4440
Epoch 37/50
71/71 [=====] - 3s 39ms/step - loss: 0.7385 - accuracy:
0.7560 - val_loss: 1.9793 - val_accuracy: 0.4453
Epoch 38/50
71/71 [=====] - 3s 39ms/step - loss: 0.6907 - accuracy:
0.7680 - val_loss: 1.9418 - val_accuracy: 0.4380
Epoch 39/50
71/71 [=====] - 3s 39ms/step - loss: 0.6850 - accuracy:
0.7756 - val_loss: 1.9826 - val_accuracy: 0.4353
Epoch 40/50
71/71 [=====] - 3s 39ms/step - loss: 0.6669 - accuracy:
0.7758 - val_loss: 2.1422 - val_accuracy: 0.4433
Epoch 41/50
71/71 [=====] - 3s 39ms/step - loss: 0.6305 - accuracy:
0.7911 - val_loss: 2.3152 - val_accuracy: 0.4287
Epoch 42/50
71/71 [=====] - 3s 39ms/step - loss: 0.6184 - accuracy:
0.7973 - val_loss: 2.1647 - val_accuracy: 0.4380

```

```

[9]: # Evaluate the CNN
loss, acc = model.evaluate(testX, testY_cat, verbose=0)
print("CNN Accuracy using model.evaluate: {}".format(acc))

```

```
CNN Accuracy using model.evaluate: 0.4493333399295807
```

## 6 Question 5

```
[10]: from tensorflow.keras.models import Sequential
      from tensorflow.keras.layers import LSTM, Flatten, Dense
      from tensorflow.keras.utils import to_categorical
      # Process the data
      os.chdir('/home/tuomas/Python/DATA.ML.200/Ex5')

      trainX = np.load('X_train.npy')
      trainX = trainX.reshape(-1,501,40)
      trainY = np.load('y_train.npy')
      trainY_cat = to_categorical(trainY, 15)

      testX = np.load('X_test.npy')
      testX = testX.reshape(-1,501,40)
      testY = np.load('y_test.npy')
      testY_cat = to_categorical(testY, 15)
```

```
[11]: # Build the RNN
      model = Sequential()

      model.add(LSTM(units=32, return_sequences=True,
      ↪kernel_initializer='he_uniform', input_shape=(501,40)))
      model.add(Flatten())
      model.add(Dense(15, activation='softmax'))
      model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

```
[12]: # Train the RNN
      epochs = 50
      batch_size = 32#16
      history = model.fit(trainX, trainY_cat,
                          batch_size=batch_size,
                          epochs=epochs,
                          use_multiprocessing=True,
                          validation_data=(testX, testY_cat),
                          #callbacks=[callback],
                          verbose=1
                          )
```

Epoch 1/50

141/141 [=====] - 3s 21ms/step - loss: 2.3836 - accuracy: 0.2862 - val\_loss: 1.8761 - val\_accuracy: 0.3053

Epoch 2/50

141/141 [=====] - 3s 19ms/step - loss: 1.5554 - accuracy: 0.4891 - val\_loss: 1.7439 - val\_accuracy: 0.4233

Epoch 3/50



141/141 [=====] - 3s 19ms/step - loss: 1.3068 - accuracy: 0.5631 - val\_loss: 1.6719 - val\_accuracy: 0.4273  
Epoch 4/50  
141/141 [=====] - 3s 19ms/step - loss: 1.1263 - accuracy: 0.6360 - val\_loss: 1.5927 - val\_accuracy: 0.4820  
Epoch 5/50  
141/141 [=====] - 3s 19ms/step - loss: 1.0088 - accuracy: 0.6780 - val\_loss: 1.5417 - val\_accuracy: 0.5067  
Epoch 6/50  
141/141 [=====] - 3s 19ms/step - loss: 0.8867 - accuracy: 0.7149 - val\_loss: 1.5727 - val\_accuracy: 0.5127  
Epoch 7/50  
141/141 [=====] - 3s 19ms/step - loss: 0.6927 - accuracy: 0.7856 - val\_loss: 1.4374 - val\_accuracy: 0.5353  
Epoch 8/50  
141/141 [=====] - 3s 19ms/step - loss: 0.6204 - accuracy: 0.8124 - val\_loss: 1.4539 - val\_accuracy: 0.5260  
Epoch 9/50  
141/141 [=====] - 3s 19ms/step - loss: 0.5757 - accuracy: 0.8338 - val\_loss: 1.5268 - val\_accuracy: 0.5127  
Epoch 10/50  
141/141 [=====] - 3s 19ms/step - loss: 0.4818 - accuracy: 0.8622 - val\_loss: 1.5199 - val\_accuracy: 0.5267  
Epoch 11/50  
141/141 [=====] - 3s 19ms/step - loss: 0.4292 - accuracy: 0.8829 - val\_loss: 1.5569 - val\_accuracy: 0.5107  
Epoch 12/50  
141/141 [=====] - 3s 19ms/step - loss: 0.3917 - accuracy: 0.8960 - val\_loss: 1.5875 - val\_accuracy: 0.5760  
Epoch 13/50  
141/141 [=====] - 3s 19ms/step - loss: 0.3532 - accuracy: 0.9082 - val\_loss: 1.4395 - val\_accuracy: 0.5407  
Epoch 14/50  
141/141 [=====] - 3s 19ms/step - loss: 0.2814 - accuracy: 0.9336 - val\_loss: 1.4081 - val\_accuracy: 0.5407  
Epoch 15/50  
141/141 [=====] - 3s 19ms/step - loss: 0.2515 - accuracy: 0.9429 - val\_loss: 1.4088 - val\_accuracy: 0.5627  
Epoch 16/50  
141/141 [=====] - 3s 19ms/step - loss: 0.2143 - accuracy: 0.9560 - val\_loss: 1.6449 - val\_accuracy: 0.4980  
Epoch 17/50  
141/141 [=====] - 3s 19ms/step - loss: 0.2092 - accuracy: 0.9542 - val\_loss: 1.7211 - val\_accuracy: 0.5093  
Epoch 18/50  
141/141 [=====] - 3s 19ms/step - loss: 0.1800 - accuracy: 0.9653 - val\_loss: 1.5291 - val\_accuracy: 0.5507  
Epoch 19/50

141/141 [=====] - 3s 19ms/step - loss: 0.1456 -  
accuracy: 0.9747 - val\_loss: 1.4634 - val\_accuracy: 0.5707  
Epoch 20/50  
141/141 [=====] - 3s 19ms/step - loss: 0.1239 -  
accuracy: 0.9822 - val\_loss: 1.5205 - val\_accuracy: 0.5947  
Epoch 21/50  
141/141 [=====] - 3s 20ms/step - loss: 0.1047 -  
accuracy: 0.9871 - val\_loss: 1.5115 - val\_accuracy: 0.5780  
Epoch 22/50  
141/141 [=====] - 3s 20ms/step - loss: 0.0717 -  
accuracy: 0.9951 - val\_loss: 1.6406 - val\_accuracy: 0.5387  
Epoch 23/50  
141/141 [=====] - 3s 20ms/step - loss: 0.0963 -  
accuracy: 0.9880 - val\_loss: 1.5859 - val\_accuracy: 0.5380  
Epoch 24/50  
141/141 [=====] - 3s 20ms/step - loss: 0.0976 -  
accuracy: 0.9867 - val\_loss: 1.6052 - val\_accuracy: 0.5633  
Epoch 25/50  
141/141 [=====] - 3s 20ms/step - loss: 0.0727 -  
accuracy: 0.9933 - val\_loss: 1.7144 - val\_accuracy: 0.5313  
Epoch 26/50  
141/141 [=====] - 3s 20ms/step - loss: 0.0721 -  
accuracy: 0.9902 - val\_loss: 1.6216 - val\_accuracy: 0.5687  
Epoch 27/50  
141/141 [=====] - 3s 20ms/step - loss: 0.0706 -  
accuracy: 0.9900 - val\_loss: 1.6315 - val\_accuracy: 0.5480  
Epoch 28/50  
141/141 [=====] - 3s 20ms/step - loss: 0.0479 -  
accuracy: 0.9987 - val\_loss: 1.6432 - val\_accuracy: 0.5800  
Epoch 29/50  
141/141 [=====] - 3s 20ms/step - loss: 0.0769 -  
accuracy: 0.9876 - val\_loss: 1.6604 - val\_accuracy: 0.5887  
Epoch 30/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0328 -  
accuracy: 0.9987 - val\_loss: 1.5897 - val\_accuracy: 0.5853  
Epoch 31/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0216 -  
accuracy: 0.9998 - val\_loss: 1.6626 - val\_accuracy: 0.5647  
Epoch 32/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0974 -  
accuracy: 0.9820 - val\_loss: 1.7337 - val\_accuracy: 0.5700  
Epoch 33/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0284 -  
accuracy: 0.9982 - val\_loss: 1.7067 - val\_accuracy: 0.5760  
Epoch 34/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0160 -  
accuracy: 1.0000 - val\_loss: 1.7495 - val\_accuracy: 0.5633  
Epoch 35/50

141/141 [=====] - 3s 19ms/step - loss: 0.0134 -  
accuracy: 1.0000 - val\_loss: 1.6221 - val\_accuracy: 0.5980  
Epoch 36/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0144 -  
accuracy: 1.0000 - val\_loss: 1.6117 - val\_accuracy: 0.5880  
Epoch 37/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0111 -  
accuracy: 1.0000 - val\_loss: 1.8765 - val\_accuracy: 0.5720  
Epoch 38/50  
141/141 [=====] - 3s 19ms/step - loss: 0.1942 -  
accuracy: 0.9431 - val\_loss: 1.6838 - val\_accuracy: 0.5440  
Epoch 39/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0425 -  
accuracy: 0.9964 - val\_loss: 1.6887 - val\_accuracy: 0.5793  
Epoch 40/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0141 -  
accuracy: 0.9998 - val\_loss: 1.7261 - val\_accuracy: 0.5873  
Epoch 41/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0104 -  
accuracy: 1.0000 - val\_loss: 1.7461 - val\_accuracy: 0.5707  
Epoch 42/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0078 -  
accuracy: 1.0000 - val\_loss: 1.7313 - val\_accuracy: 0.5967  
Epoch 43/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0066 -  
accuracy: 1.0000 - val\_loss: 1.7412 - val\_accuracy: 0.5773  
Epoch 44/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0060 -  
accuracy: 1.0000 - val\_loss: 1.7814 - val\_accuracy: 0.5860  
Epoch 45/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0053 -  
accuracy: 1.0000 - val\_loss: 1.7709 - val\_accuracy: 0.5873  
Epoch 46/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0056 -  
accuracy: 1.0000 - val\_loss: 1.7482 - val\_accuracy: 0.5947  
Epoch 47/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0048 -  
accuracy: 1.0000 - val\_loss: 1.7739 - val\_accuracy: 0.5853  
Epoch 48/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0053 -  
accuracy: 1.0000 - val\_loss: 1.7828 - val\_accuracy: 0.5933  
Epoch 49/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0042 -  
accuracy: 1.0000 - val\_loss: 1.7949 - val\_accuracy: 0.5867  
Epoch 50/50  
141/141 [=====] - 3s 19ms/step - loss: 0.0040 -  
accuracy: 1.0000 - val\_loss: 1.7664 - val\_accuracy: 0.5893

```
[13]: # Evaluate the RNN
      loss, acc = model.evaluate(testX, testY_cat, verbose=2)
      print("Accuracy : {}".format(acc))
```

```
47/47 - 0s - loss: 1.7664 - accuracy: 0.5893
Accuracy : 0.5893333554267883
```

```
[ ]:
```