Lab 10: Implement a Convolutional Neural Network to Classify Images on Fashion MNIST Data

Date: 13 December 2023

Problem Description: Using Keras build a Convolutional Neural Network model and train it using Fashion MNIST dataset for doing Apparel Category Classification. Make use of two convolutional layers, each followed by a Max Pooling layer of size 2. The first Conv Layer shoould use 64 filters whereas second should use 32 filters. Use kernel size 3 or 5 in Conv Layers. Add a feedforward dense NN classifier after the last MaxPooling layer. It should have one hidden layer with 64 units and 'relu' activation. Make use of Softmax Layer as the output layer with 10 units.

Experiment with 'SAME' padding and 'VALID' padding to find out which is better.

Regularize the whole network using Dropout regularization. Let dropout rate be 0.3 in Conv layers and 0.5 in the feedforward dense layers.

Finally evaluate the performnance of the model on Test Dataset provided in Fashion MNIST

Download the Fashion MNIST Data

```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt

#Load the fashion mnist dataset both training and testing data
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.fashion_mnist.load_data()

print("x_train shape: ", x_train.shape, " y_train shape: ", y_train.shape)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-la
32768/29515 [=================================] - 0s 0us/step
40960/29515 [=========================================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-im
26427392/26421880 [==============================] - 0s 0us/step
26435584/26421880 [==============================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-lab
16384/5148 [==============================================================================
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-ima
4423680/4422102 [==============================] - 0s 0us/step
4431872/4422102 [==============================] - 0s 0us/step
x_train shape:  (60000, 28, 28)  y_train shape:  (60000,)
```

Double-click (or enter) to edit

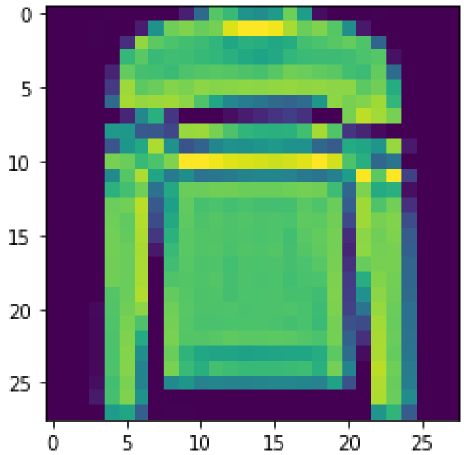
```
print("x_train shape: ", x_train.shape, " y_train shape: ", y_train.shape)
print("x_test shape: ", x_test.shape, " y_test shape: ", y_test.shape)
```

```
x_train shape:  (60000, 28, 28)  y_train shape:  (60000,)
x_test shape:  (10000, 28, 28)  y_test shape:  (10000,)
```

```
# Define the text labels
fashion_mnist_labels = ["T-shirt/top",  # label 0
                        "Trouser",      # label 1
                        "Pullover",     # label 2
                        "Dress",        # label 3
                        "Coat",         # label 4
                        "Sandal",       # label 5
                        "Shirt",        # label 6
                        "Sneaker",      # label 7
                        "Bag",          # label 8
                        "Ankle boot"]   # label 9
```

```
# Image index, you can pick any number between 0 and 59,999
i = 5
# y_train contains the lables, ranging from 0 to 9
label = y_train[i]
# Print the label, for example 2 Pullover
print ("y = " + str(label) + " " +(fashion_mnist_labels[label]))
# # Show one of the images from the training dataset
plt.imshow(x_train[i])
```

```
y = 2 Pullover
<matplotlib.image.AxesImage at 0x7f64bc9e5b90>
```



Data Normalization

Normalize the pixel integer values which are between 0 and 255 so that they are between 0 and 1

```
x_train = x_train.astype('float32')/255
x_test = x_test.astype('float32')/255
```

```
len(x_train)
```

```
60000
```

```
len(x_test)
```

```
10000
```

Splitting Data Into Training, Validation, and Testing Data

- Training Data: used for training the model
- Validation Data: used for tuning the hyper-parameters and to evaluate the model
- Test Data: used to test the model after it goes through training and initial vetting by the validation data

```
# Further break the training data such that 55 k examples are in training set and
# remaining 5k are in validation set

(x_train, x_valid) = x_train[5000:], x_train[:5000]
(y_train, y_valid) = y_train[5000:], y_train[:5000]

# Reshape the input data to add the channel dimension
w, h = 28, 28
x_train = x_train.reshape(x_train.shape[0], w, h, 1)
x_valid = x_valid.reshape(x_valid.shape[0], w, h, 1)
x_test = x_test.reshape(x_test.shape[0], w, h, 1)

# One-hot encode the labels
y_train = tf.keras.utils.to_categorical(y_train, 10)
y_valid = tf.keras.utils.to_categorical(y_valid, 10)
y_test = tf.keras.utils.to_categorical(y_test, 10)

# Print the training set shape
print("x_train shape: ",x_train.shape, "y_train shape: ", y_train.shape)

# Print the number of training , validation, and test datasets
print(x_train.shape[0], 'training set')
print(x_valid.shape[0], 'validation set')
print(x_test.shape[0], 'test set')
```

```
x_train shape:  (55000, 28, 28, 1) y_train shape:  (55000, 10)
55000 training set
5000 validation set
10000 test set
```

Step1: Define the CNN Model

```
model = tf.keras.Sequential()

# Must define the input shape in the first layer of the neural network
model.add(tf.keras.layers.Conv2D(filters=64, kernel_size=2, padding="same", activation="relu",
                                 input_shape=(28,28,1)))
model.add(tf.keras.layers.MaxPooling2D(pool_size=2))
model.add(tf.keras.layers.Dropout(0.3))


model.add(tf.keras.layers.Conv2D(filters=32, kernel_size=2, padding="same", activation="relu")
model.add(tf.keras.layers.MaxPooling2D(pool_size=2))
model.add(tf.keras.layers.Dropout(0.3))

model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(256, activation='relu'))
model.add(tf.keras.layers.Dropout(0.5))
model.add(tf.keras.layers.Dense(10, activation="softmax"))

# Take a look at the model summary
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 28, 28, 64)        320

 max_pooling2d (MaxPooling2D  (None, 14, 14, 64)       0
 )

 dropout (Dropout)           (None, 14, 14, 64)        0

 conv2d_1 (Conv2D)           (None, 14, 14, 32)        8224

 max_pooling2d_1 (MaxPooling  (None, 7, 7, 32)         0
 2D)

 dropout_1 (Dropout)         (None, 7, 7, 32)          0

 flatten (Flatten)           (None, 1568)              0

 dense (Dense)               (None, 256)               401664

 dropout_2 (Dropout)         (None, 256)               0

 dense_1 (Dense)             (None, 10)                2570

=================================================================
Total params: 412,778
Trainable params: 412,778
Non-trainable params: 0
_________________________________________________________________
```

Step2: Compile the CNN Model

```
# We have to specify the Optimizer, the Loss Function and Evaluation Metric to be used
model.compile(loss="categorical_crossentropy", optimizer="adam", metrics=["accuracy"])
```

Step 3: Train the Model using Training set

```
from keras.callbacks import ModelCheckpoint

checkpointer = ModelCheckpoint(filepath='model.weights.best.hdf5', verbose=1, save_best_only=Tru
model.fit(x_train, y_train, batch_size=64, epochs=10,
          validation_data=(x_valid,y_valid),
          callbacks=[checkpointer])
```

```
Epoch 1/10
859/860 [============================>.] - ETA: 0s - loss: 0.6079 - accuracy: 0.7758
Epoch 00001: val_loss improved from inf to 0.37433, saving model to model.weights.best.hdf
860/860 [==============================] - 76s 87ms/step - loss: 0.6078 - accuracy: 0.7759
Epoch 2/10
859/860 [============================>.] - ETA: 0s - loss: 0.4191 - accuracy: 0.8471
Epoch 00002: val_loss improved from 0.37433 to 0.32634, saving model to model.weights.best
860/860 [==============================] - 73s 85ms/step - loss: 0.4192 - accuracy: 0.8471
Epoch 3/10
859/860 [============================>.] - ETA: 0s - loss: 0.3731 - accuracy: 0.8633
Epoch 00003: val_loss improved from 0.32634 to 0.29865, saving model to model.weights.best
860/860 [==============================] - 74s 86ms/step - loss: 0.3731 - accuracy: 0.8633
Epoch 4/10
859/860 [============================>.] - ETA: 0s - loss: 0.3468 - accuracy: 0.8738
Epoch 00004: val_loss improved from 0.29865 to 0.27284, saving model to model.weights.best
860/860 [==============================] - 74s 86ms/step - loss: 0.3468 - accuracy: 0.8739
Epoch 5/10
859/860 [============================>.] - ETA: 0s - loss: 0.3217 - accuracy: 0.8821
Epoch 00005: val_loss improved from 0.27284 to 0.27071, saving model to model.weights.best
860/860 [==============================] - 74s 86ms/step - loss: 0.3217 - accuracy: 0.8821
Epoch 6/10
859/860 [============================>.] - ETA: 0s - loss: 0.3093 - accuracy: 0.8860
Epoch 00006: val_loss improved from 0.27071 to 0.25872, saving model to model.weights.best
860/860 [==============================] - 74s 86ms/step - loss: 0.3094 - accuracy: 0.8859
Epoch 7/10
859/860 [============================>.] - ETA: 0s - loss: 0.2966 - accuracy: 0.8914
Epoch 00007: val_loss improved from 0.25872 to 0.24623, saving model to model.weights.best
860/860 [==============================] - 73s 85ms/step - loss: 0.2965 - accuracy: 0.8914
Epoch 8/10
859/860 [============================>.] - ETA: 0s - loss: 0.2842 - accuracy: 0.8961
Epoch 00008: val_loss improved from 0.24623 to 0.23700, saving model to model.weights.best
860/860 [==============================] - 76s 88ms/step - loss: 0.2843 - accuracy: 0.8961
Epoch 9/10
859/860 [============================>.] - ETA: 0s - loss: 0.2763 - accuracy: 0.8990
Epoch 00009: val_loss did not improve from 0.23700
860/860 [==============================] - 80s 93ms/step - loss: 0.2763 - accuracy: 0.8989
Epoch 10/10
859/860 [============================>.] - ETA: 0s - loss: 0.2686 - accuracy: 0.9012
Epoch 00010: val_loss improved from 0.23700 to 0.22846, saving model to model.weights.best
860/860 [==============================] - 79s 92ms/step - loss: 0.2686 - accuracy: 0.9012
<keras.callbacks.History at 0x7f64b3bb31d0>
```

Step 3.1 : - Load the Model with Best Validation Accuracy

```
# Load the weights with the best validation accuracy
model.load_weights('model.weights.best.hdf5')
```

Step 4 - Testing the Model on Test Dataset and Getting Test Accuracy

```
# Evaluate the model on test dataset
score = model.evaluate(x_test, y_test, verbose=0)

# Print the test accuracy
print('\n', 'Test Accuracy: ', score[1])
```

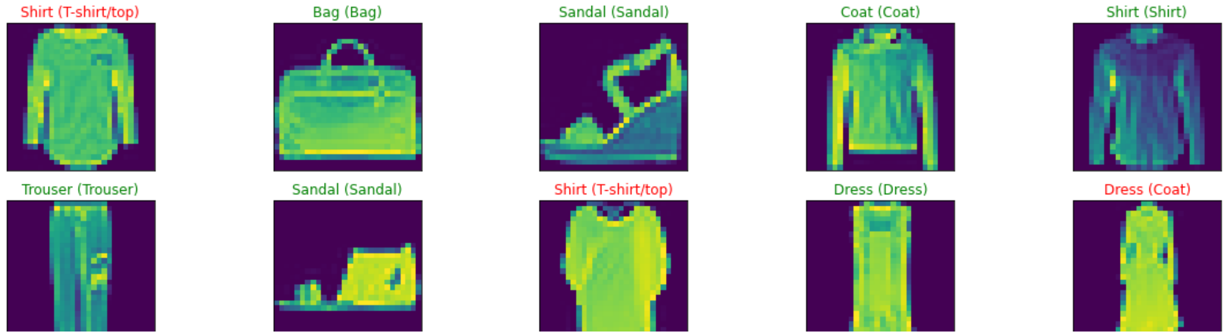
```
 Test Accuracy:  0.9110000133514404
```

Step 5 - Use the Model to Predict on New Example and Visualize the Prediction

- First we get the predictions with the model from the test data.
- Then we print out 10 images from the test data set, and set the titles with the prediction (and the groud truth label).
- If the prediction matches the true label, the title will be green; otherwise it's displayed in red.

```
y_predict = model.predict(x_test)

# Plot a random sample of 15 test images, their predicted labels and ground truth
figure = plt.figure(figsize=(20, 8))
for i, index in enumerate(np.random.choice(x_test.shape[0], size=15, replace=False)):
    ax = figure.add_subplot(3, 5, i + 1, xticks=[], yticks=[])
    # Display each image
    ax.imshow(np.squeeze(x_test[index]))
    predict_index = np.argmax(y_predict[index])
    true_index = np.argmax(y_test[index])
    # Set the title for each image
    ax.set_title("{} ({})".format(fashion_mnist_labels[predict_index],
                                  fashion_mnist_labels[true_index]),
                                  color=("green" if predict_index == true_index else "red"))
```



Congragulations!

You have successfully trained a CNN to classify fashion-MNIST with near 90% accuracy.