dl-practical-three

April 9, 2025

[ ]:
```
# This Python 3 environment comes with many helpful analytics libraries␣
↪installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/
↪docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list␣
↪all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that␣
↪gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved␣
↪outside of the current session
```

[1]:
```
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.datasets import fashion_mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,␣
↪Dropout, Input
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.optimizers import Adam
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
print("TensorFlow Version:", tf.__version__)
```

```
TensorFlow Version: 2.17.1
```

[3]:
```
IMG_ROWS, IMG_COLS = 28, 28
NUM_CLASSES = 10
BATCH_SIZE = 128
EPOCHS = 15
```

[4]:
```
print("\n--- Loading Fashion MNIST dataset ---")
(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()

print(f"x_train shape: {x_train.shape}")
print(f"y_train shape: {y_train.shape}")
print(f"x_test shape: {x_test.shape}")
print(f"y_test shape: {y_test.shape}")
```

```
--- Loading Fashion MNIST dataset ---
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/train-labels-idx1-ubyte.gz
29515/29515             0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/train-images-idx3-ubyte.gz
26421880/26421880             0s
0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/t10k-labels-idx1-ubyte.gz
5148/5148             0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/t10k-images-idx3-ubyte.gz
4422102/4422102             0s
0us/step
x_train shape: (60000, 28, 28)
y_train shape: (60000,)
x_test shape: (10000, 28, 28)
y_test shape: (10000,)
```

[6]:
```
print("\n--- Exploratory Data Analysis ---")

# 4.1 Define Class Names
class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
               'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']

# 4.2 Visualize Sample Images
print("\nSample images from the training set:\n\n")
plt.figure(figsize=(10, 10))
for i in range(25):
    plt.subplot(5, 5, i + 1)
```

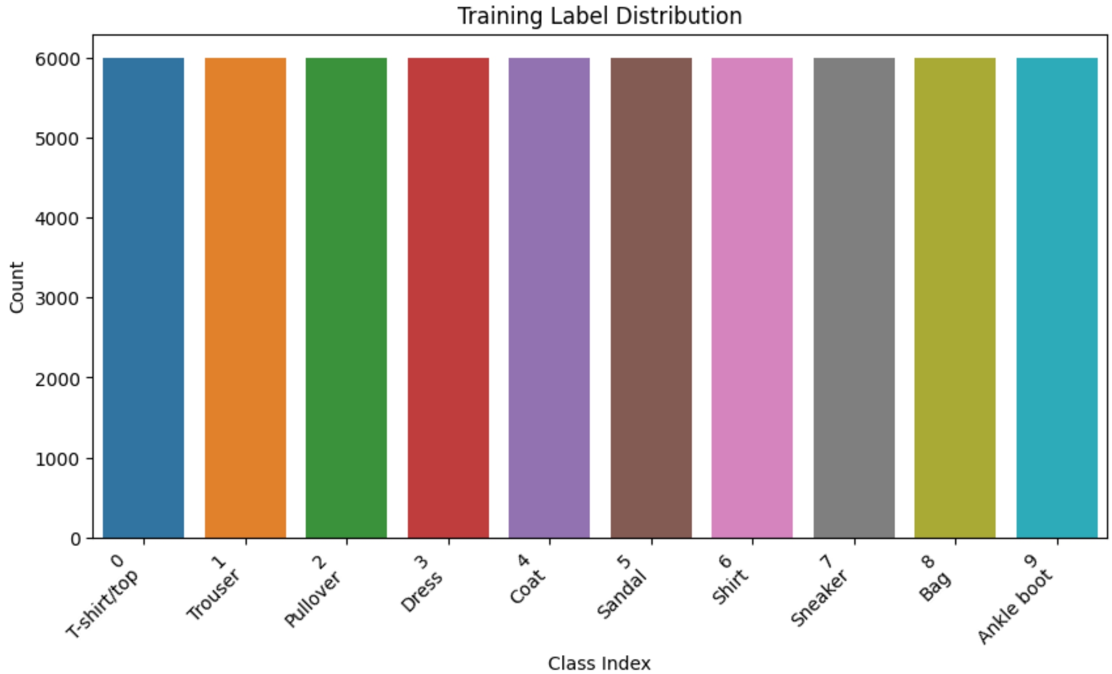
```
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(x_train[i], cmap=plt.cm.binary) # Use binary colormap for␣
 ↪grayscale
    plt.xlabel(class_names[y_train[i]])
plt.suptitle("Sample Training Images with Labels", y=0.92)
plt.show()
```

```
--- Exploratory Data Analysis ---

Sample images from the training set:
```

[7]:
```python
print("\nLabel Distribution in Training Set:")
unique_labels, counts = np.unique(y_train, return_counts=True)
print(dict(zip(class_names, counts)))

plt.figure(figsize=(10, 5))
sns.countplot(x=y_train)
plt.title('Training Label Distribution')
plt.xlabel('Class Index')
plt.ylabel('Count')
plt.xticks(ticks=range(NUM_CLASSES), labels=[f"{i}\n{name}" for i, name in
 ↪enumerate(class_names)], rotation=45, ha='right')
```

```
plt.show()
```

```
Label Distribution in Training Set:
{'T-shirt/top': 6000, 'Trouser': 6000, 'Pullover': 6000, 'Dress': 6000, 'Coat':
6000, 'Sandal': 6000, 'Shirt': 6000, 'Sneaker': 6000, 'Bag': 6000, 'Ankle boot':
6000}
```



[8]:
```
print("\n--- Preprocessing Data ---")

# 5.1 Reshape Data for CNN (Add Channel Dimension)
# Keras expects (batch_size, rows, cols, channels)
if keras.backend.image_data_format() == 'channels_first':
    x_train_reshaped = x_train.reshape(x_train.shape[0], 1, IMG_ROWS, IMG_COLS)
    x_test_reshaped = x_test.reshape(x_test.shape[0], 1, IMG_ROWS, IMG_COLS)
    input_shape = (1, IMG_ROWS, IMG_COLS)
else: # 'channels_last'
    x_train_reshaped = x_train.reshape(x_train.shape[0], IMG_ROWS, IMG_COLS, 1)
    x_test_reshaped = x_test.reshape(x_test.shape[0], IMG_ROWS, IMG_COLS, 1)
    input_shape = (IMG_ROWS, IMG_COLS, 1)

print(f"Reshaped x_train shape: {x_train_reshaped.shape}")
print(f"Reshaped x_test shape: {x_test_reshaped.shape}")
print(f"Input shape for CNN: {input_shape}")
```

```
--- Preprocessing Data ---
Reshaped x_train shape: (60000, 28, 28, 1)
Reshaped x_test shape: (10000, 28, 28, 1)
Input shape for CNN: (28, 28, 1)
```

[9]:
```
# 5.2 Normalize Pixel Values (Scale to 0-1)
x_train_processed = x_train_reshaped.astype('float32') / 255.0
x_test_processed = x_test_reshaped.astype('float32') / 255.0
print(f"Min/Max pixel value after normalization: {x_train_processed.min()},␣
↪{x_train_processed.max()}")
```

```
Min/Max pixel value after normalization: 0.0, 1.0
```

[10]:
```
# 5.3 One-Hot Encode Labels
y_train_cat = to_categorical(y_train, NUM_CLASSES)
y_test_cat = to_categorical(y_test, NUM_CLASSES)
print(f"Original label example: {y_train[0]}")
print(f"One-hot encoded label example: {y_train_cat[0]}")
print(f"Shape of y_train_cat: {y_train_cat.shape}")
print(f"Shape of y_test_cat: {y_test_cat.shape}")
```

```
Original label example: 9
One-hot encoded label example: [0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]
Shape of y_train_cat: (60000, 10)
Shape of y_test_cat: (10000, 10)
```

[11]:
```
print("\n--- Building the CNN Model ---")
model = Sequential([
    Input(shape=input_shape), # Explicit Input layer

    # Convolutional Block 1
    Conv2D(32, kernel_size=(3, 3), activation='relu', padding='same'),
    MaxPooling2D(pool_size=(2, 2)),
    # Dropout(0.25), # Optional dropout

    # Convolutional Block 2
    Conv2D(64, kernel_size=(3, 3), activation='relu', padding='same'),
    MaxPooling2D(pool_size=(2, 2)),
    # Dropout(0.25), # Optional dropout

    Flatten(), # Flatten the feature maps

    # Dense Classifier Head
    Dense(128, activation='relu'),
    Dropout(0.5), # Dropout for regularization
    Dense(NUM_CLASSES, activation='softmax') # Output layer for multi-class␣
↪classification
```

```
])
```

--- Building the CNN Model ---

[12]:
```
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='categorical_crossentropy', # Use categorical for one-hot␣
 ↪labels
              metrics=['accuracy'])

model.summary()
```

```
Model: "sequential"


 Layer (type)                        Output Shape                            ␣
 ↪Param #

 conv2d (Conv2D)                     (None, 28, 28, 32)                        ␣
 ↪320

 max_pooling2d (MaxPooling2D)        (None, 14, 14, 32)                        ␣
 ↪  0

 conv2d_1 (Conv2D)                   (None, 14, 14, 64)                     ␣
 ↪18,496

 max_pooling2d_1 (MaxPooling2D)      (None, 7, 7, 64)                          ␣
 ↪  0

 flatten (Flatten)                   (None, 3136)                              ␣
 ↪  0

 dense (Dense)                       (None, 128)                            ␣
 ↪401,536

 dropout (Dropout)                   (None, 128)                               ␣
 ↪  0

 dense_1 (Dense)                     (None, 10)                               ␣
 ↪1,290


 Total params: 421,642 (1.61 MB)
```

Trainable params: 421,642 (1.61 MB)

Non-trainable params: 0 (0.00 B)

[13]:

```
print("\n--- Training the Model ---")
history = model.fit(x_train_processed,
                    y_train_cat,
                    epochs=EPOCHS,
                    batch_size=BATCH_SIZE,
                    validation_data=(x_test_processed, y_test_cat),
                    verbose=1)
```

```
--- Training the Model ---
Epoch 1/15
469/469             10s 10ms/step -
accuracy: 0.7001 - loss: 0.8377 - val_accuracy: 0.8656 - val_loss: 0.3711
Epoch 2/15
469/469             2s 4ms/step -
accuracy: 0.8629 - loss: 0.3936 - val_accuracy: 0.8766 - val_loss: 0.3307
Epoch 3/15
469/469             2s 4ms/step -
accuracy: 0.8789 - loss: 0.3392 - val_accuracy: 0.8964 - val_loss: 0.2866
Epoch 4/15
469/469             2s 4ms/step -
accuracy: 0.8924 - loss: 0.2964 - val_accuracy: 0.9011 - val_loss: 0.2691
Epoch 5/15
469/469             2s 4ms/step -
accuracy: 0.9047 - loss: 0.2709 - val_accuracy: 0.9104 - val_loss: 0.2520
Epoch 6/15
469/469             2s 4ms/step -
accuracy: 0.9120 - loss: 0.2483 - val_accuracy: 0.9071 - val_loss: 0.2539
Epoch 7/15
469/469             2s 4ms/step -
accuracy: 0.9163 - loss: 0.2293 - val_accuracy: 0.9171 - val_loss: 0.2299
Epoch 8/15
469/469             2s 4ms/step -
accuracy: 0.9218 - loss: 0.2168 - val_accuracy: 0.9141 - val_loss: 0.2397
Epoch 9/15
469/469             2s 4ms/step -
accuracy: 0.9251 - loss: 0.2051 - val_accuracy: 0.9166 - val_loss: 0.2301
Epoch 10/15
469/469             2s 4ms/step -
accuracy: 0.9302 - loss: 0.1900 - val_accuracy: 0.9182 - val_loss: 0.2239
Epoch 11/15
469/469             2s 4ms/step -
```

```
accuracy: 0.9328 - loss: 0.1821 - val_accuracy: 0.9216 - val_loss: 0.2229
Epoch 12/15
469/469              2s 4ms/step -
accuracy: 0.9369 - loss: 0.1735 - val_accuracy: 0.9161 - val_loss: 0.2259
Epoch 13/15
469/469              2s 4ms/step -
accuracy: 0.9378 - loss: 0.1654 - val_accuracy: 0.9224 - val_loss: 0.2227
Epoch 14/15
469/469              2s 4ms/step -
accuracy: 0.9440 - loss: 0.1517 - val_accuracy: 0.9222 - val_loss: 0.2244
Epoch 15/15
469/469              2s 4ms/step -
accuracy: 0.9445 - loss: 0.1497 - val_accuracy: 0.9231 - val_loss: 0.2200
```

[14]:

```
print("\n--- Evaluating the Model ---")
loss, accuracy = model.evaluate(x_test_processed, y_test_cat, verbose=0)
print(f"Test Loss: {loss:.4f}")
print(f"Test Accuracy: {accuracy:.4f} ({accuracy*100:.2f}%)")
```

```
--- Evaluating the Model ---
Test Loss: 0.2200
Test Accuracy: 0.9231 (92.31%)
```

[15]:

```
print("\n--- Visualizing Training History ---")
history_dict = history.history

acc = history_dict['accuracy']
val_acc = history_dict['val_accuracy']
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']

epochs_range = range(1, EPOCHS + 1)

plt.figure(figsize=(12, 5))

# Plot Training & Validation Accuracy
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, 'bo-', label='Training Accuracy')
plt.plot(epochs_range, val_acc, 'ro-', label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)

# Plot Training & Validation Loss
```

```
plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss_values, 'bo-', label='Training Loss')
plt.plot(epochs_range, val_loss_values, 'ro-', label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)

plt.tight_layout()
plt.show()
```

```
--- Visualizing Training History ---
```