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1 Fashion MNIST Classification with CNN

This notebook demonstrates how to build a Convolutional Neural Network (CNN) to classify Fashion MNIST images. Fashion MNIST is a dataset of Zalando's article images consisting of 60,000 training examples and 10,000 test examples. Each example is a 28x28 grayscale image, associated with a label from 10 classes.

1.1 Step 1: Import Required Libraries

First, we import the necessary libraries: - pandas: for data manipulation and analysis - numpy: for numerical operations - matplotlib: for data visualization - tensorflow.keras: for building and training neural networks

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, Flatten, Dense
```

1.2 Step 2: Load the Dataset

Load the Fashion MNIST dataset from CSV files. The dataset is already split into training and testing sets. Each CSV file contains the pixel values (784 columns representing a flattened 28x28 image) and a label column.

[2]:
```
train_df = pd.read_csv('datasets/fashion-mnist_train.csv')
test_df = pd.read_csv('datasets/fashion-mnist_test.csv')
```

1.3 Step 3: Inspect the Dataset

Examine the dataset to understand its structure, distribution, and check for any missing values or anomalies. This helps us understand what we're working with before preprocessing.

[3]:
```
print(train_df.shape)
print(train_df.describe())
```

```
(60000, 785)
              label        pixel1        pixel2        pixel3        pixel4  \
count  60000.000000  60000.000000  60000.000000  60000.000000  60000.000000
```

mean	4.500000	0.000900	0.006150	0.035333	0.101933
std	2.872305	0.094689	0.271011	1.222324	2.452871
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	2.000000	0.000000	0.000000	0.000000	0.000000
50%	4.500000	0.000000	0.000000	0.000000	0.000000
75%	7.000000	0.000000	0.000000	0.000000	0.000000
max	9.000000	16.000000	36.000000	226.000000	164.000000

	pixel5	pixel6	pixel7	pixel8	pixel9 \
count	60000.000000	60000.000000	60000.000000	60000.000000	60000.000000
mean	0.247967	0.411467	0.805767	2.198283	5.682000
std	4.306912	5.836188	8.215169	14.093378	23.819481
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	227.000000	230.000000	224.000000	255.000000	254.000000

	…	pixel775	pixel776	pixel777	pixel778 \
count	…	60000.000000	60000.000000	60000.000000	60000.000000
mean	…	34.625400	23.300683	16.588267	17.869433
std	…	57.545242	48.854427	41.979611	43.966032
min	…	0.000000	0.000000	0.000000	0.000000
25%	…	0.000000	0.000000	0.000000	0.000000
50%	…	0.000000	0.000000	0.000000	0.000000
75%	…	58.000000	9.000000	0.000000	0.000000
max	…	255.000000	255.000000	255.000000	255.000000

	pixel779	pixel780	pixel781	pixel782	pixel783 \
count	60000.000000	60000.000000	60000.000000	60000.000000	60000.000000
mean	22.814817	17.911483	8.520633	2.753300	0.855517
std	51.830477	45.149388	29.614859	17.397652	9.356960
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	255.000000	255.000000	255.000000	255.000000	255.000000

	pixel784
count	60000.00000
mean	0.07025
std	2.12587
min	0.00000
25%	0.00000
50%	0.00000
75%	0.00000
max	170.00000

```
[8 rows x 785 columns]
```

[4]:
```
print(train_df.info())
print(train_df.isnull().sum())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 60000 entries, 0 to 59999
Columns: 785 entries, label to pixel784
dtypes: int64(785)
memory usage: 359.3 MB
None
label       0
pixel1      0
pixel2      0
pixel3      0
pixel4      0
           ..
pixel780    0
pixel781    0
pixel782    0
pixel783    0
pixel784    0
Length: 785, dtype: int64
```

[5]:
```
print("Unique Labels:", train_df.label.unique())
```

```
Unique Labels: [2 9 6 0 3 4 5 8 7 1]
```

1.4 Step 4: Define Label Names

Create a mapping of numerical labels to clothing item names for better readability and interpretation of results.

[6]:
```
class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
               'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']
```

1.5 Step 5: Prepare Data

Process the raw data to make it suitable for CNN training: 1. Separate features (pixel values) from labels 2. Reshape the flattened pixel arrays into 28×28 images with a single channel 3. Normalize pixel values to be between 0 and 1 (divide by 255)

These preprocessing steps are essential for efficient training and better performance.

[7]:
```
# Separate features and labels, reshape 784 pixels into 28x28 images, and␣
↪normalize (divide by 255)
X_train = train_df.drop('label', axis=1).values.reshape(-1, 28, 28, 1) / 255.0
y_train = train_df['label'].values
X_test = test_df.drop('label', axis=1).values.reshape(-1, 28, 28, 1) / 255.0
```

```
y_test = test_df['label'].values
```

1.6 Step 6: Visualize Sample Images

Visualize a subset of training images to better understand the data. This helps us confirm that the images are loaded correctly and get a feel for what the model will be trained on.

[8]:
```
plt.figure(figsize=(10, 10))
for i in range(25):
    plt.subplot(5, 5, i + 1)
    plt.imshow(X_train[i].reshape(28, 28), cmap='binary')
    plt.axis('off')
    plt.title(f"{class_names[y_train[i]]}", fontsize=10)
plt.tight_layout()
plt.show()
```

1.7 Step 7: Build a CNN Model

Create a Convolutional Neural Network architecture for image classification: 1. Conv2D layer with 32 filters to extract features from the images 2. MaxPooling2D layer to reduce spatial dimensions 3. Flatten layer to convert 3D feature maps to 1D feature vectors 4. Dense output layer with softmax activation for 10-class classification

This simple CNN architecture is effective for basic image classification tasks.

[9]:
```
model = Sequential([
    Input(shape=(28, 28, 1)),  # Explicit Input layer
    Conv2D(32, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(10, activation='softmax')
])
```

1.8 Step 8: Compile the Model

Configure the model for training by specifying: - Optimizer: Adam, an efficient stochastic gradient descent algorithm - Loss function: sparse_categorical_crossentropy, appropriate for integer labels - Metrics: accuracy, to monitor classification performance

These choices are standard for multi-class classification problems.

[10]:
```
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

1.9 Step 9: Train the Model

Train the compiled model on the training data for 5 epochs with batches of 64 samples. We also validate on the test data after each epoch to monitor for overfitting.

[11]:
```
history = model.fit(X_train, y_train, epochs=5, batch_size=64,
 ↪validation_data=(X_test, y_test))
```

```
Epoch 1/5
938/938             8s 7ms/step -
accuracy: 0.7666 - loss: 0.6762 - val_accuracy: 0.8779 - val_loss: 0.3573
Epoch 2/5
938/938             7s 8ms/step -
accuracy: 0.8774 - loss: 0.3475 - val_accuracy: 0.8887 - val_loss: 0.3261
Epoch 3/5
938/938             7s 8ms/step -
accuracy: 0.8931 - loss: 0.3069 - val_accuracy: 0.8976 - val_loss: 0.2957
Epoch 4/5
```

```
938/938              6s 7ms/step -
accuracy: 0.9027 - loss: 0.2774 - val_accuracy: 0.8979 - val_loss: 0.2935
Epoch 5/5
938/938              7s 7ms/step -
accuracy: 0.9070 - loss: 0.2674 - val_accuracy: 0.9042 - val_loss: 0.2745
```

1.10 Step 10: Model Summary

Display a summary of the model architecture, showing layer details and parameter counts. This helps us understand the complexity and structure of our CNN.

[12]:
```python
model.summary()
```

```
Model: "sequential"


 Layer (type)                      Output Shape                    ␣
↪Param #

 conv2d (Conv2D)                   (None, 26, 26, 32)                ␣
↪320

 max_pooling2d (MaxPooling2D)      (None, 13, 13, 32)                ␣
↪  0

 flatten (Flatten)                 (None, 5408)                      ␣
↪  0

 dense (Dense)                     (None, 10)                      ␣
↪54,090


 Total params: 163,232 (637.63 KB)

 Trainable params: 54,410 (212.54 KB)

 Non-trainable params: 0 (0.00 B)

 Optimizer params: 108,822 (425.09 KB)
```

1.11 Step 11: Evaluate the Model

Evaluate the trained model on the test set to get an unbiased estimate of its performance. This provides the final accuracy metric that reflects how well the model generalizes to new data.

[13]:
```
accuracy = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {accuracy[1]:.2f}")
```

```
313/313              1s 3ms/step -
accuracy: 0.8987 - loss: 0.2781
Test Accuracy: 0.90
```

1.12 Step 12: Make Predictions

Use the trained model to make predictions on the test set: 1. Get probability distributions for each class 2. Convert probabilities to class labels by taking the argmax

This allows us to see how the model classifies new examples.

[14]:
```
y_probas = model.predict(X_test)
y_pred = y_probas.argmax(axis=-1)
```

```
313/313              1s 3ms/step
```

1.13 Step 13: Visualize Predictions

Visualize test images alongside their predicted labels. This helps us understand where the model succeeds and where it might be making mistakes.

[15]:
```
plt.figure(figsize=(10, 10))
for i in range(25):
    plt.subplot(5, 5, i + 1)
    plt.imshow(X_test[i].reshape(28, 28), cmap='binary')
    plt.axis('off')
    plt.title(f"Pred: {class_names[y_pred[i]]}", fontsize=10)
plt.tight_layout()
plt.show()
```

1.14 Step 14: Plot Learning Curves (Optional)

Visualize the model's learning progress by plotting training and validation metrics over epochs. This helps us identify potential overfitting or underfitting.

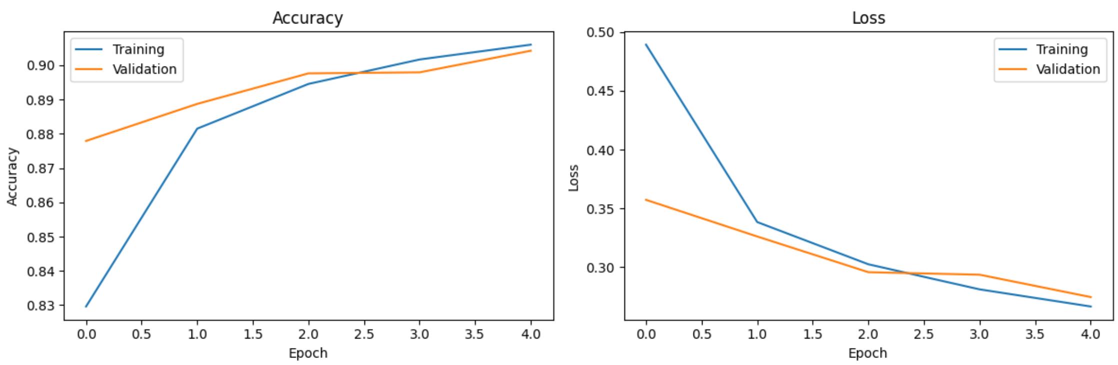
[16]:
```
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training')
plt.plot(history.history['val_accuracy'], label='Validation')
plt.title('Accuracy')
plt.xlabel('Epoch')
```

```
plt.ylabel('Accuracy')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training')
plt.plot(history.history['val_loss'], label='Validation')
plt.title('Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

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



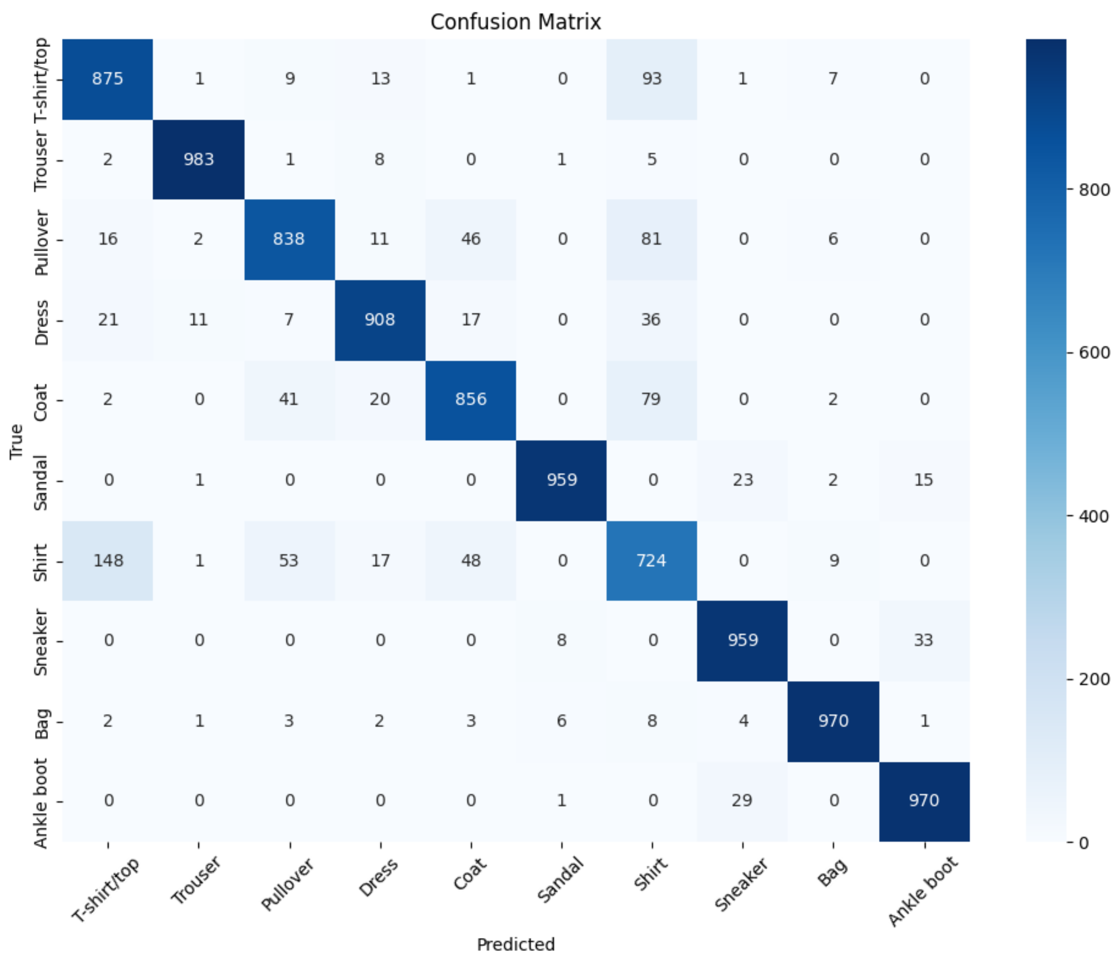
1.15 Step 15: Confusion Matrix (Optional)

Create a confusion matrix to visualize the model's performance across all classes. This helps identify which classes are frequently confused with each other.

[17]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns

cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names,␣
↪yticklabels=class_names)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



1.16 Step 16: Save Model (Optional)

Save the trained model to disk for future use without retraining.

[18]:
```python
model.save('fashion_mnist_cnn_model.h5')
print("Model saved to disk")
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.
```

```
Model saved to disk
```