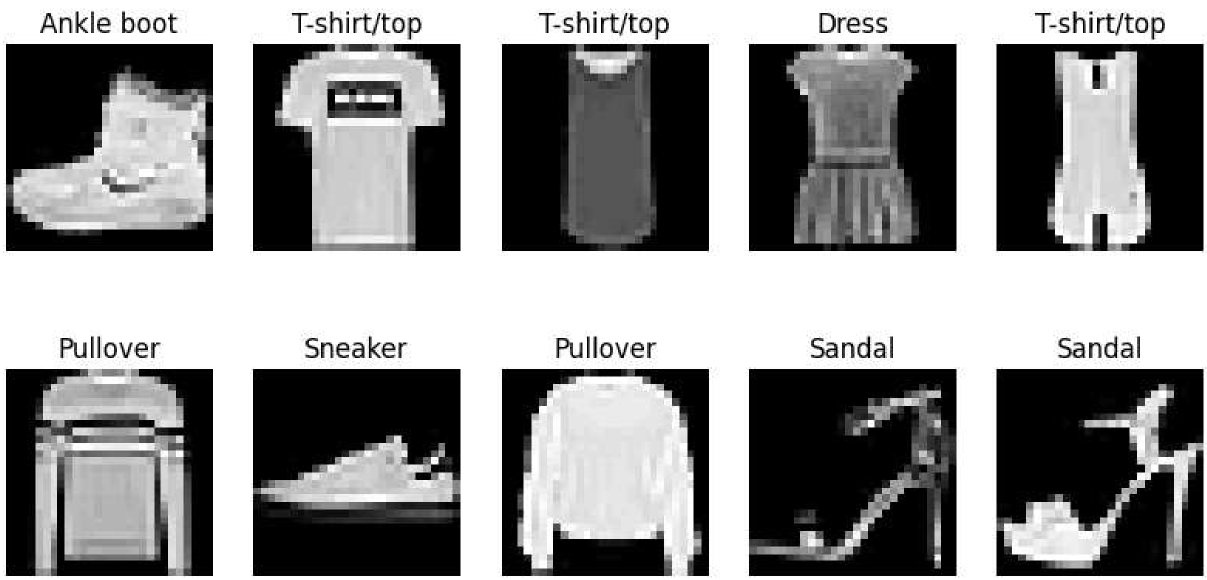
```
# ----------------------------------------------
# 1. IMPORT LIBRARIES
# ----------------------------------------------
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from tensorflow.keras.datasets import fashion_mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.metrics import classification_report, confusion_matrix
import tensorflow as tf
```

```
# Load Fashion MNIST dataset
(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()

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

print("Training samples:", x_train.shape)
print("Test samples:", x_test.shape)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-dataset
29515/29515 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-dataset
26421880/26421880 ━━━━━━━━━━━━━━━━━━━━ 2s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-dataset
5148/5148 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-dataset
4422102/4422102 ━━━━━━━━━━━━━━━━━━━━ 1s 0us/step
Training samples: (60000, 28, 28)
Test samples: (10000, 28, 28)
```

Visualize Sample images

```
plt.figure(figsize=(10,5))
for i in range(10):
    plt.subplot(2,5,i+1)
    plt.imshow(x_train[i], cmap='gray')
    plt.title(class_names[y_train[i]])
    plt.axis('off')
plt.show()
```




```
# Normalize images
x_train = x_train / 255.0
x_test = x_test / 255.0

# One-hot encode labels
y_train_cat = to_categorical(y_train, 10)
y_test_cat = to_categorical(y_test, 10)

# OPTIONAL: Data augmentation
datagen = ImageDataGenerator(
    rotation_range=10,
    width_shift_range=0.1,
    height_shift_range=0.1,
    horizontal_flip=False
)
datagen.fit(x_train.reshape(-1, 28, 28, 1))
```

BUILD FEEDFORWARD NEURAL NETWORK

```
model = Sequential([
    Flatten(input_shape=(28,28)),
    Dense(256, activation='relu'),
    Dense(128, activation='relu'),
    Dense(10, activation='softmax')
])
```

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

model.summary()
```

```
/usr/local/lib/python3.12/dist-packages/keras/src/layers/reshaping/flatten.py:37
  super().__init__(**kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 784)	0
dense (Dense)	(None, 256)	200,960
dense_1 (Dense)	(None, 128)	32,896
dense_2 (Dense)	(None, 10)	1,290

Total params: 235,146 (918.54 KB)
Trainable params: 235,146 (918.54 KB)
Non-trainable params: 0 (0.00 B)

Train the model

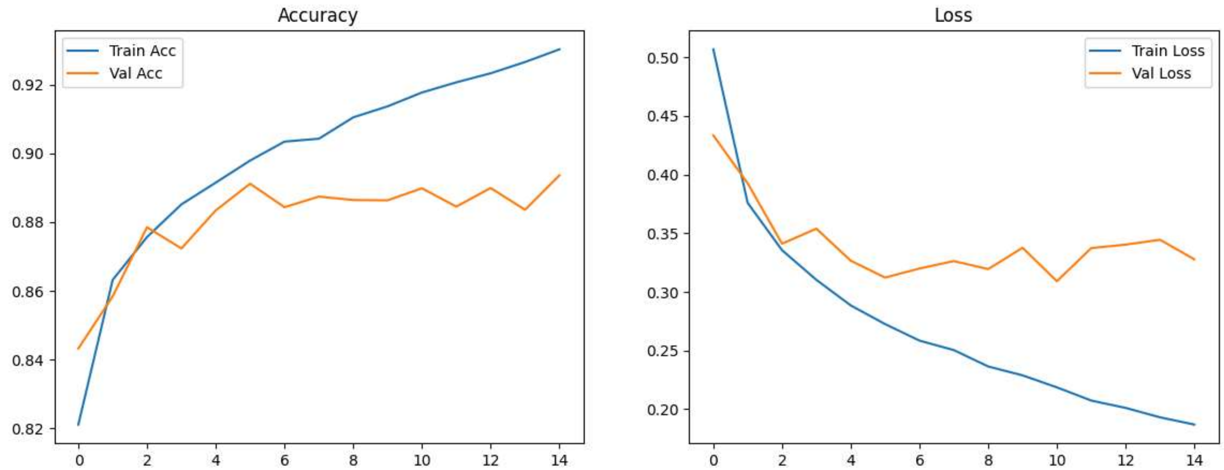
```
history = model.fit(
    x_train, y_train_cat,
    epochs=15,
    batch_size=64,
    validation_split=0.2,
    verbose=1
)
```

```
Epoch 1/15
750/750 ━━━━━━━━━━━━━━━━━━━━ 8s 8ms/step - accuracy: 0.7704 - loss: 0.6630 - val
Epoch 2/15
750/750 ━━━━━━━━━━━━━━━━━━━━ 5s 7ms/step - accuracy: 0.8598 - loss: 0.3872 - val
Epoch 3/15
750/750 ━━━━━━━━━━━━━━━━━━━━ 6s 8ms/step - accuracy: 0.8756 - loss: 0.3365 - val
Epoch 4/15
750/750 ━━━━━━━━━━━━━━━━━━━━ 5s 7ms/step - accuracy: 0.8860 - loss: 0.3113 - val
Epoch 5/15
750/750 ━━━━━━━━━━━━━━━━━━━━ 6s 8ms/step - accuracy: 0.8922 - loss: 0.2873 - val
Epoch 6/15
750/750 ━━━━━━━━━━━━━━━━━━━━ 5s 7ms/step - accuracy: 0.8987 - loss: 0.2724 - val
Epoch 7/15
750/750 ━━━━━━━━━━━━━━━━━━━━ 5s 7ms/step - accuracy: 0.9063 - loss: 0.2519 - val
Epoch 8/15
750/750 ━━━━━━━━━━━━━━━━━━━━ 6s 8ms/step - accuracy: 0.9031 - loss: 0.2529 - val
Epoch 9/15
```

```
750/750 ━━━━━━━━━━━━━━━━━━━━ 5s 7ms/step - accuracy: 0.9123 - loss: 0.2350 - val
Epoch 10/15
750/750 ━━━━━━━━━━━━━━━━━━━━ 6s 8ms/step - accuracy: 0.9158 - loss: 0.2240 - val
Epoch 11/15
750/750 ━━━━━━━━━━━━━━━━━━━━ 5s 7ms/step - accuracy: 0.9184 - loss: 0.2185 - val
Epoch 12/15
750/750 ━━━━━━━━━━━━━━━━━━━━ 7s 9ms/step - accuracy: 0.9198 - loss: 0.2054 - val
Epoch 13/15
750/750 ━━━━━━━━━━━━━━━━━━━━ 5s 7ms/step - accuracy: 0.9228 - loss: 0.2049 - val
Epoch 14/15
750/750 ━━━━━━━━━━━━━━━━━━━━ 6s 8ms/step - accuracy: 0.9269 - loss: 0.1909 - val
Epoch 15/15
750/750 ━━━━━━━━━━━━━━━━━━━━ 5s 7ms/step - accuracy: 0.9312 - loss: 0.1845 - val
```

Training Graphs

```
plt.figure(figsize=(14,5))

# Accuracy
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.title("Accuracy")
plt.legend()

# Loss
plt.subplot(1,2,2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title("Loss")
plt.legend()

plt.show()
```



Evaluate Test set

```
test_loss, test_acc = model.evaluate(x_test, y_test_cat, verbose=0)
print("Test Accuracy:", test_acc)
print("Test Loss:", test_loss)
```

```
Test Accuracy: 0.8891000151634216
Test Loss: 0.3550165891647339
```

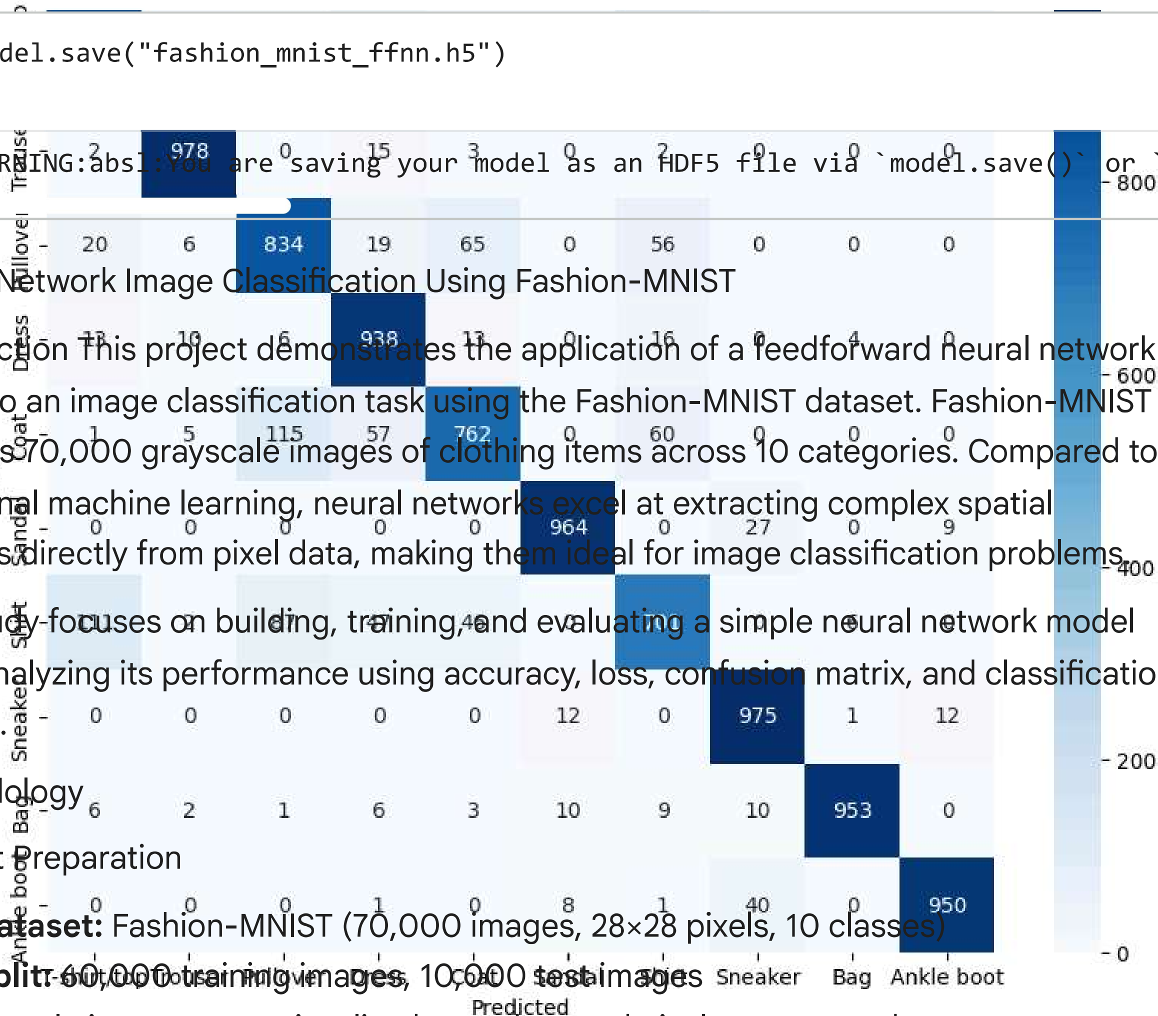
Confusion Matrix

```
# Predictions
y_pred = model.predict(x_test)
y_pred_classes = np.argmax(y_pred, axis=1)

# Confusion matrix
cm = confusion_matrix(y_test, y_pred_classes)

plt.figure(figsize=(10,8))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
            xticklabels=class_names,
            yticklabels=class_names)
```

```python
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.show()

print(classification_report(y_test, y_pred_classes, target_names=class_names))
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step
```

Confusion Matrix




```
model.save("fashion_mnist_ffnn.h5")
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `ke
```

```
              precision    recall  f1-score   support

 T-shirt/top       0.85      0.84      0.84      1000
     Trouser       0.97      0.98      0.98      1000
    Pullover       0.79      0.83      0.81      1000
       Dress       0.83      0.94      0.88      1000
        Coat       0.85      0.76      0.81      1000
      Sandal       0.97      0.96      0.97      1000
       Shirt       0.74      0.70      0.72      1000
     Sneaker       0.93      0.97      0.95      1000
         Bag       0.98      0.95      0.97      1000
  Ankle boot       0.98      0.95      0.96      1000

    accuracy                           0.89     10000
   macro avg       0.89      0.89      0.89     10000
weighted avg       0.89      0.89      0.89     10000
```

Neural Network Image Classification Using Fashion-MNIST

Introduction This project demonstrates the application of a feedforward neural network (ANN) to an image classification task using the Fashion-MNIST dataset. Fashion-MNIST contains 70,000 grayscale images of clothing items across 10 categories. Compared to traditional machine learning, neural networks excel at extracting complex spatial features directly from pixel data, making them ideal for image classification problems.

This study focuses on building, training, and evaluating a simple neural network model while analyzing its performance using accuracy, loss, confusion matrix, and classification metrics.

Methodology

Dataset Preparation

- **Dataset:** Fashion-MNIST (70,000 images, 28×28 pixels, 10 classes)
- **Split:** 60,000 training images, 10,000 test images
- Sample images were visualized to understand pixel patterns and category variations.

Preprocessing

- **Normalization:** Pixel values scaled from 0–255 to 0–1.
- **One-hot encoding:** Converted labels into 10-class categorical vectors.
- **Optional Augmentation:** Rotation, shifting transformations using ImageDataGenerator.

Model Architecture A simple feedforward neural network (ANN) was implemented:

- Flatten Layer
- Dense(256, ReLU)
- Dense(128, ReLU)
- Dense(10, Softmax)

Model Compilation

- **Optimizer:** Adam
- **Loss:** Categorical Crossentropy

- **Metrics:** Accuracy

Training

- 15 epochs
- Batch size: 64
- Validation split: 20%

Training and validation accuracy/loss were plotted for visual performance analysis.

Results

Training and Validation Curves The plots show:

- Increasing training accuracy
- Validation accuracy stabilizing around ~0.89
- Loss decreasing steadily

Test Performance

- **Test Accuracy:** ~0.889
- **Test Loss:** ~0.355

Confusion Matrix A confusion matrix was generated for deeper class-level insights