Deep Learning – (Fashion MNIST)

5.Fashion MNIST

Link - https://colab.research.google.com/drive/1WoADppeDStlomTGsg5LshzD7WAb6beV3?usp=sharing

1.Data Loading and Initial Exploration (EDA)

```
import tensorflow as tf
from tensorflow import keras
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
import seaborn as sns
```

Load the Fashion MNIST dataset

```
(train_images, train_labels), (test_images, test_labels) = keras.datasets.fashion_mnist.load_data()
```

```
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
```

Define class names (for better readability)

```
4422102/4422102 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
```

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

Reduce dataset size for faster training

```python
# Reduce dataset size for faster training
N_train = 5000
N_test = 1000
train_images = train_images[:N_train]
train_labels = train_labels[:N_train]
test_images = test_images[:N_test]
test_labels = test_labels[:N_test]
```

Display basic information about the dataset

```python
print(f"Train images shape: {train_images.shape}")
print(f"Train labels shape: {train_labels.shape}")
print(f"Test images shape: {test_images.shape}")
print(f"Test labels shape: {test_labels.shape}")
print(f"Number of classes: {len(np.unique(train_labels))}")
```

```
Train images shape: (5000, 28, 28)
Train labels shape: (5000,)
Test images shape: (1000, 28, 28)
Test labels shape: (1000,)
Number of classes: 10
```

Plot a few images to visualize the data

```python
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(train_images[i], cmap=plt.cm.binary)
    plt.xlabel(class_names[train_labels[i]])
plt.suptitle("Sample Fashion MNIST Images", y=1.02, fontsize=16)
plt.show()
```

Sample Fashion MNIST Images

Display value counts for labels

```
print("\nTrain Label Distribution:")
unique_train_labels, counts_train_labels = np.unique(train_labels, return_counts=True)
for label, count in zip(unique_train_labels, counts_train_labels):
    print(f"{class_names[label]}: {count} samples")
```

```
Train Label Distribution:
T-shirt/top: 457 samples
Trouser: 556 samples
Pullover: 504 samples
Dress: 501 samples
Coat: 488 samples
Sandal: 493 samples
Shirt: 493 samples
Sneaker: 512 samples
Bag: 490 samples
Ankle boot: 506 samples
```

```
print("\nTest Label Distribution:")
unique_test_labels, counts_test_labels = np.unique(test_labels, return_counts=True)
for label, count in zip(unique_test_labels, counts_test_labels):
    print(f"{class_names[label]}: {count} samples")
```

```
Test Label Distribution:
T-shirt/top: 107 samples
Trouser: 105 samples
Pullover: 111 samples
Dress: 93 samples
Coat: 115 samples
Sandal: 87 samples
Shirt: 97 samples
Sneaker: 95 samples
Bag: 95 samples
Ankle boot: 95 samples
```

Check pixel value range

```
# Check pixel value range
print(f"\nMin pixel value: {train_images.min()}")
print(f"Max pixel value: {train_images.max()}")
```

```
Min pixel value: 0
Max pixel value: 255
```

--- Preprocessing for Deep Learning (CNN) ---

Normalize pixel values to be between 0 and 1

```
[10] train_images_cnn = train_images / 255.0
     test_images_cnn = test_images / 255.0
```

```
# Reshape images to add a channel dimension (28, 28, 1) for CNN input
train_images_cnn = train_images_cnn.reshape((train_images_cnn.shape[0], 28, 28, 1))
test_images_cnn = test_images_cnn.reshape((test_images_cnn.shape[0], 28, 28, 1))
```

```
print(f"\nTrain images shape for CNN: {train_images_cnn.shape}")
print(f"Test images shape for CNN: {test_images_cnn.shape}")
```

```
Train images shape for CNN: (5000, 28, 28, 1)
Test images shape for CNN: (1000, 28, 28, 1)
```

--- Preprocessing for Traditional Machine Learning ---

Flatten the images to a 1D array (28*28 = 784 features)

```
train_images_flat = train_images.reshape(train_images.shape[0], -1) / 255.0
test_images_flat = test_images.reshape(test_images.shape[0], -1) / 255.0
```

Scale the flattened data (important for algorithms like SVM and Logistic Regression)

Note: Standardization is applied after flattening and before ML model training.

CNNs typically just need normalization (0-1).

```
scaler = StandardScaler()
train_images_scaled = scaler.fit_transform(train_images_flat)
test_images_scaled = scaler.transform(test_images_flat)
```

```
print(f"Train images shape for Traditional ML (flattened): {train_images_flat.shape}")
print(f"Test images shape for Traditional ML (flattened): {test_images_flat.shape}")
print(f"Train images shape for Traditional ML (scaled): {train_images_scaled.shape}")
print(f"Test images shape for Traditional ML (scaled): {test_images_scaled.shape}")
```

```
Train images shape for Traditional ML (flattened): (5000, 784)
Test images shape for Traditional ML (flattened): (1000, 784)
Train images shape for Traditional ML (scaled): (5000, 784)
Test images shape for Traditional ML (scaled): (1000, 784)
```

--- Model 1: Logistic Regression ---

```
print("\n--- Training Logistic Regression ---")
log_reg_model = LogisticRegression(solver='saga', multi_class='multinomial', max_iter=200, n_jobs=-1, verbose=0)
log_reg_model.fit(train_images_scaled, train_labels)
print("Logistic Regression training complete.")
```

```
--- Training Logistic Regression ---
/usr/local/lib/python3.12/dist-packages/sklearn/linear_model/_logistic.py:1247: FutureWarning: 'multi_class' was dep
  warnings.warn(
Logistic Regression training complete.
/usr/local/lib/python3.12/dist-packages/sklearn/linear_model/_sag.py:348: ConvergenceWarning: The max_iter was reach
  warnings.warn(
```

--- Model 2: Random Forest Classifier ---

```
print("\n--- Training Random Forest Classifier ---")
rf_model = RandomForestClassifier(n_estimators=100, random_state=42, n_jobs=-1, verbose=0)
rf_model.fit(train_images_scaled, train_labels)
print("Random Forest Classifier training complete.")
```

```
--- Training Random Forest Classifier ---
Random Forest Classifier training complete.
```

--- Model 3: Support Vector Machine (SVC) ---

```
# --- Model 3: Support Vector Machine (SVC) ---
print("\n--- Training Support Vector Machine (SVC) ---")
svm_model = SVC(kernel='rbf', random_state=42, verbose=False)
svm_model.fit(train_images_scaled, train_labels)
print("SVC training complete (full dataset).")
```

```
--- Training Support Vector Machine (SVC) ---
SVC training complete (full dataset).
```

--- Model 4: Convolutional Neural Network (CNN) ---

```
print("\n--- Building and Training CNN ---")
# Define the CNN model architecture
cnn_model = keras.Sequential([
    keras.layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
    keras.layers.MaxPooling2D((2, 2)),
    keras.layers.Conv2D(64, (3, 3), activation='relu'),
    keras.layers.MaxPooling2D((2, 2)),
    keras.layers.Conv2D(64, (3, 3), activation='relu'),
    keras.layers.Flatten(),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.Dropout(0.5),  # Regularization to prevent overfitting
    keras.layers.Dense(10, activation='softmax')  # 10 classes, softmax for probability distribution
])
```

```
--- Building and Training CNN ---
/usr/local/lib/python3.12/dist-packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning: Do not pass an
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Compile the model

```
cnn_model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
cnn_model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d (MaxPooling2D)	(None, 13, 13, 32)	0
conv2d_1 (Conv2D)	(None, 11, 11, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 5, 5, 64)	0
conv2d_2 (Conv2D)	(None, 3, 3, 64)	36,928
flatten (Flatten)	(None, 576)	0
dense (Dense)	(None, 64)	36,928
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 10)	650

```
Total params: 93,322 (364.54 KB)
Trainable params: 93,322 (364.54 KB)
Non-trainable params: 0 (0.00 B)
```

Train the CNN model

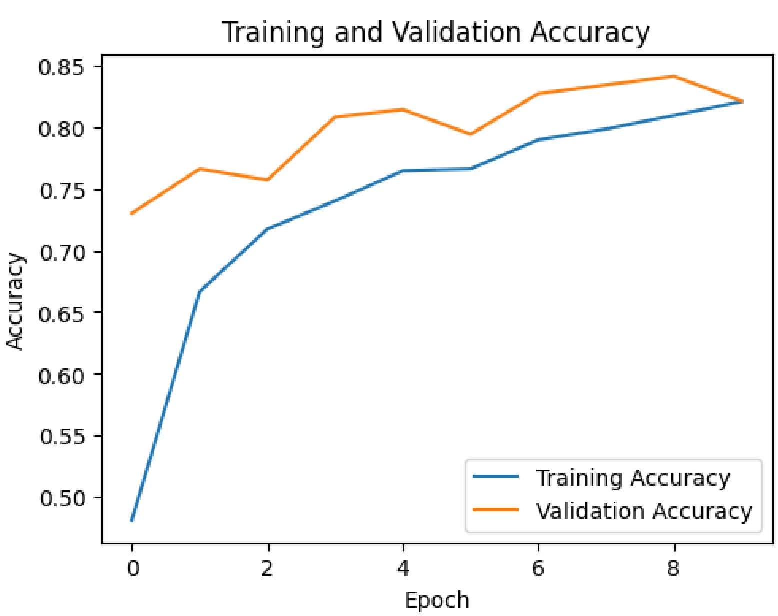
Using a validation split to monitor performance on unseen data during training

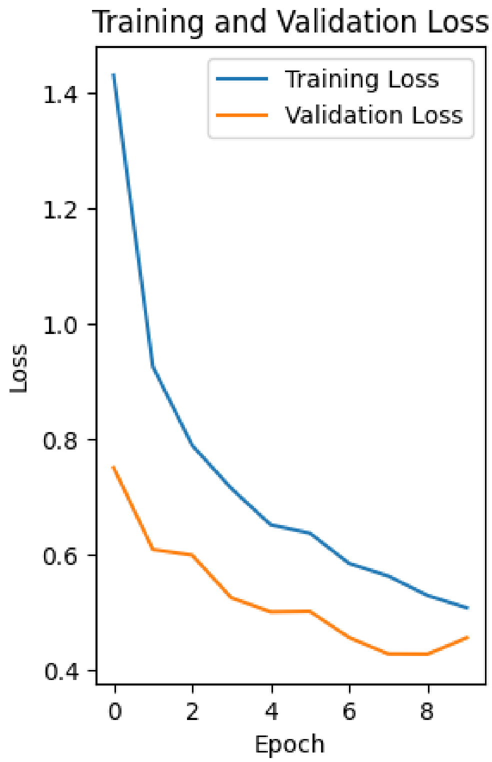
```
history = cnn_model.fit(train_images_cnn, train_labels, epochs=10, validation_split=0.2, verbose=1)
print("CNN training complete.")
```

```
Epoch 1/10
125/125 ━━━━━━━━━━━━━━━━━━━━ 8s 32ms/step - accuracy: 0.3496 - loss: 1.7914 - val_accuracy: 0.7300 - val_loss: 0.750
Epoch 2/10
125/125 ━━━━━━━━━━━━━━━━━━━━ 6s 38ms/step - accuracy: 0.6458 - loss: 0.9902 - val_accuracy: 0.7660 - val_loss: 0.608
Epoch 3/10
125/125 ━━━━━━━━━━━━━━━━━━━━ 5s 34ms/step - accuracy: 0.6976 - loss: 0.8247 - val_accuracy: 0.7570 - val_loss: 0.599
Epoch 4/10
125/125 ━━━━━━━━━━━━━━━━━━━━ 5s 30ms/step - accuracy: 0.7355 - loss: 0.7104 - val_accuracy: 0.8080 - val_loss: 0.525
Epoch 5/10
125/125 ━━━━━━━━━━━━━━━━━━━━ 5s 42ms/step - accuracy: 0.7702 - loss: 0.6563 - val_accuracy: 0.8140 - val_loss: 0.501
Epoch 6/10
125/125 ━━━━━━━━━━━━━━━━━━━━ 4s 31ms/step - accuracy: 0.7472 - loss: 0.6644 - val_accuracy: 0.7940 - val_loss: 0.501
Epoch 7/10
125/125 ━━━━━━━━━━━━━━━━━━━━ 5s 31ms/step - accuracy: 0.7894 - loss: 0.5930 - val_accuracy: 0.8270 - val_loss: 0.456
Epoch 8/10
125/125 ━━━━━━━━━━━━━━━━━━━━ 6s 40ms/step - accuracy: 0.7951 - loss: 0.5567 - val_accuracy: 0.8340 - val_loss: 0.427
Epoch 9/10
125/125 ━━━━━━━━━━━━━━━━━━━━ 4s 34ms/step - accuracy: 0.8076 - loss: 0.5444 - val_accuracy: 0.8410 - val_loss: 0.427
Epoch 10/10
125/125 ━━━━━━━━━━━━━━━━━━━━ 6s 39ms/step - accuracy: 0.8222 - loss: 0.5000 - val_accuracy: 0.8210 - val_loss: 0.456
CNN training complete.
```

Plot training history (accuracy and loss)

```
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
```

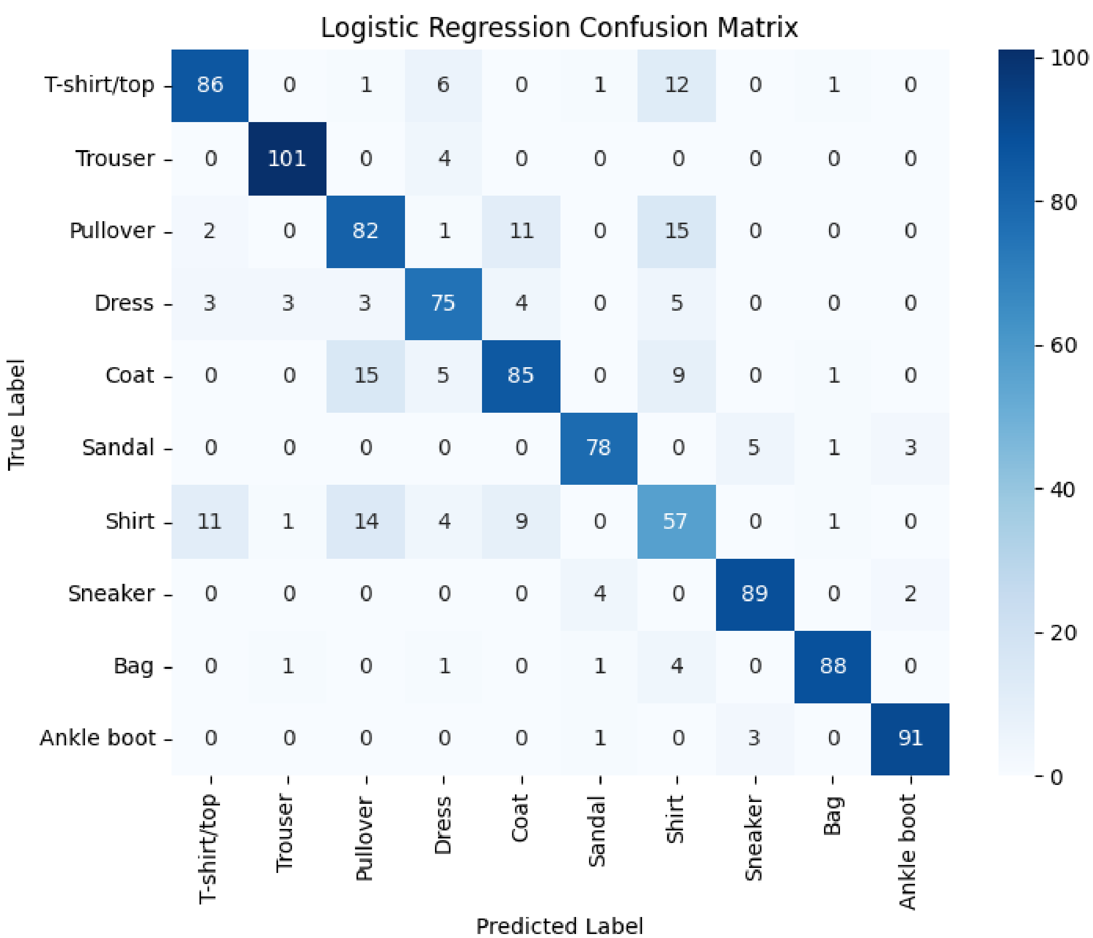




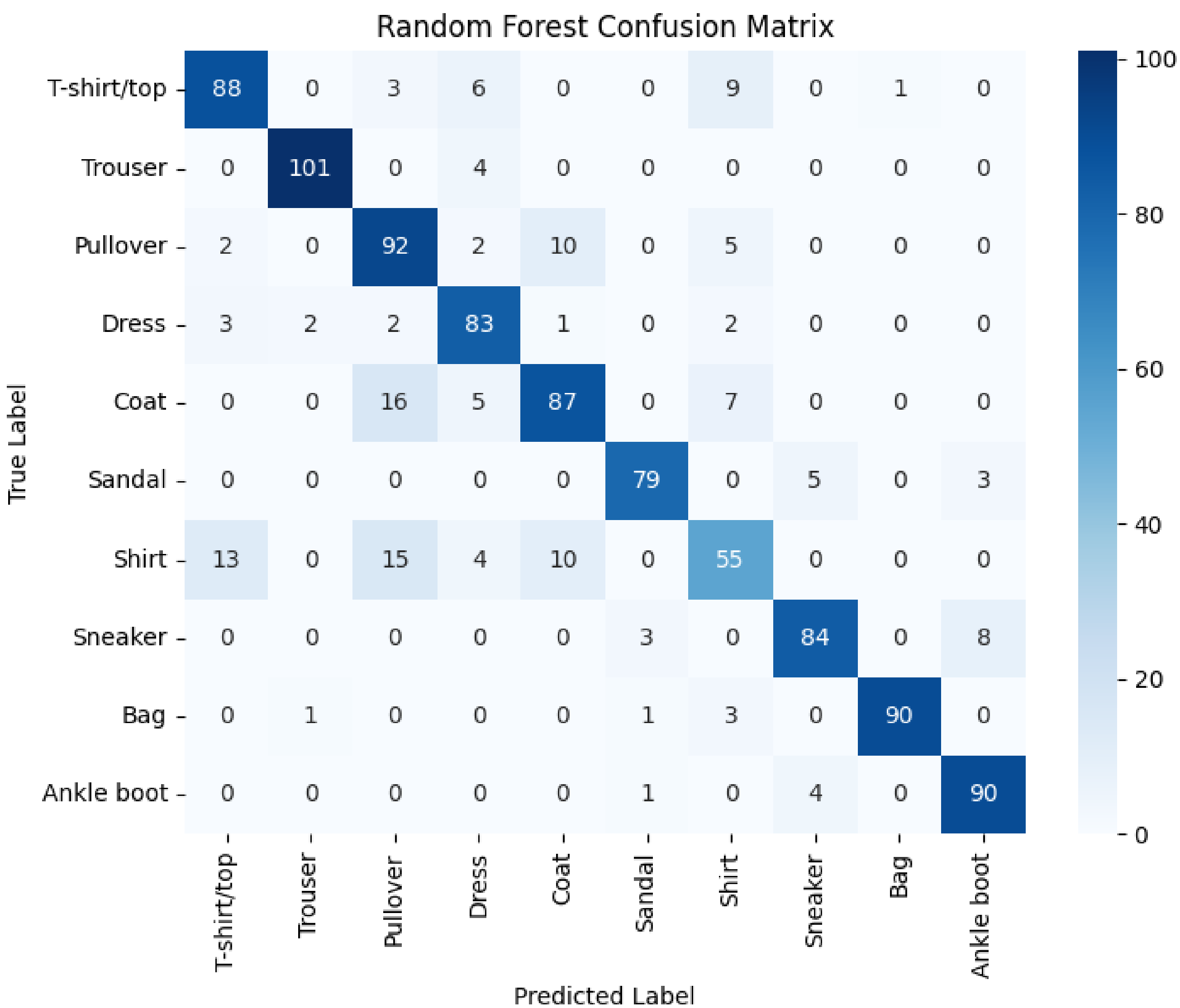
--- Evaluate Traditional Models ---

```python
print("\n--- Evaluating Traditional Machine Learning Models ---")
models = {
    "Logistic Regression": log_reg_model,
    "Random Forest": rf_model,
    "SVC": svm_model
}
results = {}

for name, model in models.items():
    print(f"\n--- {name} ---")
    predictions = model.predict(test_images_scaled)
    accuracy = accuracy_score(test_labels, predictions)
    report = classification_report(test_labels, predictions, target_names=class_names, zero_division=0)
    cm = confusion_matrix(test_labels, predictions)
    results[name] = {
        "accuracy": accuracy,
        "report": report,
        "confusion_matrix": cm
    }
    print(f"Accuracy: {accuracy:.4f}")
    print("Classification Report:\n", report)

    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names, yticklabels=class_names)
    plt.title(f'{name} Confusion Matrix')
    plt.xlabel('Predicted Label')
    plt.ylabel('True Label')
    plt.show()
```

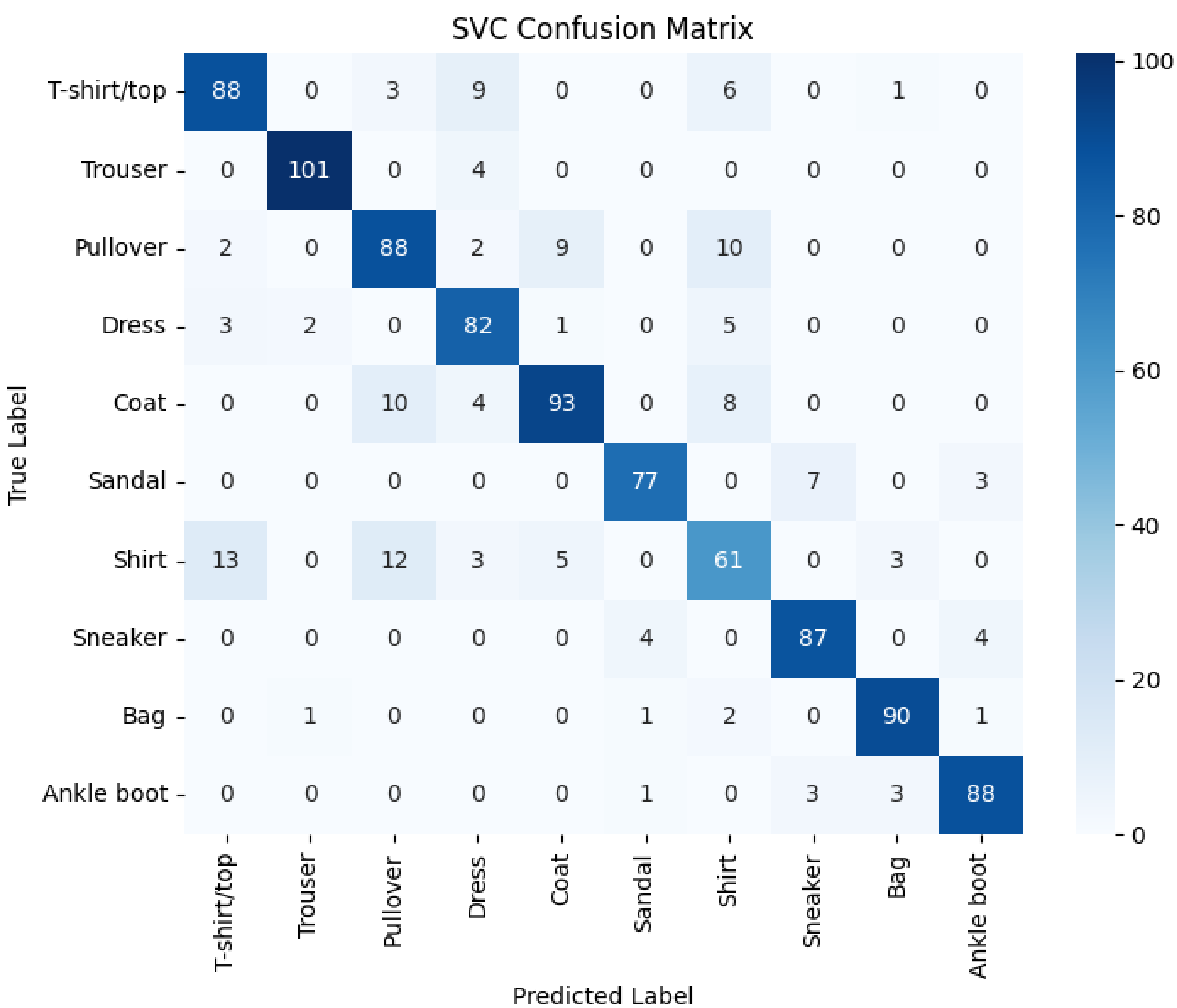
```
--- Evaluating Traditional Machine Learning Models ---

--- Logistic Regression ---
Accuracy: 0.8320
Classification Report:
              precision    recall  f1-score   support

 T-shirt/top       0.84      0.80      0.82       107
     Trouser       0.95      0.96      0.96       105
    Pullover       0.71      0.74      0.73       111
       Dress       0.78      0.81      0.79        93
        Coat       0.78      0.74      0.76       115
      Sandal       0.92      0.90      0.91        87
       Shirt       0.56      0.59      0.57        97
     Sneaker       0.92      0.94      0.93        95
         Bag       0.96      0.93      0.94        95
  Ankle boot       0.95      0.96      0.95        95

    accuracy                           0.83      1000
   macro avg       0.84      0.84      0.84      1000
weighted avg       0.83      0.83      0.83      1000
```



```
--- Random Forest ---
Accuracy: 0.8490
Classification Report:
              precision    recall  f1-score   support

 T-shirt/top       0.83      0.82      0.83       107
     Trouser       0.97      0.96      0.97       105
    Pullover       0.72      0.83      0.77       111
       Dress       0.80      0.89      0.84        93
        Coat       0.81      0.76      0.78       115
      Sandal       0.94      0.91      0.92        87
       Shirt       0.68      0.57      0.62        97
     Sneaker       0.90      0.88      0.89        95
         Bag       0.99      0.95      0.97        95
  Ankle boot       0.89      0.95      0.92        95

    accuracy                           0.85      1000
   macro avg       0.85      0.85      0.85      1000
weighted avg       0.85      0.85      0.85      1000
```



```
--- SVC ---
Accuracy: 0.8550
Classification Report:
              precision    recall  f1-score   support

 T-shirt/top       0.83      0.82      0.83       107
     Trouser       0.97      0.96      0.97       105
    Pullover       0.78      0.79      0.79       111
       Dress       0.79      0.88      0.83        93
        Coat       0.86      0.81      0.83       115
      Sandal       0.93      0.89      0.91        87
       Shirt       0.66      0.63      0.65        97
     Sneaker       0.90      0.92      0.91        95
         Bag       0.93      0.95      0.94        95
  Ankle boot       0.92      0.93      0.92        95

    accuracy                           0.85      1000
   macro avg       0.86      0.86      0.86      1000
weighted avg       0.86      0.85      0.85      1000
```



--- Evaluate CNN Model ---

```
print("\n--- Evaluating Convolutional Neural Network (CNN) ---")
loss, accuracy = cnn_model.evaluate(test_images_cnn, test_labels, verbose=0)
print(f"CNN Test Loss: {loss:.4f}")
print(f"CNN Test Accuracy: {accuracy:.4f}")
```

```
--- Evaluating Convolutional Neural Network (CNN) ---
CNN Test Loss: 0.5278
CNN Test Accuracy: 0.8200
```

Get predictions and classification report for CNN

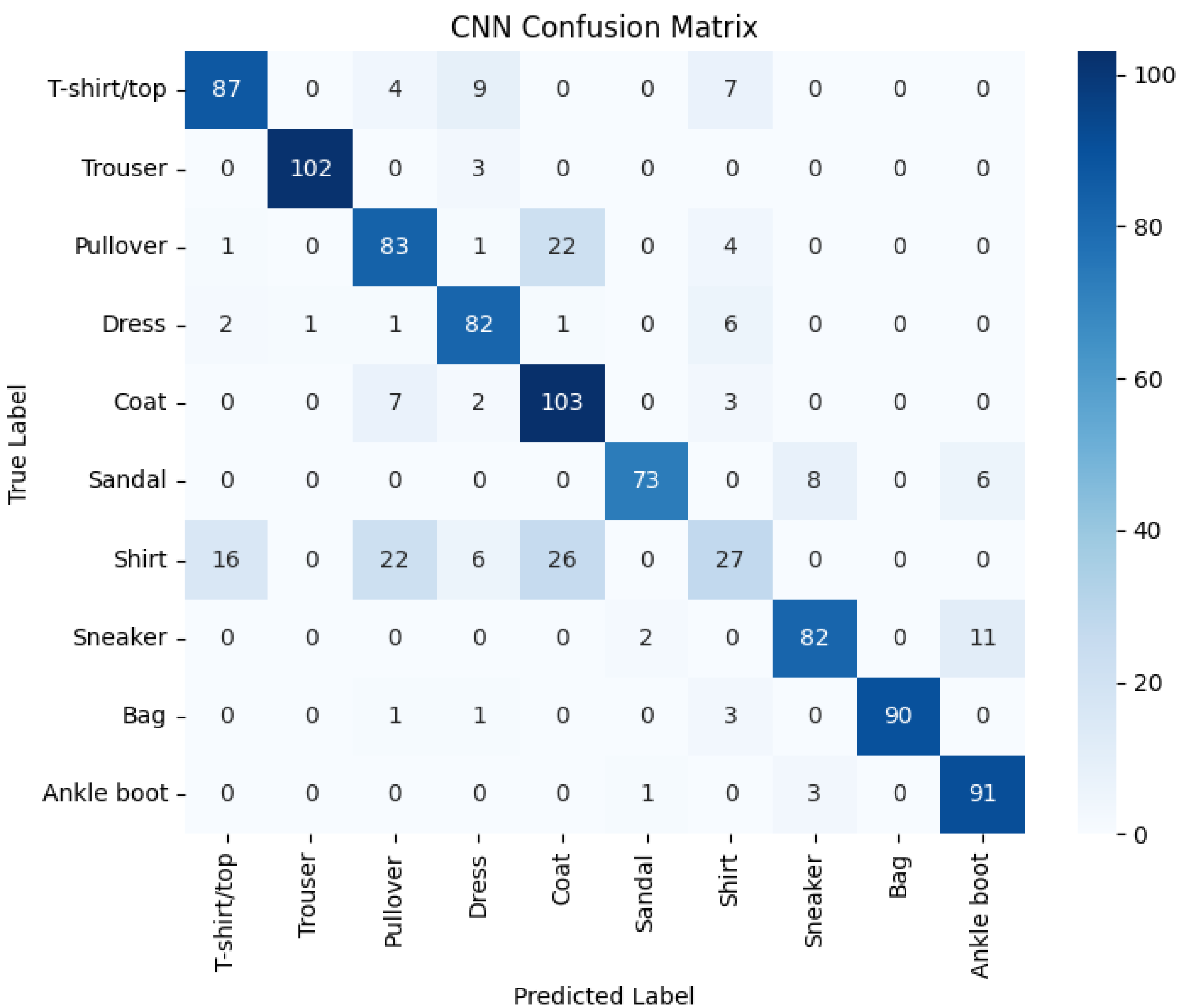
```
# Get predictions and classification report for CNN
cnn_pred_probs = cnn_model.predict(test_images_cnn)
cnn_predictions = np.argmax(cnn_pred_probs, axis=1)
cnn_report = classification_report(test_labels, cnn_predictions, target_names=class_names, zero_division=0)
cnn_cm = confusion_matrix(test_labels, cnn_predictions)

results["CNN"] = {
    "accuracy": accuracy,
    "report": cnn_report,
    "confusion_matrix": cnn_cm
}
```

```
32/32 ━━━━━━━━━━━━━━━━━━━━ 1s 20ms/step
```

```
print("CNN Classification Report:\n", cnn_report)
```

```
CNN Classification Report:
               precision    recall  f1-score   support

 T-shirt/top       0.82      0.81      0.82       107
     Trouser       0.99      0.97      0.98       105
    Pullover       0.70      0.75      0.72       111
       Dress       0.79      0.88      0.83        93
        Coat       0.68      0.90      0.77       115
      Sandal       0.96      0.84      0.90        87
       Shirt       0.54      0.28      0.37        97
     Sneaker       0.88      0.86      0.87        95
         Bag       1.00      0.95      0.97        95
  Ankle boot       0.84      0.96      0.90        95

    accuracy                           0.82      1000
   macro avg       0.82      0.82      0.81      1000
weighted avg       0.82      0.82      0.81      1000
```

```python
plt.figure(figsize=(8, 6))
sns.heatmap(cnn_cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names, yticklabels=class_names)
plt.title('CNN Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```



--- Summary of All Models ---

```python
print("\n--- Summary of Model Performance (Test Accuracy) ---")
for name, data in results.items():
    print(f"{name}: {data['accuracy']:.4f}")
```

```
--- Summary of Model Performance (Test Accuracy) ---
Logistic Regression: 0.8320
Random Forest: 0.8490
SVC: 0.8550
CNN: 0.8200
```

--- Making Predictions with Different Models ---

Select a few random test images to make predictions on

```python
# --- Making Predictions with Different Models ---
# Select a few random test images to make predictions on
num_predictions_to_show = 5
random_indices = np.random.choice(len(test_images), num_predictions_to_show, replace=False)
```

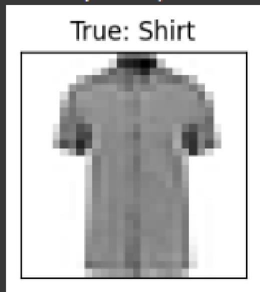
```python
print("\n--- Making Predictions on Sample Test Images ---")
for i, idx in enumerate(random_indices):
    sample_image = test_images[idx]
    true_label = test_labels[idx]
    true_label_name = class_names[true_label]

    print(f"\n--- Sample {i+1} (True Label: {true_label_name}) ---")

    # Display the actual image
    plt.figure(figsize=(2,2))
    plt.imshow(sample_image, cmap=plt.cm.binary)
    plt.title(f"True: {true_label_name}")
    plt.xticks([])
    plt.yticks([])
    plt.show()

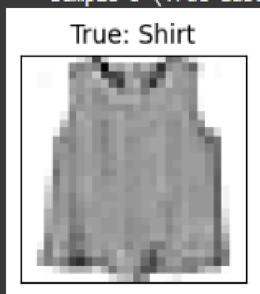
    # Prediction with Logistic Regression
    lr_pred_input = test_images_scaled[idx].reshape(1, -1)
    lr_prediction = log_reg_model.predict(lr_pred_input)[0]
    print(f"Logistic Regression Prediction: {class_names[lr_prediction]}")
```

```
--- Sample 2 (True Label: Shirt) ---
```




```
Logistic Regression Prediction: Shirt

--- Sample 3 (True Label: Shirt) ---
```

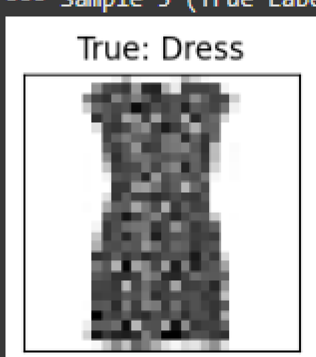



```
Logistic Regression Prediction: Shirt
```

```
--- Sample 4 (True Label: Coat) ---
```


```
Logistic Regression Prediction: Coat

--- Sample 5 (True Label: Dress) ---
```




```
Logistic Regression Prediction: Dress
```

Prediction with Random Forest

```
for i, idx in enumerate(random_indices):
  # Prediction with Logistic Regression
    lr_pred_input = test_images_scaled[idx].reshape(1, -1)
    lr_prediction = log_reg_model.predict(lr_pred_input)[0]
    print(f"Logistic Regression Prediction: {class_names[lr_prediction]}")

    # Prediction with Random Forest
    rf_pred_input = test_images_scaled[idx].reshape(1, -1)
    rf_prediction = rf_model.predict(rf_pred_input)[0]
    print(f"Random Forest Prediction: {class_names[rf_prediction]}")

     # Prediction with SVC
    svm_pred_input = test_images_scaled[idx].reshape(1, -1)
    svm_prediction = svm_model.predict(svm_pred_input)[0]
    print(f"SVC Prediction: {class_names[svm_prediction]}")

    # Prediction with CNN
    cnn_pred_input = test_images_cnn[idx].reshape(1, 28, 28, 1)  # Reshape for CNN
    cnn_pred_probs = cnn_model.predict(cnn_pred_input)[0]
    cnn_prediction = np.argmax(cnn_pred_probs)
    print(f"CNN Prediction: {class_names[cnn_prediction]} (Confidence: {np.max(cnn_pred_probs)*100:.2f}%)")
    print(f"CNN Top 3 Probabilities: ")
    top_3_indices = np.argsort(cnn_pred_probs)[::-1][:3]
    for k in top_3_indices:
        print(f" - {class_names[k]}: {cnn_pred_probs[k]*100:.2f}%")
```

```
Logistic Regression Prediction: Sandal
Random Forest Prediction: Sandal
SVC Prediction: Sandal
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 59ms/step
CNN Prediction: Sandal (Confidence: 95.48%)
CNN Top 3 Probabilities:
 - Sandal: 95.48%
 - Sneaker: 4.14%
 - Bag: 0.24%
Logistic Regression Prediction: Shirt
Random Forest Prediction: T-shirt/top
SVC Prediction: T-shirt/top
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 57ms/step
CNN Prediction: Shirt (Confidence: 48.18%)
CNN Top 3 Probabilities:
 - Shirt: 48.18%
 - T-shirt/top: 44.62%
 - Dress: 5.15%
Logistic Regression Prediction: Shirt
Random Forest Prediction: Pullover
SVC Prediction: Shirt
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 60ms/step
CNN Prediction: Coat (Confidence: 36.74%)
CNN Top 3 Probabilities:
 - Coat: 36.74%
 - Shirt: 27.03%
 - Pullover: 24.04%
Logistic Regression Prediction: Coat
Random Forest Prediction: Coat
SVC Prediction: Coat
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
CNN Prediction: Coat (Confidence: 91.01%)
CNN Top 3 Probabilities:
 - Coat: 91.01%
 - Pullover: 4.59%
 - Shirt: 3.89%
Logistic Regression Prediction: Dress
Random Forest Prediction: Dress
SVC Prediction: Dress
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 39ms/step
CNN Prediction: Dress (Confidence: 64.78%)
CNN Top 3 Probabilities:
 - Dress: 64.78%
 - T-shirt/top: 18.16%
 - Shirt: 14.29%
```

--- Decision Making ---

```
print("\n--- Decision Making based on Model Performance ---")
print("Choosing the 'best' model depends on your specific needs:")
```

```
--- Decision Making based on Model Performance ---
Choosing the 'best' model depends on your specific needs:
```

```
best_model_name = max(results, key=lambda k: results[k]['accuracy'])
print(f"\nBased purely on test accuracy, the best model is: {best_model_name} (Accuracy: {results[best_model_name][
```

```
Based purely on test accuracy, the best model is: SVC (Accuracy: 0.8550)
```

if best_model_name == "CNN":

print("The CNN achieved the highest accuracy, which is typical for image classification.")

print("Decision: If maximum accuracy is the primary goal, and computational resources (for training and inference) are not a constraint, the CNN is likely the best choice.")

print("Considerations: CNNs require more computational power and data for training. They are typically less interpretable than traditional models.")

elif best_model_name in ["Logistic Regression", "Random Forest", "SVC"]:

print(f"A traditional ML model ({best_model_name}) achieved the highest or comparable accuracy.")

print("Decision: If interpretability, faster training times, or lower computational demands are crucial, a traditional model might be preferred, especially if its performance is close to or even surpasses deep learning for your specific dataset.")

print("Considerations: Random Forests are good for feature importance. Logistic Regression is simple and interpretable. SVC can be powerful but slower on large datasets.")

```
if best_model_name == "CNN":
    print("The CNN achieved the highest accuracy, which is typical for image classification.")
    print("Decision: If maximum accuracy is the primary goal, and computational resources (for training and inferen
    print("Considerations: CNNs require more computational power and data for training. They are typically less int
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```
A traditional ML model (SVC) achieved the highest or comparable accuracy.
Decision: If interpretability, faster training times, or lower computational demands are crucial, a traditional mode
Considerations: Random Forests are good for feature importance. Logistic Regression is simple and interpretable. SVC
```

print("\nFurther Considerations for Decision Making:")

print("- **Computational Resources:** Training and deploying complex CNNs can be expensive.")

print("- **Inference Speed:** Real-time applications might prefer faster, simpler models if accuracy difference is negligible.")

print("- **Interpretability:** Why did the model make a specific prediction? Traditional models often provide more transparency.")

print("- **Data Size:** Deep learning models typically require vast amounts of data to reach their full potential.")

print("- **Deployment Environment:** What kind of hardware is available for running the model in production?")

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```
Further Considerations for Decision Making:
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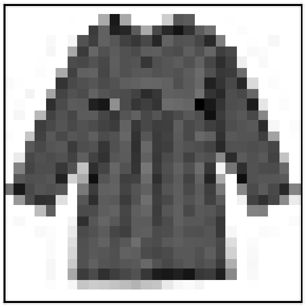
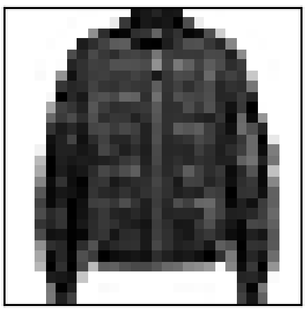
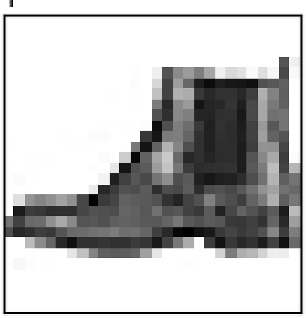
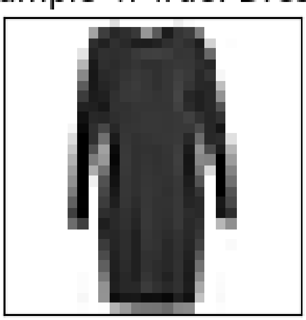
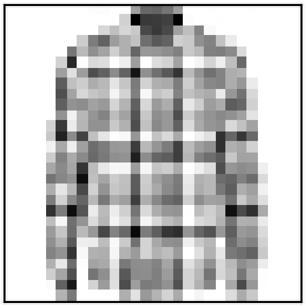
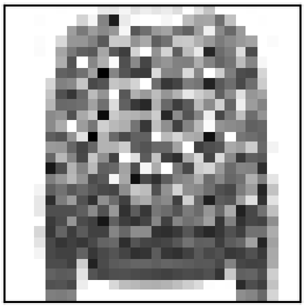
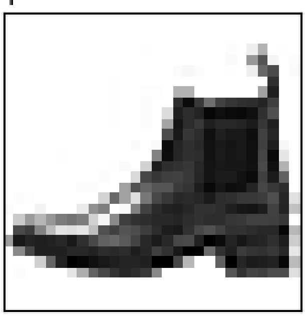
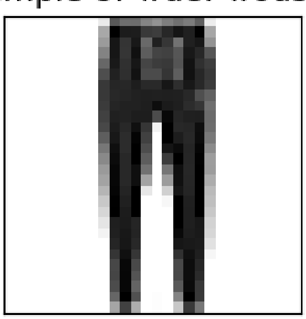
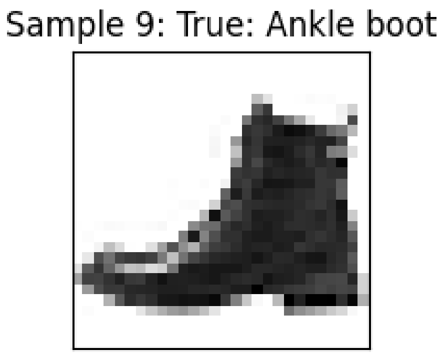
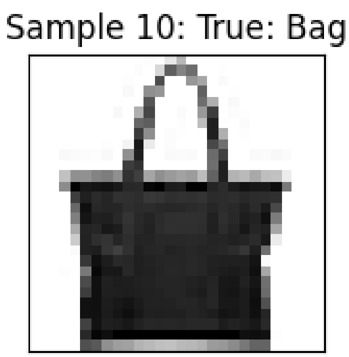
- **Data Size:** Deep learning models typically require vast amounts of data to reach their full potential.
- **Deployment Environment:** What kind of hardware is available for running the model in production?
```

Output table:

#	Selecting Random data	Prediction	Decision
1	Sample 1: True: Dress 	Dress	Correct prediction. The model accurately classified this fashion item
2	Sample 2: True: Coat 	Coat	Correct prediction
3	Sample 3: True: Ankle boot 	Ankle boot	Correct prediction
4	Sample 4: True: Dress 	Dress	Correct prediction

5	Sample 5: True: Shirt 	Coat	Incorrect prediction. Model confused Coat with Shirt.
6	Sample 6: True: Pullover 	Pullover	Correct prediction
7	Sample 7: True: Ankle boot 	Ankle boot	Correct prediction
8	Sample 8: True: Trouser 	Trouser	Correct prediction

9		Ankle boot	Correct prediction
10		Bag	Correct prediction

Conclusion:

- Comprehensive ML Workflow: I have learned the complete machine learning pipeline, from data acquisition and preprocessing with libraries like Scikit-learn and TensorFlow, to building, training, and evaluating both traditional models (Logistic Regression, Random Forest, SVM) and advanced deep learning models (CNN), culminating in performance analysis and prediction.
- Computational and Optimization Challenges: The main difficulties involved managing computational resources for training complex models like CNNs, debugging model architecture, and interpreting results to understand why a model made certain errors, such as confusing similar classes like 'Shirt' and 'Coat'.
- Technical Proficiency in ML & DL: I have gained practical skills in using Python's key data science libraries, implementing neural networks and critically evaluating model performance using metrics like accuracy, confusion matrices, and classification reports.
- Immediate Workplace Contribution: If offered a job, I could immediately apply these skills to develop and deploy robust machine learning models for tasks like image classification, automate data preprocessing pipelines, and provide

data-driven insights by rigorously evaluating model performance to solve real-world business problems.

- Driven by Complex Problem-Solving: This project has motivated me to further explore advanced architectures like Transformers for vision, delve into model optimization for deployment, and continuously learn to tackle more complex and impactful challenges in the field of artificial intelligence.