Fashion-MNIST Image Classification

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Abstract

In this project, I compare two supervised learning models on the Fashion-MNIST dataset: an MLP Classifier and a Convolutional Neural Network (CNN). The MLP must flatten each image into a long vector, while the CNN keeps the 2-D structure. I train both models and test them on the same dataset to see how they perform. The results show that the MLP reaches 89.04% accuracy, and the CNN reaches 92.01% accuracy. This project helps me understand how different model structures affect image classification performance.

Introduction

The goal of this project is to classify clothing images from the Fashion-MNIST dataset. This dataset contains 70,000 grayscale images of size 28×28. There are ten categories, such as T-shirt/top, Trouser, Dress, Coat, Bag, and more. Each image has one correct label. In class, we learned about simple neural networks. Professor explained that MLPs flatten the image, which removes the spatial patterns inside it. CNNs keep the image shape and usually perform better on image tasks. Because of this, I train both models and compare their performance. This helps me understand why CNNs are more effective for image data.

Data

This project uses the Fashion-MNIST dataset from Zalando. The dataset has 70,000 grayscale images of clothing items, each with size 28X28 pixels. There are 10 classes: T-shirt/top, Trouser, Pullover, Dress, Coat, Sandal, Shirt, Sneaker, Bag, and Ankle boot. Each image has one label from 0 to 9 that tells which clothing class it belongs to. I use 60,000 images for training and 10,000 images for testing.

To prepare the data, I first load the dataset and scale the pixel values to be between 0 and 1 by dividing by 255. This normalization step makes training more stable for both the MLP and the CNN. The main code is:

```
fashion_mnist = tf.keras.datasets.fashion_mnist

(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()

# normalize
x_train = x_train / 255.0
x_test = x_test / 255.0
```

The CNN part of the project is written in PyTorch, so after normalization I convert the NumPy arrays into PyTorch tensors. I also add a channel dimension so that each image has shape (1, 28, 28), which is the standard format for convolutional layers (channels, height, width). Then I wrap the tensors in a TensorDataset and use DataLoader to create mini batches with shape (batch_size, 1, 28, 28) for training and testing. The main lines are:

```
# convert numpy arrays to PyTorch tensors with channel dimension (N, 1, 28, 28)
X_train_torch = torch.tensor(x_train, dtype=torch.float32).unsqueeze(1)
X_test_torch = torch.tensor(x_test, dtype=torch.float32).unsqueeze(1)

y_train_torch = torch.tensor(y_train, dtype=torch.long)
y_test_torch = torch.tensor(y_test, dtype=torch.long)

train_ds = TensorDataset(X_train_torch, y_train_torch)
test_ds = TensorDataset(X_test_torch, y_test_torch)

train_loader = DataLoader(train_ds, batch_size=64, shuffle=True)
test_loader = DataLoader(test_ds, batch_size=64, shuffle=False)
```

Modeling

Basic Neural Network (MLP Classifier) The MLP is a feed-forward neural network from scikit-learn. Because it cannot use the 2-D structure of images, each 28×28 image must be flattened into a 784-dimensional vector before training.

```python
# reshape images for scikit-learn (flatten)
X_train_flat = x_train.reshape(len(x_train), 28 * 28)
X_test_flat = x_test.reshape(len(x_test), 28 * 28)

print("Flattened shape:", X_train_flat.shape)
```

```
Flattened shape: (60000, 784)
```

I then define and train the MLP. In the updated version of the project, I use a deeper and wider MLP with two hidden layers (256, 128), ReLU activation, Adam optimizer, small L2 regularization (alpha=1e-4), and a larger max_iter = 200 for better optimization.

```python
# train MLPClassifier
mlp = MLPClassifier(
    hidden_layer_sizes=(256, 128),   # deeper network
    activation='relu',
    solver='adam',
    alpha=1e-4,                      # L2 regularization
    learning_rate_init=0.001,
    max_iter=200,                    # train longer (very important)
    random_state=0
)

mlp.fit(X_train_flat, y_train)

y_pred_basic = mlp.predict(X_test_flat)
test_acc_basic = accuracy_score(y_test, y_pred_basic)

print("MLPClassifier test accuracy:", test_acc_basic)
```

This larger network improves accuracy because it can learn more complex patterns than the small, single-layer MLP. However, the MLP still treats every pixel as an independent input feature and does not know that nearby pixels form meaningful shapes or edges.

Convolutional Neural Network (CNN) Unlike the MLP, the CNN keeps the image in its original 2-D form with shape (1, 28, 28) and uses convolution layers to learn spatial patterns directly. I use a LeNet-style CNN implemented in PyTorch. The first convolution layer takes the single-channel image and produces 32 feature maps with a 5×5 kernel and padding, followed by a 2×2 max-pooling layer. The second convolution layer increases the depth from 32 to 64 feature maps with another 5×5 kernel, again followed by max-pooling.

After the two convolution-and-pooling stages, the feature maps are flattened into a vector of size 64 * 5 * 5, which is passed through two fully connected layers of sizes 256 and 128. I apply ReLU activations after each layer and insert a dropout layer with probability 0.5 after the first fully connected layer to reduce overfitting by randomly dropping half of the activations during training. The final linear layer outputs 10 logits, one for each Fashion-MNIST class.

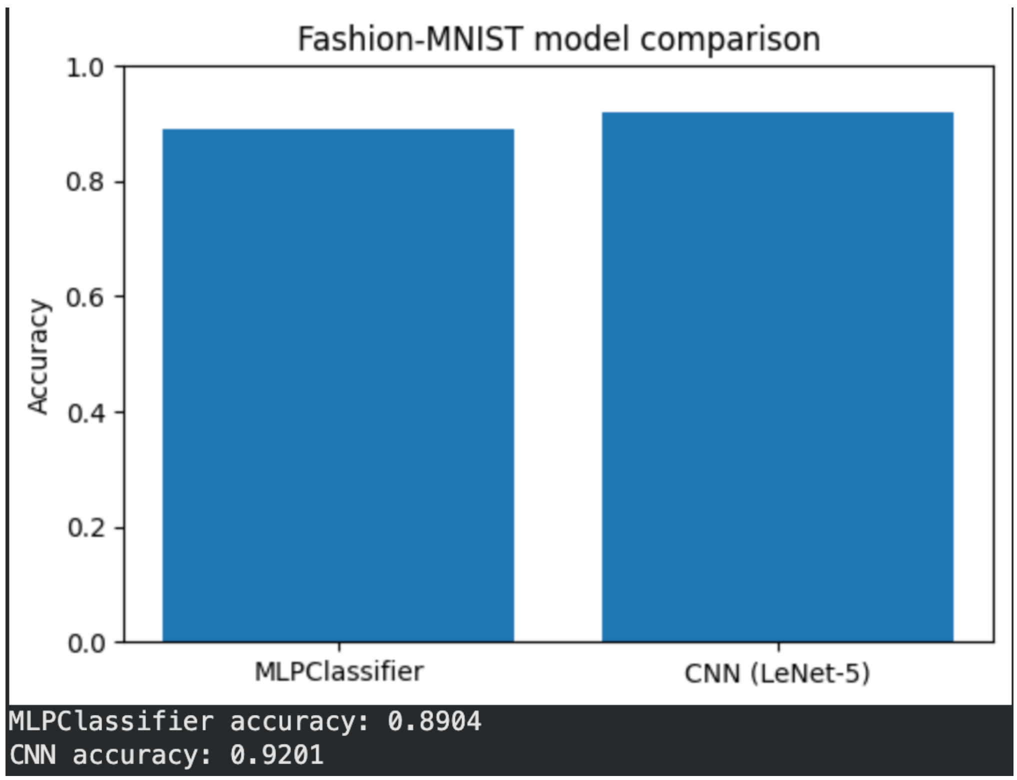
```python
class LeNet5(nn.Module):
    def __init__(self, num_classes=10):
        super(LeNet5, self).__init__()
        self.conv1 = nn.Conv2d(1, 32, kernel_size=5, padding=2)
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)

        self.conv2 = nn.Conv2d(32, 64, kernel_size=5)
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)

        self.fc1 = nn.Linear(64 * 5 * 5, 256)
        self.fc2 = nn.Linear(256, 128)
        self.fc3 = nn.Linear(128, num_classes)

        self.dropout = nn.Dropout(p=0.5)

    def forward(self, x):
        x = self.pool1(F.relu(self.conv1(x)))
        x = self.pool2(F.relu(self.conv2(x)))
        x = x.view(x.size(0), -1)          # flatten
        x = F.relu(self.fc1(x))
        x = self.dropout(x)                # dropout after first FC
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

I train this CNN for 15 epochs using the Adam optimizer with learning rate 0.001 and cross-entropy loss. In each epoch the model iterates over all mini batches from the training DataLoader, computes the loss, backpropagates the gradients, and updates the weights. I record the average loss per epoch to monitor convergence.

```
model_cnn = LeNet5(num_classes=10)
optimizer = torch.optim.Adam(model_cnn.parameters(), lr=0.001)
criterion = nn.CrossEntropyLoss()

n_epochs = 15
losses_cnn = []

for epoch in range(n_epochs):
    model_cnn.train()
    running_loss = 0.0

    for Xb, yb in train_loader:
        optimizer.zero_grad()
        outputs = model_cnn(Xb)
        loss = criterion(outputs, yb)
        loss.backward()
        optimizer.step()
        running_loss += loss.item()

    avg_loss = running_loss / len(train_loader)
    losses_cnn.append(avg_loss)
    print(f"epoch {epoch}, loss {avg_loss:.4f}")
```

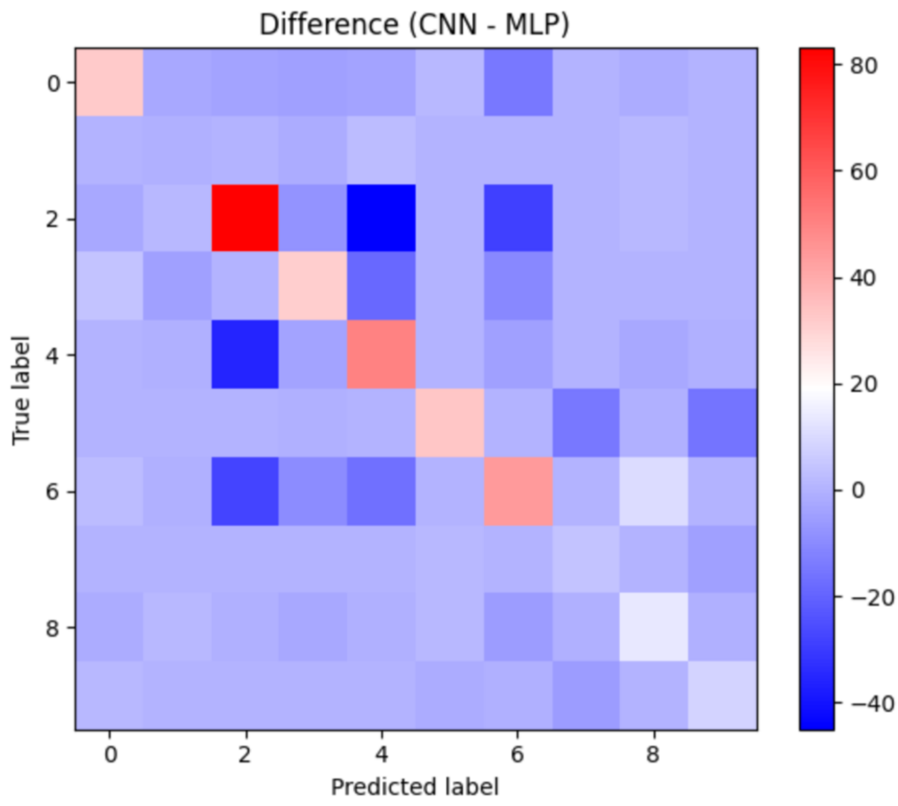
4 Results

The MLP Classifier reaches a test accuracy of 0.8904, while the CNN (LeNet-5) achieves a higher accuracy of 0.9201. The bar chart below summarizes the performance of the two models on the Fashion-MNIST test set.



In the difference matrix (CNN − MLP), each number tells how many more images the CNN placed in that cell compared to the MLP. Positive values on the diagonal, such as 32 at (0,0) and 8 at (9,9), mean the CNN correctly classified 32 more T-shirts and 8 more ankle boots than the MLP. Negative values off the diagonal show where the MLP handled certain confusions slightly better, for example, the −45 at (3,5) means the MLP made 45 fewer mistakes than the CNN, and −28 at (7,3) shows fewer errors. The color plot simply visualizes these numbers: red areas mark positive entries where the CNN improves over the MLP, and blue areas mark negative entries where the MLP performs a bit better.

```
Difference matrix (CNN - MLP):
[[ 32  -3  -4  -5  -4   1 -15   0  -2   0]
 [  0  -1   0  -2   2   0   0   0   1   0]
 [ -3   1  83  -8 -45   0 -29   0   1   0]
 [  4  -5   0  31 -19   0 -11   0   0   0]
 [  0  -1 -36  -4  50   0  -5   0  -3  -1]
 [  0   0   0  -1   0  33   0 -15  -1 -16]
 [  2  -1 -28 -10 -17   0  44   0  10   0]
 [  0   0   0   0   0   1   0   4   0  -5]
 [ -2   1  -1  -3  -1   1  -6  -1  13  -1]
 [  1   0   0   0   0  -2  -1  -6   0   8]]
```



5 Discussion

The results demonstrate that the CNN performs better than the MLP. This makes sense for me to understand their differences since the MLP flattens the image and loses the spatial layout, the MLP has trouble learning important visual patterns and edges. This causes mistakes when classes look similar. The CNN keeps the 2-D shape. Its filters learn local patterns. Because of this, the CNN achieves higher accuracy. Training time also differs. The MLP trains a bit fast, while the CNN takes longer. But the accuracy gain from the CNN is meaningful, so the extra time is worth it for image tasks. These results support professor's explanation that simple feed-forward networks are not the best choice for images. Convolution helps the model understand shape and structure, which is important for visual data.

6 Conclusion

This project was my first step in comparing different models on a real dataset. I learned how to build and train a basic MLP and a simple CNN, and how to compare them with the same data and metrics. The work shows that keeping the 2-D image structure and using convolution layers can give better accuracy than flattening the image and using a plain MLP. In the future, I can reuse this setup to test other architectures or small changes and see how much they really help. This project gives me a simple template for later work: choose a clear task, build a few models, and compare them fairly so I can understand not only which model is better, but also why it is better and when I should use it.