Fashion-MNIST

GEL521 - Machine Learning
202420

PRESENTED TO
Dr Hayssam SERHAN

PRESENTED BY
Antonio HADDAD 202200238
Elias-Charbel SALAMEH 202201047

Agenda

Preparation

After learning how to use the Artificial Neural Network for various endpoints, we aim to operate on a Fashion-MNIST dataset.

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Proposed Solutions

Solution # 1

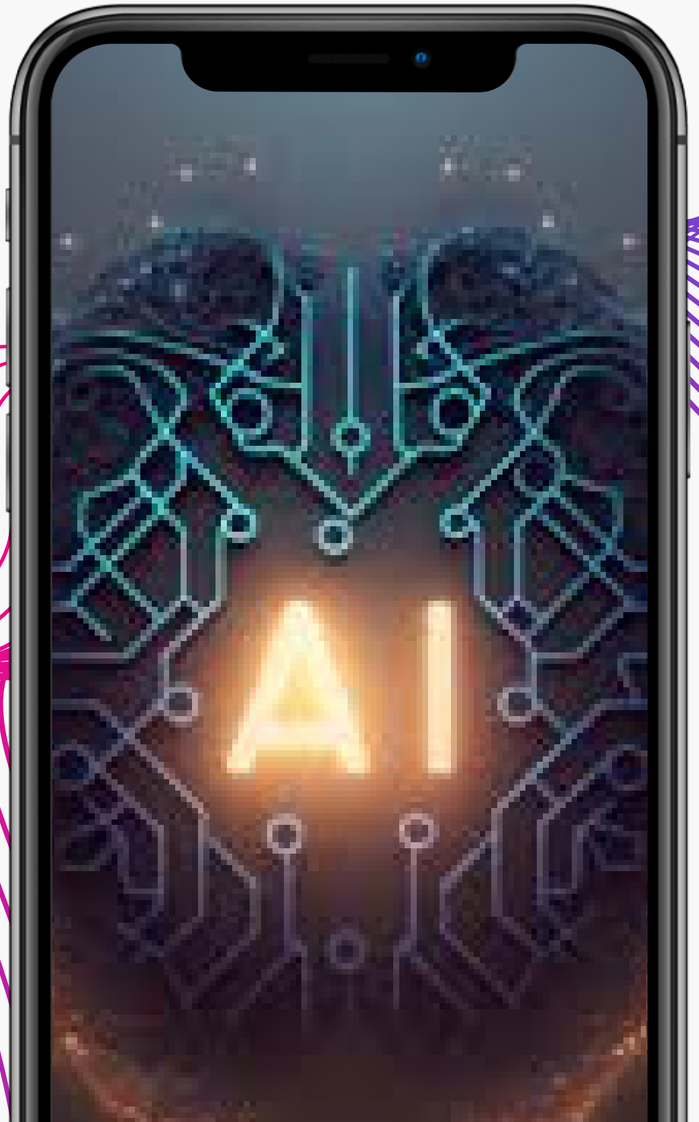
Using the MLPClassifier

Solution # 2

Using the Convolutional Neural Network

Solution # 3

Using our own developed code



Objectives

T = P

around 90%

MATCH THE TRUE OUTPUT
Using a CNN, we need to avoid having mismatches between predicted and true values

IMPROVE THE ACCURACY
Using the ANN increase the accuracy as much as possible

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Labels

Each training and test example is assigned to one of the following labels:

Label	Description
0	T-shirt/top
1	Trouser
2	Pullover
3	Dress
4	Coat
5	Sandal
6	Shirt
7	Sneaker
8	Bag
9	Ankle boot

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This is the desired output for the fashion mnist dataset.

Using an MLP Multi-Layer Perceptron Classifier library

```python
from sklearn.neural_network import MLPClassifier
from sklearn.datasets import fetch_openml
from sklearn.model_selection import train_test_split
import numpy as np

# Load MNIST data from openml
fashion_mnist = fetch_openml('Fashion-MNIST') # mnist_784
X = fashion_mnist.data / 255.0  # Scale pixel values to [0, 1]
y = np.array(fashion_mnist.target, dtype=int)
```

```
The number of features is:  784
The number of samples is:  70000
The dimension of X is:  (70000, 784)
```

```python
# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create MLPClassifier model with desired hyperparameters
model = MLPClassifier(hidden_layer_sizes=(512,512,128,), activation='relu', solver='adam', max_iter=300, verbose=True)

# Train the model on the training data
model.fit(X_train, y_train)

# Evaluate the model on the testing data
accuracy_train = model.score(X_train,y_train)
accuracy_test = model.score(X_test, y_test)
print("Train set accuracy: {:.2f}".format(accuracy_train * 100))
print("Test set accuracy: {:.2f}".format(accuracy_test * 100))
```

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```
Iteration 73, loss = 0.03449245
Iteration 74, loss = 0.03790863
Iteration 75, loss = 0.03711825
Iteration 76, loss = 0.02952226
Iteration 77, loss = 0.02931881
Iteration 78, loss = 0.03665593
Iteration 79, loss = 0.03027270
Iteration 80, loss = 0.02968127
Iteration 81, loss = 0.02659590
Iteration 82, loss = 0.03948406
Iteration 83, loss = 0.02727297
Iteration 84, loss = 0.03260940
Iteration 85, loss = 0.02836959
Iteration 86, loss = 0.02843672
Iteration 87, loss = 0.02989809
Iteration 88, loss = 0.01780911
Iteration 89, loss = 0.03861433
Iteration 90, loss = 0.02471355
Iteration 91, loss = 0.01968715
Iteration 92, loss = 0.03941532
Iteration 93, loss = 0.01912692
Iteration 94, loss = 0.02992083
Iteration 95, loss = 0.02960254
Iteration 96, loss = 0.01979922
Iteration 97, loss = 0.03463665
Iteration 98, loss = 0.02079060
Iteration 99, loss = 0.02968828
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Stopping.
Train set accuracy: 99.36
Test set accuracy: 90.14
```

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Using the keras CNN Convolutional Neural Network

```python
import tensorflow as tf
import matplotlib.pyplot as plt
import numpy as np
from tensorflow import keras
from keras import layers

# Load MNIST dataset
fashion_mnist = keras.datasets.fashion_mnist
(train_images, train_labels), (test_images, test_labels) = fashion_mnist.load_data()

# Preprocess input images
train_images = train_images.reshape((60000, 28, 28, 1))
train_images = train_images.astype('float32') / 255.0
test_images = test_images.reshape((10000, 28, 28, 1))
test_images = test_images.astype('float32') / 255.0

# Define model architecture
model = keras.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(10)
])

# Compile model
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])

# Train model
model.fit(train_images, train_labels, epochs=30, batch_size=128)

# Evaluate model
test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
print(f'Test accuracy: {test_acc}')
```

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```
Epoch 1/30
469/469 ━━━━━━━━━━━━━━━━━━━━ 4s 7ms/step - accuracy: 0.6885 - loss: 0.8948
Epoch 2/30
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - accuracy: 0.8523 - loss: 0.4069
Epoch 3/30
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - accuracy: 0.8790 - loss: 0.3339
Epoch 4/30
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - accuracy: 0.8916 - loss: 0.2971
Epoch 5/30
469/469 ━━━━━━━━━━━━━━━━━━━━ 4s 8ms/step - accuracy: 0.8989 - loss: 0.2775
Epoch 6/30
469/469 ━━━━━━━━━━━━━━━━━━━━ 4s 8ms/step - accuracy: 0.9116 - loss: 0.2444
Epoch 7/30
469/469 ━━━━━━━━━━━━━━━━━━━━ 4s 7ms/step - accuracy: 0.9120 - loss: 0.2368
Epoch 8/30
469/469 ━━━━━━━━━━━━━━━━━━━━ 4s 8ms/step - accuracy: 0.9194 - loss: 0.2185
Epoch 9/30
469/469 ━━━━━━━━━━━━━━━━━━━━ 4s 8ms/step - accuracy: 0.9245 - loss: 0.2066
Epoch 10/30
469/469 ━━━━━━━━━━━━━━━━━━━━ 4s 8ms/step - accuracy: 0.9312 - loss: 0.1916
Epoch 11/30
469/469 ━━━━━━━━━━━━━━━━━━━━ 4s 8ms/step - accuracy: 0.9349 - loss: 0.1823
Epoch 12/30
469/469 ━━━━━━━━━━━━━━━━━━━━ 4s 8ms/step - accuracy: 0.9360 - loss: 0.1733
Epoch 13/30
...
Epoch 30/30
469/469 ━━━━━━━━━━━━━━━━━━━━ 4s 8ms/step - accuracy: 0.9815 - loss: 0.0498
313/313 - 1s - 2ms/step - accuracy: 0.9066 - loss: 0.4260
Test accuracy: 0.9065999984741211
```

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```python
# Get 16 random indices for the test set
#indices = np.random.choice(len(test_images), size=16, replace=False)
#indices = np.where(np.random.rand(len(test_images)) < 0.025)[0]
indices = [1024, 1025, 1026, 1027, 1028, 1029, 1030, 1031, 1032, 1033, 1034, 1035, 1036, 1037, 1038, 1039]
print(indices)
# Make predictions on the test set
y_pred_logits = model.predict(test_images[indices])
y_pred = np.argmax(y_pred_logits, axis=-1)

# Create a figure with 16 subplots
fig, axs = plt.subplots(nrows=4, ncols=4, figsize=(10, 8))

# For each subplot, plot the corresponding image and write the true and predicted labels on top
for i, ax in enumerate(axs.flatten()):
    if i < len(indices):
        img_index = indices[i]
        ax.imshow(test_images[img_index], cmap='gray')
        ax.set_title(f'T: {test_labels[img_index]}, P: {y_pred[i]}', fontsize=12)
        ax.axis('off')

#for i, ax in zip(indices, axs.flatten()):
#    ax.imshow(test_images[i], cmap='gray')
    #ax.set_title(f'True: {test_labels[i]}, Pred: {y_pred[i]}', fontsize=12)
#    ax.set_title(f'T {test_labels[i]}, P {y_pred[i]}', fontsize=12)
#    ax.axis('off')

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

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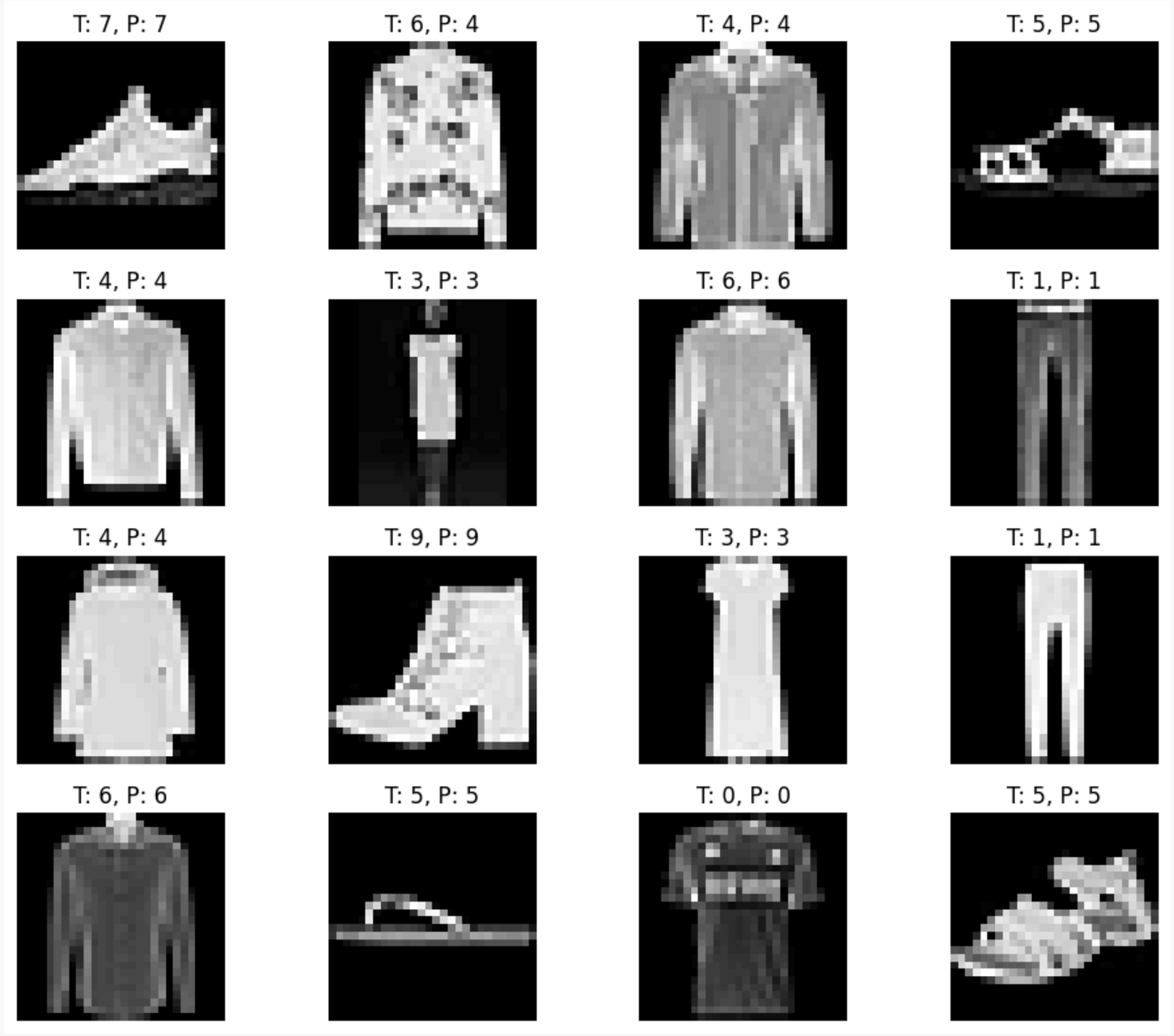

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Using our personal ANN-Artificial Neural Network

After trying to implement the Fashion-MNIST dataset on our personal code, we added:

- categorical cross-entropy calculation
- one-hot encoding
- batching
- 10 output neurons instead of just 1

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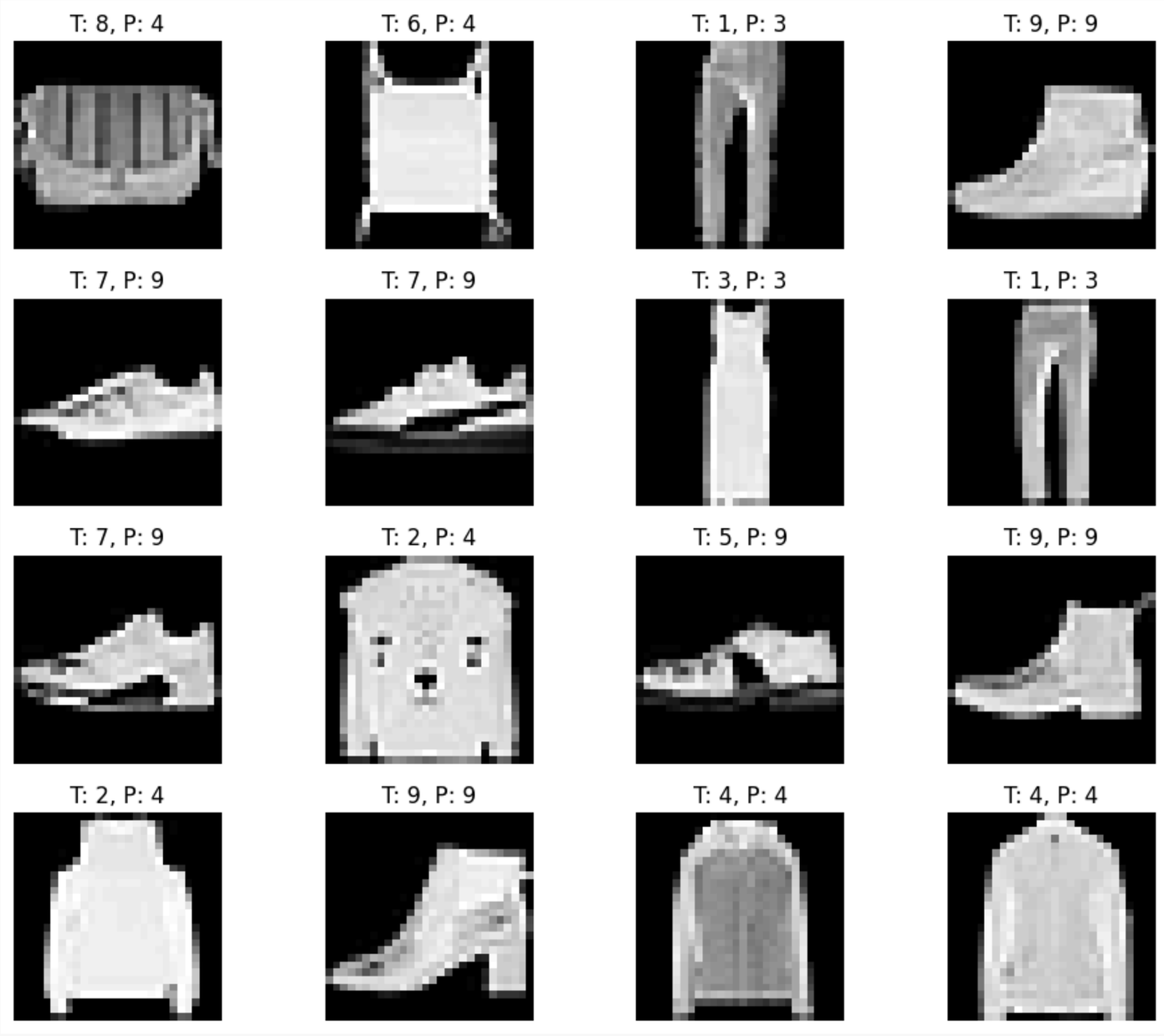
LR=0.01 - MF=0.9 - structure = [794, 1024, 1024, 512, 10] - batch size = 128 - epochs = 100

```
Epoch 1/100, Accuracy: 40.62%
Epoch 2/100, Accuracy: 62.73%
Epoch 3/100, Accuracy: 66.39%
Epoch 4/100, Accuracy: 68.98%
Epoch 5/100, Accuracy: 70.16%
Epoch 6/100, Accuracy: 71.78%
Epoch 7/100, Accuracy: 73.43%
Epoch 8/100, Accuracy: 73.33%
Epoch 9/100, Accuracy: 74.14%
Epoch 10/100, Accuracy: 75.60%
Epoch 11/100, Accuracy: 76.49%
Epoch 12/100, Accuracy: 76.64%
Epoch 13/100, Accuracy: 77.50%
Epoch 14/100, Accuracy: 77.81%
Epoch 15/100, Accuracy: 78.84%
Epoch 16/100, Accuracy: 78.01%
Epoch 17/100, Accuracy: 78.68%
Epoch 18/100, Accuracy: 79.19%
Epoch 19/100, Accuracy: 79.09%
Epoch 20/100, Accuracy: 79.95%
Epoch 21/100, Accuracy: 80.08%
Epoch 22/100, Accuracy: 80.25%
Epoch 23/100, Accuracy: 80.20%
Epoch 24/100, Accuracy: 80.19%
Epoch 25/100, Accuracy: 80.58%
...
Epoch 50/100, Accuracy: 81.68%
Epoch 51/100, Accuracy: 81.29%
Epoch 52/100, Accuracy: 81.76%
Epoch 53/100, Accuracy: 81.18%
```



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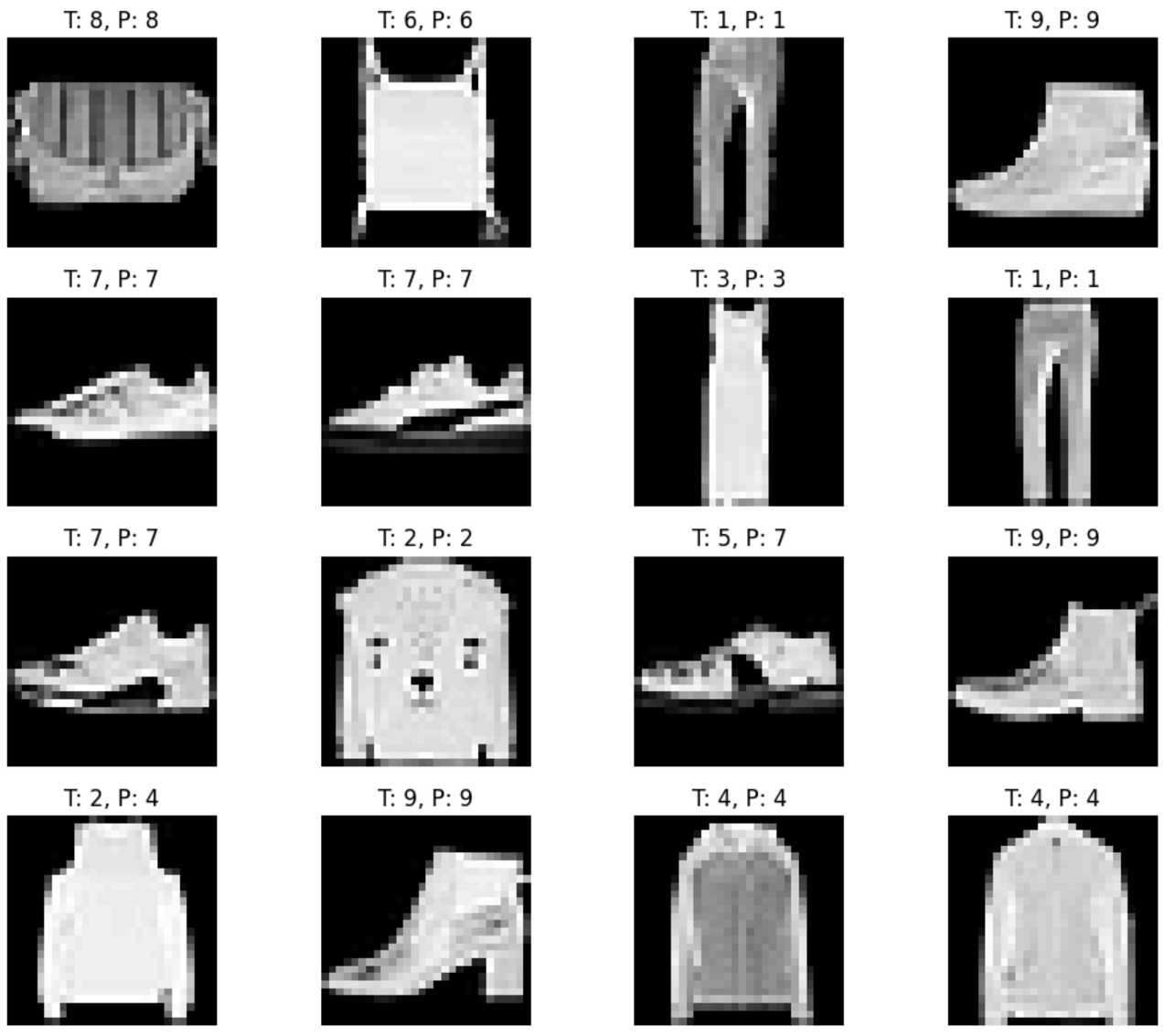
LR=0.01 - MF=0.1 - structure = [794, 512, 10] - batch size = 64 - epochs = 10

```
Epoch 1/10, Accuracy: 74.44%, Average Loss: 2.3188
Epoch 2/10, Accuracy: 80.41%, Average Loss: 1.1689
Epoch 3/10, Accuracy: 82.71%, Average Loss: 0.9311
Epoch 4/10, Accuracy: 83.86%, Average Loss: 0.8079
Epoch 5/10, Accuracy: 84.83%, Average Loss: 0.7175
Epoch 6/10, Accuracy: 85.59%, Average Loss: 0.6495
Epoch 7/10, Accuracy: 86.16%, Average Loss: 0.6070
Epoch 8/10, Accuracy: 86.86%, Average Loss: 0.5664
Epoch 9/10, Accuracy: 87.47%, Average Loss: 0.5276
Epoch 10/10, Accuracy: 87.93%, Average Loss: 0.5018
Highest accuracy reached: 87.93%
```

```
Epoch 1/10, Accuracy: 73.78%, Average Loss: 2.4643
Epoch 2/10, Accuracy: 80.17%, Average Loss: 1.1861
Epoch 3/10, Accuracy: 82.35%, Average Loss: 0.9270
Epoch 4/10, Accuracy: 83.59%, Average Loss: 0.8125
Epoch 5/10, Accuracy: 84.72%, Average Loss: 0.7144
Epoch 6/10, Accuracy: 85.45%, Average Loss: 0.6520
Epoch 7/10, Accuracy: 86.34%, Average Loss: 0.5919
Epoch 8/10, Accuracy: 86.93%, Average Loss: 0.5585
Epoch 9/10, Accuracy: 87.50%, Average Loss: 0.5211
Epoch 10/10, Accuracy: 88.03%, Average Loss: 0.4845
Highest accuracy reached: 88.03%
```



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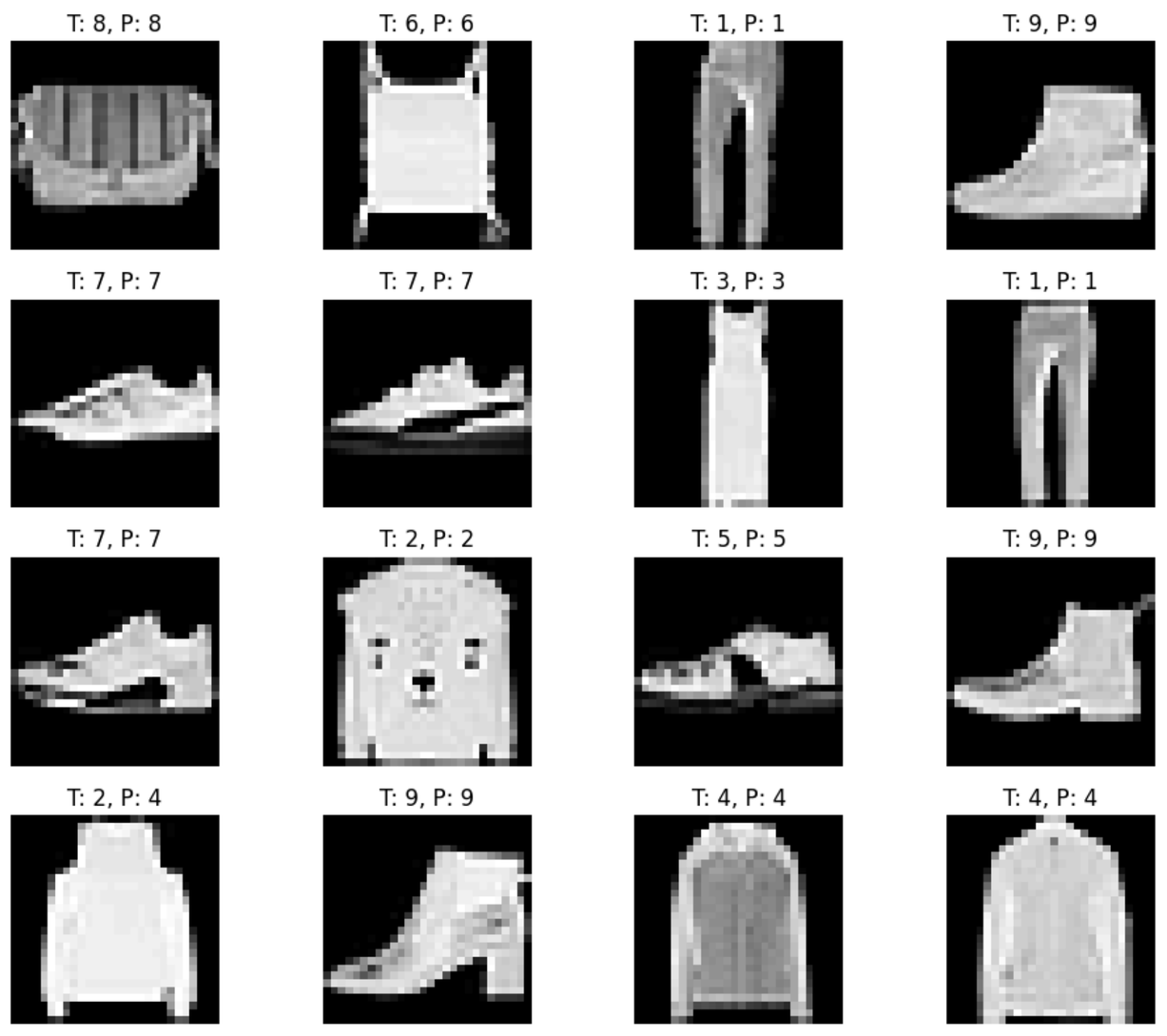
LR=0.01 - MF=0.9 - structure = [794, 512, 10] - batch size = 32 - epochs = 100

Training accuracy of 99.61%

```
Epoch 1/100, Accuracy: 76.61%, Average Loss: 1.3812
Epoch 2/100, Accuracy: 81.96%, Average Loss: 0.8205
Epoch 3/100, Accuracy: 83.87%, Average Loss: 0.6853
Epoch 4/100, Accuracy: 85.11%, Average Loss: 0.6030
Epoch 5/100, Accuracy: 85.93%, Average Loss: 0.5503
Epoch 6/100, Accuracy: 86.59%, Average Loss: 0.5107
Epoch 7/100, Accuracy: 87.30%, Average Loss: 0.4765
Epoch 8/100, Accuracy: 87.83%, Average Loss: 0.4494
Epoch 9/100, Accuracy: 88.38%, Average Loss: 0.4273
Epoch 10/100, Accuracy: 88.90%, Average Loss: 0.4064
Epoch 11/100, Accuracy: 89.33%, Average Loss: 0.3877
Epoch 12/100, Accuracy: 89.66%, Average Loss: 0.3704
Epoch 13/100, Accuracy: 90.09%, Average Loss: 0.3531
Epoch 14/100, Accuracy: 90.46%, Average Loss: 0.3386
Epoch 15/100, Accuracy: 90.77%, Average Loss: 0.3254
Epoch 16/100, Accuracy: 91.11%, Average Loss: 0.3131
Epoch 17/100, Accuracy: 91.39%, Average Loss: 0.3017
Epoch 18/100, Accuracy: 91.69%, Average Loss: 0.2913
Epoch 19/100, Accuracy: 91.98%, Average Loss: 0.2812
Epoch 20/100, Accuracy: 92.27%, Average Loss: 0.2717
Epoch 21/100, Accuracy: 92.54%, Average Loss: 0.2627
Epoch 22/100, Accuracy: 92.80%, Average Loss: 0.2542
Epoch 23/100, Accuracy: 93.07%, Average Loss: 0.2460
Epoch 24/100, Accuracy: 93.29%, Average Loss: 0.2380
Epoch 25/100, Accuracy: 93.54%, Average Loss: 0.2304
...
Epoch 98/100, Accuracy: 99.58%, Average Loss: 0.0334
Epoch 99/100, Accuracy: 99.60%, Average Loss: 0.0326
Epoch 100/100, Accuracy: 99.61%, Average Loss: 0.0320
Highest accuracy reached: 99.61%
```



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Our Code

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Thank you all!