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STD. \_\_\_\_\_ DIV. \_\_\_\_\_

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3		study of the classifiers with respect to statistical parameters	7/8/25	<del>off</del> 11/8/25
4		Build a simple feed forward neural network to recognize hand written character	14/8/25	<del>off</del> 14/8/25
5		Study of activation function and its role	28-8-25	<del>off</del> 11/9/25
6		Implement gradient descent & back propagation in deep neural network	09-9-25	<del>off</del> 11/9/25
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14-08-25

4. Build a simple feed forward neural network to recognize hand written characters.

Aim : to design and implement a simple feed forward neural network using open source dataset to recognize hand written characters

Algorithm :

Objective :

- ① To load and preprocess the MNIST dataset for neural network input
- ② to build feed forward network model with hidden layers
- ③ to train the model using gradient descent optimizer and sparse cross-entropy loss
- ④ evaluate the trained model on test data and measure its accuracy
- ⑤ to predict the accuracy of a image of hand written character.

Pseudo Code :

Start

load MNIST dataset

Pattern each image from  $28 \times 28$  to 784 features

normalize pixel values to range  $[0, 1]$

output :  
training

Epoch	Accuracy	Loss
1	0.8748	0.4363
2	0.9649	0.1134
3	0.9775	0.0715
4	0.9897	0.0545
5	0.9861	0.0431

accuracy : 0.9698

loss : 0.0963

testing:

accuracy : 97.46%

Create a sequential neural network

layer 1: dense (128 neurons, Relu activation)

layer 2: dense (64 neurons, Relu activation)

output layer: dense (10 neurons, softmax activation)

Compile model :-

optimizer = stochastic gradient descent

loss = sparse categorical\_crossentropy

metric = accuracy

train model on training data for epochs

evaluate model on testing data

observation :-

→ the loss decrease with each showing that model is learning

→ Accuracy improves steadily during learning

Result :- Successfully built a simple feed forward neural network to recognize handwritten characters and accuracy while testing is 97.46%.

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```
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, transforms
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
```

#### # Step 1: Transformations

```
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])
```

#### # Step 2: Load MNIST dataset

```
train_dataset = datasets.MNIST(root="./data", train=True, transform=transform, download=True)
test_dataset = datasets.MNIST(root="./data", train=False, transform=transform, download=True)
```

```
train_loader = DataLoader(train_dataset, batch_size=64, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=64, shuffle=False)
```

#### # Step 3: Define Feedforward Neural Network

```
class FeedforwardNN(nn.Module):
    def __init__(self):
        super(FeedforwardNN, self).__init__()
        self.fc1 = nn.Linear(28*28, 128)
        self.fc2 = nn.Linear(128, 64)
        self.fc3 = nn.Linear(64, 10)
        self.relu = nn.ReLU()
        self.softmax = nn.LogSoftmax(dim=1)

    def forward(self, x):
        x = x.view(-1, 28*28)
        x = self.relu(self.fc1(x))
        x = self.relu(self.fc2(x))
        x = self.fc3(x)
```

```
# Step 4: Loss and optimizer
criterion = nn.NLLLoss()
optimizer = optim.Adam(model.parameters()), lr=0.001)

# To store training history
train_losses = []
train_accuracies = []

# Step 5: Train the model
for epoch in range(5):
    model.train()
    total_loss = 0
    correct, total = 0, 0

    for images, labels in train_loader:
        optimizer.zero_grad()
        output = model(images)
        loss = criterion(output, labels)
        loss.backward()
        optimizer.step()

        total_loss += loss.item()
        _, predicted = torch.max(output.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

    avg_loss = total_loss / len(train_loader)
    accuracy = 100 * correct / total
    train_losses.append(avg_loss)
    train_accuracies.append(accuracy)

    print(f"Epoch {epoch+1}, Loss: {avg_loss:.4f}, Accuracy: {accuracy:.2f}%")
```

▶ # Step 6: Evaluate model on test data

```
model.eval()
```

```
correct, total = 0, 0
```

```
with torch.no_grad():
```

```
    for images, labels in test_loader:
```

```
        output = model(images)
```

```
        _, predicted = torch.max(output.data, 1)
```

```
        total += labels.size(0)
```

```
        correct += (predicted == labels).sum().item()
```

```
print(f"Final Test Accuracy: {100 * correct / total:.2f}%")
```

# Step 7: Visualization

```
plt.figure(figsize=(12,5))
```

```
plt.subplot(1,2,1)
```

```
plt.plot(train_losses, marker='o')
```

```
plt.title("Training Loss per Epoch")
```

```
plt.xlabel("Epoch")
```

```
plt.ylabel("Loss")
```

```
plt.subplot(1,2,2)
```

```
plt.plot(train_accuracies, marker='o')
```

```
plt.title("Training Accuracy per Epoch")
```

```
plt.xlabel("Epoch")
```

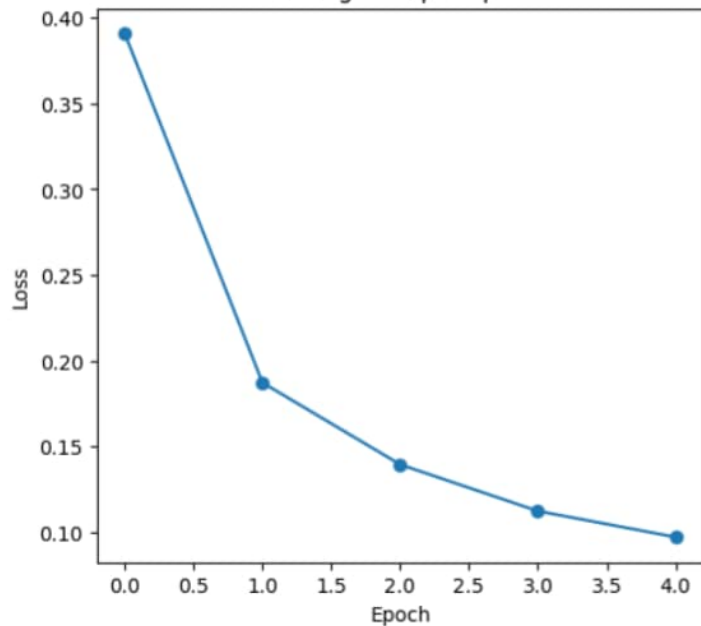
```
plt.ylabel("Accuracy (%)")
```

```
plt.show()
```



Epoch 1, Loss: 0.3909, Accuracy: 88.39%  
Epoch 2, Loss: 0.1871, Accuracy: 94.38%  
Epoch 3, Loss: 0.1394, Accuracy: 95.76%  
Epoch 4, Loss: 0.1122, Accuracy: 96.63%  
Epoch 5, Loss: 0.0970, Accuracy: 96.95%  
Final Test Accuracy: 96.50%

Training Loss per Epoch



Training Accuracy per Epoch

