EX 3 COMPARISON OF SGD WITH MOMENTUM VS ADAM OPTIMIZER **DATE: 28/8/25**

Problem Statement:

Implement a training algorithm using Stochastic Gradient Descent (SGD) with momentum and compare it with the Adam optimizer. Train both models on a dataset and compare their convergence rates and performance.

Suggested Dataset: CIFAR-10

Objectives:

1. Understand the principles of optimization algorithms in deep learning.
2. Implement and train models using SGD with momentum and Adam.
3. Analyze and compare the learning behavior and convergence patterns of the two optimizers.
4. Visualize loss and accuracy across epochs for both optimization methods.

Scope:

This experiment gives students a comparative understanding of two widely used optimization strategies: SGD with momentum and Adam. Using a basic MLP and the CIFAR-10 dataset, students will learn the impact of optimizer choice on model convergence and final accuracy.

Tools and Libraries Used:

1. Python 3.x
2. PyTorch
3. Matplotlib
4. torchvision (for CIFAR-10 dataset) **Implementation Steps:**

Step 1: Import Necessary Libraries

```
import torch
import torch.nn
as nn import
torch.optim as
optim import
torchvision
import torchvision.transforms as
transforms import matplotlib.pyplot as
plt
```

Step 2: Set Device and Load Dataset

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

```
transform = transforms.Compose([
transforms.ToTensor(),
transforms.Normalize((0.5,), (0.5,)) ])
trainset = torchvision.datasets.CIFAR10(root='./data', train=True, transform=transform, download=True) trainloader = torch.utils.data.DataLoader(trainset, batch_size=128, shuffle=True)
```

Step 3: Define MLP Model

```
class
MLP(nn.Module):
def __init__(self):
super().__init__()
self.flatten =
nn.Flatten()
self.net =
nn.Sequential(
nn.Linear(3*32*32,
256),
        nn.ReLU(),
nn.Linear(256, 10)
    )

  def
forward(self,
x):      x =
self.flatten(x)
return
self.net(x)
```

Step 4: Define Training Function

```
def train(model, optimizer, epochs=10):
model.to(device)
  loss_fn =
nn.CrossEntropyLoss()
losses = []
  accuracies = []

  for epoch in range(epochs):

total_loss
= 0
correct =
0
total = 0
model.trai
n()
```

```
    for imgs, labels in trainloader:
imgs, labels = imgs.to(device),
labels.to(device)

        outputs =
model(imgs)          loss =
loss_fn(outputs, labels)

        optimizer.zero_grad()
loss.backward()
        optimizer.step()

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

    avg_loss = total_loss /
len(trainloader)       accuracy = 100.0 *
correct / total

    losses.append(avg_loss)
    accuracies.append(accuracy)

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

  return losses, accuracies
```

Step 5: Train with SGD + Momentum and with Adam

```
model_sgd = MLP()
sgd = optim.SGD(model_sgd.parameters(), lr=0.01, momentum=0.9)
losses_sgd, acc_sgd = train(model_sgd, sgd)
model_adam = MLP() adam =
optim.Adam(model_adam.parameters(),
lr=0.001) losses_adam, acc_adam =
train(model_adam, adam)
```

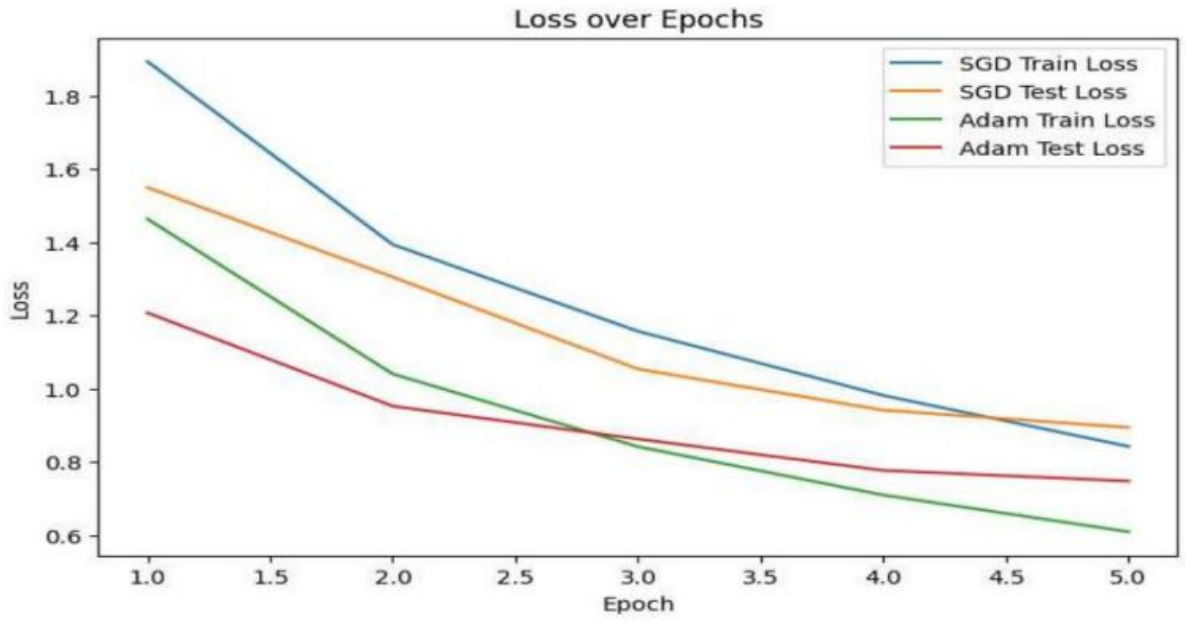
Step 6: Visualize Loss and Accuracy Comparison

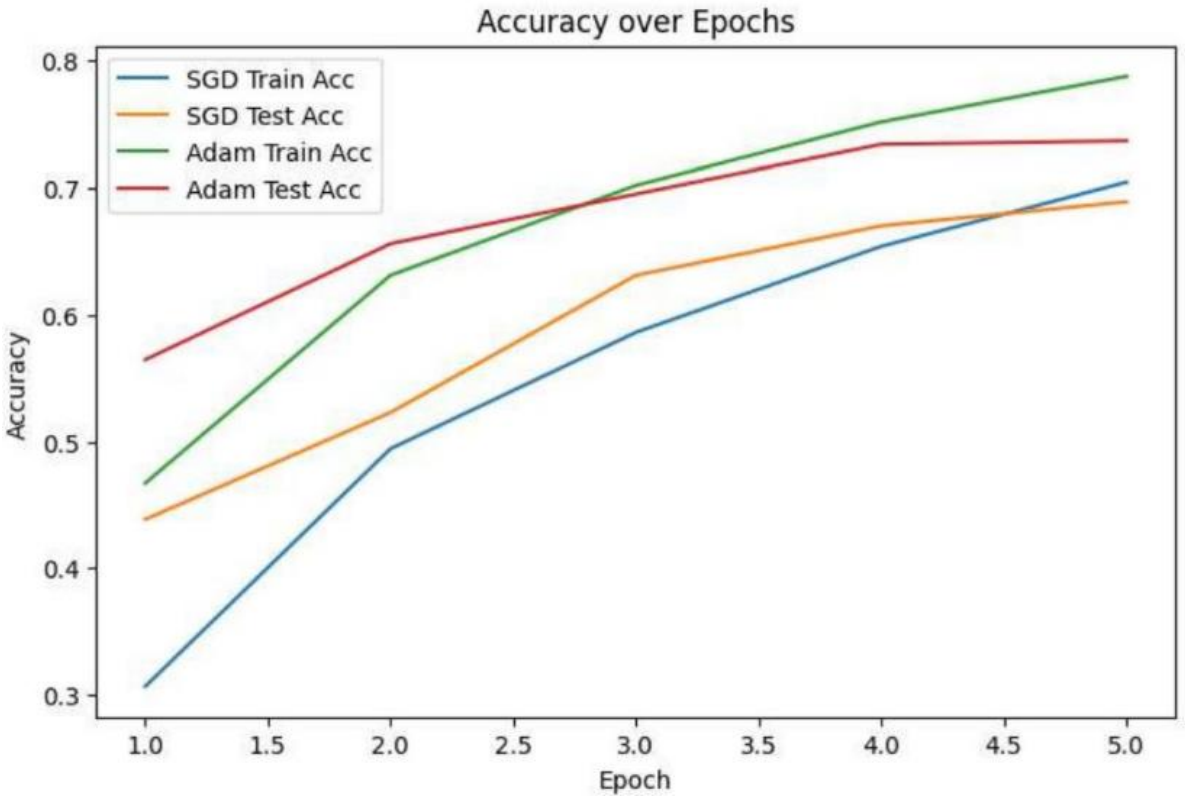
```
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(losses_sgd, label="SGD +
Momentum") plt.plot(losses_adam,
```

```
label="Adam") plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.title("Loss Comparison on CIFAR-10 (MLP)")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(acc_sgd, label="SGD + Momentum")
plt.plot(acc_adam, label="Adam")
plt.xlabel("Epoch")
plt.ylabel("Accuracy (%)")
plt.title("Accuracy Comparison on CIFAR-
10 (MLP)") plt.legend() plt.tight_layout()
plt.show()
```





Conclusion:

This experiment shows a practical implementation of two optimization techniques and highlights their impact on model performance. Adam typically converges faster due to adaptive learning rates, while SGD with momentum offers more controlled, gradual learning. Choosing the right optimizer depends on the nature of the data and the task complexity.