

```
In [ ]: import torch
        from torchvision import datasets, transforms
        from sklearn.model_selection import train_test_split
        from torch.utils.data import DataLoader
```

```
In [ ]: trans = transforms.Compose([
        transforms.ToTensor(), #it is like numpy array for pytorch
        transforms.Normalize((0.5,), (0.5,)) #this normalizes the data betwe
    ])
    #download the data
    train_data = datasets.MNIST(
        root="./data",
        train=True,
        transform=trans,
    )
    test_data = datasets.MNIST(
        root="./data",
        transform=trans,
        train=False,
    )
    #print the length of the data
    print(len(train_data))
    print(len(test_data))
```

60000

10000

```
In [ ]: #split the data into train and validation using sklearn
        train_data, val_data = train_test_split(train_data, test_size=0.2, random
        print(len(train_data))
        print(len(val_data))
```

48000

12000

```
In [ ]: #load the data using dataloader
        #what does data loader do?it loads the data in batches-it shuffles the dat
        #what is the batch size?it is the number of samples that will be passed t
        #what is shuffle?it shuffles the data so that the model will not learn th
        batch_sz = 16
        train_loader = DataLoader(train_data, batch_size=batch_sz, shuffle=True)
        val_loader = DataLoader(val_data, batch_size=batch_sz, shuffle=True)
        test_loader = DataLoader(test_data, batch_size=batch_sz, shuffle=True)
```

```
In [ ]: print(len(train_loader))
        #750 is the number of batches it came from 48000(the length of the train
        print(len(val_loader))
        #188 is the number of batches it came from 12000(the length of the valida
        print(len(test_loader))
        #157 is the number of batches it came from 10000(the length of the test d
```

3000

750

625

```
In [ ]: import torch.nn as nn
        from torch import optim
```

```
In [ ]: class neural_model(nn.Module):
    def __init__(self, lr):
        super().__init__()
        self.layers = nn.Sequential(
            nn.Flatten(),
            nn.Linear(28 * 28, 400), #input layer_input=28*28=784 output
            nn.LayerNorm(400), # Layer Normalization to speed up the trai
            nn.Dropout(0.5), #droping out the unwanted overfitting feature
            nn.ReLU(),
            nn.Linear(400, 200), #input h_layer_1=200 output h_layer_2=10
            nn.ReLU(),
            nn.Linear(200, 100), #input h_layer_2=200 output h_layer_2=10
            nn.ReLU(),
            nn.Linear(100, 10), #input output_layer=100 output output_lay
        )
        self.loss = nn.CrossEntropyLoss()
        self.learning_rate = lr
        self.optimizer = optim.SGD(self.parameters(), lr=self.learning_ra

    def forward(self, x):
        x = self.layers(x)
        return x

    def fit(self, x, y):
        self.optimizer.zero_grad() #this is to reset the gradients to ze
        y_output = self.forward(x) #this is to get the predictions
        loss = self.loss(y_output, y) #this is to get the loss
        loss.backward() #this is to backpropagate the loss
        self.optimizer.step() #this is to update the weights
        return loss.item() #this is to return the loss

    def predict(self, x):
        with torch.no_grad():
            output = self.forward(x)
            _, predicted = torch.max(output, 1)
        return predicted
```

```
In [ ]: model = neural_model(0.01)
```

```
In [ ]: #train the model
epochs = 5
train_losses = []
val_losses = []
train_acc = []
val_acc = []
for epoch in range(epochs):
    train_loss = 0
    val_loss = 0
    train_accuracy = 0
    val_accuracy = 0
    model.eval()
    for x, y in train_loader:
        train_loss += model.fit(x, y)
        train_accuracy += torch.sum(model.predict(x) == y).item()

    train_losses.append(train_loss / len(train_loader))
    train_acc.append(train_accuracy / len(train_data))
    for x, y in val_loader:
        val_loss += model.fit(x, y)
```

```

        val_accuracy += torch.sum(model.predict(x) == y).item()
    val_losses.append(val_loss / len(val_loader))
    val_acc.append(val_accuracy / len(val_data))
    print(
        f"Epoch {epoch + 1}/{epochs}.. "
        f"Train loss: {train_losses[-1]:.3f}.. "
        f"Val loss: {val_losses[-1]:.3f}.. "
        f"Train accuracy: {train_acc[-1]:.3f}.. "
        f"Val accuracy: {val_acc[-1]:.3f}"
    )

```

```

Epoch 1/5.. Train loss: 0.501.. Val loss: 0.208.. Train accuracy: 0.927..
Val accuracy: 0.988
Epoch 2/5.. Train loss: 0.165.. Val loss: 0.138.. Train accuracy: 0.993..
Val accuracy: 0.994
Epoch 3/5.. Train loss: 0.119.. Val loss: 0.103.. Train accuracy: 0.996..
Val accuracy: 0.996
Epoch 4/5.. Train loss: 0.095.. Val loss: 0.086.. Train accuracy: 0.997..
Val accuracy: 0.997
Epoch 5/5.. Train loss: 0.079.. Val loss: 0.071.. Train accuracy: 0.998..
Val accuracy: 0.999

```

```

In [ ]: from matplotlib import pyplot as plt
import numpy as np
model.eval()

i = np.random.randint(0, len(test_data))

# input = input.type(torch.FloatTensor).to(device)
# input = input.unsqueeze(0) # Adding batch dimension as models usually

with torch.no_grad():
    input = test_data[i][0].unsqueeze(0).to('cpu')

    output = model(input)

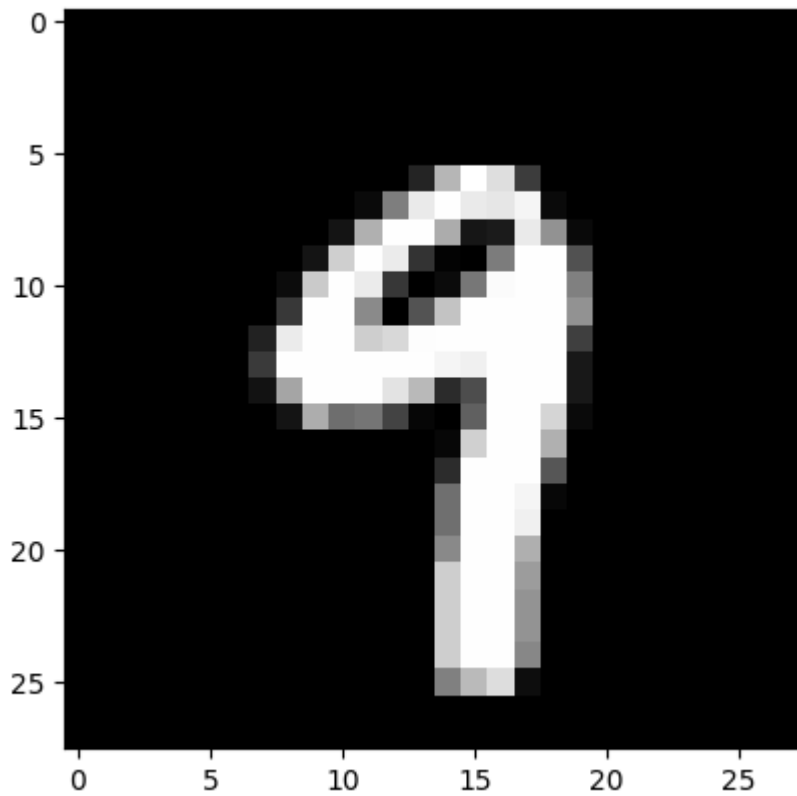
    output = (torch.max(torch.exp(output), 1)[1]).data.cpu().numpy()
    # output = model(input)

    # label = torch.argmax(output, dim=1).cpu().numpy()
    print("Predicted Label:", [output[0]])

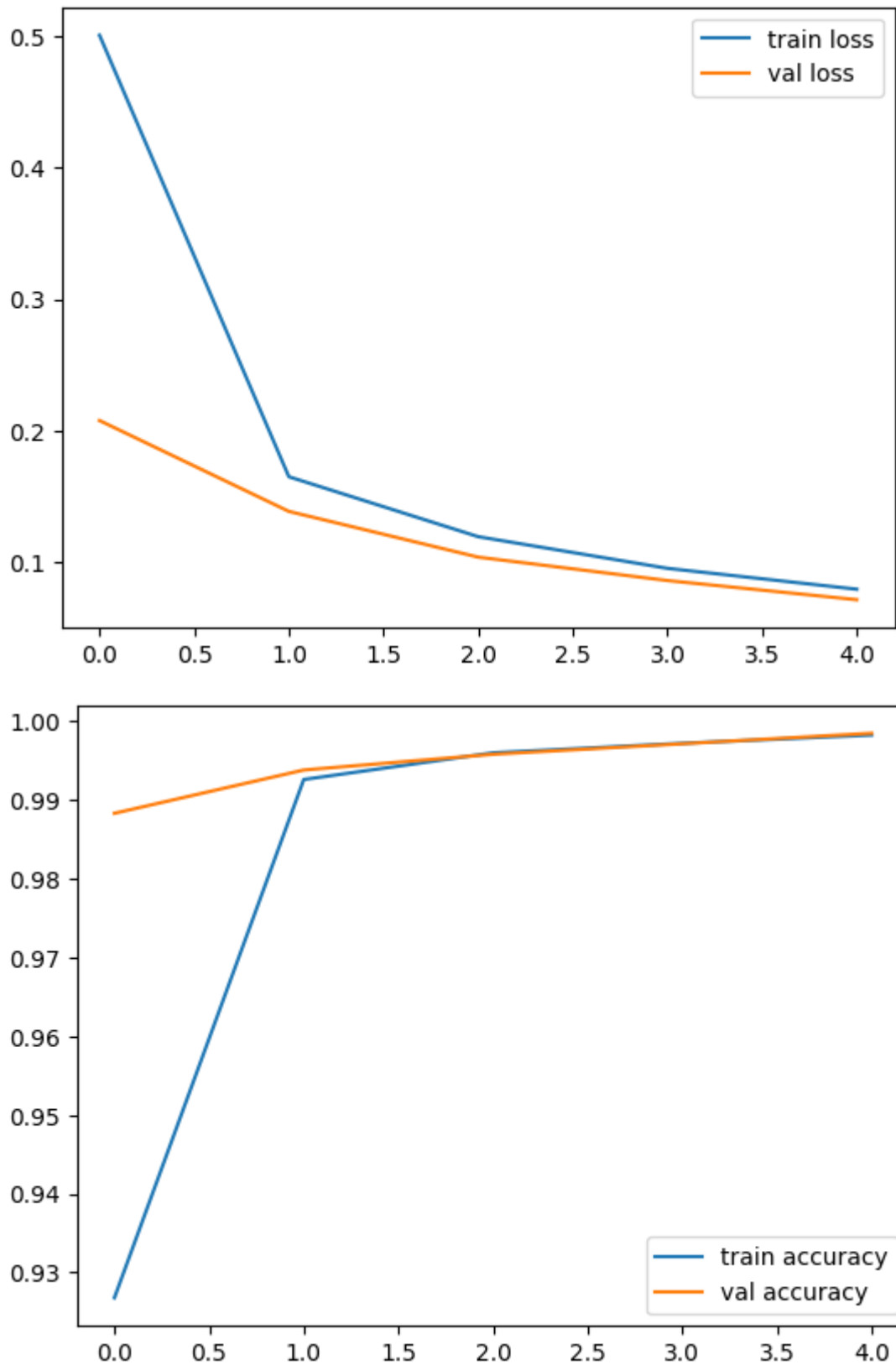
    # input_image = input.squeeze().permute(1, 2, 0).cpu().numpy()
    plt.imshow(input.squeeze().cpu().numpy(), cmap='gray') # Show the input
    plt.show()

```

Predicted Label: [9]



```
In [ ]: # #plot the losses – the loss should decrease  
# #plot the accuracy – the accuracy should increase  
import matplotlib.pyplot as plt  
  
plt.plot(train_losses, label="train loss")  
plt.plot(val_losses, label="val loss")  
plt.legend()  
plt.show()  
plt.plot(train_acc, label="train accuracy")  
plt.plot(val_acc, label="val accuracy")  
plt.legend()  
plt.show()
```



```
In [ ]: import matplotlib.pyplot as plt

learning_rates = [0.5, 0.05, 0.005, 0.0005, 0.00005]
batch_sizes = [20, 45, 85, 125, 280]
results = []

train_losses = []
train_accuracies = []
val_losses = []
val_accuracies = []
```

```

for lr in learning_rates:
    for b in batch_sizes:
        # ... (previous code remains the same)
        model = neural_model(lr)
        train_loss = 0
        val_loss = 0
        train_correct = 0
        val_correct = 0

        train_loader = DataLoader(train_data, batch_size=b, shuffle=True)
        val_loader = DataLoader(val_data, batch_size=b, shuffle=False)

        for x, y in train_loader:
            train_loss += model.fit(x, y)
            y_pred = model.predict(x)
            train_correct += torch.sum(y_pred == y).item()

        train_loss /= len(train_loader)
        train_accuracy = train_correct / len(train_data)

        model.eval()
        with torch.no_grad():
            for x_val, y_val in val_loader:
                output_val = model.forward(x_val)
                val_loss += model.loss(output_val, y_val).item()
                y_pred_val = model.predict(x_val)
                val_correct += torch.sum(y_pred_val == y_val).item()

            val_loss = val_loss / (len(val_loader))
            val_accuracy = (val_correct / len(val_data))

        # Store values in lists
        train_losses.append(train_loss)
        train_accuracies.append(train_accuracy)
        val_losses.append(val_loss)
        val_accuracies.append(val_accuracy)

        # append results to list of dictionaries for printing
        results.append({
            'learning_rate': lr,
            'batch_size': b,
            'train_loss': train_loss,
            'train_accuracy': train_accuracy,
            'val_loss': val_loss,
            'val_accuracy': val_accuracy
        })

    # Reshape lists for plotting
    train_losses = [train_losses[i:i + len(batch_sizes)] for i in range(0, len(train_losses), len(batch_sizes))]
    train_accuracies = [train_accuracies[i:i + len(batch_sizes)] for i in range(0, len(train_accuracies), len(batch_sizes))]
    val_losses = [val_losses[i:i + len(batch_sizes)] for i in range(0, len(val_losses), len(batch_sizes))]
    val_accuracies = [val_accuracies[i:i + len(batch_sizes)] for i in range(0, len(val_accuracies), len(batch_sizes))]

    # Plotting
    fig, axs = plt.subplots(2, 2, figsize=(12, 8))
    fig.suptitle('Training and Validation Metrics')

    for i in range(len(learning_rates)):

```

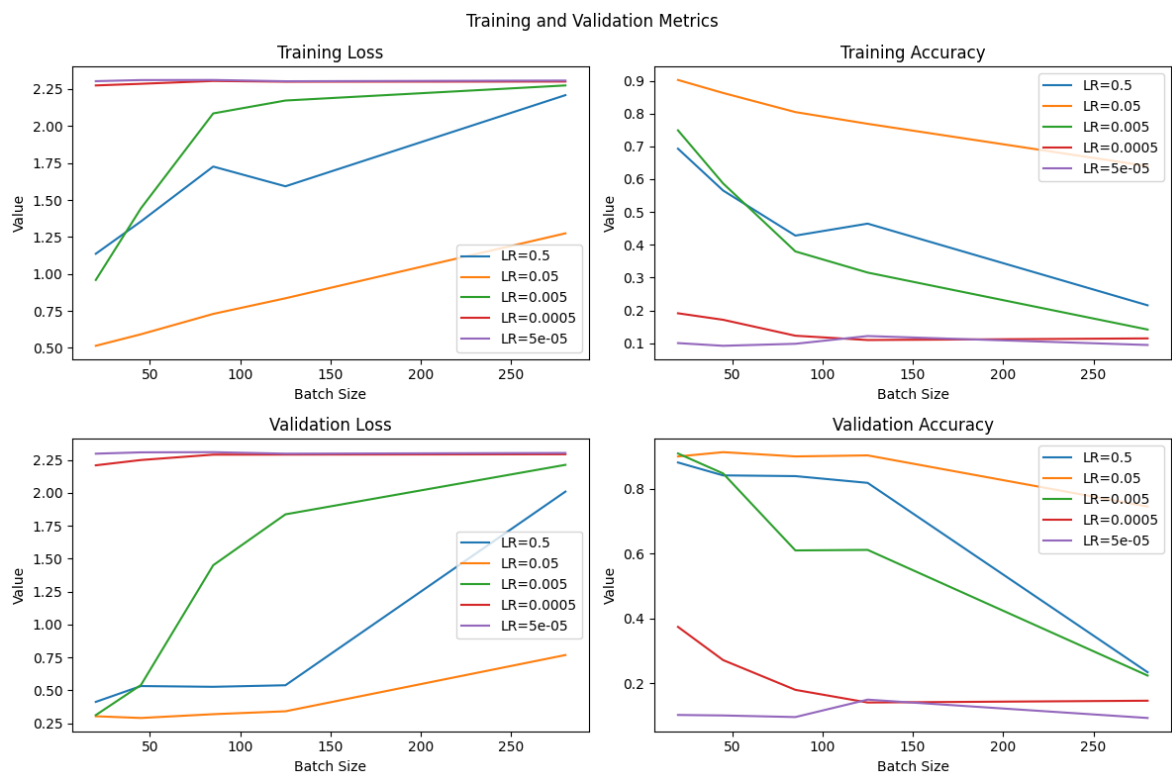
```

axs[0, 0].plot(batch_sizes, train_losses[i], label=f"LR={learning_rat
axs[0, 0].set_title('Training Loss')
axs[0, 1].plot(batch_sizes, train_accuracies[i], label=f"LR={learning
axs[0, 1].set_title('Training Accuracy')
axs[1, 0].plot(batch_sizes, val_losses[i], label=f"LR={learning_rates
axs[1, 0].set_title('Validation Loss')
axs[1, 1].plot(batch_sizes, val_accuracies[i], label=f"LR={learning_r
axs[1, 1].set_title('Validation Accuracy')

for ax in axs.flat:
    ax.set(xlabel='Batch Size', ylabel='Value')
    ax.legend()

plt.tight_layout()
plt.show()

```



```

In [ ]: #print statement of the results
for result in results:
    print(f"lr: {result['learning_rate']}, batch size: {result['batch_si
    print(f"lr: {result['learning_rate']}, batch size: {result['batch_si
    print(f"-----")

```

```
lr: 0.5, batch size: 20, train loss: 1.1362699457040677, train accuracy:
0.692875
lr: 0.5, batch size: 20, val loss: 0.41168081014727553, val accuracy: 0.88
058333333333334
-----
lr: 0.5, batch size: 45, train loss: 1.3551156631729373, train accuracy:
0.5653958333333333
lr: 0.5, batch size: 45, val loss: 0.5318885759802793, val accuracy: 0.840
83333333333333
-----
lr: 0.5, batch size: 85, train loss: 1.7260847787941451, train accuracy:
0.428125
lr: 0.5, batch size: 85, val loss: 0.5262178303280347, val accuracy: 0.838
58333333333333
-----
lr: 0.5, batch size: 125, train loss: 1.5926295218523592, train accuracy:
0.46460416666666665
lr: 0.5, batch size: 125, val loss: 0.5379975587129593, val accuracy: 0.81
775
-----
lr: 0.5, batch size: 280, train loss: 2.209247794955276, train accuracy:
0.21572916666666667
lr: 0.5, batch size: 280, val loss: 2.009900459023409, val accuracy: 0.233
583333333333334
-----
lr: 0.05, batch size: 20, train loss: 0.5137568657961674, train accuracy:
0.9022708333333334
lr: 0.05, batch size: 20, val loss: 0.3023469832601647, val accuracy: 0.89
916666666666667
-----
lr: 0.05, batch size: 45, train loss: 0.5917083802087462, train accuracy:
0.8626666666666667
lr: 0.05, batch size: 45, val loss: 0.28931753400169063, val accuracy: 0.9
125
-----
lr: 0.05, batch size: 85, train loss: 0.7293825796220155, train accuracy:
0.8044166666666667
lr: 0.05, batch size: 85, val loss: 0.31812720926819554, val accuracy: 0.8
9933333333333333
-----
lr: 0.05, batch size: 125, train loss: 0.835186971972386, train accuracy:
0.7687083333333333
lr: 0.05, batch size: 125, val loss: 0.34011754222835106, val accuracy: 0.
9025
-----
lr: 0.05, batch size: 280, train loss: 1.2744344694669856, train accuracy:
0.6399166666666667
lr: 0.05, batch size: 280, val loss: 0.7676215074783148, val accuracy: 0.7
4475
-----
lr: 0.005, batch size: 20, train loss: 0.9590186238335445, train accuracy:
0.7488333333333334
lr: 0.005, batch size: 20, val loss: 0.31111472891643643, val accuracy: 0.
9084166666666667
-----
lr: 0.005, batch size: 45, train loss: 1.4438614030809411, train accuracy:
0.5869583333333334
lr: 0.005, batch size: 45, val loss: 0.5399252066897989, val accuracy: 0.8
4675
-----
```



```
lr: 0.005, batch size: 85, train loss: 2.0856188046193758, train accuracy: 0.379875
lr: 0.005, batch size: 85, val loss: 1.4501339171973753, val accuracy: 0.6093333333333333
-----
lr: 0.005, batch size: 125, train loss: 2.1728346260885396, train accuracy: 0.31547916666666664
lr: 0.005, batch size: 125, val loss: 1.8370666454235713, val accuracy: 0.611
-----
lr: 0.005, batch size: 280, train loss: 2.2747964512470156, train accuracy: 0.1419375
lr: 0.005, batch size: 280, val loss: 2.2132574292116387, val accuracy: 0.22333333333333333
-----
lr: 0.0005, batch size: 20, train loss: 2.2748840550581613, train accuracy: 0.1914375
lr: 0.0005, batch size: 20, val loss: 2.2096824280420937, val accuracy: 0.3735
-----
lr: 0.0005, batch size: 45, train loss: 2.285951790456584, train accuracy: 0.171625
lr: 0.0005, batch size: 45, val loss: 2.2498864859677434, val accuracy: 0.271
-----
lr: 0.0005, batch size: 85, train loss: 2.3051325447791444, train accuracy: 0.12310416666666667
lr: 0.0005, batch size: 85, val loss: 2.2906570703210964, val accuracy: 0.17925
-----
lr: 0.0005, batch size: 125, train loss: 2.30012045117716, train accuracy: 0.10995833333333334
lr: 0.0005, batch size: 125, val loss: 2.2911691119273505, val accuracy: 0.14025
-----
lr: 0.0005, batch size: 280, train loss: 2.301095573014991, train accuracy: 0.1149375
lr: 0.0005, batch size: 280, val loss: 2.2935615029445913, val accuracy: 0.14575
-----
lr: 5e-05, batch size: 20, train loss: 2.3038235036532084, train accuracy: 0.10060416666666666
lr: 5e-05, batch size: 20, val loss: 2.298100584745407, val accuracy: 0.10183333333333333
-----
lr: 5e-05, batch size: 45, train loss: 2.3111491225652863, train accuracy: 0.09241666666666666
lr: 5e-05, batch size: 45, val loss: 2.3081786266426914, val accuracy: 0.10025
-----
lr: 5e-05, batch size: 85, train loss: 2.311866031072836, train accuracy: 0.09852083333333334
lr: 5e-05, batch size: 85, val loss: 2.3096442373705584, val accuracy: 0.09533333333333334
-----
lr: 5e-05, batch size: 125, train loss: 2.303193747997284, train accuracy: 0.122125
lr: 5e-05, batch size: 125, val loss: 2.2980536594986916, val accuracy: 0.14908333333333335
-----
```

```
lr: 5e-05, batch size: 280, train loss: 2.3079203256340914, train accuracy: 0.094875  
lr: 5e-05, batch size: 280, val loss: 2.303438341894815, val accuracy: 0.0925
```

insights

in this project working with neural networks we concluded the following: to prevent overfitting we need to work on finding the best learning rate "lr" which for us was 0.05 with validation accuracy of 91% to even give it a further boost we used a dropout layer set to "0.5" to drop the unnecessary features causing overfitting, new accuracy jumped to 93% unnecessary*

here what we used:

- used layer normalization to speed up the training process
- used relu activation function to speed up the training process
- used softmax activation function to get the probabilities of the output layer
- used cross entropy loss function to calculate the loss
- used stochastic gradient descent optimizer to update the weights
- used the dataloader to load the data in batches
- used the train_test_split to split the data into train and validation