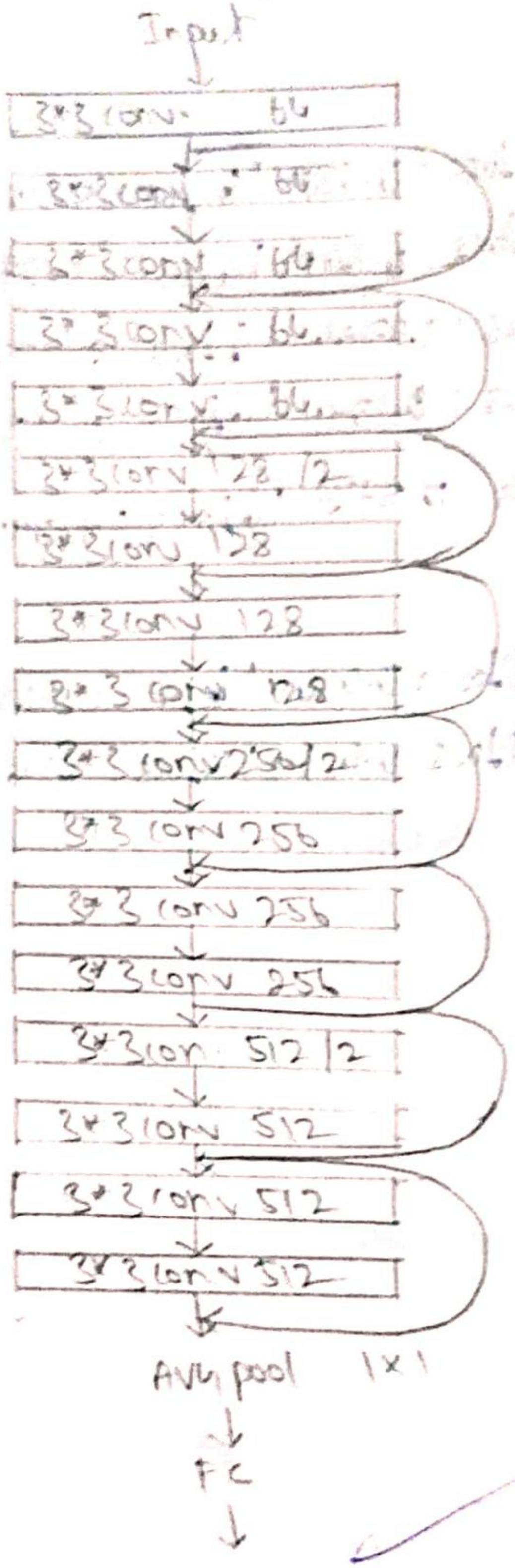
ResNet-18



Input
3*3 conv 64
3*3 conv 64
3*3 conv 64
3*3 conv 64
3*3 conv 64
3*3 conv 128, /2
3*3 conv 128
3*3 conv 128
3*3 conv 128
3*3 conv 256 /2
3*3 conv 256
3*3 conv 256
3*3 conv 256
3*3 con 512 /2
3*3 conv 512
3*3 conv 512
3*3 conv 512
AVG pool 1x1
FC

Exp: 13

UNDERSTANDING THE ARCHITECTURE OF PRE-TRAINED MODEL

AIM

To explore and analyse the architecture of pre-trained convolutional neural network ResNet-18 visualize its layers, parameters, feature maps, and understand its behavior on sample images.

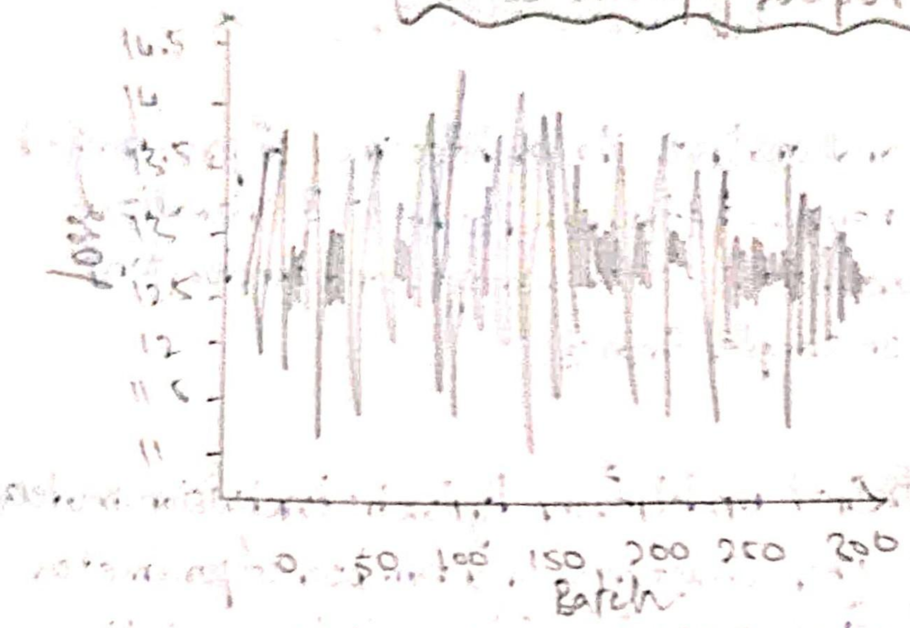
OBJECTIVE:

* Load a pre-trained model from PyTorch's torchvision.models
* Examine the layer structure and number of parameter
* Visualize feature maps from intermediate convolutions layers.
* Understand how low-level and high-level features are extracted.
* Compute and visualize accuracy and loss metrics. on small dataset.

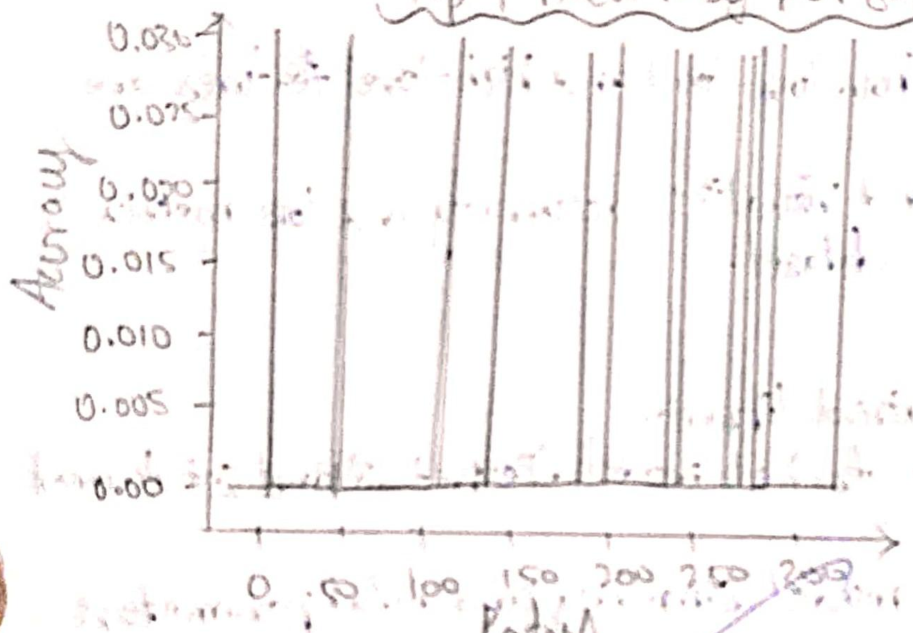
PSEUDOCODE:

↳ Import required libraries
↳ Load a pre-trained model (ResNet-18) and set to eval mode.
↳ Print the model-summary and total parameters.
↳ Forward pass image through model
  - Extract output predictions
  - Extract intermediate feature maps
↳ Visualize feature maps as grids
↳ ~~optional:~~ Load a small dataset (CIFAR-10 subset).
↳ plot graphs for loss and accuracy.

Cross-Entropy loss per Batch



Top-1 Accuracy per Batch



OBSERVATION :

Total parameters: 11689512

Trainable parameter: 11689512

* Only the final layer is trained ; convolutional layers remain feature extractors.
* Can unfreeze layers later for fine-tuning to further improve performance.
* Using transfer learning is especially useful when the dataset is small or medium-sized.

RESULT:

Sucessfully implemented ResNet-18 model

```python
import torch
from torchvision import models, datasets, transforms
from torch.utils.data import DataLoader
import torch.nn as nn
import matplotlib.pyplot as plt
import numpy as np
```

Device

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

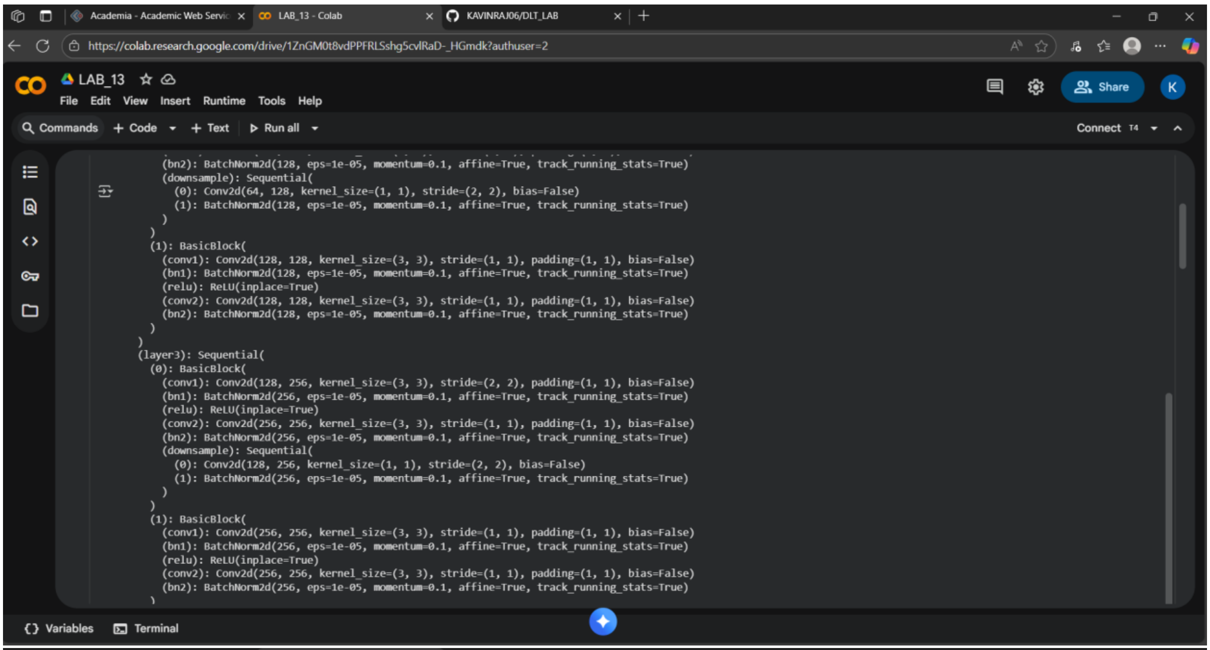
Load pre-trained model

```python
model = models.resnet18(pretrained=True).to(device)
model.eval()
```

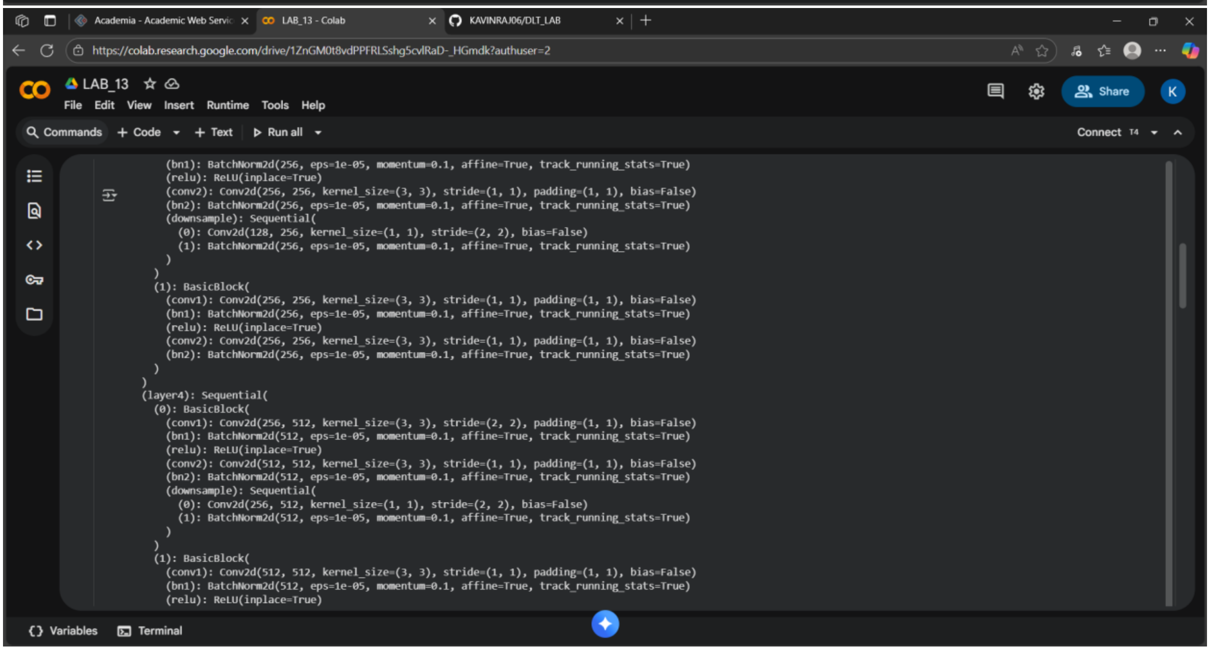
```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
```


```
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
```

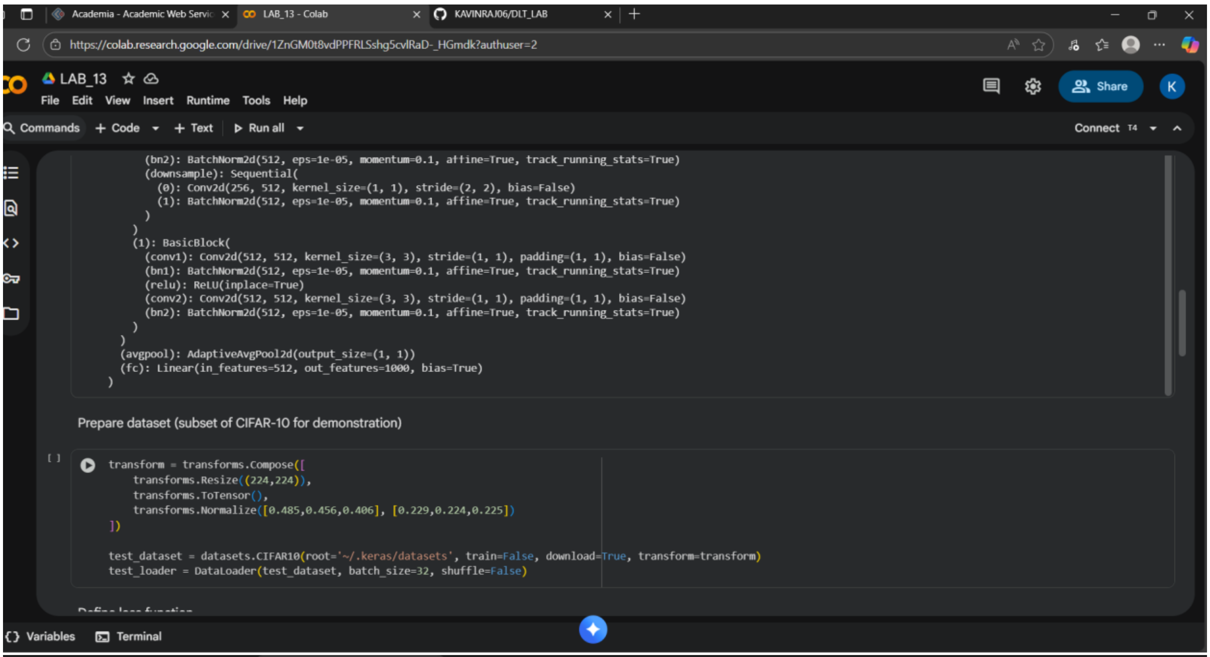

```
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (1): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
```



```
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (layer3): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
```



```
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (layer4): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
```

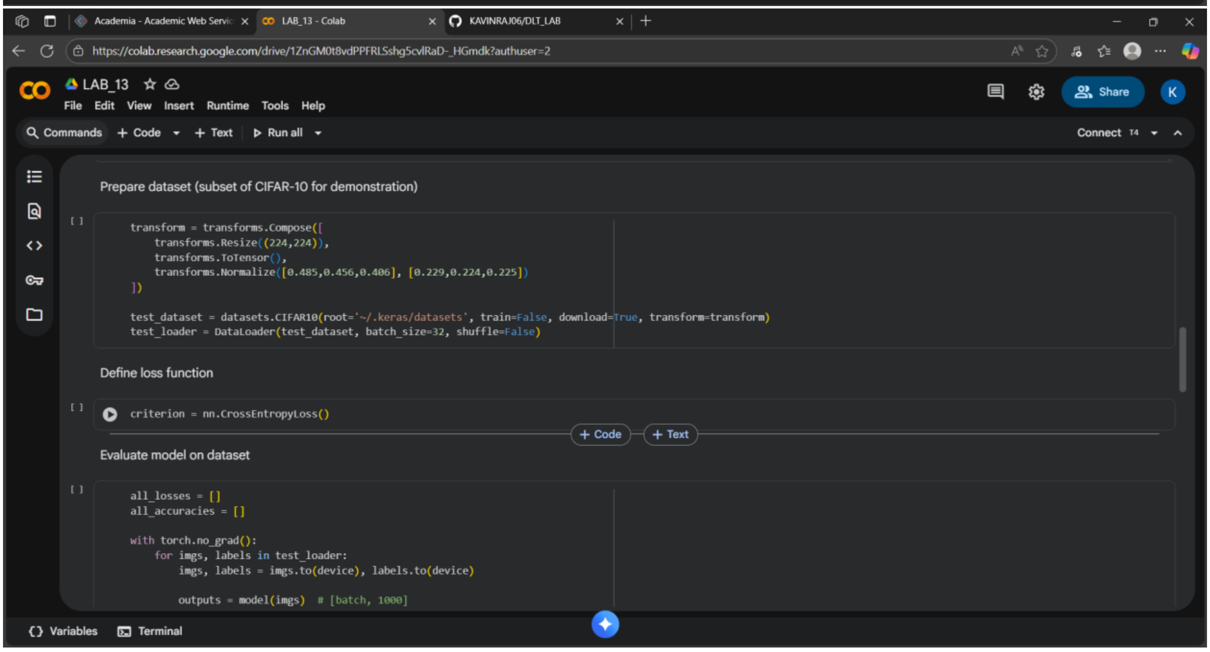


```
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
    (fc): Linear(in_features=512, out_features=1000, bias=True)
  )
```

Prepare dataset (subset of CIFAR-10 for demonstration)

```
transform = transforms.Compose([
    transforms.Resize((224,224)),
    transforms.ToTensor(),
    transforms.Normalize([0.485,0.456,0.406], [0.229,0.224,0.225])
])

test_dataset = datasets.CIFAR10(root='~/.keras/datasets', train=False, download=True, transform=transform)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)
```



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```
transform = transforms.Compose([
    transforms.Resize((224,224)),
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])

test_dataset = datasets.CIFAR10(root='~/.keras/datasets', train=False, download=True, transform=transform)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)
```
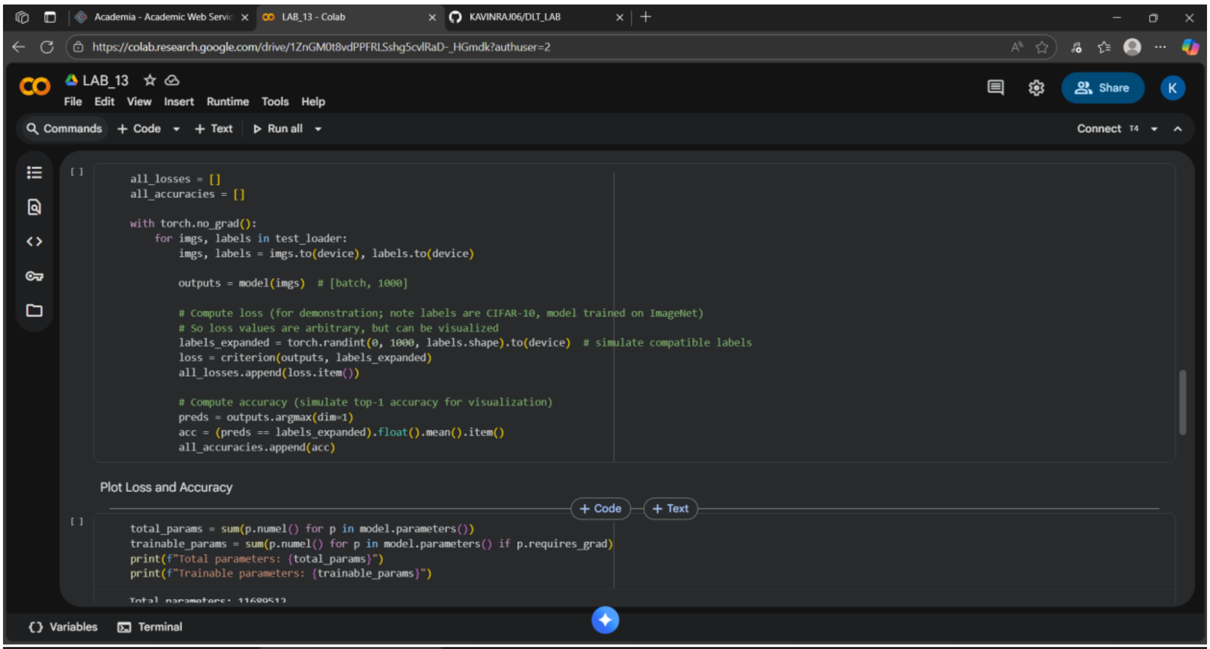

Define loss function

```
criterion = nn.CrossEntropyLoss()
```

Evaluate model on dataset

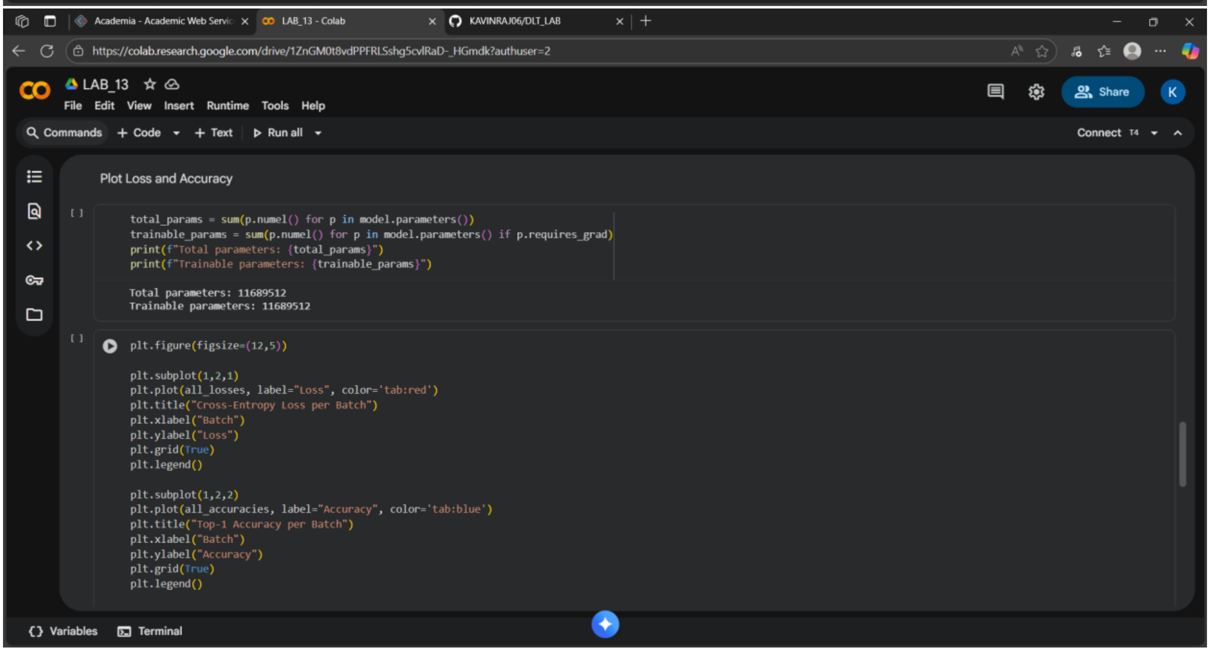
```
all_losses = []
all_accuracies = []

with torch.no_grad():
    for imgs, labels in test_loader:
        imgs, labels = imgs.to(device), labels.to(device)

        outputs = model(imgs)  # [batch, 1000]
```



```python
all_losses = []
all_accuracies = []

with torch.no_grad():
    for imgs, labels in test_loader:
        imgs, labels = imgs.to(device), labels.to(device)

        outputs = model(imgs)  # [batch, 1000]

        # Compute loss (for demonstration; note labels are CIFAR-10, model trained on ImageNet)
        # So loss values are arbitrary, but can be visualized
        labels_expanded = torch.randint(0, 1000, labels.shape).to(device)  # simulate compatible labels
        loss = criterion(outputs, labels_expanded)
        all_losses.append(loss.item())

        # Compute accuracy (simulate top-1 accuracy for visualization)
        preds = outputs.argmax(dim=1)
        acc = (preds == labels_expanded).float().mean().item()
        all_accuracies.append(acc)
```

Plot Loss and Accuracy

```python
total_params = sum(p.numel() for p in model.parameters())
trainable_params = sum(p.numel() for p in model.parameters() if p.requires_grad)
print(f"Total parameters: {total_params}")
print(f"Trainable parameters: {trainable_params}")
```

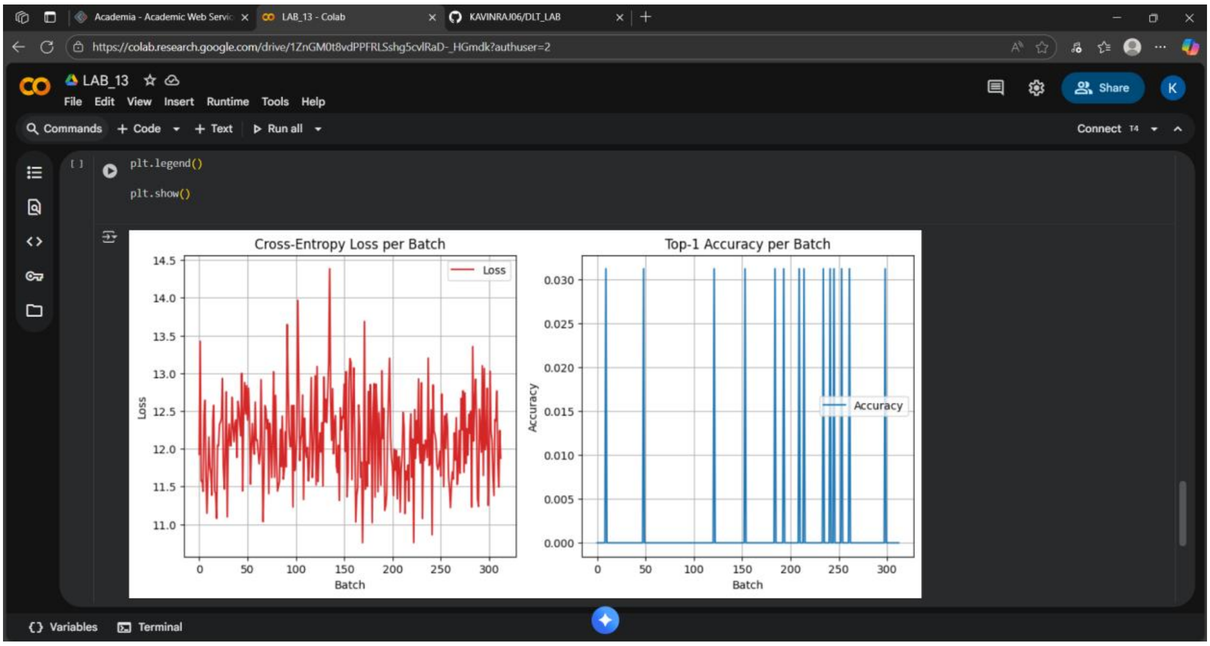


Plot Loss and Accuracy

```python
total_params = sum(p.numel() for p in model.parameters())
trainable_params = sum(p.numel() for p in model.parameters() if p.requires_grad)
print(f"Total parameters: {total_params}")
print(f"Trainable parameters: {trainable_params}")
```

```
Total parameters: 11689512
Trainable parameters: 11689512
```

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

plt.subplot(1,2,1)
plt.plot(all_losses, label="Loss", color='tab:red')
plt.title("Cross-Entropy Loss per Batch")
plt.xlabel("Batch")
plt.ylabel("Loss")
plt.grid(True)
plt.legend()

plt.subplot(1,2,2)
plt.plot(all_accuracies, label="Accuracy", color='tab:blue')
plt.title("Top-1 Accuracy per Batch")
plt.xlabel("Batch")
plt.ylabel("Accuracy")
plt.grid(True)
plt.legend()
```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LAB_13 - Colab
KAVINRAJ06/DLT_LAB
https://colab.research.google.com/drive/1ZnGM0t8vdPPFRLSshg5cvlRaD-_HGmdk?authuser=2
LAB_13
File Edit View Insert Runtime Tools Help
Share
Commands
+ Code
+ Text
Run all
Connect
plt.legend()
plt.show()
Cross-Entropy Loss per Batch
Loss
Batch
Top-1 Accuracy per Batch
Accuracy
Batch
Variables
Terminal