```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()
```

```
/usr/local/lib/python3.12/dist-packages/torchvision/models/
_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated
since 0.13 and may be removed in the future, please use 'weights'
instead.
  warnings.warn(
/usr/local/lib/python3.12/dist-packages/torchvision/models/_utils.py:2
23: UserWarning: Arguments other than a weight enum or `None` for
'weights' are deprecated since 0.13 and may be removed in the future.
The current behavior is equivalent to passing
`weights=ResNet18_Weights.IMAGENET1K_V1`. You can also use
`weights=ResNet18_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)

Downloading: "https://download.pytorch.org/models/resnet18-
f37072fd.pth" to /root/.cache/torch/hub/checkpoints/resnet18-
f37072fd.pth

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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)
      (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)
      )
    )
    (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)
    )
  )
  (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)
      (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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```

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]

        # 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

```
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}")
```

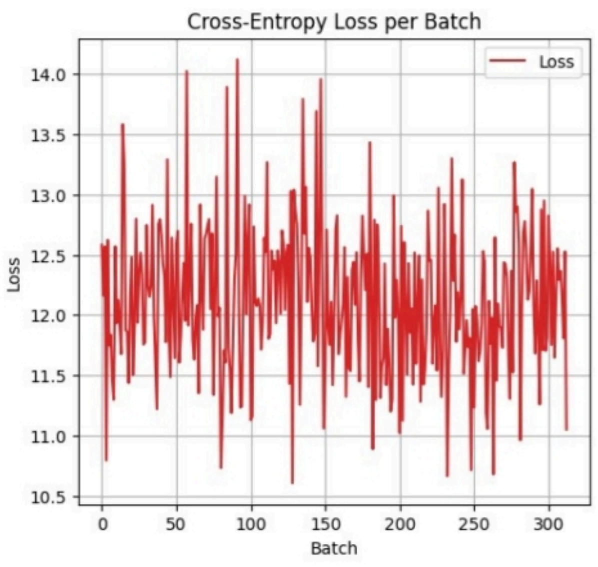
```
Total parameters: 11689512
Trainable parameters: 11689512
```

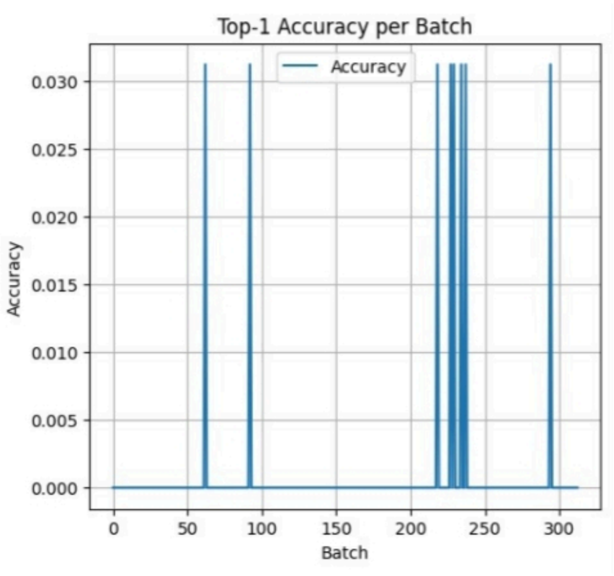
```
plt.figure(figsize=(12,5))

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()

plt.show()
```


Cross-Entropy Loss per Batch
Loss
Loss
Batch
14.0
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0
50
100
150
200
250
300


Top-1 Accuracy per Batch
Accuracy
Accuracy
Batch
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
50
100
150
200
250
300

		TITLE	PAGE NO.	TEACHER'S SIGN
12.		Generate complex color Image		[illegible]
13.		Understanding the Architecture of pre-trained model		
14.		Implement a pre-trained CNN model as a feature extractor		
15.		Implement a YOLO model object detection.		

Completed

[illegible]

13. UNDERSTANDING THE ARCHITECTURE OF PRE-TRAINED MODEL

AIM:

TO UNDERSTAND THE ARCHITECTURE OF Pre-trained model

OBJECTIVE:

Load a pre-trained model from a deep learning library (e.g. Pytorch or Tensorflow)

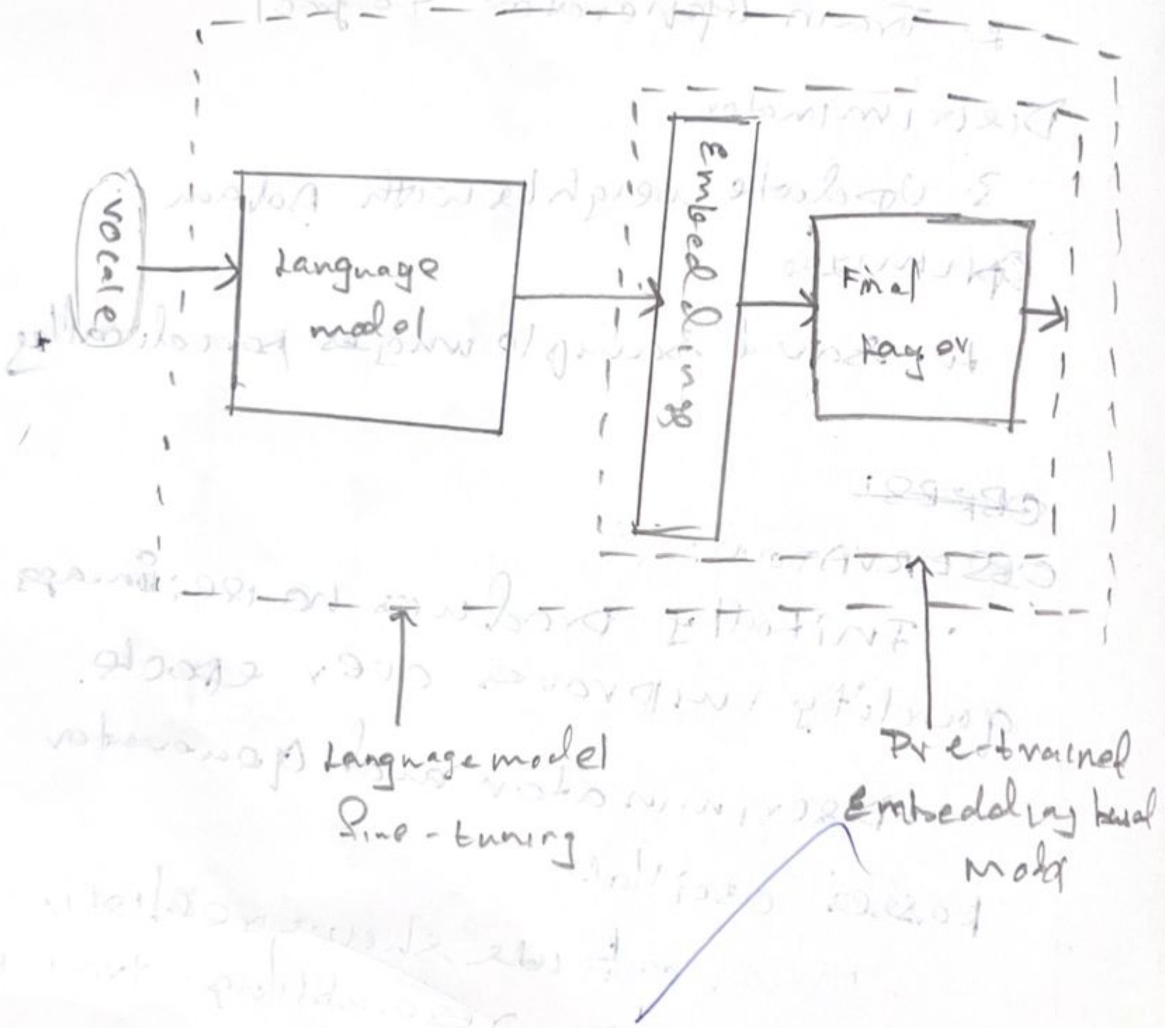
Visualize and study it layer structure and parameters

Identify feature extraction and classification component

Understand how transfer learning utilizes pre-trained weights.

PSEUDOCODE:

```
Import required libraries
Load pre-trained model (e.g. model = torchvision
model. resnet50 (pretrained = TRUE)
Print or visualize model summary
For each layer in model
Display layer name, type, and parameters
Freeze feature extraction layers if needed
Add/modify final layer for new classification
```


vocale
Language model
Embedding
Final layer
Language model fine-tuning
Pre-trained Embedding based Model

OBSERVATION:

The model is composed of convolutional, Pooling activation and fully connected layers.

Pre-trained model provide high accuracy and faster convergence with minimal training data

Early layers, capture edges and textures while deeper layer learn complex features

RESULT:

89 Therefore this experiment is successfully completed.