en3160-210174x-a03

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EN3160 Assignment 03: Neural Networks

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- Assignment Codes on: Google Colab

Check CUDA setup

[ ]:
```
import torch
print(torch.cuda.device_count())
print(torch.cuda.get_device_name(0))
```

```
1
NVIDIA GeForce RTX 2060
```

[ ]:
```
# Since I tried some examples with both torch and tensorflow, here I checked it␣
↪as well
import tensorflow as tf
print(tf.config.list_physical_devices('GPU'))
```

```
[PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU')]
```

1 Dense layer network with manually computed forward path and backpropagations for CIFAR10 dataset

[8]:
```
import torch
import torch.nn as nn  # Import neural network module
import torch.optim as optim  # Import optimization algorithms
import torchvision  # Import torchvision for datasets and image manipulation
import torchvision.transforms as transforms  # Import image transformation␣
↪utilities
import matplotlib.pyplot as plt  # Import for plotting graphs
```

[21]:
```
# 1. Dataloading
transform = transforms.Compose([  # Define a sequence of image transformations
    transforms.ToTensor(),  # Convert images to PyTorch tensors
```

```
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))  # Normalize images␣
↪with mean and standard deviation
])

batch_size = 50  # Define batch size for loading data
trainset = torchvision.datasets.CIFAR10(root='./data', train=True,  # Load␣
↪CIFAR-10 training dataset
                                        download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=batch_size,  #␣
↪Create DataLoader for training set
                                          shuffle=True, num_workers=2)
testset = torchvision.datasets.CIFAR10(root='./data', train=False,  # Load␣
↪CIFAR-10 test dataset
                                       download=True, transform=transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=batch_size,  #␣
↪Create DataLoader for test set
                                         shuffle=False, num_workers=2)

classes = ('plane', 'car', 'bird', 'cat',  # List of CIFAR-10 class names
           'deer', 'dog', 'frog', 'horse', 'ship', 'truck')
```

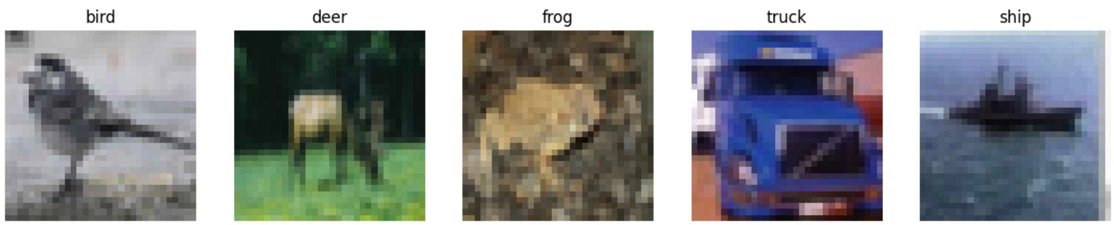
```
Files already downloaded and verified
Files already downloaded and verified
```

[24]:
```
# Get a batch of training data
dataiter = iter(trainloader)
images, labels = next(dataiter)

# Plot the first 5 images, one from each class
fig, axes = plt.subplots(1, 5, figsize=(15, 5))
found_classes = set()
count = 0

for i in range(len(labels)):
    if labels[i].item() not in found_classes:
        # Since images are normalized, unnormalize them for visualization
        img = images[i] / 2 + 0.5  # Unnormalize the image
        img = img.numpy()
        axes[count].imshow(np.transpose(img, (1, 2, 0)))
        axes[count].set_title(f'{classes[labels[i]]}')
        axes[count].axis('off')
        found_classes.add(labels[i].item())
        count += 1
    if count == 5:
        break

plt.show()
```



[10]:
```
# 2. Define Network Parameters
Din = 3 * 32 * 32  # Input size (flattened CIFAR10 image size)
H = 100  # Number of nodes in the hidden layer
K = 10  # Output size (number of classes in CIFAR10)
std = 1e-5  # Standard deviation for weight initialization

# Initialize weights and biases
w1 = torch.randn(Din, H) * std  # Weights for input to hidden layer, initialized randomly
b1 = torch.zeros(H)  # Bias for hidden layer, initialized to zero
w2 = torch.randn(H, K) * std  # Weights for hidden to output layer, initialized randomly
b2 = torch.zeros(K)  # Bias for output layer, initialized to zero

# Hyperparameters
iterations = 10  # Number of training iterations
lr = 1e-3  # Learning rate
lr_decay = 0.9  # Learning rate decay factor
reg = 0  # Regularization strength
loss_history = []  # List to store loss values for plotting

# Cross-Entropy Loss Function
def cross_entropy_loss(y_pred, y_true):  # Custom cross-entropy loss function
    return -torch.sum(y_true * torch.log(y_pred + 1e-9)) / y_true.shape[0]  # Calculate loss

# Sigmoid Activation Function
def sigmoid(x):  # Define sigmoid activation function
    return 1 / (1 + torch.exp(-x))  # Apply sigmoid to input

# 3. Training Loop
for t in range(iterations):  # Iterate through epochs
    running_loss = 0.0  # Initialize running loss for each epoch
    correct = 0  # Initialize correct predictions count
    total = 0  # Initialize total sample count

    for i, data in enumerate(trainloader, 0):  # Loop through training batches
```

```
        # Get inputs and labels
        inputs, labels = data  # Unpack data (inputs and labels)
        Ntr = inputs.shape[0]  # Batch size
        x_train = inputs.view(Ntr, -1)  # Flatten input to (Ntr, Din)
        y_train_onehot = nn.functional.one_hot(labels, K).float()  # Convert labels to one-hot encoding

        # Forward pass - Hidden Layer
        hidden_output = sigmoid(x_train.mm(w1) + b1)  # Calculate hidden layer output
        # Forward pass - Output Layer
        y_pred = torch.softmax(hidden_output.mm(w2) + b2, dim=1)  # Calculate output layer predictions

        # Loss calculation (Cross-Entropy Loss with regularization)
        loss = cross_entropy_loss(y_pred, y_train_onehot) + reg * (torch.sum(w1 ** 2) + torch.sum(w2 ** 2))  # Compute loss
        loss_history.append(loss.item())  # Store loss value
        running_loss += loss.item()  # Accumulate running loss

        # Backpropagation
        dy_pred = y_pred - y_train_onehot  # Derivative of loss w.r.t output
        dw2 = hidden_output.t().mm(dy_pred) + reg * w2  # Gradient for w2
        db2 = dy_pred.sum(dim=0)  # Gradient for b2
        dhidden = dy_pred.mm(w2.t()) * hidden_output * (1 - hidden_output)  # Derivative for hidden layer
        dw1 = x_train.t().mm(dhidden) + reg * w1  # Gradient for w1
        db1 = dhidden.sum(dim=0)  # Gradient for b1

        # Parameter update
        w1 -= lr * dw1  # Update weights for input to hidden layer
        b1 -= lr * db1  # Update bias for hidden layer
        w2 -= lr * dw2  # Update weights for hidden to output layer
        b2 -= lr * db2  # Update bias for output layer

        # Calculate accuracy
        _, predicted = torch.max(y_pred, 1)  # Get predicted class index
        total += labels.size(0)  # Update total samples
        correct += (predicted == labels).sum().item()  # Update correct predictions count

    train_accuracy = 100 * correct / total  # Calculate training accuracy
    print(f'Epoch [{t + 1}/{iterations}], Loss: {running_loss / len(trainloader):.4f}, Training Accuracy: {train_accuracy:.2f}%')  # Print epoch stats
```

```
    # Learning rate decay
    lr *= lr_decay  # Apply learning rate decay
```

```
Epoch [1/10], Loss: 2.1591, Training Accuracy: 16.74%
Epoch [2/10], Loss: 1.9055, Training Accuracy: 30.71%
Epoch [3/10], Loss: 1.8063, Training Accuracy: 35.76%
Epoch [4/10], Loss: 1.7478, Training Accuracy: 38.15%
Epoch [5/10], Loss: 1.7082, Training Accuracy: 39.92%
Epoch [6/10], Loss: 1.6797, Training Accuracy: 41.34%
Epoch [7/10], Loss: 1.6568, Training Accuracy: 42.10%
Epoch [8/10], Loss: 1.6378, Training Accuracy: 42.92%
Epoch [9/10], Loss: 1.6215, Training Accuracy: 43.80%
Epoch [10/10], Loss: 1.6069, Training Accuracy: 44.23%
```

This is a simple neural network with one hidden layer, applied to the CIFAR-10 dataset. The architecture and training use the cross-entropy loss function and stochastic gradient descent (SGD) for parameter updates.

1. Network Parameters

- **Input Size (`Din`)**: The input size is $3 \times 32 \times 32 = 3072$, which corresponds to the flattened image from CIFAR-10 (32x32 with 3 color channels).
- **Hidden Layer Size (`H`)**: The number of hidden units is 100.
- **Output Size (`K`)**: The output size is 10, which corresponds to the 10 classes in CIFAR-10.

The weights and biases are initialized as follows: - $W_1 \in \mathbb{R}^{3072\times 100}$, $b_1 \in \mathbb{R}^{100}$ are weights and biases for the input to hidden layer. - $W_2 \in \mathbb{R}^{100\times 10}$, $b_2 \in \mathbb{R}^{10}$ are weights and biases for the hidden to output layer.

2. Forward Propagation Equations

- **Hidden Layer Computation**:

$$h = \sigma(XW_1 + b_1)$$

  Where:
  - $X \in \mathbb{R}^{N\times 3072}$ is the batch of input data, where N is the batch size.
  - $W_1 \in \mathbb{R}^{3072\times 100}$ are the weights from input to hidden layer.
  - $b_1 \in \mathbb{R}^{100}$ is the bias for the hidden layer.
  - σ is the sigmoid activation function defined as:

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

- **Output Layer Computation**:

$$y_{\text{pred}} = \text{softmax}(hW_2 + b_2)$$

  Where:
  - $h \in \mathbb{R}^{N\times 100}$ is the output from the hidden layer.
  - $W_2 \in \mathbb{R}^{100\times 10}$ are the weights from hidden to output layer.
  - $b_2 \in \mathbb{R}^{10}$ is the bias for the output layer.

- **Softmax function** is used to produce a probability distribution over the output classes:

$$\text{softmax}(z_j) = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}}$$

Where z_j is the j-th element of the input to softmax, representing the score for class j.

3. Cross-Entropy Loss The **cross-entropy loss** is used to measure the difference between the predicted output and the true labels:

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{K} y_{ij} \log(y_{\text{pred},ij})$$

Where: - y_{ij} is the true label (one-hot encoded) for the i-th sample and class j. - $y_{\text{pred},ij}$ is the predicted probability for the i-th sample and class j.

4. Backpropagation and Gradients The gradients for backpropagation are calculated as follows:

- **Gradient w.r.t. Output Weights** W_2:

$$\frac{\partial \mathcal{L}}{\partial W_2} = h^T (y_{\text{pred}} - y)$$

  Where:

  - $y_{\text{pred}} - y$ is the difference between the predicted and true labels.

- **Gradient w.r.t. Output Bias** b_2:

$$\frac{\partial \mathcal{L}}{\partial b_2} = \sum_{i=1}^{N} (y_{\text{pred},i} - y_i)$$

- **Gradient w.r.t. Hidden Layer Output**:

$$\delta_h = (y_{\text{pred}} - y) W_2^T \cdot h \cdot (1 - h)$$

  Where δ_h represents the gradient flowing back to the hidden layer. The term $h \cdot (1 - h)$ is the derivative of the sigmoid function.

- **Gradient w.r.t. Hidden Weights** W_1:

$$\frac{\partial \mathcal{L}}{\partial W_1} = X^T \delta_h$$

- **Gradient w.r.t. Hidden Bias** b_1:

$$\frac{\partial \mathcal{L}}{\partial b_1} = \sum_{i=1}^{N} \delta_{h_i}$$

5. Parameter Updates Using Gradient Descent Using **Stochastic Gradient Descent (SGD)**, the weights are updated as follows:

- **Update Rule for Weights**:

$$W_1 = W_1 - \eta \frac{\partial \mathcal{L}}{\partial W_1}$$

$$W_2 = W_2 - \eta \frac{\partial \mathcal{L}}{\partial W_2}$$

  Where η is the learning rate.

- **Update Rule for Biases**:

$$b_1 = b_1 - \eta \frac{\partial \mathcal{L}}{\partial b_1}$$

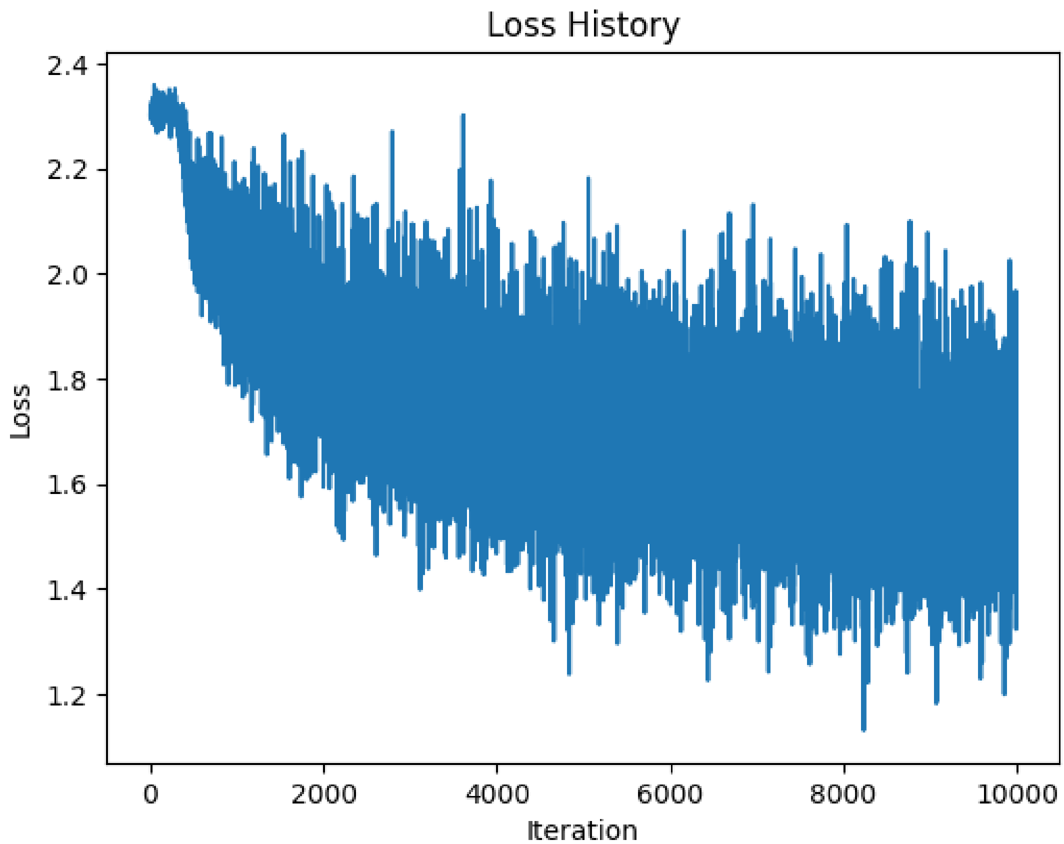
$$b_2 = b_2 - \eta \frac{\partial \mathcal{L}}{\partial b_2}$$

These equations reflect the application of backpropagation and gradient descent to update the weights and biases in the network based on the cross-entropy loss function.

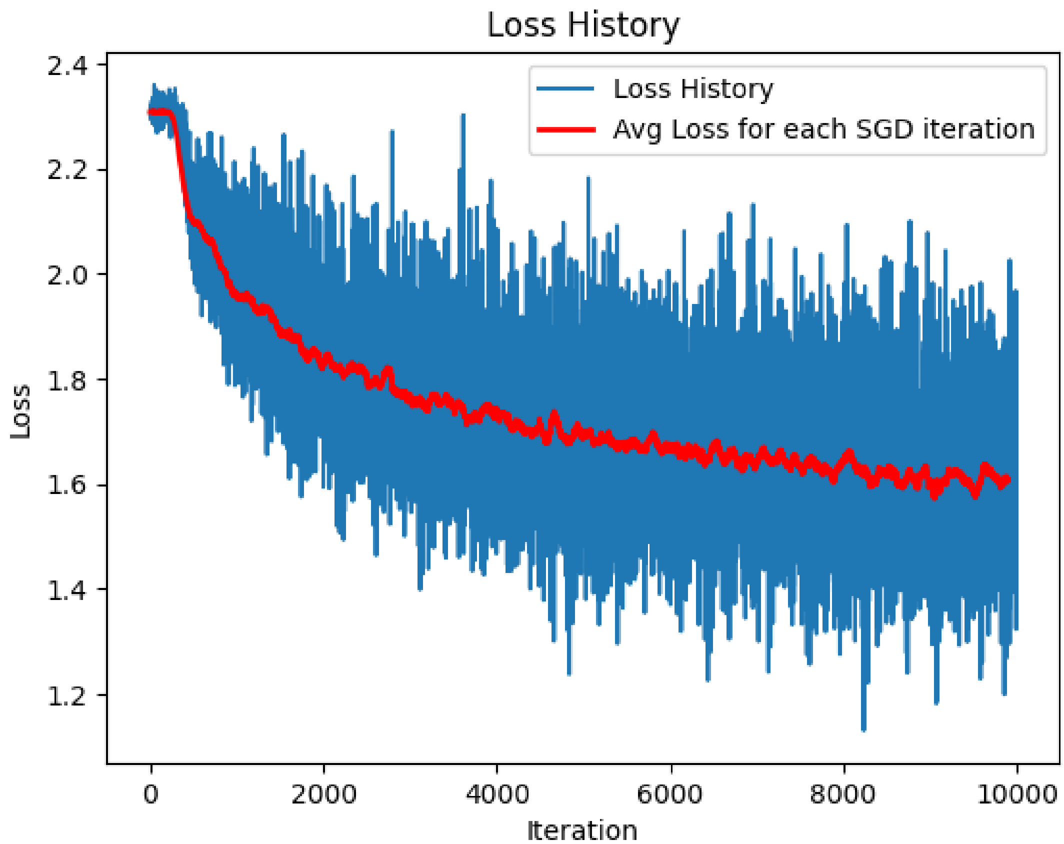
1.0.1 Main code blocks;

- **Forward Pass**: Computes the output of the network using sigmoid activation in the hidden layer and softmax in the output layer.
- **Loss Calculation**: Uses cross-entropy loss to measure the error between predictions and true labels.
- **Backpropagation**: Computes the gradients for each weight and bias.
- **Parameter Update**: Applies SGD to update weights and biases based on computed gradients, following the equations shown in the image.

[11]:
```
# 4. Plotting the Loss History
plt.plot(loss_history)  # Plot loss over iterations
plt.title("Loss History")  # Plot title
plt.xlabel("Iteration")  # X-axis label
plt.ylabel("Loss")  # Y-axis label
plt.show()  # Display plot
```



[29]:
```
# 4. Plotting the Loss History
plt.plot(loss_history, label='Loss History')  # Plot loss over iterations
smoothed_loss = np.convolve(loss_history, np.ones(100)/100, mode='valid')  #␣
↪Calculate smoothed loss using moving average
plt.plot(smoothed_loss, color='r', linewidth=2, label='Avg Loss for each SGD␣
↪iteration')  # Plot the smoothed loss as a red line
plt.title("Loss History")  # Plot title
plt.xlabel("Iteration")  # X-axis label
plt.ylabel("Loss")  # Y-axis label
plt.legend()  # Display legend
plt.show()  # Display plot
```



[12]:
```
# 5. Calculate Accuracy on Training Set
correct_train = 0  # Initialize correct count for training set
total_train = 0  # Initialize total sample count for training set
with torch.no_grad():  # Disable gradient computation
    for data in trainloader:  # Loop through training data
        inputs, labels = data  # Unpack data
        Ntr = inputs.shape[0]  # Batch size
        x_train = inputs.view(Ntr, -1)  # Flatten input

        # Forward pass
        hidden_output = sigmoid(x_train.mm(w1) + b1)  # Calculate hidden layer␣
↪output
        y_train_pred = torch.softmax(hidden_output.mm(w2) + b2, dim=1)  #␣
↪Calculate output layer predictions
        predicted_train = torch.argmax(y_train_pred, dim=1)  # Get predicted␣
↪class
        total_train += labels.size(0)  # Update total count
        correct_train += (predicted_train == labels).sum().item()  # Update␣
↪correct count
```

```
train_acc = 100 * correct_train / total_train  # Calculate training accuracy
print(f"Training accuracy: {train_acc:.2f}%")  # Print training accuracy
```

Training accuracy: 44.72%

[13]:
```
# 6. Calculate Accuracy on Test Set
correct_test = 0  # Initialize correct count for test set
total_test = 0  # Initialize total sample count for test set
with torch.no_grad():  # Disable gradient computation
    for data in testloader:  # Loop through test data
        inputs, labels = data  # Unpack data
        Nte = inputs.shape[0]  # Batch size
        x_test = inputs.view(Nte, -1)  # Flatten input

        # Forward pass
        hidden_output = sigmoid(x_test.mm(w1) + b1)  # Calculate hidden layer␣
 ↪output
        y_test_pred = torch.softmax(hidden_output.mm(w2) + b2, dim=1)  #␣
 ↪Calculate output layer predictions
        predicted_test = torch.argmax(y_test_pred, dim=1)  # Get predicted class
        total_test += labels.size(0)  # Update total count
        correct_test += (predicted_test == labels).sum().item()  # Update␣
 ↪correct count

test_acc = 100 * correct_test / total_test  # Calculate test accuracy
print(f"Test accuracy: {test_acc:.2f}%")  # Print test accuracy
```

Test accuracy: 43.37%

2 Create a LeNet-5 network for MNIST Dataset using Pytorch

[ ]:
```
import torch
import torch.nn as nn  # Import the neural network module
import torch.optim as optim  # Import optimization algorithms
import torchvision  # Import torchvision for datasets and image manipulation
import torchvision.transforms as transforms  # Import transforms for data␣
 ↪preprocessing
from torch.utils.data import DataLoader  # Import DataLoader for batching data
```

2.0.1 Check if GPU is available, otherwise use CPU

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

2.1 LeNet-5 Model Definition

1. First Convolutional Layer (Conv2D):
   - Input: 1 channel, Output: 6 channels, Kernel size: 5x5
   - Activation: ReLU
   - Max Pooling with kernel size 2x2, stride 2
2. Second Convolutional Layer (Conv2D):
   - Input: 6 channels, Output: 16 channels, Kernel size: 5x5
   - Activation: ReLU
   - Max Pooling with kernel size 2x2, stride 2
3. Flatten the Convolutional Output
4. First Fully Connected Layer (Dense Layer):
   - Input Size: 16 * 5 * 5, Output Size: 120
   - Activation: ReLU
5. Second Fully Connected Layer (Dense Layer):
   - Input Size: 120, Output Size: 84
   - Activation: ReLU
6. Output Layer (Dense Layer):
   - Input Size: 84, Output Size: 10 (Number of classes)

2.1.1 PyTorch Method 1: Standard Layer-by-Layer Definition

[ ]:
```
import torch
import torch.nn as nn

class LeNet5(nn.Module):  # Define LeNet-5 model as a subclass of nn.Module
    def __init__(self):  # Constructor method to initialize the model layers
        super(LeNet5, self).__init__()  # Call the parent class constructor
        self.conv1 = nn.Conv2d(1, 6, kernel_size=5, stride=1, padding=2)  #␣
↪First convolutional layer (input channels: 1, output channels: 6)
        self.conv2 = nn.Conv2d(6, 16, kernel_size=5, stride=1)  # Second␣
↪convolutional layer (input channels: 6, output channels: 16)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)  # First fully connected layer␣
↪(input size: 16 * 5 * 5, output size: 120)
        self.fc2 = nn.Linear(120, 84)  # Second fully connected layer (input␣
↪size: 120, output size: 84)
        self.fc3 = nn.Linear(84, 10)  # Third fully connected layer (input size:
↪ 84, output size: 10)

    def forward(self, x):  # Define the forward pass
        x = torch.relu(self.conv1(x))  # Apply ReLU activation to the output of␣
↪the first convolutional layer
```

```
        x = torch.max_pool2d(x, kernel_size=2, stride=2)  # Apply max pooling␣
↪with kernel size 2 and stride 2
        x = torch.relu(self.conv2(x))  # Apply ReLU activation to the output of␣
↪the second convolutional layer
        x = torch.max_pool2d(x, kernel_size=2, stride=2)  # Apply max pooling␣
↪with kernel size 2 and stride 2
        x = x.view(-1, 16 * 5 * 5)  # Flatten the tensor to prepare for fully␣
↪connected layers
        x = torch.relu(self.fc1(x))  # Apply ReLU activation to the first fully␣
↪connected layer
        x = torch.relu(self.fc2(x))  # Apply ReLU activation to the second␣
↪fully connected layer
        x = self.fc3(x)  # Output layer (no activation, logits for␣
↪classification)
        return x  # Return the final output
```

2.1.2 PyTorch Method 2: Using nn.Sequential for Convolution Layers

[ ]:
```
import torch
import torch.nn as nn

class LeNet5(nn.Module):
    def __init__(self):
        super(LeNet5, self).__init__()
        self.conv_layers = nn.Sequential(
            nn.Conv2d(1, 6, kernel_size=5, stride=1, padding=2),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),
            nn.Conv2d(6, 16, kernel_size=5, stride=1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2)
        )
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = self.conv_layers(x)
        x = x.view(-1, 16 * 5 * 5)
        x = torch.relu(self.fc1(x))
        x = torch.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

2.1.3 TensorFlow Method 3: Functional

[ ]:
```
import tensorflow as tf

def LeNet5(inputs):
    x = tf.keras.layers.Conv2D(6, kernel_size=5, strides=1, padding='same',␣
 ↪activation='relu')(inputs)
    x = tf.keras.layers.MaxPooling2D(pool_size=2, strides=2)(x)
    x = tf.keras.layers.Conv2D(16, kernel_size=5, strides=1,␣
 ↪activation='relu')(x)
    x = tf.keras.layers.MaxPooling2D(pool_size=2, strides=2)(x)
    x = tf.keras.layers.Flatten()(x)
    x = tf.keras.layers.Dense(120, activation='relu')(x)
    x = tf.keras.layers.Dense(84, activation='relu')(x)
    x = tf.keras.layers.Dense(10, activation='softmax',␣
 ↪name="classification")(x)
    return x

inputs = tf.keras.Input(shape=(32, 32, 1))
outputs = LeNet5(inputs)
model = tf.keras.Model(inputs=inputs, outputs=outputs)

model.compile(optimizer='sgd', loss='sparse_categorical_crossentropy',␣
 ↪metrics=['accuracy'])
model.summary()
```

2.1.4 TensorFlow Method 4: Sequential

[ ]:
```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense

model = Sequential()
model.add(Conv2D(6, kernel_size=5, strides=1, padding='same',␣
 ↪activation='relu', input_shape=(32, 32, 1)))
model.add(MaxPooling2D(pool_size=2, strides=2))
model.add(Conv2D(16, kernel_size=5, strides=1, activation='relu'))
model.add(MaxPooling2D(pool_size=2, strides=2))
model.add(Flatten())
model.add(Dense(120, activation='relu'))
model.add(Dense(84, activation='relu'))
model.add(Dense(10, activation='softmax'))

model.compile(optimizer='sgd', loss='sparse_categorical_crossentropy',␣
 ↪metrics=['accuracy'])
model.summary()
```

2.1.5 Summary of the Four Approaches:

1. **PyTorch Method 1 (Standard Layer-by-Layer Definition)**:
   - PyTorch model layers are defined individually in the constructor.
   - This allows you to maintain flexibility, as each layer is instantiated separately.
   - Pros: Good for learning and understanding each layer individually. Fine control over the architecture.
   - Cons: Slightly verbose and harder to maintain as models grow more complex.
2. **PyTorch Method 2 (Using `nn.Sequential`)**:
   - Uses `nn.Sequential` to create a block of layers that are automatically stacked.
   - Simplifies the model definition by removing the need to write individual forward propagation.
   - Pros: Easier to write and maintain for simpler models. Reduces verbosity in the forward function.
   - Cons: Not as flexible if the model needs custom branching or multiple input/output.
3. **TensorFlow Method 3 (Functional API)**:
   - The Functional API provides explicit connectivity between each layer.
   - Useful for more advanced models that might need multiple inputs/outputs or branching.
   - Pros: Highly flexible, and good for any complex architecture. More explicit.
   - Cons: Verbose for simple models. More effort is needed to connect layers manually.
4. **TensorFlow Method 4 (Sequential API)**:
   - Defines the model as a linear stack of layers using `Sequential`.
   - Ideal for simple models without any need for branching.
   - Pros: Very easy to implement for straightforward models. Concise and readable.
   - Cons: Not suitable for complex architectures, such as those with shared layers or multiple paths.

2.1.6 When to Use Each Approach:

- **PyTorch Layer-by-Layer & TensorFlow Functional API ()**:
  - Useful when you need the flexibility to define complex models, including shared weights, multiple inputs/outputs, and non-linear data flows.
  - Ideal for research and advanced model development where custom operations are required.
- ** PyTorch `nn.Sequential` & TensorFlow Sequential API**:
  - Ideal for simple feed-forward models or when developing models rapidly without needing branching structures.
  - Great for beginners or simple prototyping where the architecture is straightforward.

2.1.7 Pros and Cons of Each Method:

Method	Pros	Cons
PyTorch Layer-by-Layer	Fine control over individual layers and flexibility.	More verbose, harder to maintain as models get complex.
PyTorch `nn.Sequential`	Concise and good for stacking layers directly.	Less flexibility if you need to add different paths or custom operations.

Method	Pros	Cons
TensorFlow Functional API	Very flexible for complex architectures (e.g., multiple inputs/outputs).	Verbose for simple models, requires explicit layer connections.
TensorFlow Sequential API	Very readable and easy for straightforward architectures.	Limited flexibility for complex model designs.

2.2 Model, Loss, and Optimizer

[ ]:
```
model = LeNet5().to(device)  # Instantiate the LeNet-5 model and move it to the␣
↪appropriate device
criterion = nn.CrossEntropyLoss()  # Define the loss function (cross-entropy␣
↪loss for classification)
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9)  # Define the␣
↪optimizer (stochastic gradient descent with momentum)
```

2.3 Data Preparation

[18]:
```
transform = transforms.Compose([  # Define a sequence of transformations for␣
↪data preprocessing
    transforms.ToTensor(),  # Convert the image to a PyTorch tensor
    transforms.Normalize((0.5,), (0.5,))  # Normalize the image with mean 0.5␣
↪and standard deviation 0.5
])

# Load MNIST dataset for training and testing
train_dataset = torchvision.datasets.MNIST(root='./data', train=True,␣
↪download=True, transform=transform)  # Load training set
test_dataset = torchvision.datasets.MNIST(root='./data', train=False,␣
↪download=True, transform=transform)  # Load test set

# Create data loaders for batching training and test datasets
train_loader = DataLoader(train_dataset, batch_size=64, shuffle=True)  #␣
↪DataLoader for training set (batch size: 64)
test_loader = DataLoader(test_dataset, batch_size=1000, shuffle=False)  #␣
↪DataLoader for test set (batch size: 1000)
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-images-
idx3-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-images-
idx3-ubyte.gz to ./data/MNIST/raw/train-images-idx3-ubyte.gz
```

```
100%|     | 9.91M/9.91M [00:00<00:00, 34.3MB/s]

Extracting ./data/MNIST/raw/train-images-idx3-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-
idx1-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-
idx1-ubyte.gz to ./data/MNIST/raw/train-labels-idx1-ubyte.gz

100%|     | 28.9k/28.9k [00:00<00:00, 1.35MB/s]

Extracting ./data/MNIST/raw/train-labels-idx1-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-
idx3-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-
idx3-ubyte.gz to ./data/MNIST/raw/t10k-images-idx3-ubyte.gz

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Extracting ./data/MNIST/raw/t10k-images-idx3-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-
idx1-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-
idx1-ubyte.gz to ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz

100%|     | 4.54k/4.54k [00:00<00:00, 3.12MB/s]

Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw
```
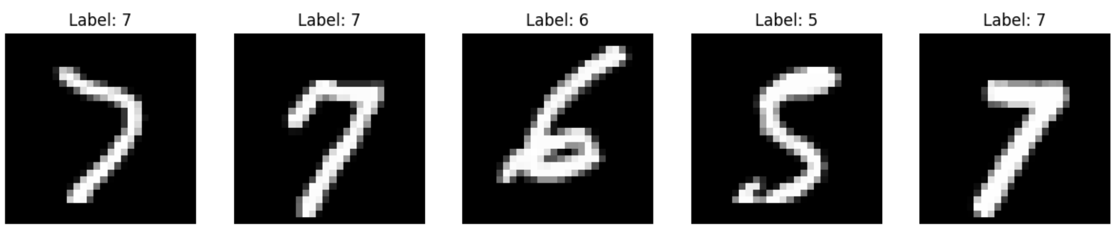

2.3.1 First few images from the batch

[19]:
```python
# Get a batch of training data
dataiter = iter(train_loader)
images, labels = next(dataiter)
```

```python
# Plot the first few images from the batch
fig, axes = plt.subplots(1, 5, figsize=(15, 5))
for i in range(5):
    # Since images are normalized, unnormalize them for visualization
    img = images[i] / 2 + 0.5  # Unnormalize the image
    img = img.numpy()
    axes[i].imshow(img[0], cmap='gray')
    axes[i].set_title(f'Label: {labels[i]}')
    axes[i].axis('off')

plt.show()
```



2.4 Training Loop

[ ]:
```python
num_epochs = 10  # Number of epochs to train the model
for epoch in range(num_epochs):  # Loop over epochs
    model.train()  # Set the model to training mode
    running_loss = 0.0  # Initialize running loss
    correct = 0  # Initialize count of correct predictions
    total = 0  # Initialize total number of samples

    for images, labels in train_loader:  # Loop over training data in batches
        images, labels = images.to(device), labels.to(device)  # Move images and labels to the device

        # Forward pass
        outputs = model(images)  # Get model predictions
        loss = criterion(outputs, labels)  # Compute the loss

        # Backward pass and optimization
        optimizer.zero_grad()  # Zero the gradients
        loss.backward()  # Backpropagate the loss
        optimizer.step()  # Update model parameters

        running_loss += loss.item()  # Accumulate the loss
```

```
            _, predicted = torch.max(outputs, 1)  # Get the predicted class with␣
↪the highest probability
            total += labels.size(0)  # Update the total count of samples
            correct += (predicted == labels).sum().item()  # Update the count of␣
↪correct predictions

    train_accuracy = 100 * correct / total  # Calculate training accuracy
    print(f'Epoch [{epoch + 1}/{num_epochs}], Loss: {running_loss /␣
↪len(train_loader):.4f}, Training Accuracy: {train_accuracy:.2f}%')  # Print␣
↪epoch summary
```

```
Epoch [1/10], Loss: 0.4019, Training Accuracy: 86.69%
Epoch [2/10], Loss: 0.0632, Training Accuracy: 98.05%
Epoch [3/10], Loss: 0.0445, Training Accuracy: 98.61%
Epoch [4/10], Loss: 0.0363, Training Accuracy: 98.89%
Epoch [5/10], Loss: 0.0276, Training Accuracy: 99.14%
Epoch [6/10], Loss: 0.0238, Training Accuracy: 99.22%
Epoch [7/10], Loss: 0.0194, Training Accuracy: 99.39%
Epoch [8/10], Loss: 0.0169, Training Accuracy: 99.45%
Epoch [9/10], Loss: 0.0146, Training Accuracy: 99.54%
Epoch [10/10], Loss: 0.0121, Training Accuracy: 99.60%
```

[ ]:
```
# Test the Model
def test():  # Define the function to test the model
    model.eval()  # Set the model to evaluation mode
    correct = 0  # Initialize count of correct predictions
    total = 0  # Initialize total number of samples
    with torch.no_grad():  # Disable gradient computation
        for images, labels in test_loader:  # Loop over test data in batches
            images, labels = images.to(device), labels.to(device)  # Move␣
↪images and labels to the device
            outputs = model(images)  # Get model predictions
            _, predicted = torch.max(outputs, 1)  # Get the predicted class␣
↪with the highest probability
            total += labels.size(0)  # Update the total count of samples
            correct += (predicted == labels).sum().item()  # Update the count␣
↪of correct predictions

    test_accuracy = 100 * correct / total  # Calculate test accuracy
    print(f'Test Accuracy: {test_accuracy:.2f}%')  # Print test accuracy

test()  # Call the test function to evaluate the model on the test set
```

```
Test Accuracy: 98.97%
```

3 Transfer learning a pre-trained ResNet18 network on ImageNet1K to classify Hymenoptera dataset.

[2]:
```
import torch
import torch.nn as nn  # Import neural network modules
import torch.optim as optim  # Import optimization algorithms
import torchvision  # Import torchvision for datasets and models
import torchvision.transforms as transforms  # Import transforms for image␣
 ↪preprocessing
import torchvision.datasets as datasets  # Import datasets module for loading␣
 ↪datasets
import torchvision.models as models  # Import models module for using␣
 ↪pre-trained models
from torch.utils.data import DataLoader  # Import DataLoader for batching data
import matplotlib.pyplot as plt  # Import for plotting graphs
import os  # Import os for interacting with the operating system
import zipfile  # Import zipfile for extracting zip files
import urllib.request  # Import urllib to download files from the internet

# Device configuration
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")  # Set␣
 ↪device to GPU if available, otherwise use CPU
```

3.1 Data Preparation

[3]:
```
# Download and extract the dataset in Google Colab
url = "https://download.pytorch.org/tutorial/hymenoptera_data.zip"  # URL of␣
 ↪the dataset
data_dir = "./hymenoptera_data"  # Directory to store the dataset

if not os.path.exists(data_dir):  # Check if the dataset directory exists
    urllib.request.urlretrieve(url, "hymenoptera_data.zip")  # Download the␣
 ↪dataset zip file
    with zipfile.ZipFile("hymenoptera_data.zip", 'r') as zip_ref:  # Open the␣
 ↪zip file
        zip_ref.extractall(".")  # Extract the contents of the zip file

# Define image transformations
transform = transforms.Compose([
    transforms.Resize(256),  # Resize the image to 256 pixels on the shorter␣
 ↪side
    transforms.CenterCrop(224),  # Crop the center of the image to 224x224␣
 ↪pixels
    transforms.ToTensor(),  # Convert the image to a PyTorch tensor
    transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])  #␣
 ↪Normalize the image with mean and std values
```

```
])

# Load the training and test datasets
train_dataset = datasets.ImageFolder(root=f'{data_dir}/train',␣
↪transform=transform)  # Load training dataset
test_dataset = datasets.ImageFolder(root=f'{data_dir}/val',␣
↪transform=transform)  # Load validation dataset

# Create data loaders for batching the data
train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True,␣
↪num_workers=4)  # DataLoader for training set
test_loader = DataLoader(test_dataset, batch_size=16, shuffle=False,␣
↪num_workers=4)  # DataLoader for test set
```

3.2 Load Pre-trained ResNet18

[4]:
```
resnet18 = models.resnet18(pretrained=True)  # Load the pre-trained ResNet18␣
↪model
```

3.3 (a) Fine-Tuning

[5]:
```
# Modify the final layer for classification of 2 classes (ants and bees)
num_features = resnet18.fc.in_features  # Get the number of input features of␣
↪the final layer
resnet18.fc = nn.Linear(num_features, 2)  # Replace the final layer with a new␣
↪layer for 2-class classification
resnet18 = resnet18.to(device)  # Move the model to the device

# Loss and Optimizer
criterion = nn.CrossEntropyLoss()  # Define the loss function (cross-entropy␣
↪loss for classification)
optimizer = optim.SGD(resnet18.parameters(), lr=0.001, momentum=0.9)  # Define␣
↪the optimizer (SGD with momentum)

# Training the Model (Fine-Tuning)
num_epochs = 10  # Number of epochs for training
resnet18.train()  # Set the model to training mode
for epoch in range(num_epochs):  # Loop through each epoch
    running_loss = 0.0  # Initialize running loss
    correct = 0  # Initialize count of correct predictions
    total = 0  # Initialize total number of samples
    for inputs, labels in train_loader:  # Loop through batches of training data
        inputs, labels = inputs.to(device), labels.to(device)  # Move inputs␣
↪and labels to the device

        # Forward pass
```

```
        outputs = resnet18(inputs)  # Get model predictions
        loss = criterion(outputs, labels)  # Compute the loss

        # Backward pass and optimization
        optimizer.zero_grad()  # Zero the gradients
        loss.backward()  # Backpropagate the loss
        optimizer.step()  # Update model parameters

        running_loss += loss.item()  # Accumulate the loss
        _, predicted = torch.max(outputs, 1)  # Get the predicted class with␣
 ↪the highest probability
        total += labels.size(0)  # Update the total count of samples
        correct += (predicted == labels).sum().item()  # Update the count of␣
 ↪correct predictions

    train_accuracy = 100 * correct / total  # Calculate training accuracy
    print(f'Epoch [{epoch + 1}/{num_epochs}], Loss: {running_loss /␣
 ↪len(train_loader):.4f}, Training Accuracy: {train_accuracy:.2f}%')  # Print␣
 ↪epoch summary

# Testing the Model (Fine-Tuning)
resnet18.eval()  # Set the model to evaluation mode
correct_test = 0  # Initialize count of correct predictions for test set
total_test = 0  # Initialize total number of test samples
with torch.no_grad():  # Disable gradient computation
    for inputs, labels in test_loader:  # Loop through batches of test data
        inputs, labels = inputs.to(device), labels.to(device)  # Move inputs␣
 ↪and labels to the device
        outputs = resnet18(inputs)  # Get model predictions
        _, predicted = torch.max(outputs, 1)  # Get the predicted class with␣
 ↪the highest probability
        total_test += labels.size(0)  # Update the total count of test samples
        correct_test += (predicted == labels).sum().item()  # Update the count␣
 ↪of correct predictions

test_accuracy = 100 * correct_test / total_test  # Calculate test accuracy
print(f'Fine-Tuning Test Accuracy: {test_accuracy:.2f}%')  # Print test accuracy
```

```
Epoch [1/10], Loss: 0.7836, Training Accuracy: 56.15%
Epoch [2/10], Loss: 0.2489, Training Accuracy: 91.39%
Epoch [3/10], Loss: 0.1193, Training Accuracy: 97.95%
Epoch [4/10], Loss: 0.0970, Training Accuracy: 95.49%
Epoch [5/10], Loss: 0.0417, Training Accuracy: 100.00%
Epoch [6/10], Loss: 0.0540, Training Accuracy: 99.18%
Epoch [7/10], Loss: 0.0281, Training Accuracy: 100.00%
Epoch [8/10], Loss: 0.0277, Training Accuracy: 100.00%
Epoch [9/10], Loss: 0.0425, Training Accuracy: 99.59%
```

```
Epoch [10/10], Loss: 0.0239, Training Accuracy: 99.59%
Fine-Tuning Test Accuracy: 96.08%
```

3.4 (b) Feature Extraction

[6]:
```
resnet18 = models.resnet18(pretrained=True)  # Reload the pre-trained ResNet18␣
 ↪model
for param in resnet18.parameters():  # Freeze all layers in the model
    param.requires_grad = False  # Do not update the parameters during training

# Modify the final layer for classification of 2 classes
num_features = resnet18.fc.in_features  # Get the number of input features of␣
 ↪the final layer
resnet18.fc = nn.Linear(num_features, 2)  # Replace the final layer with a new␣
 ↪layer for 2-class classification
resnet18 = resnet18.to(device)  # Move the model to the device

# Only train the final layer
optimizer = optim.SGD(resnet18.fc.parameters(), lr=0.001, momentum=0.9)  #␣
 ↪Define the optimizer for the final layer

# Training the Model (Feature Extraction)
resnet18.train()  # Set the model to training mode
for epoch in range(num_epochs):  # Loop through each epoch
    running_loss = 0.0  # Initialize running loss
    correct = 0  # Initialize count of correct predictions
    total = 0  # Initialize total number of samples
    for inputs, labels in train_loader:  # Loop through batches of training data
        inputs, labels = inputs.to(device), labels.to(device)  # Move inputs␣
 ↪and labels to the device

        # Forward pass
        outputs = resnet18(inputs)  # Get model predictions
        loss = criterion(outputs, labels)  # Compute the loss

        # Backward pass and optimization
        optimizer.zero_grad()  # Zero the gradients
        loss.backward()  # Backpropagate the loss
        optimizer.step()  # Update model parameters (only the final layer)

        running_loss += loss.item()  # Accumulate the loss
        _, predicted = torch.max(outputs, 1)  # Get the predicted class with␣
 ↪the highest probability
        total += labels.size(0)  # Update the total count of samples
        correct += (predicted == labels).sum().item()  # Update the count of␣
 ↪correct predictions
```

```
    train_accuracy = 100 * correct / total  # Calculate training accuracy
    print(f'Epoch [{epoch + 1}/{num_epochs}], Loss: {running_loss /␣
↪len(train_loader):.4f}, Training Accuracy: {train_accuracy:.2f}%')  # Print␣
↪epoch summary

# Testing the Model (Feature Extraction)
resnet18.eval()  # Set the model to evaluation mode
correct_test = 0  # Initialize count of correct predictions for test set
total_test = 0  # Initialize total number of test samples
with torch.no_grad():  # Disable gradient computation
    for inputs, labels in test_loader:  # Loop through batches of test data
        inputs, labels = inputs.to(device), labels.to(device)  # Move inputs␣
↪and labels to the device
        outputs = resnet18(inputs)  # Get model predictions
        _, predicted = torch.max(outputs, 1)  # Get the predicted class with␣
↪the highest probability
        total_test += labels.size(0)  # Update the total count of test samples
        correct_test += (predicted == labels).sum().item()  # Update the count␣
↪of correct predictions

test_accuracy = 100 * correct_test / total_test  # Calculate test accuracy
print(f'Feature Extraction Test Accuracy: {test_accuracy:.2f}%')  # Print test␣
↪accuracy
```

```
Epoch [1/10], Loss: 0.6826, Training Accuracy: 60.66%
Epoch [2/10], Loss: 0.3843, Training Accuracy: 83.61%
Epoch [3/10], Loss: 0.2437, Training Accuracy: 92.62%
Epoch [4/10], Loss: 0.2304, Training Accuracy: 93.03%
Epoch [5/10], Loss: 0.2123, Training Accuracy: 93.03%
Epoch [6/10], Loss: 0.1702, Training Accuracy: 94.26%
Epoch [7/10], Loss: 0.2295, Training Accuracy: 91.39%
Epoch [8/10], Loss: 0.1765, Training Accuracy: 93.44%
Epoch [9/10], Loss: 0.1620, Training Accuracy: 96.72%
Epoch [10/10], Loss: 0.1491, Training Accuracy: 94.26%
Feature Extraction Test Accuracy: 94.77%
```