Assignment-1-Part-2-1

April 25, 2025

1 Assignment 1 Part 2.1

1.1 Import necessary modules

[1]:
```
import torch
import torch.nn as nn
import os
import mlflow
from datetime import datetime
import matplotlib.pyplot as plt
import torchvision
import torchvision.transforms as transforms
from torch.utils.data import DataLoader
```

1.2 Layer class

[2]:
```
class Layer:
    def __init__(self, neurons_size: int, inputs_size: int, activation: str =␣
 ↪'none',
                 leaky_slope: float = 0.01, softmax_dim: int = 0):
        '''
        Initialize the layer with random weights and biases

        Parameters:
            neurons_size: int
                The number of neurons in the layer
            inputs_size: int
                The number of inputs to the layer
            activation: str
                The activation function to use
            leaky_slope: float
                The slope of the leaky relu activation function
            softmax_dim: int
                The dimension of the softmax activation function
        '''

        # initialize weights and biases with random values
```

```python
        # use the He initialization method to initialize the weights if the activation function is relu or leaky relu else use the Xavier initialization method
        if activation == 'relu' or activation == 'leaky_relu':
            self._weights: torch.Tensor = torch.randn(
                neurons_size, inputs_size) * torch.sqrt(2 / torch.tensor(inputs_size, dtype=torch.float32))
        else:
            self._weights: torch.Tensor = torch.randn(
                neurons_size, inputs_size) * torch.sqrt(1 / torch.tensor(inputs_size, dtype=torch.float32))
        self._biases: torch.Tensor = torch.zeros(neurons_size)
        self._activation: str = activation
        self._leaky_slope: float = leaky_slope
        self._softmax_dim: int = softmax_dim

        self._activation_function: dict[str, callable] = {
            'sigmoid': nn.Sigmoid(),
            'tanh': nn.Tanh(),
            'relu': nn.ReLU(),
            'leaky_relu': nn.LeakyReLU(negative_slope=self._leaky_slope),
            'softmax': nn.Softmax(dim=self._softmax_dim),
            'none': nn.Identity()
        }

    def set_weights(self, weights: torch.Tensor):
        '''
        Set the weights of the layer

        Parameters:
            weights: torch.Tensor
                The weights to set
        '''
        self._weights = weights

    def get_weights(self) -> torch.Tensor:
        '''
        Get the weights of the layer

        Returns:
            torch.Tensor
                The weights of the layer
        '''
        return self._weights

    def set_biases(self, biases: torch.Tensor):
        '''
```

```python
        Set the biases of the layer

        Parameters:
            biases: torch.Tensor
                The biases to set
        '''
        self._biases = biases

    def get_biases(self) -> torch.Tensor:
        '''
        Get the biases of the layer

        Returns:
            torch.Tensor
                The biases of the layer
        '''
        return self._biases

    def forward(self, inputs: torch.Tensor) -> torch.Tensor:
        '''
        Forward pass

        Parameters:
            inputs: torch.Tensor
                The inputs to the layer
            activation: str
                The activation function to use
        Returns:
            torch.Tensor
                The outputs of the layer
        '''
        # calculate the sum of the inputs multiplied by the weights and add the␣
↪biases
        if inputs.dim() == 2:
            sum: torch.Tensor = torch.matmul(
                inputs, self._weights.t()) + self._biases
        else:
            sum: torch.Tensor = torch.matmul(
                inputs, self._weights) + self._biases

        if self._activation in self._activation_function:
            return self._activation_function[self._activation](sum)
        else:
            raise ValueError(
                f"Activation function {self._activation} not found")
```

1.3 Custom Layer class

[3]:
```
class CustomLayer(nn.Module):
    def __init__(self, neurons_size: int, inputs_size: int, activation: str =␣
↪'none',
                 leaky_slope: float = 0.01, softmax_dim: int = 0):
        super(CustomLayer, self).__init__()

        '''
        Initialize the custom layer with the given neurons size, inputs size,
        activation, leaky slope, and softmax dimension

        '''

        # initialize the custom layer
        self.layer = Layer(neurons_size, inputs_size,
                           activation, leaky_slope, softmax_dim)

        # register the weights and biases as parameters to PyTorch
        self.weights = nn.Parameter(self.layer.get_weights())
        self.biases = nn.Parameter(self.layer.get_biases())

        # point the layer parameters to the PyTorch parameters
        self.layer.set_weights(self.weights)
        self.layer.set_biases(self.biases)

        # store the activation function parameters
        self.activation = activation
        self.leaky_slope = leaky_slope
        self.softmax_dim = softmax_dim

    def forward(self, inputs: torch.Tensor) -> torch.Tensor:

        # use custom layer forward method
        return self.layer.forward(inputs)
```

1.4 Perceptron class

[4]:
```
class Perceptron(nn.Module):
    def __init__(self, input_size: int, hidden_size: int, output_size: int,␣
↪hidden_activation: str = 'relu',
                 output_activation: str = 'none', leaky_slope: float = 0.01,␣
↪softmax_dim: int = 0):
        super(Perceptron, self).__init__()

        '''
```

```
        Initialize the perceptron with the given input size, hidden size,␣
↪output size,
        hidden activation, output activation, leaky slope, and softmax dimension

        Parameters:
            input_size: int
                The size of the input layer
            hidden_size: int
                The size of the hidden layer
            output_size: int
                The size of the output layer
            hidden_activation: str
                The activation function to use for the hidden layer
            output_activation: str
                The activation function to use for the output layer
            leaky_slope: float
                The slope of the leaky relu activation function
            softmax_dim: int
                The dimension of the softmax activation function
        '''

        # create a list of layer sizes including the input and output sizes
        layer_sizes: list[int] = [input_size] + hidden_size + [output_size]
        layers: list[CustomLayer] = []

        # create hidden layers
        for i in range(len(layer_sizes) - 2):
            layers.append(CustomLayer(
                layer_sizes[i+1], layer_sizes[i], hidden_activation,␣
↪leaky_slope, softmax_dim))

        # create output layer
        layers.append(CustomLayer(
            layer_sizes[-1], layer_sizes[-2], output_activation, leaky_slope,␣
↪softmax_dim))

        # store the layers
        self.layers = nn.ModuleList(layers)

    def forward(self, inputs: torch.Tensor) -> torch.Tensor:
        '''
        Forward pass

        Parameters:
            inputs: torch.Tensor
                The inputs to the perceptron
```

```
        Returns:
            torch.Tensor
            The outputs of the perceptron
        '''

        # process the input through the layers
        x = inputs
        for layer in self.layers:
            x = layer(x)
        return x
```

1.5 Trainer class

[5]:
```
class Trainer:
    def __init__(self,
                 model,
                 criterion,
                 optimizer,
                 train_loader,
                 val_loader=None,
                 test_loader=None,
                 device=None,
                 scheduler=None,
                 checkpoint_dir='./checkpoints',
                 experiment_name=None):
        """
        Initialize the trainer with model, criterion, optimizer, and data␣
 ↪loaders

        Parameters:
            model: nn.Module
                The model to train
            criterion: loss function
                The loss function to use
            optimizer: torch.optim
                The optimizer to use
            train_loader: DataLoader
                The data loader for training data
            val_loader: DataLoader
                The data loader for validation data
            test_loader: DataLoader
                The data loader for test data
            device: torch.device
                The device to use for training
            scheduler: torch.optim.lr_scheduler
                Learning rate scheduler (optional)
            checkpoint_dir: str
```

```
            Directory to save checkpoints
        experiment_name: str
            Name of the experiment for MLflow tracking
    """
    self.model = model
    self.criterion = criterion
    self.optimizer = optimizer
    self.train_loader = train_loader
    self.val_loader = val_loader if val_loader is not None else test_loader
    self.test_loader = test_loader
    self.device = device if device is not None else torch.device(
        'cuda' if torch.cuda.is_available() else 'cpu')
    self.scheduler = scheduler
    self.checkpoint_dir = checkpoint_dir
    self.experiment_name = experiment_name
    self.input_size = None  # will be set during first forward pass

    # create checkpoint directory if it doesn't exist
    os.makedirs(checkpoint_dir, exist_ok=True)

    # move model to device
    self.model.to(self.device)

    # initialize training metrics
    self.best_accuracy = 0.0
    self.best_loss = float('inf')
    self.history = {
        'train_loss': [],
        'val_loss': [],
        'val_accuracy': [],
        'learning_rates': []
    }

def train_epoch(self, epoch, num_epochs):
    """
    Train the model for one epoch
    """
    self.model.train()
    running_loss = 0.0

    for i, (inputs, labels) in enumerate(self.train_loader):
        # get input size from first batch if not set
        if self.input_size is None and hasattr(inputs, 'view'):
            self.input_size = inputs.view(inputs.size(0), -1).size(1)

        # prepare inputs
        if hasattr(inputs, 'view'):
```

```
                # for image data, flatten if needed
                inputs = inputs.view(inputs.size(0), -1).to(self.device)
            else:
                inputs = inputs.to(self.device)

            labels = labels.to(self.device)

            # forward pass
            outputs = self.model(inputs)
            loss = self.criterion(outputs, labels)

            # backward and optimize
            self.optimizer.zero_grad()
            loss.backward()
            self.optimizer.step()

            # update statistics
            running_loss += loss.detach().item()

            # print progress
            if (i+1) % 100 == 0:
                print(
                    f'Epoch [{epoch+1}/{num_epochs}], Step [{i+1}/{len(self.
↪train_loader)}], Loss: {loss.detach().item():.4f}')

        # calculate average loss for the epoch
        epoch_loss = running_loss / len(self.train_loader)
        self.history['train_loss'].append(epoch_loss)

        # track learning rate
        current_lr = self.optimizer.param_groups[0]['lr']
        self.history['learning_rates'].append(current_lr)

        return epoch_loss

    def validate(self, epoch=None):
        """
        Validate the model on validation data
        """
        if self.val_loader is None:
            return None, None

        self.model.eval()
        running_loss = 0.0
        correct = 0
        total = 0
```

```
        with torch.no_grad():
            for inputs, labels in self.val_loader:
                # prepare inputs
                if hasattr(inputs, 'view'):
                    # for image data
                    inputs = inputs.view(inputs.size(0), -1).to(self.device)
                else:
                    inputs = inputs.to(self.device)

                labels = labels.to(self.device)

                # forward pass
                outputs = self.model(inputs)
                loss = self.criterion(outputs, labels)

                # update statistics
                running_loss += loss.item()

                # calculate accuracy
                _, predicted = torch.max(outputs.data, 1)
                total += labels.size(0)
                correct += (predicted == labels).sum().item()

        # calculate average loss and accuracy
        val_loss = running_loss / len(self.val_loader)
        val_accuracy = 100 * correct / total

        if epoch is not None:
            self.history['val_loss'].append(val_loss)
            self.history['val_accuracy'].append(val_accuracy)

        return val_loss, val_accuracy

    def test(self):
        """
        Test the model on test data
        """
        if self.test_loader is None:
            return None, None

        return self.validate()  # reuse validation code for testing

    def save_checkpoint(self, epoch, train_loss, val_loss=None,␣
↪val_accuracy=None, is_best=False):
        """
        Save a checkpoint of the model
        """
```

```python
        checkpoint = {
            'epoch': epoch + 1,
            'model_state_dict': self.model.state_dict(),
            'optimizer_state_dict': self.optimizer.state_dict(),
            'loss': train_loss
        }

        if val_loss is not None:
            checkpoint['val_loss'] = val_loss

        if val_accuracy is not None:
            checkpoint['val_accuracy'] = val_accuracy

        if self.scheduler is not None:
            checkpoint['scheduler_state_dict'] = self.scheduler.state_dict()

        # save regular checkpoint
        checkpoint_path = os.path.join(
            self.checkpoint_dir, f'checkpoint_epoch_{epoch+1}.pt')
        torch.save(checkpoint, checkpoint_path)

        # save as best model if applicable
        if is_best:
            best_model_path = os.path.join(
                self.checkpoint_dir, 'best_model.pt')
            torch.save(checkpoint, best_model_path)
            print(f'New best model saved with accuracy: {val_accuracy:.2f}%')

        return checkpoint_path

    def load_checkpoint(self, checkpoint_path):
        """
        Load a checkpoint
        """
        print(f"Loading checkpoint from {checkpoint_path}")
        checkpoint = torch.load(checkpoint_path, map_location=self.device)

        self.model.load_state_dict(checkpoint['model_state_dict'])
        self.optimizer.load_state_dict(checkpoint['optimizer_state_dict'])

        if 'scheduler_state_dict' in checkpoint and self.scheduler is not None:
            self.scheduler.load_state_dict(checkpoint['scheduler_state_dict'])

        start_epoch = checkpoint['epoch']
        loss = checkpoint.get('loss', 0)
        val_loss = checkpoint.get('val_loss', 0)
        val_accuracy = checkpoint.get('val_accuracy', 0)
```

```python
        print(
            f"Checkpoint loaded - Epoch: {start_epoch}, Loss: {loss:.4f}, Val␣
↪Loss: {val_loss:.4f}, Val Accuracy: {val_accuracy:.2f}%")

        return start_epoch

    def train(self, num_epochs, start_epoch=0, log_to_mlflow=True,␣
↪early_stopping_patience=None):
        """
        Train the model for multiple epochs

        Parameters:
            num_epochs: int
                Number of epochs to train for
            start_epoch: int
                Starting epoch (useful when resuming training)
            log_to_mlflow: bool
                Whether to log metrics to MLflow
            early_stopping_patience: int
                Number of epochs to wait for improvement before stopping
        """
        # set mlflow experiment if provided
        if log_to_mlflow and self.experiment_name:
            mlflow.set_experiment(self.experiment_name)

        # initialize early stopping variables
        if early_stopping_patience is not None:
            early_stopping_counter = 0
            best_val_loss = float('inf')

        # start mlflow run if applicable
        run_context = mlflow.start_run(
            run_name=f"{self.model.__class__.__name__}_{datetime.now().
↪strftime('%Y%m%d_%H%M%S')}") if log_to_mlflow else DummyContextManager()

        # store previous learning rate to detect changes
        prev_lr = self.optimizer.param_groups[0]['lr']

        with run_context:
            # log parameters if using mlflow
            if log_to_mlflow:
                params = {
                    "optimizer": self.optimizer.__class__.__name__,
                    "learning_rate": self.optimizer.param_groups[0]['lr'],
                    "num_epochs": num_epochs
                }
```

```
            # add model architecture params if available
            if hasattr(self.model, 'input_size'):
                params["input_size"] = self.model.input_size
            mlflow.log_params(params)

        print("Starting training...")
        for epoch in range(start_epoch, num_epochs):
            # train for one epoch
            print('')
            train_loss = self.train_epoch(epoch, num_epochs)
            print(
                f'Epoch [{epoch+1}/{num_epochs}], Loss: {train_loss:.4f}')

            # validate
            val_loss, val_accuracy = self.validate(epoch)

            # early stopping check for overfitting
            if early_stopping_patience is not None and val_loss is not None:
                if val_loss < best_val_loss:
                    best_val_loss = val_loss
                    early_stopping_counter = 0
                else:
                    early_stopping_counter += 1
                    print(
                        f'EarlyStopping counter: {early_stopping_counter}␣
↪out of {early_stopping_patience}')

                    if early_stopping_counter >= early_stopping_patience:
                        print(
                            f'Early stopping triggered after epoch␣
↪{epoch+1}')
                        break

            # log metrics
            if log_to_mlflow:
                mlflow.log_metric("train_loss", train_loss, step=epoch)
                if val_loss is not None:
                    mlflow.log_metric("val_loss", val_loss, step=epoch)
                if val_accuracy is not None:
                    mlflow.log_metric(
                        "val_accuracy", val_accuracy, step=epoch)

            # print validation results
            if val_loss is not None and val_accuracy is not None:
                print(
                    f'Validation - Epoch [{epoch+1}/{num_epochs}], Loss:␣
↪{val_loss:.4f}, Accuracy: {val_accuracy:.2f}%')
```

```python
                # check if this is the best model so far
                is_best = False
                if val_accuracy is not None and val_accuracy > self.
↪best_accuracy:
                    self.best_accuracy = val_accuracy
                    is_best = True

                # save checkpoint
                self.save_checkpoint(
                    epoch, train_loss, val_loss, val_accuracy, is_best)

                # update learning rate if scheduler is provided
                if self.scheduler is not None:
                    if isinstance(self.scheduler, torch.optim.lr_scheduler.
↪ReduceLROnPlateau):
                        self.scheduler.step(val_loss)
                    else:
                        self.scheduler.step()

                 # check if learning rate changed
                current_lr = self.optimizer.param_groups[0]['lr']
                if current_lr != prev_lr:
                    print(
                        f"Learning rate changed from {prev_lr:.6f} to␣
↪{current_lr:.6f}")
                    prev_lr = current_lr

            print("Training complete!")

            # final evaluation
            print("\nFinal Evaluation:")
            test_loss, test_accuracy = self.test()
            if test_loss is not None and test_accuracy is not None:
                print(f'Final Test Loss: {test_loss:.4f}')
                print(f'Final Test Accuracy: {test_accuracy:.2f}%')

                # log final metrics
                if log_to_mlflow:
                    mlflow.log_metric("test_loss", test_loss)
                    mlflow.log_metric("test_accuracy", test_accuracy)

            # save the final model
            model_timestamp = datetime.now().strftime("%Y%m%d_%H%M%S")
            final_model_path = os.path.join(
                self.checkpoint_dir, f"final_model_{model_timestamp}.pt")
            torch.save(self.model.state_dict(), final_model_path)
```

```
        print(f"Final model saved as {final_model_path}\n")

        # log the model with mlflow
        if log_to_mlflow and self.input_size is not None:

            model_to_log = self.model.to('cpu')

            # create an input example
            sample_input = torch.rand(1, self.input_size).numpy()

            # create custom pip requirements
            pip_requirements = [
                f"torch=={torch.__version__}",
                "torchvision",
                "mlflow"
            ]

            # log the model
            mlflow.pytorch.log_model(
                model_to_log,
                "model",
                input_example=sample_input,
                pip_requirements=pip_requirements
            )

            # move the model back to the original device
            self.model = self.model.to(self.device)

        # plot and save training curves
        self.plot_training_curves()

        return self.history

def plot_training_curves(self):
    """
    plot and save the training curves
    """
    if len(self.history['train_loss']) == 0:
        return

    # create plots directory
    plots_dir = os.path.join(self.checkpoint_dir, 'plots')
    os.makedirs(plots_dir, exist_ok=True)

    # plot training and validation loss
    plt.figure(figsize=(10, 6))
    epochs = range(1, len(self.history['train_loss']) + 1)
```

```
        plt.plot(epochs, self.history['train_loss'],
                 'b-', label='Training Loss')

        if len(self.history['val_loss']) > 0:
            plt.plot(epochs, self.history['val_loss'],
                     'r-', label='Validation Loss')

        plt.title('Training and Validation Loss')
        plt.xlabel('Epochs')
        plt.ylabel('Loss')
        plt.legend()
        plt.grid(True)
        plt.savefig(os.path.join(plots_dir, 'loss_curves.png')) # save the plot␣
↪as a png file
        plt.tight_layout()
        plt.show()

        # plot validation accuracy if available
        if len(self.history['val_accuracy']) > 0:
            plt.figure(figsize=(10, 6))
            plt.plot(epochs, self.history['val_accuracy'], 'g-')
            plt.title('Validation Accuracy')
            plt.xlabel('Epochs')
            plt.ylabel('Accuracy (%)')
            plt.grid(True)
            plt.savefig(os.path.join(plots_dir, 'accuracy_curve.png')) # save␣
↪the plot as a png file
            plt.tight_layout()
            plt.show()


# helper class for context management when not using mlflow
class DummyContextManager:
    def __enter__(self):
        return None

    def __exit__(self, *args):
        pass
```

1.6 Runner

[6]:
```
# set random seed for reproducibility
torch.manual_seed(42)

# check for gpu availability
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f'Using device: {device}\n')
```

```
# define transformations
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

# load mnist dataset
train_dataset = torchvision.datasets.MNIST(
    root='./data',
    train=True,
    download=True,
    transform=transform
)

test_dataset = torchvision.datasets.MNIST(
    root='./data',
    train=False,
    download=True,
    transform=transform
)

# create data loaders
train_loader = DataLoader(
    train_dataset, batch_size=64, shuffle=True, pin_memory=True)
test_loader = DataLoader(test_dataset, batch_size=64,
                         shuffle=False, pin_memory=True)

# create model
input_size = 28 * 28  # MNIST images are 28x28 pixels
hidden_size = [128]  # one hidden layer
output_size = 10  # 10 classes (digits 0-9)
model = Perceptron(
    input_size=input_size,
    hidden_size=hidden_size,
    output_size=output_size,
    softmax_dim=-1
)

# define loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)

# create a learning rate scheduler for overfitting
scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(
    optimizer,
    mode='min',
```

```python
    factor=0.1,
    patience=3,
)

# create our trainer
trainer = Trainer(
    model=model,
    criterion=criterion,
    optimizer=optimizer,
    train_loader=train_loader,
    test_loader=test_loader,  # using test set as validation set
    device=device,
    scheduler=scheduler,
    checkpoint_dir='./checkpoints',
    experiment_name="MNIST_Perceptron_Model"
)

# train the model
history = trainer.train(
    num_epochs=10,
    log_to_mlflow=True,
    early_stopping_patience=5  # enable early stopping for overfitting
)

# uncomment to resume training from a checkpoint
# don't forget to change the checkpoint path
# checkpoint_path = './checkpoints/checkpoint_epoch_2.pt'
# start_epoch = trainer.load_checkpoint(checkpoint_path)
# trainer.train(num_epochs=10, start_epoch=start_epoch)

# uncomment to use the best model for inference
# trainer.load_checkpoint('./checkpoints/best_model.pt')
```

```
Using device: cuda

Starting training…

Epoch [1/10], Step [100/938], Loss: 0.4322
Epoch [1/10], Step [200/938], Loss: 0.3024
Epoch [1/10], Step [300/938], Loss: 0.3595
Epoch [1/10], Step [400/938], Loss: 0.2423
Epoch [1/10], Step [500/938], Loss: 0.2881
Epoch [1/10], Step [600/938], Loss: 0.3294
Epoch [1/10], Step [700/938], Loss: 0.3723
Epoch [1/10], Step [800/938], Loss: 0.2187
Epoch [1/10], Step [900/938], Loss: 0.1286
Epoch [1/10], Loss: 0.3607
Validation - Epoch [1/10], Loss: 0.2217, Accuracy: 93.28%
```

```
New best model saved with accuracy: 93.28%

Epoch [2/10], Step [100/938], Loss: 0.4463
Epoch [2/10], Step [200/938], Loss: 0.1599
Epoch [2/10], Step [300/938], Loss: 0.3721
Epoch [2/10], Step [400/938], Loss: 0.2644
Epoch [2/10], Step [500/938], Loss: 0.2724
Epoch [2/10], Step [600/938], Loss: 0.2156
Epoch [2/10], Step [700/938], Loss: 0.1613
Epoch [2/10], Step [800/938], Loss: 0.1414
Epoch [2/10], Step [900/938], Loss: 0.1897
Epoch [2/10], Loss: 0.1879
Validation - Epoch [2/10], Loss: 0.1493, Accuracy: 95.53%
New best model saved with accuracy: 95.53%

Epoch [3/10], Step [100/938], Loss: 0.1784
Epoch [3/10], Step [200/938], Loss: 0.1165
Epoch [3/10], Step [300/938], Loss: 0.1515
Epoch [3/10], Step [400/938], Loss: 0.2542
Epoch [3/10], Step [500/938], Loss: 0.0659
Epoch [3/10], Step [600/938], Loss: 0.1272
Epoch [3/10], Step [700/938], Loss: 0.3140
Epoch [3/10], Step [800/938], Loss: 0.1646
Epoch [3/10], Step [900/938], Loss: 0.0224
Epoch [3/10], Loss: 0.1383
Validation - Epoch [3/10], Loss: 0.1256, Accuracy: 96.14%
New best model saved with accuracy: 96.14%

Epoch [4/10], Step [100/938], Loss: 0.3256
Epoch [4/10], Step [200/938], Loss: 0.0810
Epoch [4/10], Step [300/938], Loss: 0.0935
Epoch [4/10], Step [400/938], Loss: 0.1180
Epoch [4/10], Step [500/938], Loss: 0.1764
Epoch [4/10], Step [600/938], Loss: 0.2124
Epoch [4/10], Step [700/938], Loss: 0.0451
Epoch [4/10], Step [800/938], Loss: 0.1489
Epoch [4/10], Step [900/938], Loss: 0.0503
Epoch [4/10], Loss: 0.1098
Validation - Epoch [4/10], Loss: 0.1031, Accuracy: 96.82%
New best model saved with accuracy: 96.82%

Epoch [5/10], Step [100/938], Loss: 0.0236
Epoch [5/10], Step [200/938], Loss: 0.1259
Epoch [5/10], Step [300/938], Loss: 0.0292
Epoch [5/10], Step [400/938], Loss: 0.1083
Epoch [5/10], Step [500/938], Loss: 0.0232
Epoch [5/10], Step [600/938], Loss: 0.0444
Epoch [5/10], Step [700/938], Loss: 0.0331
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Epoch [5/10], Step [800/938], Loss: 0.0711
Epoch [5/10], Step [900/938], Loss: 0.1074
Epoch [5/10], Loss: 0.0960
EarlyStopping counter: 1 out of 5
Validation - Epoch [5/10], Loss: 0.1063, Accuracy: 96.51%

Epoch [6/10], Step [100/938], Loss: 0.0274
Epoch [6/10], Step [200/938], Loss: 0.0241
Epoch [6/10], Step [300/938], Loss: 0.0546
Epoch [6/10], Step [400/938], Loss: 0.1778
Epoch [6/10], Step [500/938], Loss: 0.0370
Epoch [6/10], Step [600/938], Loss: 0.0572
Epoch [6/10], Step [700/938], Loss: 0.0574
Epoch [6/10], Step [800/938], Loss: 0.1473
Epoch [6/10], Step [900/938], Loss: 0.0581
Epoch [6/10], Loss: 0.0862
Validation - Epoch [6/10], Loss: 0.0915, Accuracy: 97.08%
New best model saved with accuracy: 97.08%

Epoch [7/10], Step [100/938], Loss: 0.1411
Epoch [7/10], Step [200/938], Loss: 0.0363
Epoch [7/10], Step [300/938], Loss: 0.0203
Epoch [7/10], Step [400/938], Loss: 0.1467
Epoch [7/10], Step [500/938], Loss: 0.0771
Epoch [7/10], Step [600/938], Loss: 0.0529
Epoch [7/10], Step [700/938], Loss: 0.0938
Epoch [7/10], Step [800/938], Loss: 0.0370
Epoch [7/10], Step [900/938], Loss: 0.0660
Epoch [7/10], Loss: 0.0731
EarlyStopping counter: 1 out of 5
Validation - Epoch [7/10], Loss: 0.0983, Accuracy: 96.92%

Epoch [8/10], Step [100/938], Loss: 0.2122
Epoch [8/10], Step [200/938], Loss: 0.0411
Epoch [8/10], Step [300/938], Loss: 0.0945
Epoch [8/10], Step [400/938], Loss: 0.0278
Epoch [8/10], Step [500/938], Loss: 0.0855
Epoch [8/10], Step [600/938], Loss: 0.0477
Epoch [8/10], Step [700/938], Loss: 0.0758
Epoch [8/10], Step [800/938], Loss: 0.0171
Epoch [8/10], Step [900/938], Loss: 0.1193
Epoch [8/10], Loss: 0.0685
EarlyStopping counter: 2 out of 5
Validation - Epoch [8/10], Loss: 0.0955, Accuracy: 97.20%
New best model saved with accuracy: 97.20%

Epoch [9/10], Step [100/938], Loss: 0.0374
Epoch [9/10], Step [200/938], Loss: 0.0376
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Epoch [9/10], Step [300/938], Loss: 0.0417
Epoch [9/10], Step [400/938], Loss: 0.0091
Epoch [9/10], Step [500/938], Loss: 0.0976
Epoch [9/10], Step [600/938], Loss: 0.0440
Epoch [9/10], Step [700/938], Loss: 0.0942
Epoch [9/10], Step [800/938], Loss: 0.0112
Epoch [9/10], Step [900/938], Loss: 0.1761
Epoch [9/10], Loss: 0.0621
EarlyStopping counter: 3 out of 5
Validation - Epoch [9/10], Loss: 0.0996, Accuracy: 96.87%

Epoch [10/10], Step [100/938], Loss: 0.0189
Epoch [10/10], Step [200/938], Loss: 0.0427
Epoch [10/10], Step [300/938], Loss: 0.0367
Epoch [10/10], Step [400/938], Loss: 0.0460
Epoch [10/10], Step [500/938], Loss: 0.1362
Epoch [10/10], Step [600/938], Loss: 0.0072
Epoch [10/10], Step [700/938], Loss: 0.0275
Epoch [10/10], Step [800/938], Loss: 0.0069
Epoch [10/10], Step [900/938], Loss: 0.0329
Epoch [10/10], Loss: 0.0547
EarlyStopping counter: 4 out of 5
Validation - Epoch [10/10], Loss: 0.0969, Accuracy: 97.12%
Learning rate changed from 0.001000 to 0.000100
Training complete!

Final Evaluation:
Final Test Loss: 0.0969
Final Test Accuracy: 97.12%
Final model saved as ./checkpoints\final_model_20250424_215421.pt
```

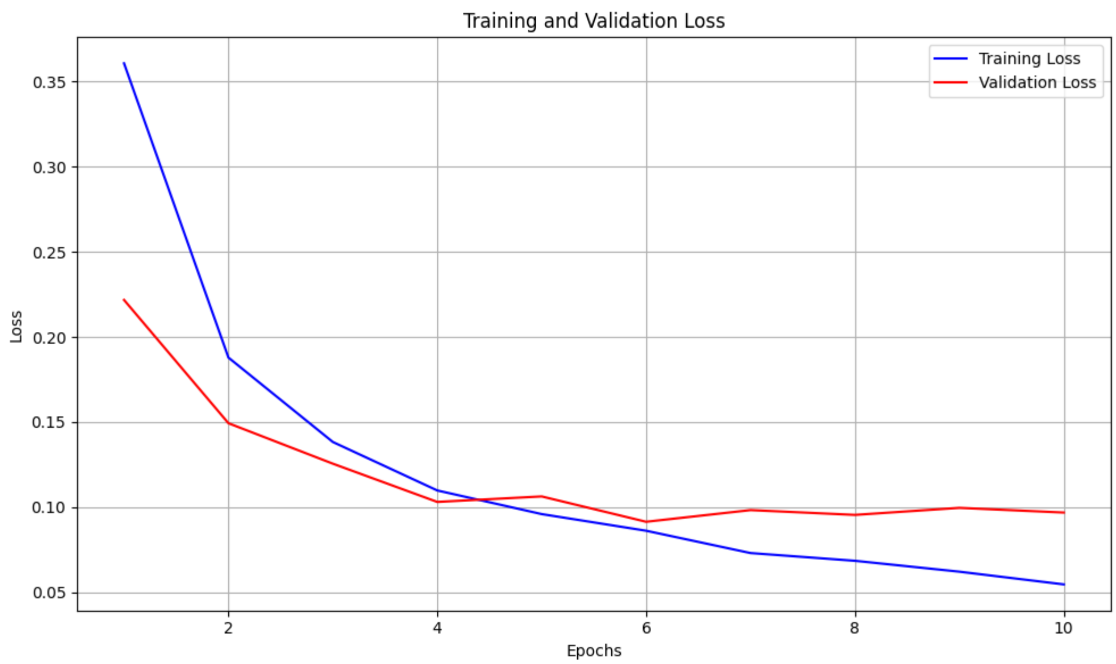

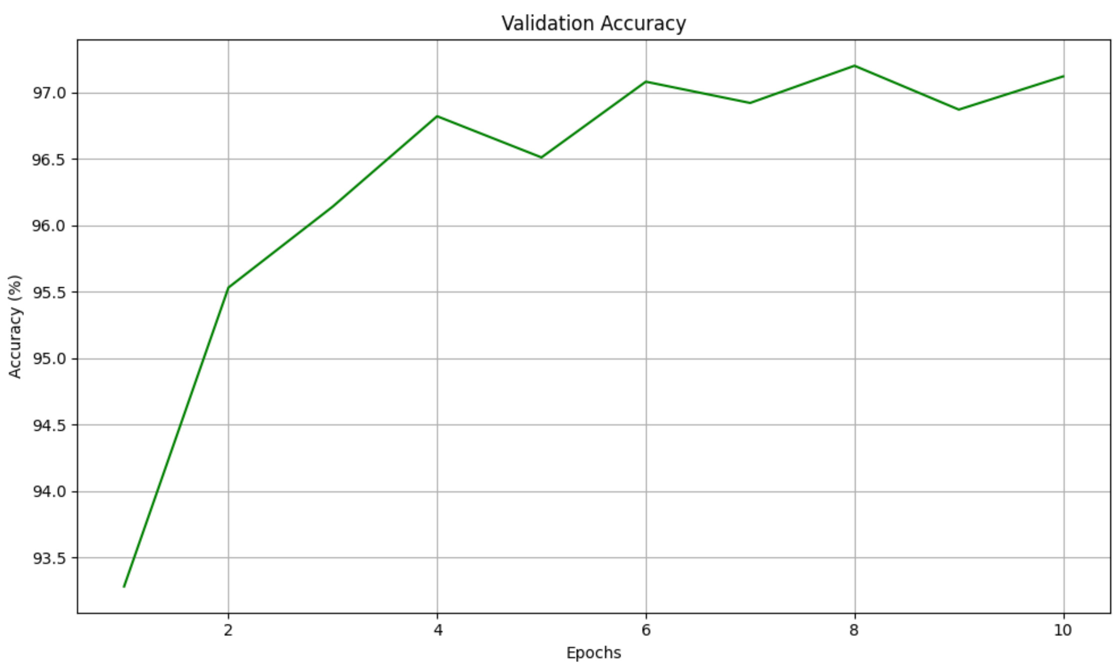

1.6.1 Other version management tools

In this part of the assignment I used MLFlow for version management but there are other tools we can use for version management. * Weights and Biases (W&B) - Cloud-based platform for experiment tracking, visualization and collaboration. * Comet.ml - Cloud-based like W&B. Tracks experiments, code, hyperparameters, metrics, etc. * Data Version Control (DVC) - Works like Git for data and model versioning * TensorBoard - A simplier option for TensorFlow and PyTorch. Great for logging and visualization.