Assignment-1-Part-2-5

April 25, 2025

1 Assignment 1 Part 2.5

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
import time
```

1.2 CNN Layer class: Modified

Added a second layer with input channel 32 and output channel 64

[2]:
```
class CNNLayer(nn.Module):
    def __init__(self, input_channels=1, num_classes=10):
        '''
        Initialize the CNNLayer class

        Parameters:
            input_channels (int): number of channels in the input image
            num_classes (int): number of classes in the output
        '''
        super(CNNLayer, self).__init__()

        # define the convolutional layers
        self.conv_layer = nn.Sequential(
            # create the first convolutional layer
            nn.Conv2d(in_channels=input_channels, out_channels=32,␣
↪kernel_size=3, padding=1),
            # add a ReLU activation function which is recommended for CNNs
            nn.ReLU(),
```

```
            # add a max pooling layer which reduces the size of the image by␣
↪half
            nn.MaxPool2d(kernel_size=2, stride=2),

            # create the second convolutional layer
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3,␣
↪padding=1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2)
        )

        # calculate the size of the flattened layer
        # after the convolutional layer, the image is reduced to 64x7x7
        flattened_size = 64 * 7 * 7

        # define the fully connected layer
        self.fc_layer = nn.Sequential(
            nn.Flatten(), # flatten the image from 3d to 1d
            nn.Linear(flattened_size, 128),
            nn.ReLU(),
            nn.Linear(128, num_classes)
        )

    def forward(self, inputs):
        '''
        Forward pass of the CNNLayer

        Parameters:
            inputs (torch.Tensor): the input image
        '''

        # pass the inputs through the convolutional layer
        outputs = self.conv_layer(inputs)

        # pass the outputs through the fully connected layer
        outputs = self.fc_layer(outputs)

        return outputs
```

1.3 Trainer class

[3]:
```
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
        self.is_cnn = isinstance(self.model, CNNLayer)

        # create checkpoint directory if it doesn't exist
```

```python
        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': [],
            'epoch_times': []  # add tracking of per-epoch times
        }

        # initialize performance tracking
        self.total_training_time = 0
        self.epoch_start_time = 0
        self.total_epochs_completed = 0

    def train_epoch(self, epoch, num_epochs):
        """
        Train the model for one epoch
        """
        # start timing the epoch
        self.epoch_start_time = time.time()

        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 not self.is_cnn and 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)

        # calculate and store epoch time
        epoch_time = time.time() - self.epoch_start_time
        self.history['epoch_times'].append(epoch_time)
        self.total_training_time += epoch_time
        self.total_epochs_completed += 1

        # Print epoch time
        print(f'Epoch time: {epoch_time:.2f} seconds')

        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 not self.is_cnn and 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
        """
        # start timer for total training run
        total_run_start_time = time.time()

        # reset performance tracking for a new training run
        if start_epoch == 0:
            self.total_training_time = 0
            self.total_epochs_completed = 0

        # 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)
                    mlflow.log_metric("epoch_time", self.
↪history['epoch_times'][-1], 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}%')

            # 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

        # Calculate total run time
        total_run_time = time.time() - total_run_start_time

        print("Training complete!")


        # Print performance summary
        print("\nTraining Performance Summary:")
```

```
        print(f"Total training time: {total_run_time:.2f} seconds ({total_run_time/60:.2f} minutes)")
        print(f"Total epochs completed: {self.total_epochs_completed}")
        print(f"Average time per epoch: {self.total_training_time/self.total_epochs_completed:.2f} seconds")
        print(f"Fastest epoch: {min(self.history['epoch_times']):.2f} seconds")
        print(f"Slowest epoch: {max(self.history['epoch_times']):.2f} seconds")

        # Log performance metrics to MLflow
        if log_to_mlflow:
            mlflow.log_metric("total_training_time", total_run_time)
            mlflow.log_metric("avg_epoch_time", self.total_training_time/self.total_epochs_completed)
            mlflow.log_metric("fastest_epoch_time", min(self.history['epoch_times']))
            mlflow.log_metric("slowest_epoch_time", max(self.history['epoch_times']))

        # 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}")

        # log the model with mlflow
        if log_to_mlflow:

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

            sample_batch = next(iter(self.train_loader))[0][:1]
```

```
                if self.is_cnn:
                    # for cnn, use the first batch of the training data
                    sample_input = sample_batch.numpy()
                else:
                    # for fnn, use the first batch of the training data
                    sample_input = sample_batch.view(sample_batch.size(0), -1).
↪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()

        # plot epoch times
        if len(self.history['epoch_times']) > 0:
            plt.figure(figsize=(10, 6))
            plt.plot(epochs, self.history['epoch_times'], 'm-')
            plt.title('Epoch Training Times')
            plt.xlabel('Epoch')
            plt.ylabel('Time (seconds)')
            plt.grid(True)
            plt.savefig(os.path.join(plots_dir, 'epoch_times.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
```

1.4 Runner

[4]:
```
# 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 for training set with augmentation
train_transform = transforms.Compose([
    transforms.RandomRotation(10),
    transforms.RandomAffine(degrees=0, translate=(0.1, 0.1), scale=(0.9, 1.1),␣
 ↪shear=5),
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

# define transformations for test set without augmentation
test_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=train_transform
)

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

```python
# create FNN 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
# )

# create CNN model
input_channels = 1
num_classes = 10
model = CNNLayer(input_channels, num_classes)

# 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',
    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_CNN_Model"
)

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

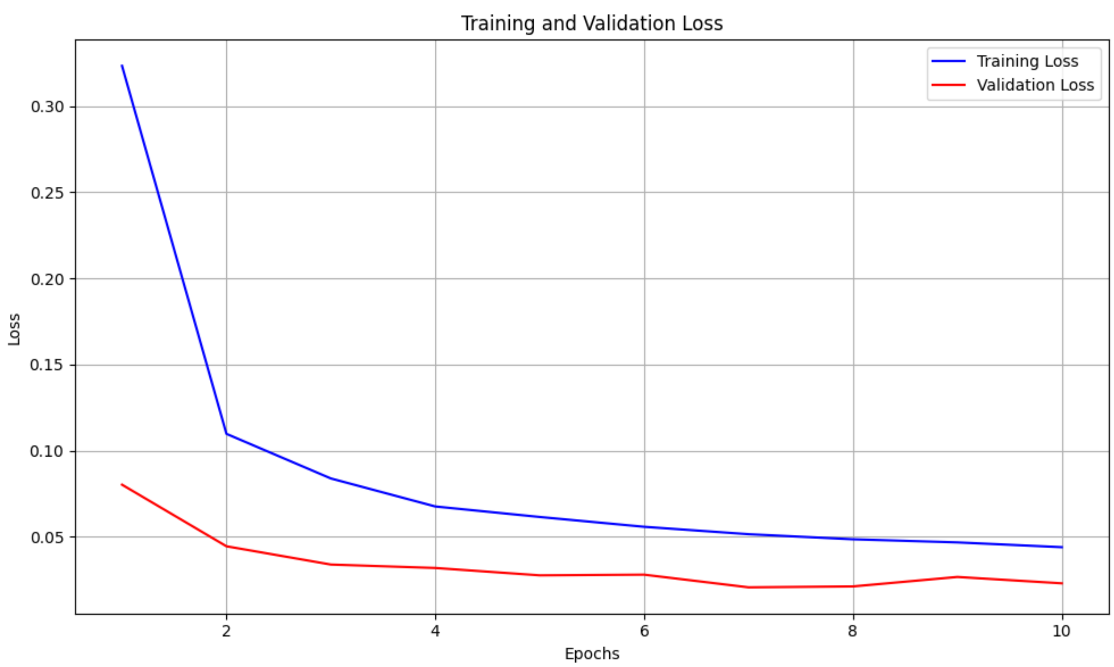
```
)

# 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')
```

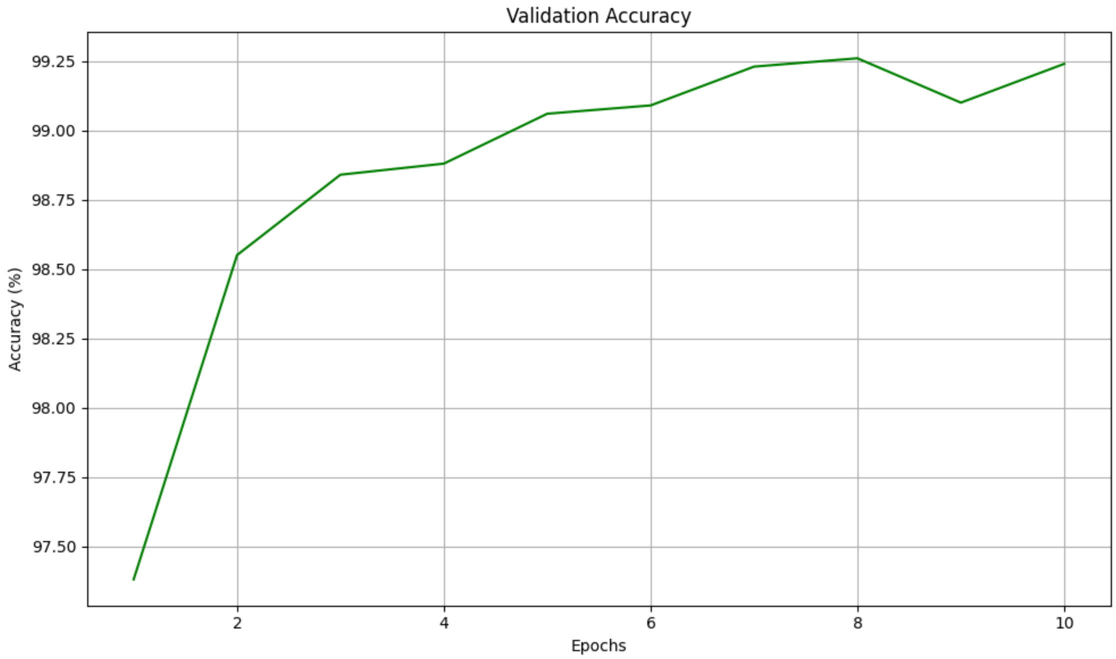
```
Using device: cuda

Starting training…

Epoch [1/10], Step [100/938], Loss: 0.5428
Epoch [1/10], Step [200/938], Loss: 0.2344
Epoch [1/10], Step [300/938], Loss: 0.2716
Epoch [1/10], Step [400/938], Loss: 0.1592
Epoch [1/10], Step [500/938], Loss: 0.0947
Epoch [1/10], Step [600/938], Loss: 0.1205
Epoch [1/10], Step [700/938], Loss: 0.1551
Epoch [1/10], Step [800/938], Loss: 0.2663
Epoch [1/10], Step [900/938], Loss: 0.1149
Epoch time: 33.48 seconds
Epoch [1/10], Loss: 0.3235
Validation - Epoch [1/10], Loss: 0.0802, Accuracy: 97.38%
New best model saved with accuracy: 97.38%

Epoch [2/10], Step [100/938], Loss: 0.1157
Epoch [2/10], Step [200/938], Loss: 0.1394
Epoch [2/10], Step [300/938], Loss: 0.0645
Epoch [2/10], Step [400/938], Loss: 0.1535
Epoch [2/10], Step [500/938], Loss: 0.1854
Epoch [2/10], Step [600/938], Loss: 0.1136
Epoch [2/10], Step [700/938], Loss: 0.0622
Epoch [2/10], Step [800/938], Loss: 0.0549
Epoch [2/10], Step [900/938], Loss: 0.0481
Epoch time: 33.06 seconds
Epoch [2/10], Loss: 0.1097
Validation - Epoch [2/10], Loss: 0.0444, Accuracy: 98.55%
New best model saved with accuracy: 98.55%

Epoch [3/10], Step [100/938], Loss: 0.0816
Epoch [3/10], Step [200/938], Loss: 0.1400
Epoch [3/10], Step [300/938], Loss: 0.0290
Epoch [3/10], Step [400/938], Loss: 0.1129
Epoch [3/10], Step [500/938], Loss: 0.0771
```

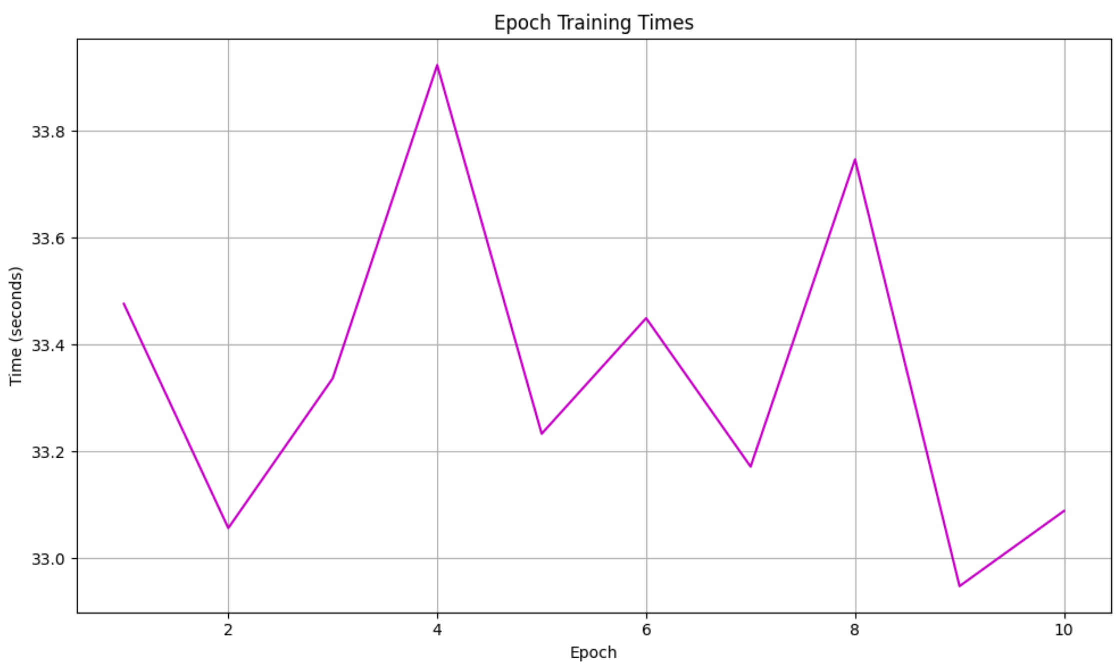
```
Epoch [3/10], Step [600/938], Loss: 0.0300
Epoch [3/10], Step [700/938], Loss: 0.0950
Epoch [3/10], Step [800/938], Loss: 0.0235
Epoch [3/10], Step [900/938], Loss: 0.0194
Epoch time: 33.34 seconds
Epoch [3/10], Loss: 0.0838
Validation - Epoch [3/10], Loss: 0.0338, Accuracy: 98.84%
New best model saved with accuracy: 98.84%

Epoch [4/10], Step [100/938], Loss: 0.0925
Epoch [4/10], Step [200/938], Loss: 0.0752
Epoch [4/10], Step [300/938], Loss: 0.0717
Epoch [4/10], Step [400/938], Loss: 0.0456
Epoch [4/10], Step [500/938], Loss: 0.0360
Epoch [4/10], Step [600/938], Loss: 0.0411
Epoch [4/10], Step [700/938], Loss: 0.1444
Epoch [4/10], Step [800/938], Loss: 0.4482
Epoch [4/10], Step [900/938], Loss: 0.0624
Epoch time: 33.92 seconds
Epoch [4/10], Loss: 0.0675
Validation - Epoch [4/10], Loss: 0.0318, Accuracy: 98.88%
New best model saved with accuracy: 98.88%

Epoch [5/10], Step [100/938], Loss: 0.0836
Epoch [5/10], Step [200/938], Loss: 0.0077
Epoch [5/10], Step [300/938], Loss: 0.0193
Epoch [5/10], Step [400/938], Loss: 0.1097
Epoch [5/10], Step [500/938], Loss: 0.0423
Epoch [5/10], Step [600/938], Loss: 0.0346
Epoch [5/10], Step [700/938], Loss: 0.1023
Epoch [5/10], Step [800/938], Loss: 0.0970
Epoch [5/10], Step [900/938], Loss: 0.0697
Epoch time: 33.23 seconds
Epoch [5/10], Loss: 0.0614
Validation - Epoch [5/10], Loss: 0.0275, Accuracy: 99.06%
New best model saved with accuracy: 99.06%

Epoch [6/10], Step [100/938], Loss: 0.0731
Epoch [6/10], Step [200/938], Loss: 0.1700
Epoch [6/10], Step [300/938], Loss: 0.0205
Epoch [6/10], Step [400/938], Loss: 0.0665
Epoch [6/10], Step [500/938], Loss: 0.1214
Epoch [6/10], Step [600/938], Loss: 0.0443
Epoch [6/10], Step [700/938], Loss: 0.0572
Epoch [6/10], Step [800/938], Loss: 0.0399
Epoch [6/10], Step [900/938], Loss: 0.0768
Epoch time: 33.45 seconds
Epoch [6/10], Loss: 0.0557
```

```
EarlyStopping counter: 1 out of 5
Validation - Epoch [6/10], Loss: 0.0279, Accuracy: 99.09%
New best model saved with accuracy: 99.09%

Epoch [7/10], Step [100/938], Loss: 0.0196
Epoch [7/10], Step [200/938], Loss: 0.0110
Epoch [7/10], Step [300/938], Loss: 0.0103
Epoch [7/10], Step [400/938], Loss: 0.0212
Epoch [7/10], Step [500/938], Loss: 0.0073
Epoch [7/10], Step [600/938], Loss: 0.0175
Epoch [7/10], Step [700/938], Loss: 0.0767
Epoch [7/10], Step [800/938], Loss: 0.0050
Epoch [7/10], Step [900/938], Loss: 0.0097
Epoch time: 33.17 seconds
Epoch [7/10], Loss: 0.0514
Validation - Epoch [7/10], Loss: 0.0206, Accuracy: 99.23%
New best model saved with accuracy: 99.23%

Epoch [8/10], Step [100/938], Loss: 0.1658
Epoch [8/10], Step [200/938], Loss: 0.0222
Epoch [8/10], Step [300/938], Loss: 0.1191
Epoch [8/10], Step [400/938], Loss: 0.0175
Epoch [8/10], Step [500/938], Loss: 0.1153
Epoch [8/10], Step [600/938], Loss: 0.0200
Epoch [8/10], Step [700/938], Loss: 0.0269
Epoch [8/10], Step [800/938], Loss: 0.0572
Epoch [8/10], Step [900/938], Loss: 0.0283
Epoch time: 33.75 seconds
Epoch [8/10], Loss: 0.0485
EarlyStopping counter: 1 out of 5
Validation - Epoch [8/10], Loss: 0.0211, Accuracy: 99.26%
New best model saved with accuracy: 99.26%

Epoch [9/10], Step [100/938], Loss: 0.0122
Epoch [9/10], Step [200/938], Loss: 0.0044
Epoch [9/10], Step [300/938], Loss: 0.0395
Epoch [9/10], Step [400/938], Loss: 0.0713
Epoch [9/10], Step [500/938], Loss: 0.0421
Epoch [9/10], Step [600/938], Loss: 0.1049
Epoch [9/10], Step [700/938], Loss: 0.0322
Epoch [9/10], Step [800/938], Loss: 0.0912
Epoch [9/10], Step [900/938], Loss: 0.0563
Epoch time: 32.95 seconds
Epoch [9/10], Loss: 0.0467
EarlyStopping counter: 2 out of 5
Validation - Epoch [9/10], Loss: 0.0266, Accuracy: 99.10%

Epoch [10/10], Step [100/938], Loss: 0.0783
```

```
Epoch [10/10], Step [200/938], Loss: 0.0027
Epoch [10/10], Step [300/938], Loss: 0.0053
Epoch [10/10], Step [400/938], Loss: 0.0073
Epoch [10/10], Step [500/938], Loss: 0.0109
Epoch [10/10], Step [600/938], Loss: 0.0067
Epoch [10/10], Step [700/938], Loss: 0.0664
Epoch [10/10], Step [800/938], Loss: 0.0197
Epoch [10/10], Step [900/938], Loss: 0.0768
Epoch time: 33.09 seconds
Epoch [10/10], Loss: 0.0439
EarlyStopping counter: 3 out of 5
Validation - Epoch [10/10], Loss: 0.0229, Accuracy: 99.24%
Training complete!

Training Performance Summary:
Total training time: 364.21 seconds (6.07 minutes)
Total epochs completed: 10
Average time per epoch: 33.34 seconds
Fastest epoch: 32.95 seconds
Slowest epoch: 33.92 seconds

Final Evaluation:
Final Test Loss: 0.0229
Final Test Accuracy: 99.24%
Final model saved as ./checkpoints\final_model_20250425_210824.pt
```




Validation Accuracy
99.25
99.00
98.75
98.50
98.25
98.00
97.75
97.50
Accuracy (%)
2
4
6
8
10
Epochs


Epoch Training Times
33.8
33.6
33.4
33.2
33.0
Time (seconds)
2
4
6
8
10
Epoch

1.4.1 How different model architecture affects the result? What type of features are typically detected by the later convolutional layers compared to the first convolutional layer?

Deeper networks (more layers) can capture more complex pattern, while wider layers (more filter per layer) can capture more variety of patterns with the same level of abstraction. In our case adding more layer can increase the performance but also can be a bit overkill because we have relatively simple task. Adding more layer (thrid and fourth) will only give us a small increase to performance.

The first layer detects visual features such as edges, lines, and simple texture with different orientations. The second layer uses the first layers simple features to detect more complex patterns.