

Introduction

what is a neural network?

A neural Network is a computational model inspired by the human brain. Each neuron receives an activation signal from the preceding layer and computes some value that is propagated forward ##### Key Concepts:

- **Input Layer:** Receives the raw input data (e.g., pixel values from an image).
- **Hidden Layers:** Perform computations to extract meaningful features.
- **Output Layer:** Produces the final predictions (e.g., the digit class).

Activation Functions: Activation functions (e.g., ReLU, sigmoid) introduce non-linearity into the model, enabling it to learn complex patterns.

Loss Function: The loss function measures the error between the predicted outputs and the true labels. In this task, we'll use Cross Entropy Loss, which is commonly used for classification problems.

Optimization: The optimizer (e.g., Stochastic Gradient Descent) updates the network's weights to minimize the loss function during training.

Problem Statement: In this assignment, we will use the MNIST dataset to train a neural network to classify handwritten digits (0-9). We'll explore various hyperparameters, analyze their effects, and optionally use advanced techniques such as convolutional layers and dropout.

1 Data Processing

before we attempt to train our model we must make sure that our data conforms with required criteria:

- the samples are tensors
- 60 % training , 20 % validation , 20 % test
- keep a "stratified" manner to avoid data skewing

```
import torch
import torch.nn as nn
import torch.optim as optim
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
import numpy as np
import pandas as pd
from torchvision import datasets, transforms
from torch.utils.data import DataLoader, Subset, ConcatDataset
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import numpy as np
```

```

# Apply transformations (convert to tensor and normalize)
transform = transforms.Compose([
    transforms.ToTensor(), #convert vector values in range [0,1]
    transforms.Normalize((0.5,), (0.5,)) # Normalize to [-1, 1] range
    (z socre)
])

# Load the MNIST dataset
train_dataset = datasets.MNIST(root='./data', train=True,
transform=transform) #this structure contains data and labels
test_dataset = datasets.MNIST(root='./data', train=False,
transform=transform)

#combine the datasets
combined_dataset=ConcatDataset([train_dataset,test_dataset])

#extract labels
train_labels=train_dataset.targets
test_labels=test_dataset.targets

# Combine labels from both train and test datasets
all_labels = torch.cat((train_labels, test_labels), dim=0)

#split into 60-40
train_idx, temp_idx = train_test_split(
    range(len(combined_dataset)), test_size=0.4, stratify=all_labels,
    random_state=42) # stratify 3lshan not to get skewed data

#split again 20-20
# Split temp (40%) into validation (20%) and test (20%)
val_idx, test_idx = train_test_split(
    temp_idx, test_size=0.5, stratify=all_labels[temp_idx],
    random_state=42) # returns indices

# Create Subset objects for train, validation, and test sets
train_data = Subset(combined_dataset, train_idx)
val_data = Subset(combined_dataset, val_idx)
test_data = Subset(combined_dataset, test_idx)

##recreate dataset w inheirt combatible structure with data loader
# Create DataLoader objects
batch_size = 32
train_loader = DataLoader(train_data, batch_size=batch_size,
shuffle=True)
val_loader = DataLoader(val_data, batch_size=batch_size,
shuffle=False)
test_loader = DataLoader(test_data, batch_size=batch_size,

```

```

shuffle=False)

# Print split sizes
print(f"Training set size: {len(train_data)}")
print(f"Validation set size: {len(val_data)}")
print(f"Test set size: {len(test_data)}")
print("Data preparation complete!")

```

```

Training set size: 42000
Validation set size: 14000
Test set size: 14000
Data preparation complete!

```

now we build our neural network architecture. we will start with a basic model containing a single hidden layer.

```

# 2 create neural network structure
class Neural_Network_1_hidden_layer(nn.Module):
    def __init__(self, input_size=28*28, hidden_size=10,
num_classes=10):
        super(Neural_Network_1_hidden_layer, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.fc2 = nn.Linear(hidden_size, num_classes)

    def forward(self, x):
        x = x.view(-1, 28*28) # Flatten the input
        x = torch.relu(self.fc1(x)) # Apply ReLU activation after
first hidden layer
        x = self.fc2(x) # Output layer
        return x

```

before we start the training process we need to make sure that we are using GPU accelerated training

```

# 3. Set device to GPU if available, else fallback to CPU
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Instantiate the model and move it to the selected device
model = Neural_Network_1_hidden_layer().to(device)

# Loss function and optimizer
criterion = nn.CrossEntropyLoss() # computd cross entropy with softmax
optimizer = optim.SGD(model.parameters(), lr=0.01)

```

we will now proceed to train our model for 10 epochs where each epoch consists of a training phase followed by a vildation phase.

4. Training Process

```
def train_model(model, train_loader, val_loader, criterion, optimizer,
num_epochs=10):
    train_losses, val_losses = [], []
    train_accuracies, val_accuracies = [], []

    for epoch in range(num_epochs):
        model.train()
        running_loss = 0.0 # this is the cumulative loss during epoch
        correct_train = 0
        total_train = 0

        # Train the model on the training set
        for images, labels in train_loader:
            images, labels = images.to(device), labels.to(device) #
            # Move to GPU

            optimizer.zero_grad()
            outputs = model(images) # Forward pass
            loss = criterion(outputs, labels) # Compute loss
            loss.backward() # Backward pass (compute gradients)
            optimizer.step() # Update weights

            running_loss += loss.item()
            _, predicted = torch.max(outputs, 1) # Get the predicted
            # class

            correct_train += (predicted == labels).sum().item()
            total_train += labels.size(0)

        avg_train_loss = running_loss / len(train_loader)
        train_accuracy = correct_train / total_train * 100
        train_losses.append(avg_train_loss)
        train_accuracies.append(train_accuracy)

        # Validation phase
        model.eval()
        running_loss = 0.0
        correct_val = 0
        total_val = 0

        with torch.no_grad():
            for images, labels in val_loader:
                images, labels = images.to(device), labels.to(device)
                # Move to GPU

                outputs = model(images) # Forward pass
                loss = criterion(outputs, labels)

                running_loss += loss.item()
                _, predicted = torch.max(outputs, 1)
```

```

        correct_val += (predicted == labels).sum().item()
        total_val += labels.size(0)

    avg_val_loss = running_loss / len(val_loader)
    val_accuracy = correct_val / total_val * 100
    val_losses.append(avg_val_loss)
    val_accuracies.append(val_accuracy)

    print(f"Epoch [{epoch+1}/{num_epochs}], "
          f"Train Loss: {avg_train_loss:.4f}, Train Accuracy: "
          f"{train_accuracy:.2f}%, "
          f"Validation Loss: {avg_val_loss:.4f}, Validation "
          f"Accuracy: {val_accuracy:.2f}%")

    return train_losses, val_losses, train_accuracies, val_accuracies

# Train the model
train_losses, val_losses, train_accuracies, val_accuracies =
train_model(
    model, train_loader, val_loader, criterion, optimizer,
    num_epochs=10
)

```

```

Epoch [1/10], Train Loss: 0.7482, Train Accuracy: 79.45%, Validation
Loss: 0.4044, Validation Accuracy: 88.41%
Epoch [2/10], Train Loss: 0.3660, Train Accuracy: 89.56%, Validation
Loss: 0.3581, Validation Accuracy: 89.84%
Epoch [3/10], Train Loss: 0.3296, Train Accuracy: 90.50%, Validation
Loss: 0.3440, Validation Accuracy: 90.03%
Epoch [4/10], Train Loss: 0.3111, Train Accuracy: 91.06%, Validation
Loss: 0.3429, Validation Accuracy: 90.07%
Epoch [5/10], Train Loss: 0.2971, Train Accuracy: 91.52%, Validation
Loss: 0.3994, Validation Accuracy: 87.59%
Epoch [6/10], Train Loss: 0.2860, Train Accuracy: 91.93%, Validation
Loss: 0.3136, Validation Accuracy: 90.84%
Epoch [7/10], Train Loss: 0.2774, Train Accuracy: 92.08%, Validation
Loss: 0.2960, Validation Accuracy: 91.43%
Epoch [8/10], Train Loss: 0.2704, Train Accuracy: 92.21%, Validation
Loss: 0.2918, Validation Accuracy: 91.71%
Epoch [9/10], Train Loss: 0.2648, Train Accuracy: 92.42%, Validation
Loss: 0.2877, Validation Accuracy: 91.74%
Epoch [10/10], Train Loss: 0.2601, Train Accuracy: 92.64%, Validation
Loss: 0.2798, Validation Accuracy: 91.90%

```

now we plot the performance of our simple model

```

# 5. Plot Training and Validation Loss
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(train_losses, label='Training Loss')

```

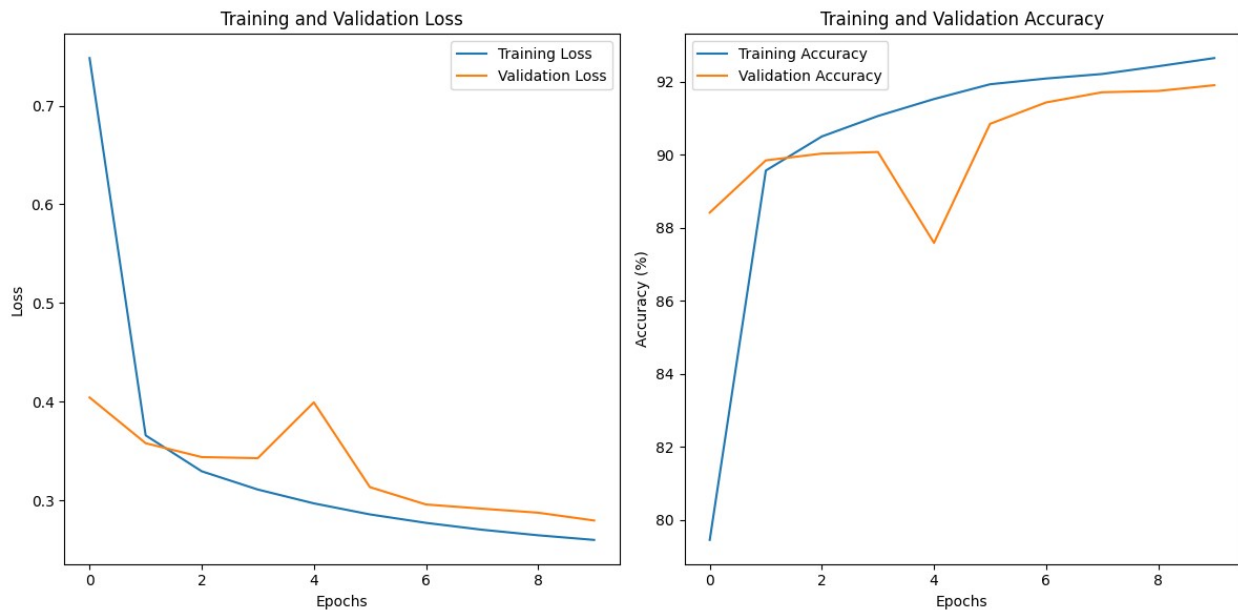
```

plt.plot(val_losses, label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# 6. Plot Training and Validation Accuracy
plt.subplot(1, 2, 2)
plt.plot(train_accuracies, label='Training Accuracy')
plt.plot(val_accuracies, label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy (%)')
plt.legend()

plt.tight_layout()
plt.show()

```



part 2

for this part we will attempt to tune the model parameters by tweaking a single paramter(the others remain constant) and retraining the model and then comparing results we will use the following paramters:

- number of hiddeden layers =[1,3,5,7]
- number of neurons per hidden layer= [10,20,30,40]
- batch size for stochastic gradient descent= [32,64,128,256]
- learning rate =[0.10.01,0.001,0.0001]

in total, we train the model for a total of 16 times.

Total iterations: 6+6+6+6=24

we will create a function that iterates over the said parameters but firstly we define our parameter ranges in a dictionary.

```
# Hyperparameters for tuning
default_params = {
    "hidden_layers": 1, # Number of hidden layers
    "hidden_size": 10, # Number of neurons per hidden layer
    "batch_size": 32, # Batch size for SGD
    "learning_rate": 0.01 # Learning rate
}

# Define the ranges for each hyperparameter
param_ranges = {
    "hidden_layers": [1, 3, 5, 7, 9, 11],
    "hidden_size": [10, 20, 30, 40, 50, 60],
    "batch_size": [32, 64, 128, 256, 500, 1000],
    "learning_rate": [0.1, 0.01, 0.001, 0.0001, 0.00001, 0.000001]
}
```

then we proceed to create a neural network class with a variable layer size

```
def train_model(model, train_loader, val_loader, criterion, optimizer,
num_epochs=10):
    train_losses, val_losses = [], []
    train_accuracies, val_accuracies = [], []
    y_true, y_pred = [], []

    for epoch in range(num_epochs):
        model.train()
        running_loss = 0.0
        correct_train = 0
        total_train = 0

        for images, labels in train_loader:
            images, labels = images.to(device), labels.to(device) #
            # Move to GPU/CPU
            optimizer.zero_grad() # remove gradients to prevent
            # gradient accumulation
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward() # calculate gradients
            optimizer.step() # update weights

            running_loss += loss.item() # add current batch loss
            _, predicted = torch.max(outputs, 1) # index of max
            # probability
            correct_train += (predicted == labels).sum().item()
            total_train += labels.size(0) # keep track of all samples
```

```

trained

    avg_train_loss = running_loss / len(train_loader)
    train_accuracy = correct_train / total_train * 100
    train_losses.append(avg_train_loss)
    train_accuracies.append(train_accuracy)

    # Validation phase
    model.eval()
    running_loss = 0.0
    correct_val = 0
    total_val = 0
    with torch.no_grad():
        for images, labels in val_loader:
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            loss = criterion(outputs, labels)
            running_loss += loss.item()
            _, predicted = torch.max(outputs, 1)
            correct_val += (predicted == labels).sum().item()
            total_val += labels.size(0)
            y_true.extend(labels.cpu().numpy()) ##move to cpu for
transforming into numpy array
            y_pred.extend(predicted.cpu().numpy())

    avg_val_loss = running_loss / len(val_loader)
    val_accuracy = correct_val / total_val * 100
    val_losses.append(avg_val_loss)
    val_accuracies.append(val_accuracy)

    print(f"Epoch [{epoch+1}/{num_epochs}], Train Loss:
    {avg_train_loss:.4f}, Train Accuracy: {train_accuracy:.2f}%, "
          f"Validation Loss: {avg_val_loss:.4f}, Validation
    Accuracy: {val_accuracy:.2f}%")

    # Return all six variables
    return train_losses, val_losses, train_accuracies, val_accuracies,
    y_true, y_pred

```

note that the softmax activation function is not applied directly since the loss criterion is a compound function.

```

# Function to build a model with variable hidden layers
class NeuralNetwork(nn.Module):
    def __init__(self, input_size, hidden_layers, hidden_size,
num_classes):
        super(NeuralNetwork, self).__init__()
        layers = []
        for i in range(hidden_layers):

```



```

        if i == 0:
            layers.append(nn.Linear(input_size, hidden_size)) #
for inout layer
        else:
            layers.append(nn.Linear(hidden_size, hidden_size))
##every layer in between
            layers.append(nn.ReLU())
            layers.append(nn.Linear(hidden_size, num_classes)) # Final
output layer
        self.network = nn.Sequential(*layers) ##link layers

def forward(self, x):
    x = x.view(-1, 28 * 28) # Flatten input
    return self.network(x)

```

a function that iterates over parameter values

```

# Hyperparameter tuning function
def tune_hyperparameters(default_params, param_ranges, num_epochs=10):
    results = []

    # Iterate over each parameter
    for param, values in param_ranges.items():
        for value in values:
            # Update the parameter value
            params = default_params.copy()
            params[param] = value

            # Update DataLoader if batch_size changes
            batch_size = params["batch_size"]
            train_loader = DataLoader(train_data,
batch_size=batch_size, shuffle=True)
            val_loader = DataLoader(val_data, batch_size=batch_size,
shuffle=False)

            # Build the model
            model = NeuralNetwork(
                input_size=28 * 28,
                hidden_layers=params["hidden_layers"],
                hidden_size=params["hidden_size"],
                num_classes=10
            ).to(device)

            # Define optimizer with new learning rate
            optimizer = optim.SGD(model.parameters(),
lr=params["learning_rate"])
            criterion = nn.CrossEntropyLoss()

            # Train the model

```

```

        train_losses, val_losses, train_accuracies,
        val_accuracies, y_true, y_pred = train_model(
            model, train_loader, val_loader, criterion, optimizer,
            num_epochs=num_epochs
        )

        # Record results
        results.append({
            "param": param,
            "value": value,
            "train_accuracy": train_accuracies[-1],
            "val_accuracy": val_accuracies[-1],
            "train_loss": train_losses[-1],
            "val_loss": val_losses[-1],
            "y_true": y_true,
            "y_pred": y_pred
        })

        print(f"Completed training for {param} = {value}")

    return results

```

```

results = tune_hyperparameters(default_params, param_ranges)

```

```

Epoch [1/10], Train Loss: 0.7375, Train Accuracy: 78.66%, Validation
Loss: 0.4049, Validation Accuracy: 88.85%
Epoch [2/10], Train Loss: 0.3615, Train Accuracy: 89.62%, Validation
Loss: 0.3425, Validation Accuracy: 90.00%
Epoch [3/10], Train Loss: 0.3255, Train Accuracy: 90.47%, Validation
Loss: 0.3280, Validation Accuracy: 90.59%
Epoch [4/10], Train Loss: 0.3084, Train Accuracy: 91.12%, Validation
Loss: 0.3418, Validation Accuracy: 90.21%
Epoch [5/10], Train Loss: 0.2994, Train Accuracy: 91.34%, Validation
Loss: 0.3279, Validation Accuracy: 90.37%
Epoch [6/10], Train Loss: 0.2913, Train Accuracy: 91.56%, Validation
Loss: 0.3195, Validation Accuracy: 90.84%
Epoch [7/10], Train Loss: 0.2862, Train Accuracy: 91.77%, Validation
Loss: 0.3006, Validation Accuracy: 91.45%
Epoch [8/10], Train Loss: 0.2806, Train Accuracy: 92.00%, Validation
Loss: 0.3118, Validation Accuracy: 91.15%
Epoch [9/10], Train Loss: 0.2762, Train Accuracy: 92.06%, Validation
Loss: 0.2992, Validation Accuracy: 91.62%
Epoch [10/10], Train Loss: 0.2725, Train Accuracy: 92.13%, Validation
Loss: 0.3069, Validation Accuracy: 91.14%
Completed training for hidden_layers = 1
Epoch [1/10], Train Loss: 1.5809, Train Accuracy: 42.68%, Validation
Loss: 0.8274, Validation Accuracy: 71.73%
Epoch [2/10], Train Loss: 0.6531, Train Accuracy: 78.79%, Validation
Loss: 0.5995, Validation Accuracy: 80.88%
Epoch [3/10], Train Loss: 0.5063, Train Accuracy: 84.48%, Validation

```

Loss: 0.5137, Validation Accuracy: 83.95%
Epoch [4/10], Train Loss: 0.4301, Train Accuracy: 87.00%, Validation
Loss: 0.4086, Validation Accuracy: 87.99%
Epoch [5/10], Train Loss: 0.3751, Train Accuracy: 88.84%, Validation
Loss: 0.4090, Validation Accuracy: 87.93%
Epoch [6/10], Train Loss: 0.3418, Train Accuracy: 90.00%, Validation
Loss: 0.3557, Validation Accuracy: 89.86%
Epoch [7/10], Train Loss: 0.3157, Train Accuracy: 90.79%, Validation
Loss: 0.3233, Validation Accuracy: 90.57%
Epoch [8/10], Train Loss: 0.2968, Train Accuracy: 91.26%, Validation
Loss: 0.3579, Validation Accuracy: 89.38%
Epoch [9/10], Train Loss: 0.2832, Train Accuracy: 91.72%, Validation
Loss: 0.2979, Validation Accuracy: 91.59%
Epoch [10/10], Train Loss: 0.2712, Train Accuracy: 92.02%, Validation
Loss: 0.3433, Validation Accuracy: 89.72%
Completed training for hidden_layers = 3
Epoch [1/10], Train Loss: 2.2908, Train Accuracy: 12.75%, Validation
Loss: 2.2298, Validation Accuracy: 18.09%
Epoch [2/10], Train Loss: 1.9531, Train Accuracy: 22.17%, Validation
Loss: 1.7552, Validation Accuracy: 27.11%
Epoch [3/10], Train Loss: 1.5279, Train Accuracy: 40.68%, Validation
Loss: 1.3227, Validation Accuracy: 52.06%
Epoch [4/10], Train Loss: 1.1080, Train Accuracy: 61.25%, Validation
Loss: 0.7788, Validation Accuracy: 75.16%
Epoch [5/10], Train Loss: 0.6799, Train Accuracy: 79.25%, Validation
Loss: 0.5745, Validation Accuracy: 83.99%
Epoch [6/10], Train Loss: 0.5219, Train Accuracy: 84.90%, Validation
Loss: 0.4639, Validation Accuracy: 86.96%
Epoch [7/10], Train Loss: 0.4530, Train Accuracy: 86.78%, Validation
Loss: 0.4664, Validation Accuracy: 86.40%
Epoch [8/10], Train Loss: 0.4098, Train Accuracy: 88.05%, Validation
Loss: 0.4443, Validation Accuracy: 87.19%
Epoch [9/10], Train Loss: 0.3797, Train Accuracy: 88.95%, Validation
Loss: 0.4168, Validation Accuracy: 87.31%
Epoch [10/10], Train Loss: 0.3539, Train Accuracy: 89.63%, Validation
Loss: 0.3976, Validation Accuracy: 88.86%
Completed training for hidden_layers = 5
Epoch [1/10], Train Loss: 2.3053, Train Accuracy: 10.67%, Validation
Loss: 2.3017, Validation Accuracy: 11.26%
Epoch [2/10], Train Loss: 2.3014, Train Accuracy: 11.25%, Validation
Loss: 2.3011, Validation Accuracy: 11.26%
Epoch [3/10], Train Loss: 2.3012, Train Accuracy: 11.25%, Validation
Loss: 2.3010, Validation Accuracy: 11.26%
Epoch [4/10], Train Loss: 2.3012, Train Accuracy: 11.25%, Validation
Loss: 2.3009, Validation Accuracy: 11.26%
Epoch [5/10], Train Loss: 2.3011, Train Accuracy: 11.25%, Validation
Loss: 2.3008, Validation Accuracy: 11.26%
Epoch [6/10], Train Loss: 2.3008, Train Accuracy: 11.25%, Validation
Loss: 2.3005, Validation Accuracy: 11.26%

Epoch [7/10], Train Loss: 2.3001, Train Accuracy: 11.25%, Validation Loss: 2.2989, Validation Accuracy: 11.26%
Epoch [8/10], Train Loss: 2.2944, Train Accuracy: 11.25%, Validation Loss: 2.2821, Validation Accuracy: 11.26%
Epoch [9/10], Train Loss: 2.1158, Train Accuracy: 20.66%, Validation Loss: 1.8593, Validation Accuracy: 19.96%
Epoch [10/10], Train Loss: 1.7073, Train Accuracy: 27.73%, Validation Loss: 1.5794, Validation Accuracy: 34.14%
Completed training for hidden_layers = 7
Epoch [1/10], Train Loss: 2.3041, Train Accuracy: 10.35%, Validation Loss: 2.3014, Validation Accuracy: 11.26%
Epoch [2/10], Train Loss: 2.3014, Train Accuracy: 11.25%, Validation Loss: 2.3011, Validation Accuracy: 11.26%
Epoch [3/10], Train Loss: 2.3013, Train Accuracy: 11.25%, Validation Loss: 2.3011, Validation Accuracy: 11.26%
Epoch [4/10], Train Loss: 2.3013, Train Accuracy: 11.25%, Validation Loss: 2.3011, Validation Accuracy: 11.26%
Epoch [5/10], Train Loss: 2.3013, Train Accuracy: 11.25%, Validation Loss: 2.3011, Validation Accuracy: 11.26%
Epoch [6/10], Train Loss: 2.3013, Train Accuracy: 11.25%, Validation Loss: 2.3011, Validation Accuracy: 11.26%
Epoch [7/10], Train Loss: 2.3012, Train Accuracy: 11.25%, Validation Loss: 2.3011, Validation Accuracy: 11.26%
Epoch [8/10], Train Loss: 2.3012, Train Accuracy: 11.25%, Validation Loss: 2.3010, Validation Accuracy: 11.26%
Epoch [9/10], Train Loss: 2.3012, Train Accuracy: 11.25%, Validation Loss: 2.3010, Validation Accuracy: 11.26%
Epoch [10/10], Train Loss: 2.3011, Train Accuracy: 11.25%, Validation Loss: 2.3009, Validation Accuracy: 11.26%
Completed training for hidden_layers = 9
Epoch [1/10], Train Loss: 2.3072, Train Accuracy: 9.87%, Validation Loss: 2.3017, Validation Accuracy: 11.26%
Epoch [2/10], Train Loss: 2.3015, Train Accuracy: 11.24%, Validation Loss: 2.3012, Validation Accuracy: 11.26%
Epoch [3/10], Train Loss: 2.3013, Train Accuracy: 11.25%, Validation Loss: 2.3011, Validation Accuracy: 11.26%
Epoch [4/10], Train Loss: 2.3013, Train Accuracy: 11.25%, Validation Loss: 2.3012, Validation Accuracy: 11.26%
Epoch [5/10], Train Loss: 2.3013, Train Accuracy: 11.25%, Validation Loss: 2.3011, Validation Accuracy: 11.26%
Epoch [6/10], Train Loss: 2.3013, Train Accuracy: 11.25%, Validation Loss: 2.3011, Validation Accuracy: 11.26%
Epoch [7/10], Train Loss: 2.3013, Train Accuracy: 11.25%, Validation Loss: 2.3011, Validation Accuracy: 11.26%
Epoch [8/10], Train Loss: 2.3013, Train Accuracy: 11.25%, Validation Loss: 2.3011, Validation Accuracy: 11.26%
Epoch [9/10], Train Loss: 2.3013, Train Accuracy: 11.25%, Validation Loss: 2.3011, Validation Accuracy: 11.26%
Epoch [10/10], Train Loss: 2.3013, Train Accuracy: 11.25%, Validation

Loss: 2.3011, Validation Accuracy: 11.26%
Completed training for hidden_layers = 11
Epoch [1/10], Train Loss: 0.7830, Train Accuracy: 78.27%, Validation Loss: 0.4372, Validation Accuracy: 87.58%
Epoch [2/10], Train Loss: 0.3814, Train Accuracy: 88.90%, Validation Loss: 0.3614, Validation Accuracy: 89.36%
Epoch [3/10], Train Loss: 0.3350, Train Accuracy: 90.36%, Validation Loss: 0.3475, Validation Accuracy: 89.90%
Epoch [4/10], Train Loss: 0.3115, Train Accuracy: 91.08%, Validation Loss: 0.3231, Validation Accuracy: 90.75%
Epoch [5/10], Train Loss: 0.2961, Train Accuracy: 91.46%, Validation Loss: 0.3086, Validation Accuracy: 90.92%
Epoch [6/10], Train Loss: 0.2833, Train Accuracy: 91.88%, Validation Loss: 0.2998, Validation Accuracy: 91.51%
Epoch [7/10], Train Loss: 0.2751, Train Accuracy: 92.00%, Validation Loss: 0.3017, Validation Accuracy: 91.36%
Epoch [8/10], Train Loss: 0.2667, Train Accuracy: 92.17%, Validation Loss: 0.2924, Validation Accuracy: 91.62%
Epoch [9/10], Train Loss: 0.2601, Train Accuracy: 92.45%, Validation Loss: 0.2847, Validation Accuracy: 91.79%
Epoch [10/10], Train Loss: 0.2547, Train Accuracy: 92.53%, Validation Loss: 0.3030, Validation Accuracy: 91.38%
Completed training for hidden_size = 10
Epoch [1/10], Train Loss: 0.7059, Train Accuracy: 80.71%, Validation Loss: 0.3968, Validation Accuracy: 88.72%
Epoch [2/10], Train Loss: 0.3519, Train Accuracy: 89.83%, Validation Loss: 0.3286, Validation Accuracy: 90.76%
Epoch [3/10], Train Loss: 0.3127, Train Accuracy: 91.00%, Validation Loss: 0.3088, Validation Accuracy: 91.26%
Epoch [4/10], Train Loss: 0.2883, Train Accuracy: 91.61%, Validation Loss: 0.2931, Validation Accuracy: 91.43%
Epoch [5/10], Train Loss: 0.2701, Train Accuracy: 92.24%, Validation Loss: 0.2775, Validation Accuracy: 91.84%
Epoch [6/10], Train Loss: 0.2552, Train Accuracy: 92.68%, Validation Loss: 0.2724, Validation Accuracy: 91.91%
Epoch [7/10], Train Loss: 0.2423, Train Accuracy: 92.93%, Validation Loss: 0.2627, Validation Accuracy: 92.46%
Epoch [8/10], Train Loss: 0.2322, Train Accuracy: 93.30%, Validation Loss: 0.2504, Validation Accuracy: 92.81%
Epoch [9/10], Train Loss: 0.2232, Train Accuracy: 93.59%, Validation Loss: 0.2501, Validation Accuracy: 92.60%
Epoch [10/10], Train Loss: 0.2144, Train Accuracy: 93.77%, Validation Loss: 0.2382, Validation Accuracy: 93.11%
Completed training for hidden_size = 20
Epoch [1/10], Train Loss: 0.6799, Train Accuracy: 82.15%, Validation Loss: 0.3854, Validation Accuracy: 88.96%
Epoch [2/10], Train Loss: 0.3493, Train Accuracy: 90.03%, Validation Loss: 0.3376, Validation Accuracy: 90.21%
Epoch [3/10], Train Loss: 0.3111, Train Accuracy: 91.03%, Validation

Loss: 0.3203, Validation Accuracy: 90.54%
Epoch [4/10], Train Loss: 0.2878, Train Accuracy: 91.74%, Validation
Loss: 0.2998, Validation Accuracy: 91.16%
Epoch [5/10], Train Loss: 0.2682, Train Accuracy: 92.25%, Validation
Loss: 0.2777, Validation Accuracy: 92.16%
Epoch [6/10], Train Loss: 0.2502, Train Accuracy: 92.82%, Validation
Loss: 0.2590, Validation Accuracy: 92.55%
Epoch [7/10], Train Loss: 0.2344, Train Accuracy: 93.33%, Validation
Loss: 0.2470, Validation Accuracy: 92.89%
Epoch [8/10], Train Loss: 0.2208, Train Accuracy: 93.64%, Validation
Loss: 0.2356, Validation Accuracy: 93.29%
Epoch [9/10], Train Loss: 0.2086, Train Accuracy: 94.15%, Validation
Loss: 0.2260, Validation Accuracy: 93.57%
Epoch [10/10], Train Loss: 0.1964, Train Accuracy: 94.40%, Validation
Loss: 0.2206, Validation Accuracy: 93.71%
Completed training for hidden_size = 30
Epoch [1/10], Train Loss: 0.6885, Train Accuracy: 82.46%, Validation
Loss: 0.3941, Validation Accuracy: 88.69%
Epoch [2/10], Train Loss: 0.3496, Train Accuracy: 89.99%, Validation
Loss: 0.3416, Validation Accuracy: 90.18%
Epoch [3/10], Train Loss: 0.3084, Train Accuracy: 91.11%, Validation
Loss: 0.3089, Validation Accuracy: 90.86%
Epoch [4/10], Train Loss: 0.2814, Train Accuracy: 91.87%, Validation
Loss: 0.2868, Validation Accuracy: 91.72%
Epoch [5/10], Train Loss: 0.2602, Train Accuracy: 92.56%, Validation
Loss: 0.2625, Validation Accuracy: 92.36%
Epoch [6/10], Train Loss: 0.2416, Train Accuracy: 93.03%, Validation
Loss: 0.2529, Validation Accuracy: 92.66%
Epoch [7/10], Train Loss: 0.2254, Train Accuracy: 93.51%, Validation
Loss: 0.2498, Validation Accuracy: 92.72%
Epoch [8/10], Train Loss: 0.2101, Train Accuracy: 94.01%, Validation
Loss: 0.2252, Validation Accuracy: 93.63%
Epoch [9/10], Train Loss: 0.1983, Train Accuracy: 94.37%, Validation
Loss: 0.2128, Validation Accuracy: 93.86%
Epoch [10/10], Train Loss: 0.1865, Train Accuracy: 94.65%, Validation
Loss: 0.2021, Validation Accuracy: 94.09%
Completed training for hidden_size = 40
Epoch [1/10], Train Loss: 0.6572, Train Accuracy: 82.99%, Validation
Loss: 0.3835, Validation Accuracy: 88.89%
Epoch [2/10], Train Loss: 0.3438, Train Accuracy: 90.05%, Validation
Loss: 0.3367, Validation Accuracy: 90.19%
Epoch [3/10], Train Loss: 0.3032, Train Accuracy: 91.23%, Validation
Loss: 0.3024, Validation Accuracy: 91.25%
Epoch [4/10], Train Loss: 0.2780, Train Accuracy: 91.93%, Validation
Loss: 0.2769, Validation Accuracy: 92.14%
Epoch [5/10], Train Loss: 0.2553, Train Accuracy: 92.55%, Validation
Loss: 0.2700, Validation Accuracy: 92.50%
Epoch [6/10], Train Loss: 0.2352, Train Accuracy: 93.25%, Validation
Loss: 0.2536, Validation Accuracy: 92.51%

Epoch [7/10], Train Loss: 0.2173, Train Accuracy: 93.80%, Validation Loss: 0.2385, Validation Accuracy: 92.94%
Epoch [8/10], Train Loss: 0.2018, Train Accuracy: 94.24%, Validation Loss: 0.2156, Validation Accuracy: 93.89%
Epoch [9/10], Train Loss: 0.1879, Train Accuracy: 94.61%, Validation Loss: 0.2070, Validation Accuracy: 94.03%
Epoch [10/10], Train Loss: 0.1769, Train Accuracy: 95.01%, Validation Loss: 0.1980, Validation Accuracy: 94.24%
Completed training for hidden_size = 50
Epoch [1/10], Train Loss: 0.6829, Train Accuracy: 82.25%, Validation Loss: 0.3841, Validation Accuracy: 88.79%
Epoch [2/10], Train Loss: 0.3431, Train Accuracy: 90.19%, Validation Loss: 0.3386, Validation Accuracy: 90.34%
Epoch [3/10], Train Loss: 0.3021, Train Accuracy: 91.25%, Validation Loss: 0.3040, Validation Accuracy: 91.05%
Epoch [4/10], Train Loss: 0.2758, Train Accuracy: 92.11%, Validation Loss: 0.2752, Validation Accuracy: 92.09%
Epoch [5/10], Train Loss: 0.2533, Train Accuracy: 92.73%, Validation Loss: 0.2658, Validation Accuracy: 92.51%
Epoch [6/10], Train Loss: 0.2325, Train Accuracy: 93.41%, Validation Loss: 0.2407, Validation Accuracy: 93.09%
Epoch [7/10], Train Loss: 0.2145, Train Accuracy: 94.00%, Validation Loss: 0.2284, Validation Accuracy: 93.46%
Epoch [8/10], Train Loss: 0.1979, Train Accuracy: 94.40%, Validation Loss: 0.2102, Validation Accuracy: 93.95%
Epoch [9/10], Train Loss: 0.1841, Train Accuracy: 94.73%, Validation Loss: 0.1988, Validation Accuracy: 94.21%
Epoch [10/10], Train Loss: 0.1720, Train Accuracy: 95.11%, Validation Loss: 0.2025, Validation Accuracy: 94.11%
Completed training for hidden_size = 60
Epoch [1/10], Train Loss: 0.7847, Train Accuracy: 76.92%, Validation Loss: 0.4333, Validation Accuracy: 87.92%
Epoch [2/10], Train Loss: 0.3829, Train Accuracy: 88.84%, Validation Loss: 0.4063, Validation Accuracy: 87.79%
Epoch [3/10], Train Loss: 0.3382, Train Accuracy: 90.24%, Validation Loss: 0.3421, Validation Accuracy: 90.31%
Epoch [4/10], Train Loss: 0.3161, Train Accuracy: 90.88%, Validation Loss: 0.3267, Validation Accuracy: 90.89%
Epoch [5/10], Train Loss: 0.3025, Train Accuracy: 91.31%, Validation Loss: 0.3163, Validation Accuracy: 91.11%
Epoch [6/10], Train Loss: 0.2929, Train Accuracy: 91.50%, Validation Loss: 0.3152, Validation Accuracy: 90.98%
Epoch [7/10], Train Loss: 0.2848, Train Accuracy: 91.84%, Validation Loss: 0.3048, Validation Accuracy: 91.55%
Epoch [8/10], Train Loss: 0.2789, Train Accuracy: 91.95%, Validation Loss: 0.3034, Validation Accuracy: 91.28%
Epoch [9/10], Train Loss: 0.2726, Train Accuracy: 92.27%, Validation Loss: 0.2915, Validation Accuracy: 91.90%
Epoch [10/10], Train Loss: 0.2675, Train Accuracy: 92.31%, Validation

Loss: 0.2954, Validation Accuracy: 91.54%
Completed training for batch_size = 32
Epoch [1/10], Train Loss: 1.1709, Train Accuracy: 67.06%, Validation Loss: 0.5740, Validation Accuracy: 84.07%
Epoch [2/10], Train Loss: 0.4599, Train Accuracy: 87.05%, Validation Loss: 0.4144, Validation Accuracy: 88.34%
Epoch [3/10], Train Loss: 0.3769, Train Accuracy: 89.15%, Validation Loss: 0.3688, Validation Accuracy: 89.34%
Epoch [4/10], Train Loss: 0.3460, Train Accuracy: 89.94%, Validation Loss: 0.3608, Validation Accuracy: 89.37%
Epoch [5/10], Train Loss: 0.3289, Train Accuracy: 90.49%, Validation Loss: 0.3336, Validation Accuracy: 90.36%
Epoch [6/10], Train Loss: 0.3163, Train Accuracy: 90.89%, Validation Loss: 0.3378, Validation Accuracy: 89.97%
Epoch [7/10], Train Loss: 0.3064, Train Accuracy: 91.24%, Validation Loss: 0.3227, Validation Accuracy: 90.85%
Epoch [8/10], Train Loss: 0.2994, Train Accuracy: 91.45%, Validation Loss: 0.3245, Validation Accuracy: 90.83%
Epoch [9/10], Train Loss: 0.2937, Train Accuracy: 91.55%, Validation Loss: 0.3337, Validation Accuracy: 90.08%
Epoch [10/10], Train Loss: 0.2875, Train Accuracy: 91.75%, Validation Loss: 0.3057, Validation Accuracy: 91.14%
Completed training for batch_size = 64
Epoch [1/10], Train Loss: 1.4954, Train Accuracy: 58.78%, Validation Loss: 0.8367, Validation Accuracy: 79.84%
Epoch [2/10], Train Loss: 0.6464, Train Accuracy: 83.33%, Validation Loss: 0.5574, Validation Accuracy: 83.61%
Epoch [3/10], Train Loss: 0.4971, Train Accuracy: 86.19%, Validation Loss: 0.4764, Validation Accuracy: 86.91%
Epoch [4/10], Train Loss: 0.4369, Train Accuracy: 87.69%, Validation Loss: 0.4433, Validation Accuracy: 86.88%
Epoch [5/10], Train Loss: 0.4001, Train Accuracy: 88.70%, Validation Loss: 0.4108, Validation Accuracy: 88.36%
Epoch [6/10], Train Loss: 0.3760, Train Accuracy: 89.44%, Validation Loss: 0.3803, Validation Accuracy: 89.29%
Epoch [7/10], Train Loss: 0.3600, Train Accuracy: 89.80%, Validation Loss: 0.3711, Validation Accuracy: 89.24%
Epoch [8/10], Train Loss: 0.3477, Train Accuracy: 90.14%, Validation Loss: 0.3587, Validation Accuracy: 89.96%
Epoch [9/10], Train Loss: 0.3385, Train Accuracy: 90.42%, Validation Loss: 0.3625, Validation Accuracy: 89.80%
Epoch [10/10], Train Loss: 0.3321, Train Accuracy: 90.58%, Validation Loss: 0.3496, Validation Accuracy: 90.22%
Completed training for batch_size = 128
Epoch [1/10], Train Loss: 1.7533, Train Accuracy: 45.45%, Validation Loss: 1.2389, Validation Accuracy: 67.31%
Epoch [2/10], Train Loss: 0.9887, Train Accuracy: 74.61%, Validation Loss: 0.8346, Validation Accuracy: 78.26%
Epoch [3/10], Train Loss: 0.7366, Train Accuracy: 80.67%, Validation

Loss: 0.6726, Validation Accuracy: 81.87%
Epoch [4/10], Train Loss: 0.6124, Train Accuracy: 83.59%, Validation
Loss: 0.5793, Validation Accuracy: 84.37%
Epoch [5/10], Train Loss: 0.5442, Train Accuracy: 85.01%, Validation
Loss: 0.5370, Validation Accuracy: 85.05%
Epoch [6/10], Train Loss: 0.4978, Train Accuracy: 86.12%, Validation
Loss: 0.4957, Validation Accuracy: 86.00%
Epoch [7/10], Train Loss: 0.4649, Train Accuracy: 86.94%, Validation
Loss: 0.4705, Validation Accuracy: 87.06%
Epoch [8/10], Train Loss: 0.4405, Train Accuracy: 87.57%, Validation
Loss: 0.4435, Validation Accuracy: 87.66%
Epoch [9/10], Train Loss: 0.4230, Train Accuracy: 88.06%, Validation
Loss: 0.4312, Validation Accuracy: 87.79%
Epoch [10/10], Train Loss: 0.4100, Train Accuracy: 88.40%, Validation
Loss: 0.4349, Validation Accuracy: 87.54%
Completed training for batch_size = 256
Epoch [1/10], Train Loss: 2.0104, Train Accuracy: 36.34%, Validation
Loss: 1.7546, Validation Accuracy: 47.26%
Epoch [2/10], Train Loss: 1.5353, Train Accuracy: 57.02%, Validation
Loss: 1.3201, Validation Accuracy: 65.65%
Epoch [3/10], Train Loss: 1.1488, Train Accuracy: 71.29%, Validation
Loss: 1.0060, Validation Accuracy: 75.84%
Epoch [4/10], Train Loss: 0.8987, Train Accuracy: 78.14%, Validation
Loss: 0.8126, Validation Accuracy: 79.60%
Epoch [5/10], Train Loss: 0.7432, Train Accuracy: 81.49%, Validation
Loss: 0.6907, Validation Accuracy: 82.15%
Epoch [6/10], Train Loss: 0.6437, Train Accuracy: 83.61%, Validation
Loss: 0.6108, Validation Accuracy: 84.04%
Epoch [7/10], Train Loss: 0.5766, Train Accuracy: 85.04%, Validation
Loss: 0.5552, Validation Accuracy: 85.52%
Epoch [8/10], Train Loss: 0.5291, Train Accuracy: 85.99%, Validation
Loss: 0.5152, Validation Accuracy: 86.49%
Epoch [9/10], Train Loss: 0.4948, Train Accuracy: 86.76%, Validation
Loss: 0.4860, Validation Accuracy: 87.16%
Epoch [10/10], Train Loss: 0.4686, Train Accuracy: 87.32%, Validation
Loss: 0.4640, Validation Accuracy: 87.65%
Completed training for batch_size = 500
Epoch [1/10], Train Loss: 2.2332, Train Accuracy: 24.44%, Validation
Loss: 2.1368, Validation Accuracy: 31.89%
Epoch [2/10], Train Loss: 2.0512, Train Accuracy: 38.74%, Validation
Loss: 1.9639, Validation Accuracy: 44.25%
Epoch [3/10], Train Loss: 1.8703, Train Accuracy: 47.13%, Validation
Loss: 1.7719, Validation Accuracy: 49.64%
Epoch [4/10], Train Loss: 1.6690, Train Accuracy: 51.03%, Validation
Loss: 1.5720, Validation Accuracy: 52.77%
Epoch [5/10], Train Loss: 1.4785, Train Accuracy: 55.17%, Validation
Loss: 1.3959, Validation Accuracy: 58.09%
Epoch [6/10], Train Loss: 1.3185, Train Accuracy: 59.60%, Validation
Loss: 1.2530, Validation Accuracy: 61.51%

Epoch [7/10], Train Loss: 1.1886, Train Accuracy: 63.81%, Validation Loss: 1.1346, Validation Accuracy: 65.31%

Epoch [8/10], Train Loss: 1.0761, Train Accuracy: 68.00%, Validation Loss: 1.0273, Validation Accuracy: 70.03%

Epoch [9/10], Train Loss: 0.9769, Train Accuracy: 72.28%, Validation Loss: 0.9377, Validation Accuracy: 74.06%

Epoch [10/10], Train Loss: 0.8952, Train Accuracy: 75.59%, Validation Loss: 0.8636, Validation Accuracy: 76.41%

Completed training for batch_size = 1000

Epoch [1/10], Train Loss: 1.5825, Train Accuracy: 40.59%, Validation Loss: 1.5127, Validation Accuracy: 43.09%

Epoch [2/10], Train Loss: 1.4450, Train Accuracy: 47.60%, Validation Loss: 1.9999, Validation Accuracy: 30.75%

Epoch [3/10], Train Loss: 1.4132, Train Accuracy: 49.45%, Validation Loss: 1.4774, Validation Accuracy: 45.89%

Epoch [4/10], Train Loss: 1.4174, Train Accuracy: 49.92%, Validation Loss: 1.2822, Validation Accuracy: 52.94%

Epoch [5/10], Train Loss: 1.3994, Train Accuracy: 50.66%, Validation Loss: 1.2698, Validation Accuracy: 55.84%

Epoch [6/10], Train Loss: 1.3902, Train Accuracy: 51.32%, Validation Loss: 1.4865, Validation Accuracy: 46.70%

Epoch [7/10], Train Loss: 1.3996, Train Accuracy: 51.24%, Validation Loss: 1.3105, Validation Accuracy: 52.69%

Epoch [8/10], Train Loss: 1.3798, Train Accuracy: 52.22%, Validation Loss: 1.5280, Validation Accuracy: 42.46%

Epoch [9/10], Train Loss: 1.3959, Train Accuracy: 51.45%, Validation Loss: 1.5854, Validation Accuracy: 48.56%

Epoch [10/10], Train Loss: 1.3954, Train Accuracy: 51.31%, Validation Loss: 1.4562, Validation Accuracy: 52.24%

Completed training for learning_rate = 0.1

Epoch [1/10], Train Loss: 0.7632, Train Accuracy: 77.65%, Validation Loss: 0.4697, Validation Accuracy: 87.01%

Epoch [2/10], Train Loss: 0.4062, Train Accuracy: 88.29%, Validation Loss: 0.3892, Validation Accuracy: 89.02%

Epoch [3/10], Train Loss: 0.3493, Train Accuracy: 89.98%, Validation Loss: 0.3756, Validation Accuracy: 88.93%

Epoch [4/10], Train Loss: 0.3238, Train Accuracy: 90.80%, Validation Loss: 0.3406, Validation Accuracy: 90.23%

Epoch [5/10], Train Loss: 0.3091, Train Accuracy: 91.28%, Validation Loss: 0.3290, Validation Accuracy: 90.48%

Epoch [6/10], Train Loss: 0.2981, Train Accuracy: 91.58%, Validation Loss: 0.3862, Validation Accuracy: 88.66%

Epoch [7/10], Train Loss: 0.2910, Train Accuracy: 91.76%, Validation Loss: 0.3117, Validation Accuracy: 91.05%

Epoch [8/10], Train Loss: 0.2847, Train Accuracy: 91.97%, Validation Loss: 0.3117, Validation Accuracy: 91.19%

Epoch [9/10], Train Loss: 0.2781, Train Accuracy: 92.16%, Validation Loss: 0.3039, Validation Accuracy: 91.27%

Epoch [10/10], Train Loss: 0.2725, Train Accuracy: 92.25%, Validation

Loss: 0.2952, Validation Accuracy: 91.54%
Completed training for learning_rate = 0.01
Epoch [1/10], Train Loss: 1.9715, Train Accuracy: 34.96%, Validation Loss: 1.6808, Validation Accuracy: 49.49%
Epoch [2/10], Train Loss: 1.4039, Train Accuracy: 63.21%, Validation Loss: 1.1364, Validation Accuracy: 73.24%
Epoch [3/10], Train Loss: 0.9567, Train Accuracy: 76.05%, Validation Loss: 0.8264, Validation Accuracy: 78.46%
Epoch [4/10], Train Loss: 0.7429, Train Accuracy: 79.79%, Validation Loss: 0.6832, Validation Accuracy: 81.44%
Epoch [5/10], Train Loss: 0.6359, Train Accuracy: 82.38%, Validation Loss: 0.6021, Validation Accuracy: 83.33%
Epoch [6/10], Train Loss: 0.5704, Train Accuracy: 84.10%, Validation Loss: 0.5497, Validation Accuracy: 84.59%
Epoch [7/10], Train Loss: 0.5250, Train Accuracy: 85.22%, Validation Loss: 0.5108, Validation Accuracy: 85.81%
Epoch [8/10], Train Loss: 0.4912, Train Accuracy: 86.13%, Validation Loss: 0.4818, Validation Accuracy: 86.36%
Epoch [9/10], Train Loss: 0.4646, Train Accuracy: 86.78%, Validation Loss: 0.4590, Validation Accuracy: 87.15%
Epoch [10/10], Train Loss: 0.4436, Train Accuracy: 87.44%, Validation Loss: 0.4409, Validation Accuracy: 87.44%
Completed training for learning_rate = 0.001
Epoch [1/10], Train Loss: 2.2552, Train Accuracy: 18.57%, Validation Loss: 2.1967, Validation Accuracy: 27.56%
Epoch [2/10], Train Loss: 2.1459, Train Accuracy: 34.03%, Validation Loss: 2.0996, Validation Accuracy: 38.24%
Epoch [3/10], Train Loss: 2.0518, Train Accuracy: 41.58%, Validation Loss: 2.0044, Validation Accuracy: 45.31%
Epoch [4/10], Train Loss: 1.9575, Train Accuracy: 48.05%, Validation Loss: 1.9144, Validation Accuracy: 50.22%
Epoch [5/10], Train Loss: 1.8720, Train Accuracy: 51.59%, Validation Loss: 1.8331, Validation Accuracy: 52.94%
Epoch [6/10], Train Loss: 1.7941, Train Accuracy: 53.77%, Validation Loss: 1.7588, Validation Accuracy: 55.06%
Epoch [7/10], Train Loss: 1.7226, Train Accuracy: 55.56%, Validation Loss: 1.6901, Validation Accuracy: 56.54%
Epoch [8/10], Train Loss: 1.6560, Train Accuracy: 57.13%, Validation Loss: 1.6256, Validation Accuracy: 57.64%
Epoch [9/10], Train Loss: 1.5934, Train Accuracy: 58.37%, Validation Loss: 1.5648, Validation Accuracy: 59.46%
Epoch [10/10], Train Loss: 1.5339, Train Accuracy: 59.72%, Validation Loss: 1.5063, Validation Accuracy: 60.79%
Completed training for learning_rate = 0.0001
Epoch [1/10], Train Loss: 2.3281, Train Accuracy: 11.28%, Validation Loss: 2.3236, Validation Accuracy: 11.39%
Epoch [2/10], Train Loss: 2.3212, Train Accuracy: 11.64%, Validation Loss: 2.3187, Validation Accuracy: 11.56%
Epoch [3/10], Train Loss: 2.3173, Train Accuracy: 11.78%, Validation

```
Loss: 2.3158, Validation Accuracy: 11.59%
Epoch [4/10], Train Loss: 2.3150, Train Accuracy: 11.83%, Validation
Loss: 2.3139, Validation Accuracy: 11.59%
Epoch [5/10], Train Loss: 2.3133, Train Accuracy: 11.85%, Validation
Loss: 2.3125, Validation Accuracy: 11.63%
Epoch [6/10], Train Loss: 2.3119, Train Accuracy: 11.86%, Validation
Loss: 2.3113, Validation Accuracy: 11.68%
Epoch [7/10], Train Loss: 2.3107, Train Accuracy: 11.94%, Validation
Loss: 2.3101, Validation Accuracy: 11.70%
Epoch [8/10], Train Loss: 2.3095, Train Accuracy: 11.95%, Validation
Loss: 2.3090, Validation Accuracy: 11.76%
Epoch [9/10], Train Loss: 2.3084, Train Accuracy: 11.97%, Validation
Loss: 2.3079, Validation Accuracy: 11.76%
Epoch [10/10], Train Loss: 2.3072, Train Accuracy: 12.06%, Validation
Loss: 2.3067, Validation Accuracy: 11.84%
Completed training for learning_rate = 1e-05
Epoch [1/10], Train Loss: 2.3287, Train Accuracy: 10.54%, Validation
Loss: 2.3273, Validation Accuracy: 10.68%
Epoch [2/10], Train Loss: 2.3270, Train Accuracy: 10.52%, Validation
Loss: 2.3256, Validation Accuracy: 10.72%
Epoch [3/10], Train Loss: 2.3253, Train Accuracy: 10.48%, Validation
Loss: 2.3239, Validation Accuracy: 10.61%
Epoch [4/10], Train Loss: 2.3237, Train Accuracy: 10.46%, Validation
Loss: 2.3224, Validation Accuracy: 10.56%
Epoch [5/10], Train Loss: 2.3221, Train Accuracy: 10.39%, Validation
Loss: 2.3208, Validation Accuracy: 10.51%
Epoch [6/10], Train Loss: 2.3206, Train Accuracy: 10.35%, Validation
Loss: 2.3194, Validation Accuracy: 10.49%
Epoch [7/10], Train Loss: 2.3191, Train Accuracy: 10.30%, Validation
Loss: 2.3179, Validation Accuracy: 10.44%
Epoch [8/10], Train Loss: 2.3177, Train Accuracy: 10.23%, Validation
Loss: 2.3165, Validation Accuracy: 10.41%
Epoch [9/10], Train Loss: 2.3163, Train Accuracy: 10.20%, Validation
Loss: 2.3152, Validation Accuracy: 10.36%
Epoch [10/10], Train Loss: 2.3150, Train Accuracy: 10.18%, Validation
Loss: 2.3138, Validation Accuracy: 10.32%
Completed training for learning_rate = 1e-06
```

```
import pandas as pd
```

```
# Convert the results list to a DataFrame
```

```
df = pd.DataFrame(results)
```

```
# Inspect the columns to ensure they match expected names
```

```
print("Columns in DataFrame:", df.columns)
```

```
# Verify sample rows to confirm data integrity
```

```
print(df.head())
```

```
Columns in DataFrame: Index(['param', 'value', 'train_accuracy',
                             'val_accuracy', 'train_loss',
                             'val_loss', 'y_true', 'y_pred'],
                             dtype='object')
```

	param	value	train_accuracy	val_accuracy	train_loss	val_loss
0	hidden_layers	1.0	92.130952	91.135714	0.272497	0.306914
1	hidden_layers	3.0	92.021429	89.721429	0.271163	0.343308
2	hidden_layers	5.0	89.633333	88.857143	0.353852	0.397629
3	hidden_layers	7.0	27.730952	34.135714	1.707313	1.579375
4	hidden_layers	9.0	11.252381	11.257143	2.301109	2.300940

	y_true
0	[3, 6, 1, 0, 3, 3, 6, 4, 0, 4, 3, 9, 1, 8, 1, ...]
1	[3, 6, 1, 0, 3, 3, 6, 4, 0, 4, 3, 9, 1, 8, 1, ...]
2	[3, 6, 1, 0, 3, 3, 6, 4, 0, 4, 3, 9, 1, 8, 1, ...]
3	[3, 6, 1, 0, 3, 3, 6, 4, 0, 4, 3, 9, 1, 8, 1, ...]
4	[3, 6, 1, 0, 3, 3, 6, 4, 0, 4, 3, 9, 1, 8, 1, ...]

	y_pred
0	[3, 6, 1, 0, 8, 3, 6, 4, 0, 4, 2, 9, 1, 8, 1, ...]
1	[5, 6, 1, 0, 7, 5, 6, 4, 0, 7, 8, 9, 1, 8, 1, ...]
2	[8, 2, 1, 6, 1, 8, 8, 1, 8, 1, 1, 1, 1, 2, 1, ...]
3	[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, ...]
4	[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, ...]

```
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix

# Plot Training & Validation Accuracy and Loss for each parameter
separately
unique_params = df["param"].unique()

for param in unique_params:
    # Filter the DataFrame for the current parameter
    subset = df[df["param"] == param]

    print(f"----- Accuracy and Loss for {param} -----")

    # Plot Training and Validation Accuracy on the same graph
    plt.figure(figsize=(7, 4))
    plt.plot(subset["value"], subset["train_accuracy"], linestyle='--',
             label="Training Accuracy")
    plt.plot(subset["value"], subset["val_accuracy"], linestyle='--',
```

```

label="Validation Accuracy")
    plt.scatter(subset["value"], subset["train_accuracy"], marker='o',
s=80, label="Training Accuracy (scatter)")
    plt.scatter(subset["value"], subset["val_accuracy"], marker='x',
s=80, label="Validation Accuracy (scatter)")
    plt.title(f"Training and Validation Accuracy vs {param}")
    plt.xlabel(f"{param} Value")
    plt.ylabel("Accuracy (%)")
    plt.grid()
    plt.legend()
    plt.show()

    # Plot Training and Validation Loss on the same graph
    plt.figure(figsize=(7, 4))
    plt.plot(subset["value"], subset["train_loss"], linestyle='--',
label="Training Loss")
    plt.plot(subset["value"], subset["val_loss"], linestyle='--',
label="Validation Loss")
    plt.scatter(subset["value"], subset["train_loss"], marker='o',
s=80, label="Training Loss (scatter)")
    plt.scatter(subset["value"], subset["val_loss"], marker='x', s=80,
label="Validation Loss (scatter)")
    plt.title(f"Training and Validation Loss vs {param}")
    plt.xlabel(f"{param} Value")
    plt.ylabel("Loss")
    plt.grid()
    plt.legend()
    plt.show()

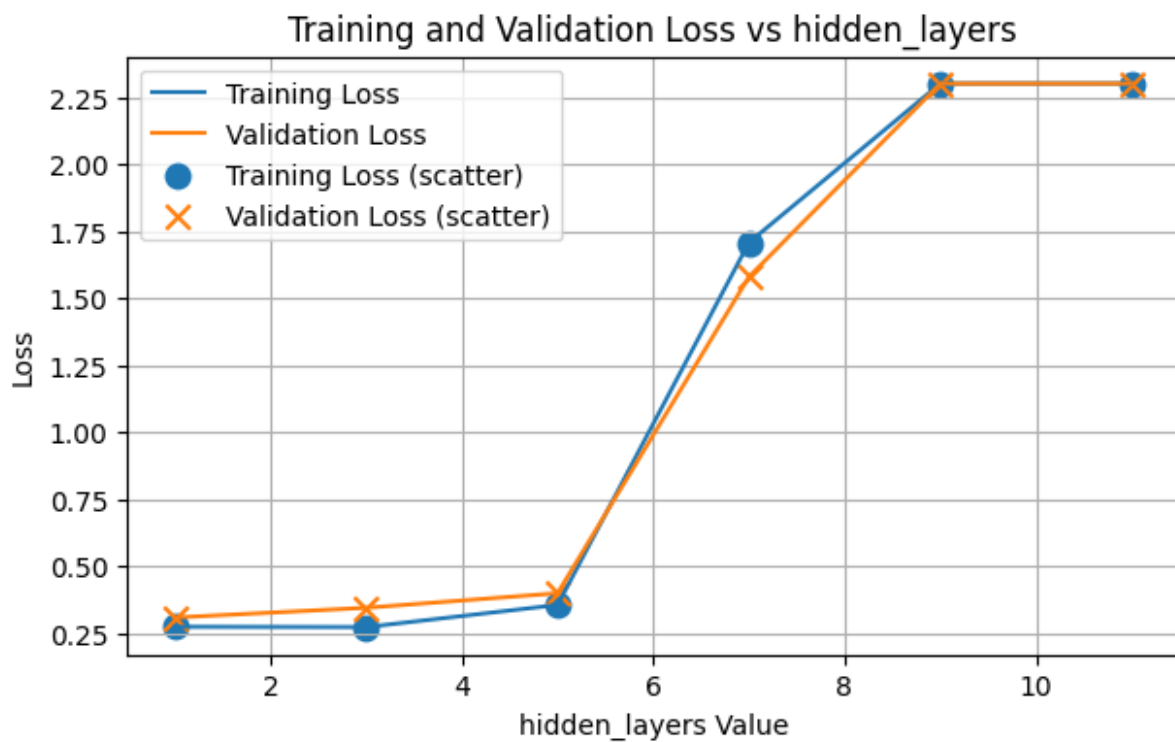
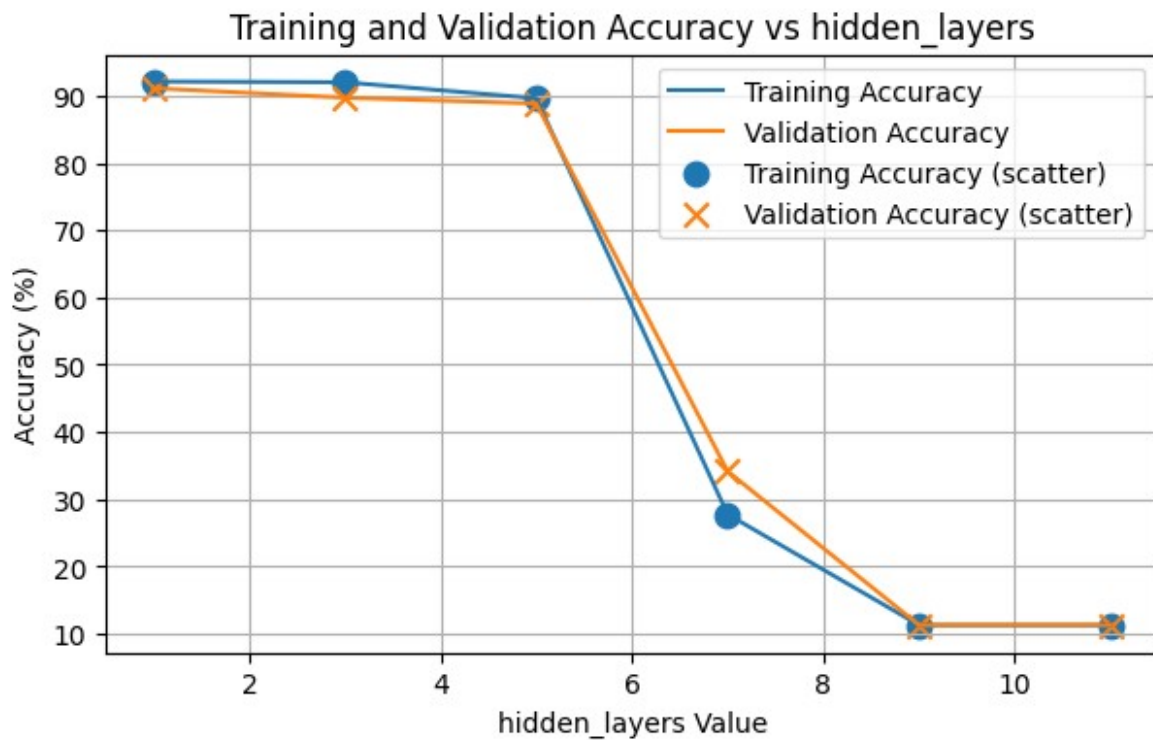
print(f"----- Confusion Matrix
for {param} ----- ")

# Plot confusion matrix for each trained model
def plot_confusion_matrix(y_true, y_pred, param, value):
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(7, 4))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
xticklabels=range(10), yticklabels=range(10))
    plt.title(f'Confusion Matrix for {param} = {value}')
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.show()

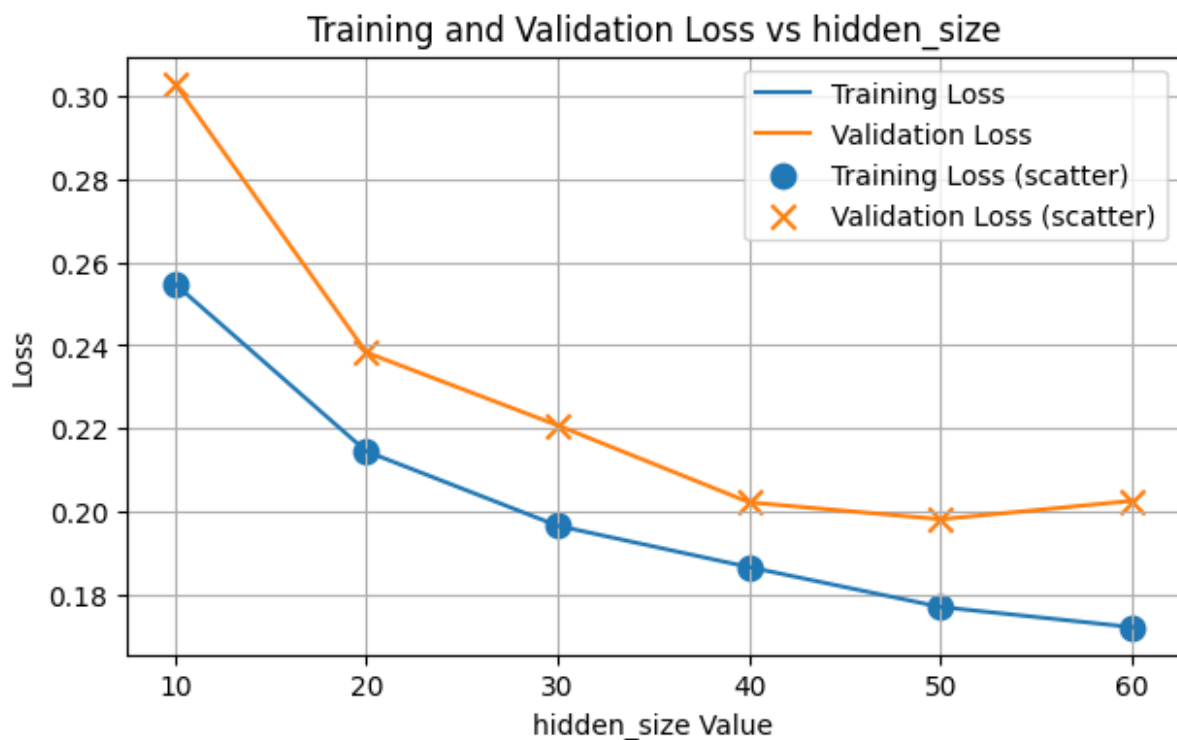
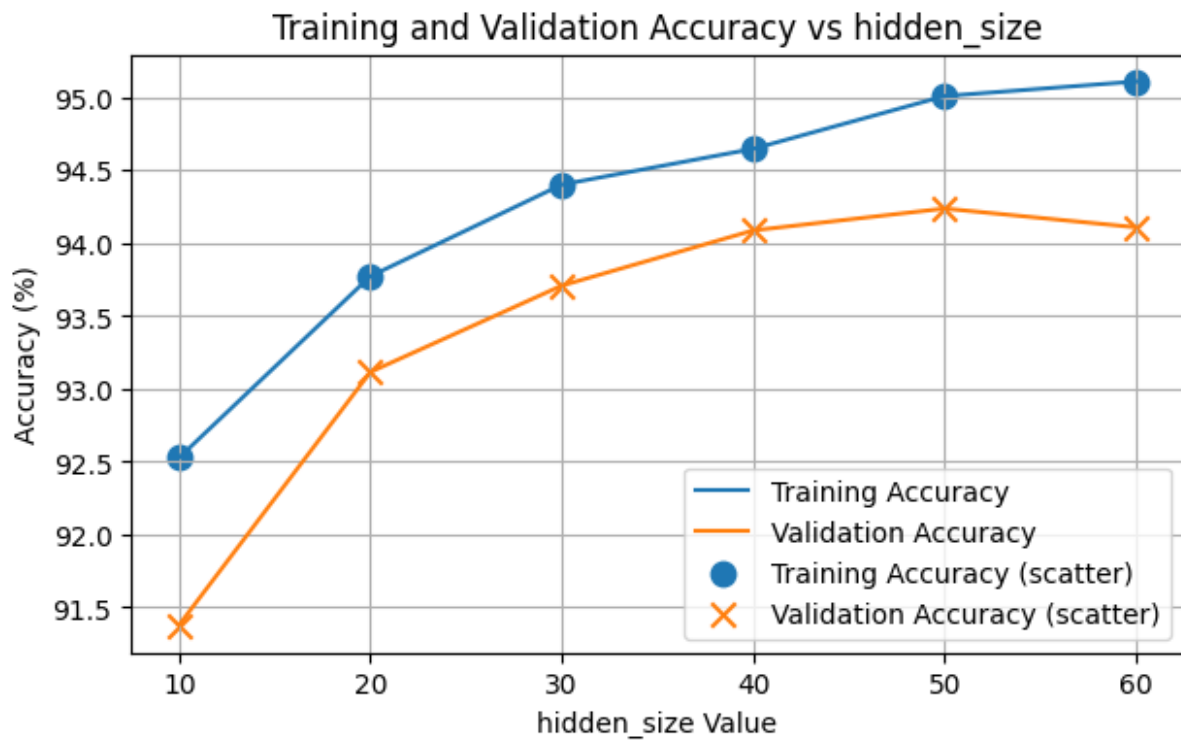
# Generate confusion matrices for each parameter and value
for idx, row in df.iterrows():
    plot_confusion_matrix(row["y_true"], row["y_pred"], row["param"],
row["value"])

----- Accuracy and Loss for
hidden_layers -----

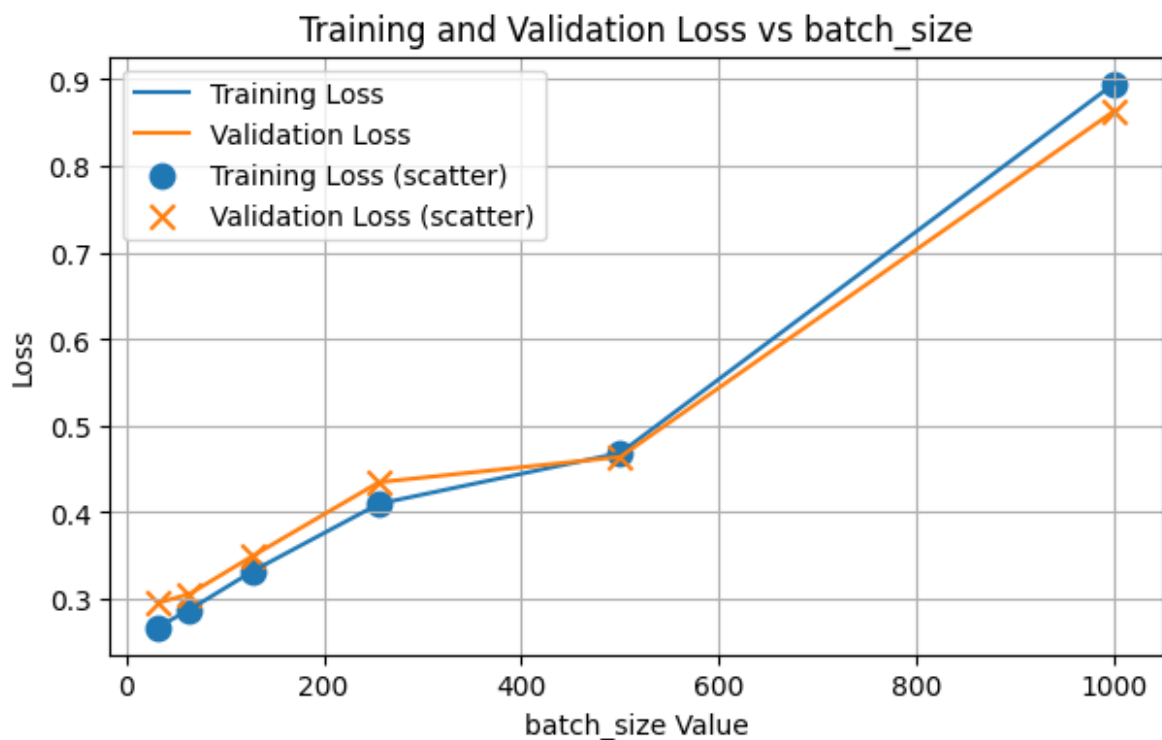
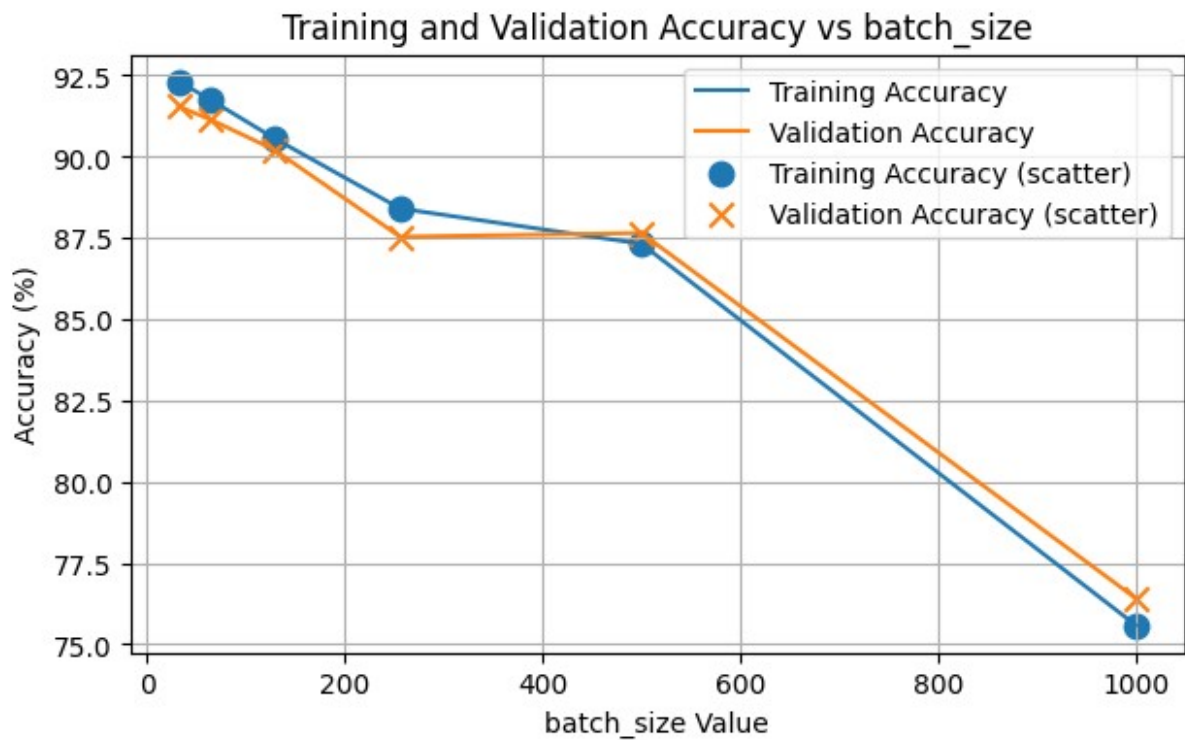
```



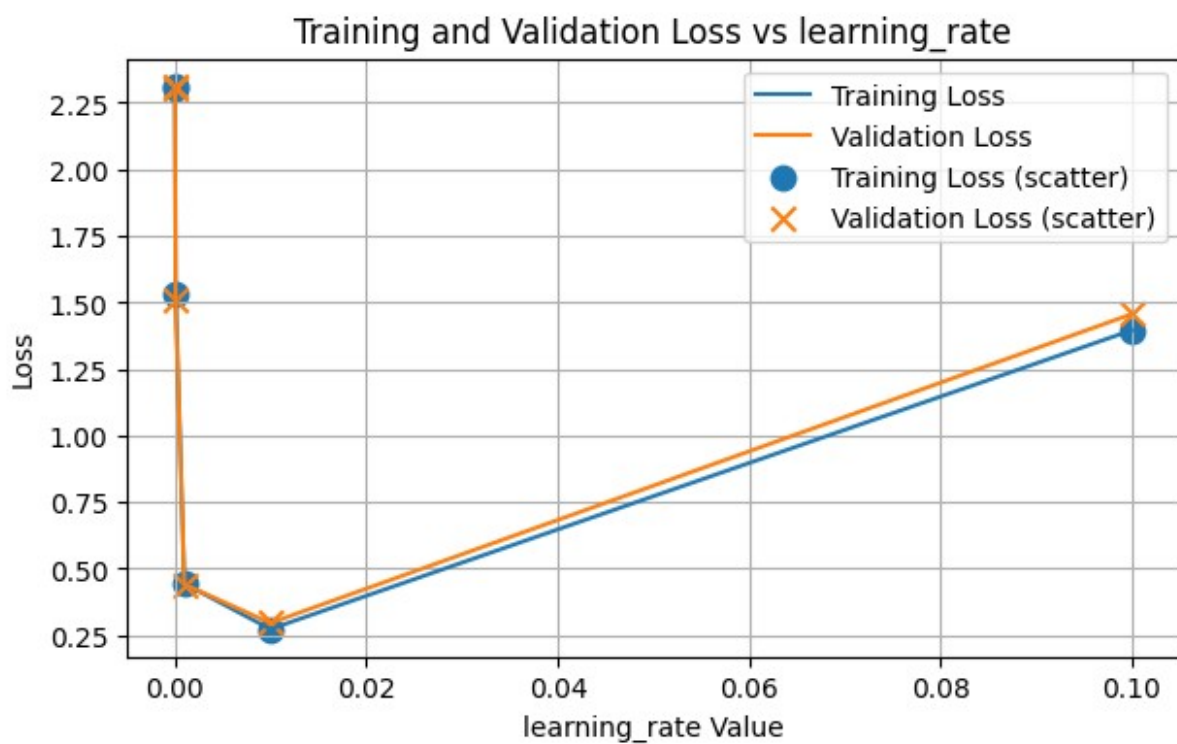
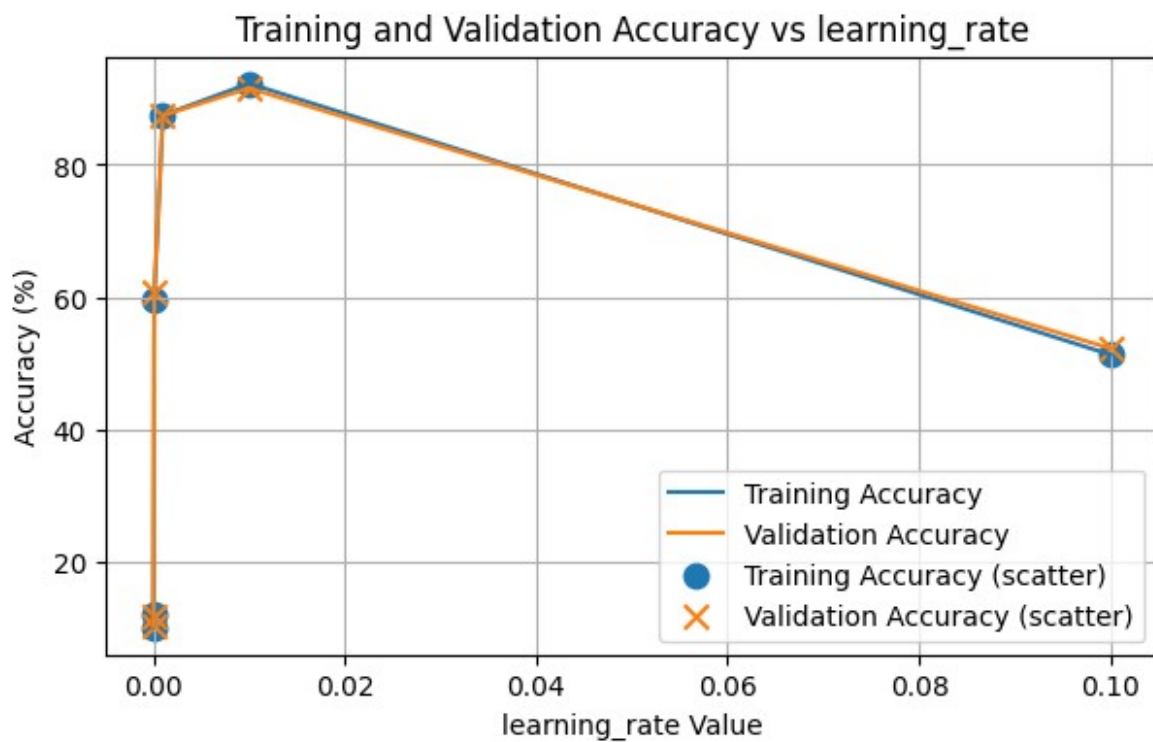
----- Accuracy and Loss for
hidden_size -----



----- Accuracy and Loss for
batch_size -----

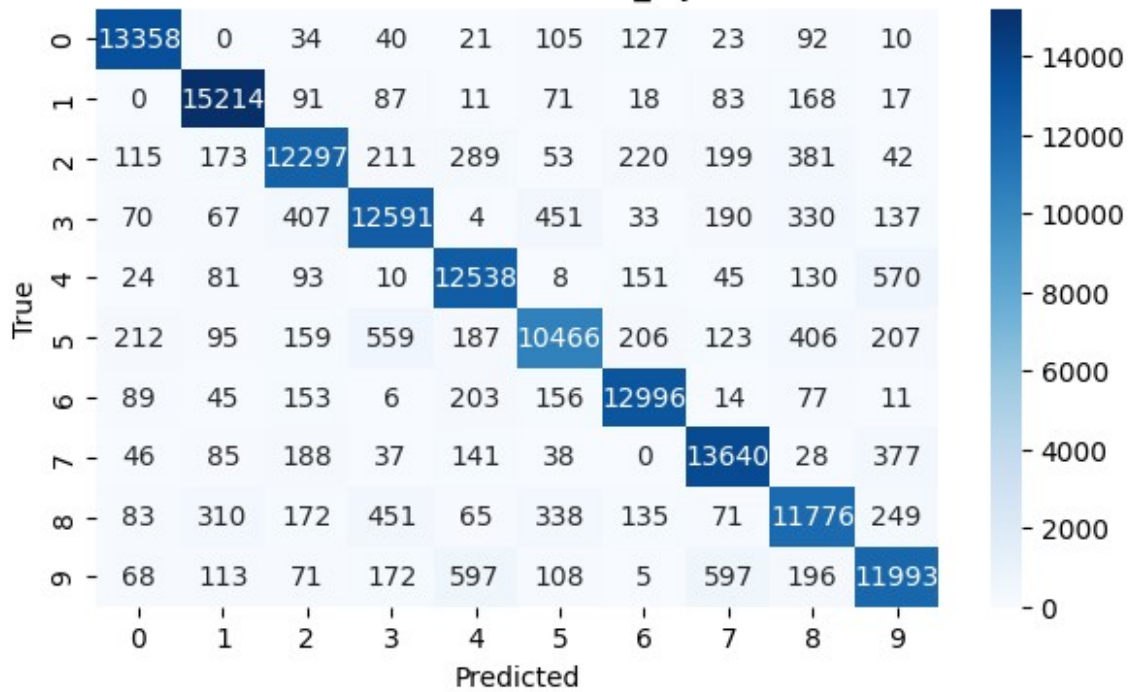


----- Accuracy and Loss for
learning_rate -----

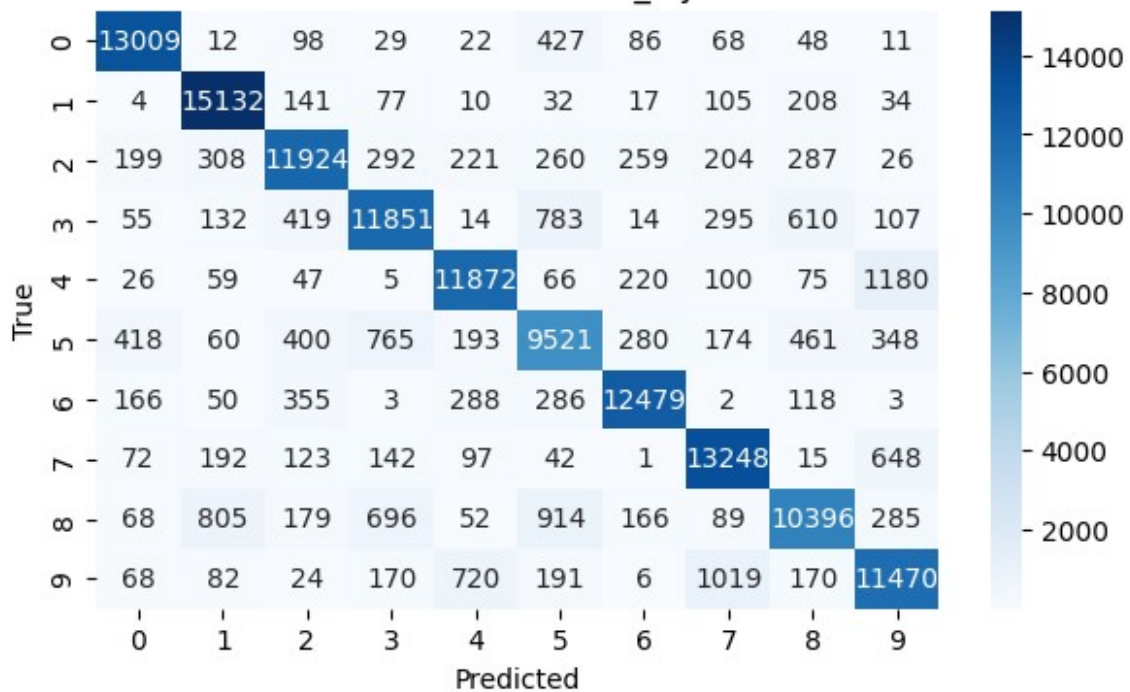


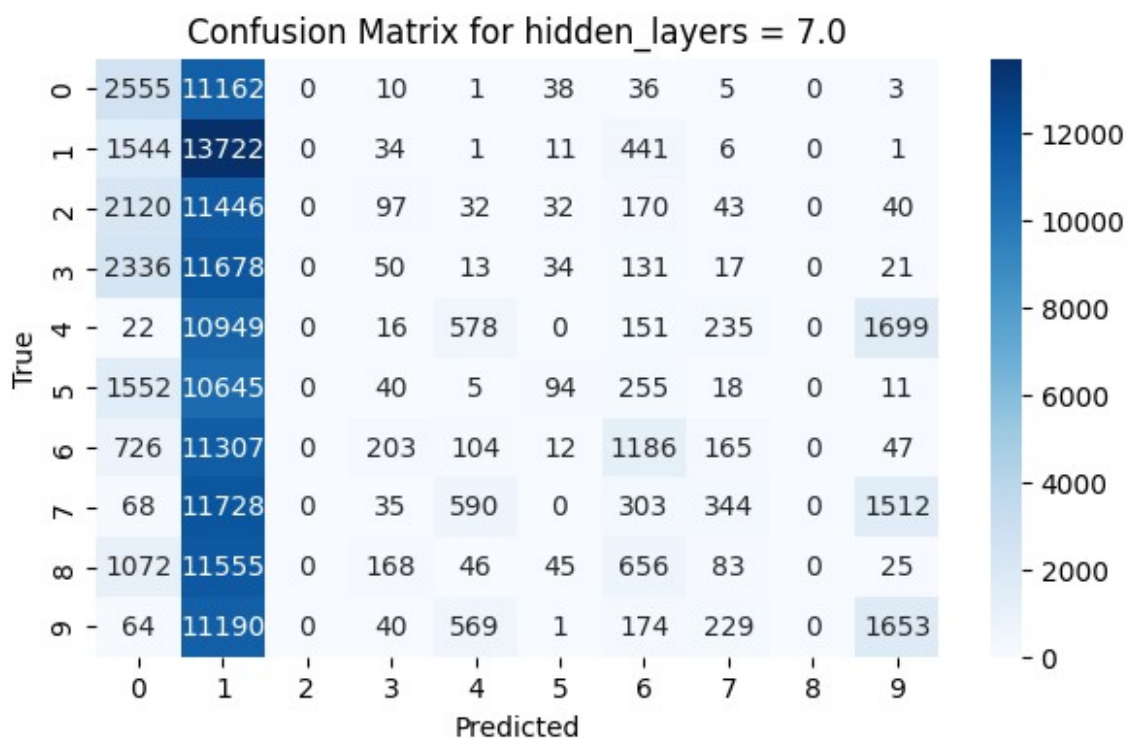
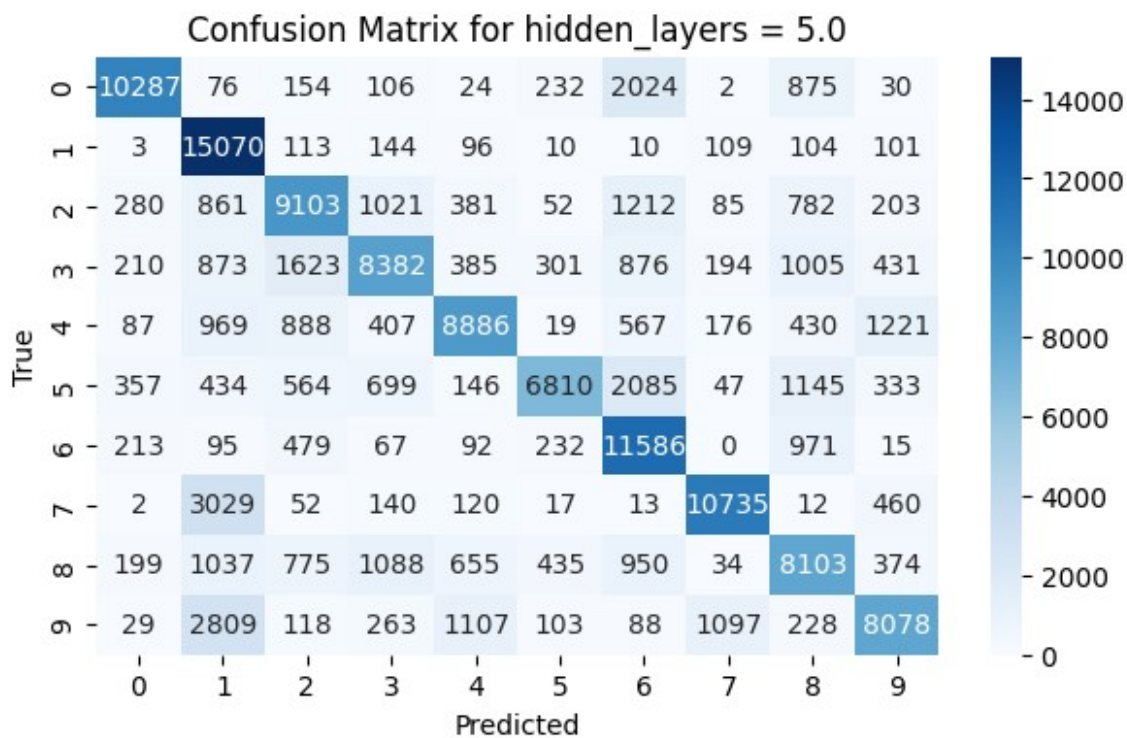
----- Confusion Matrix for
learning_rate -----

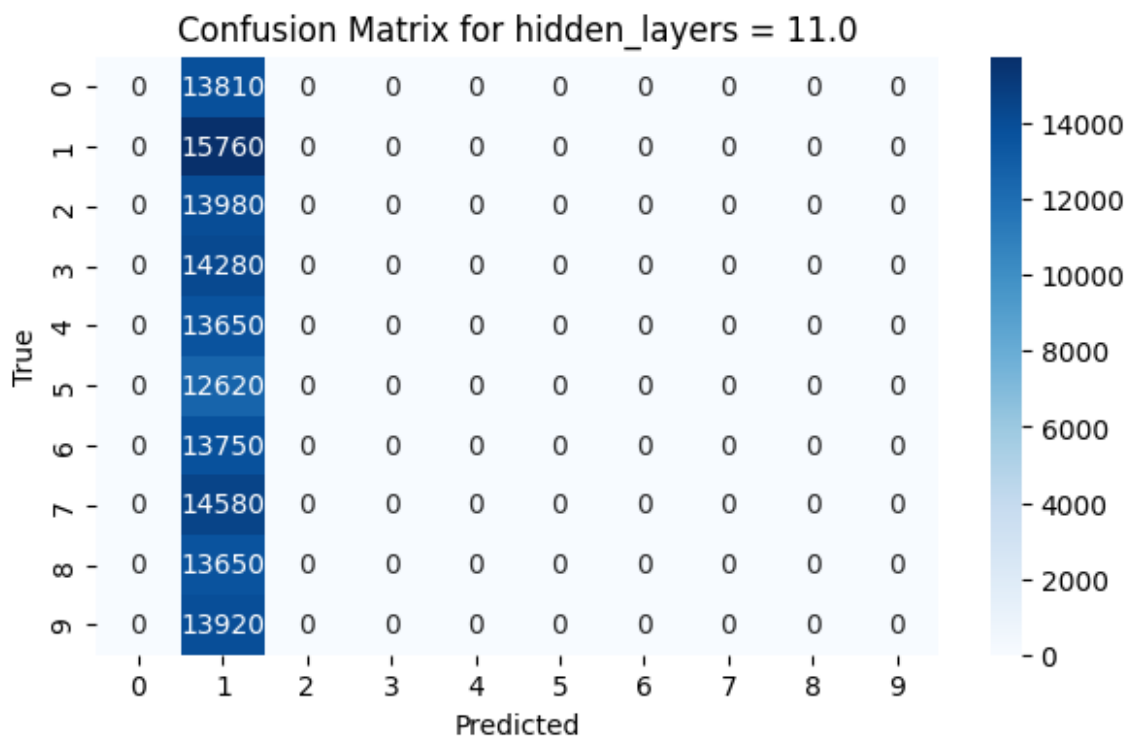
Confusion Matrix for hidden_layers = 1.0



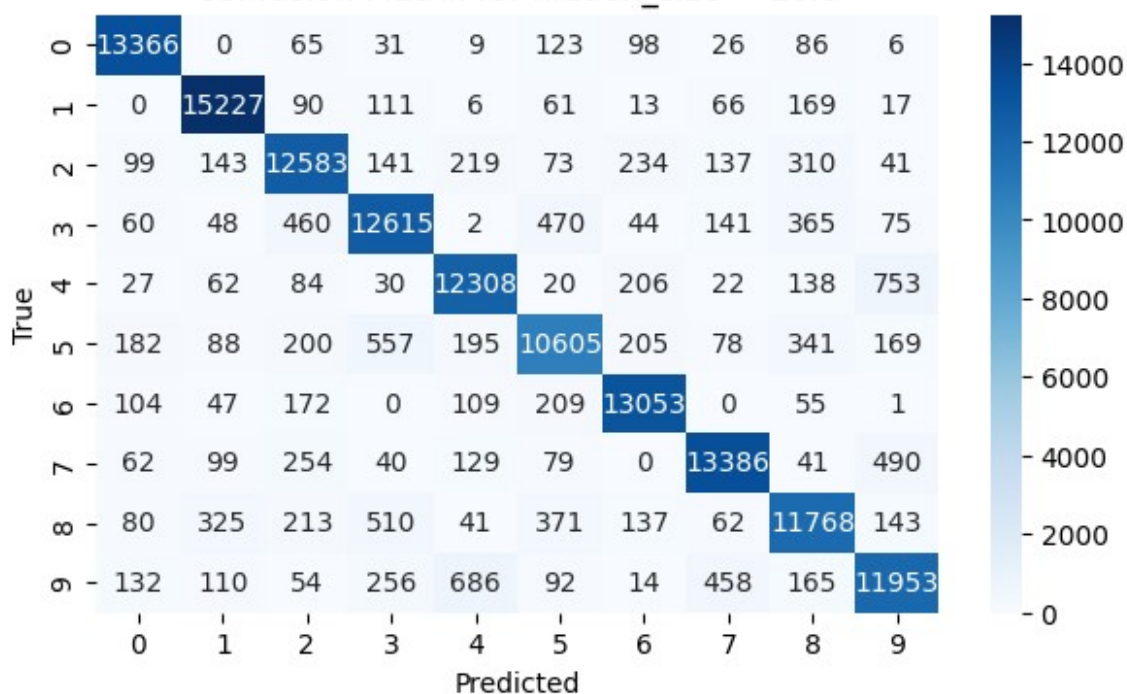
Confusion Matrix for hidden_layers = 3.0



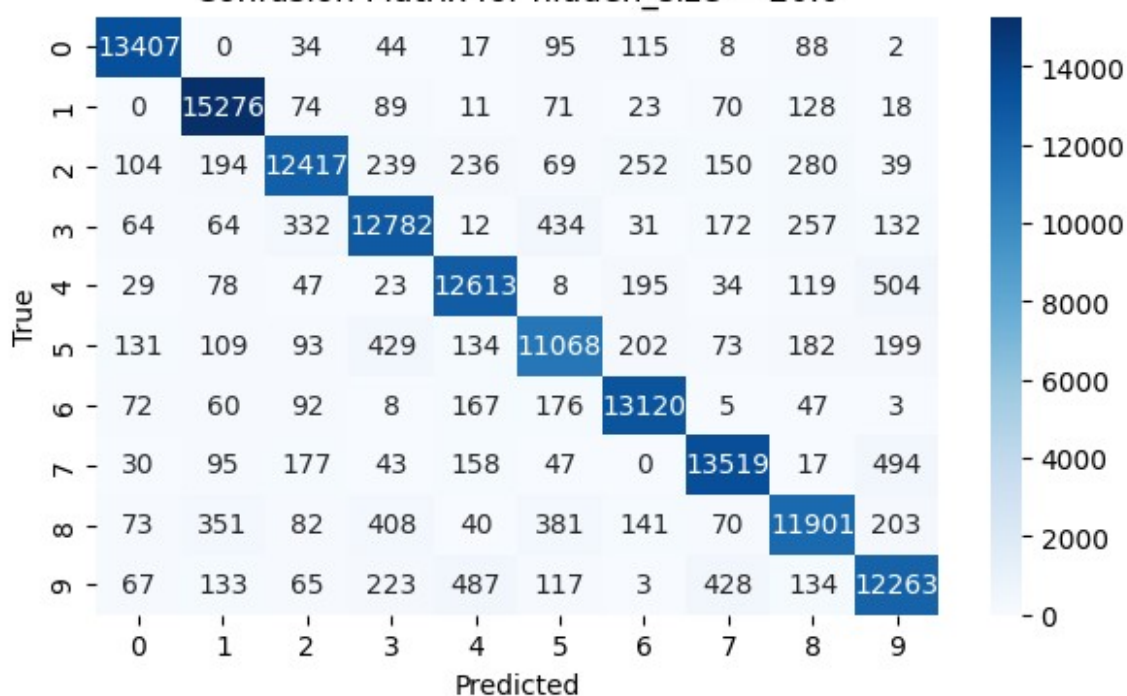


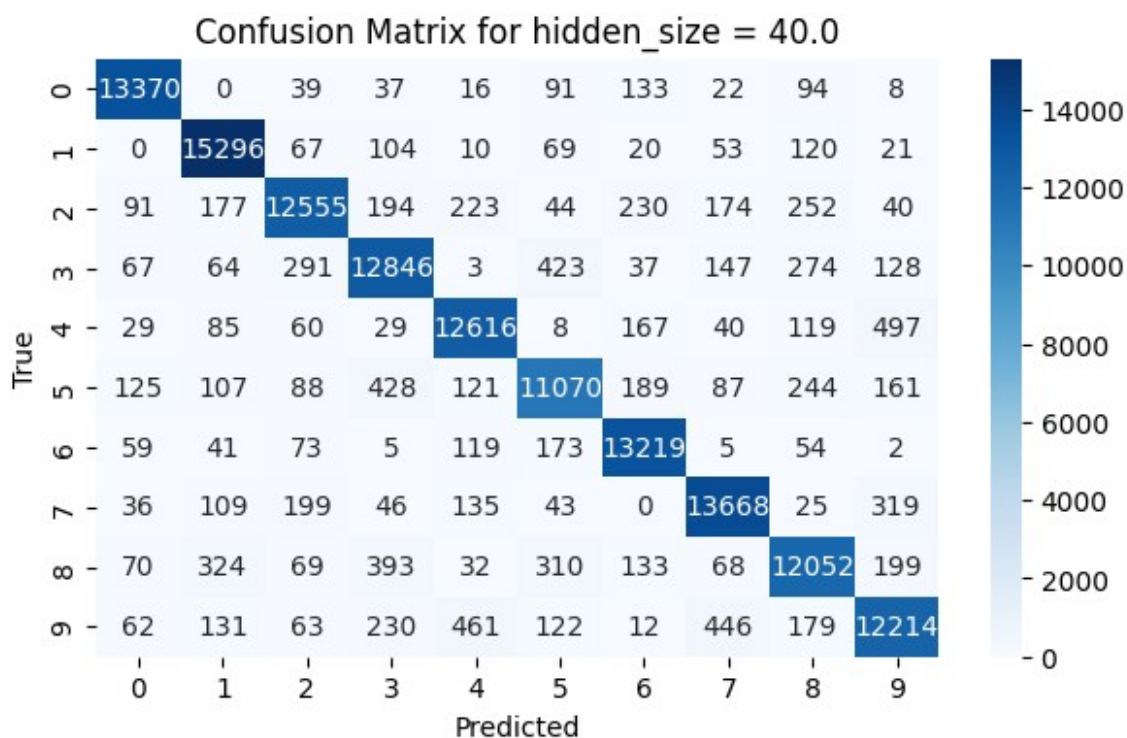
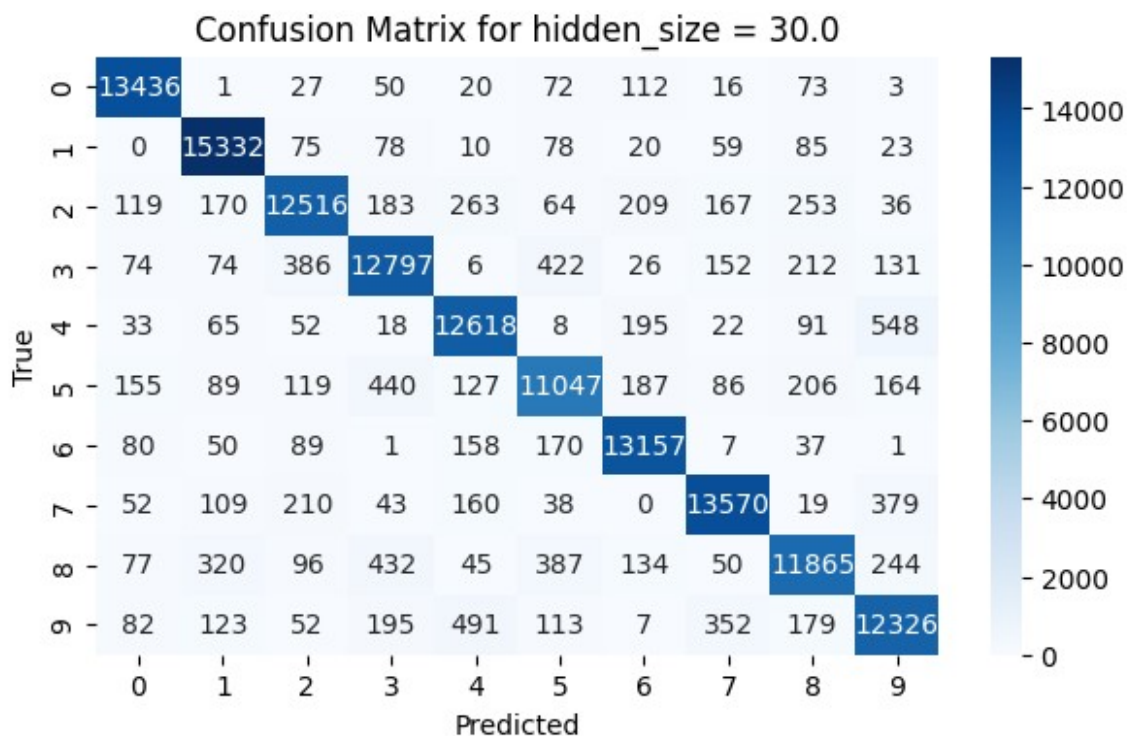
[illegible]

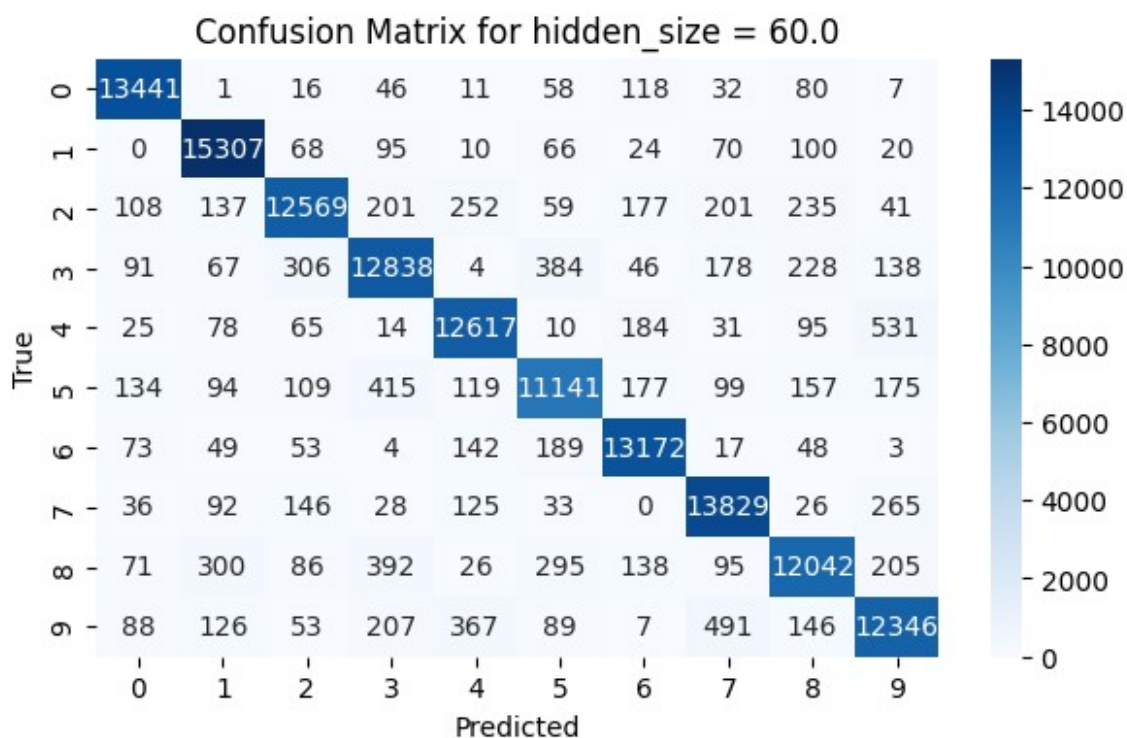
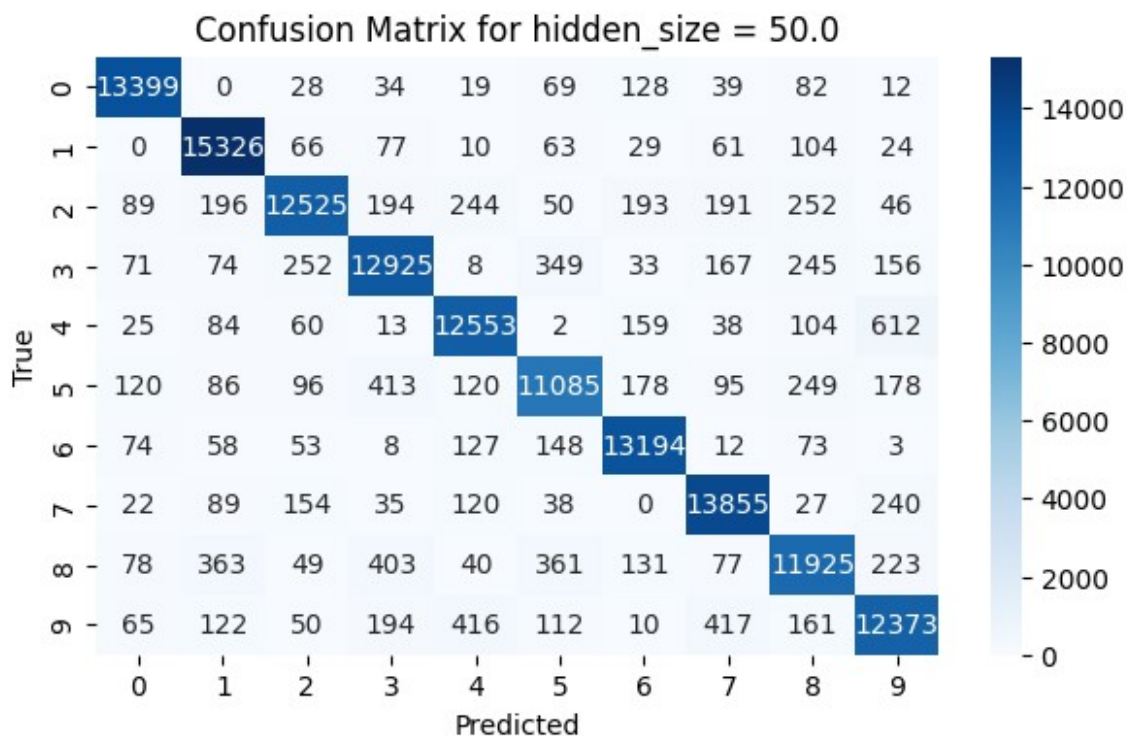
Confusion Matrix for hidden_size = 10.0

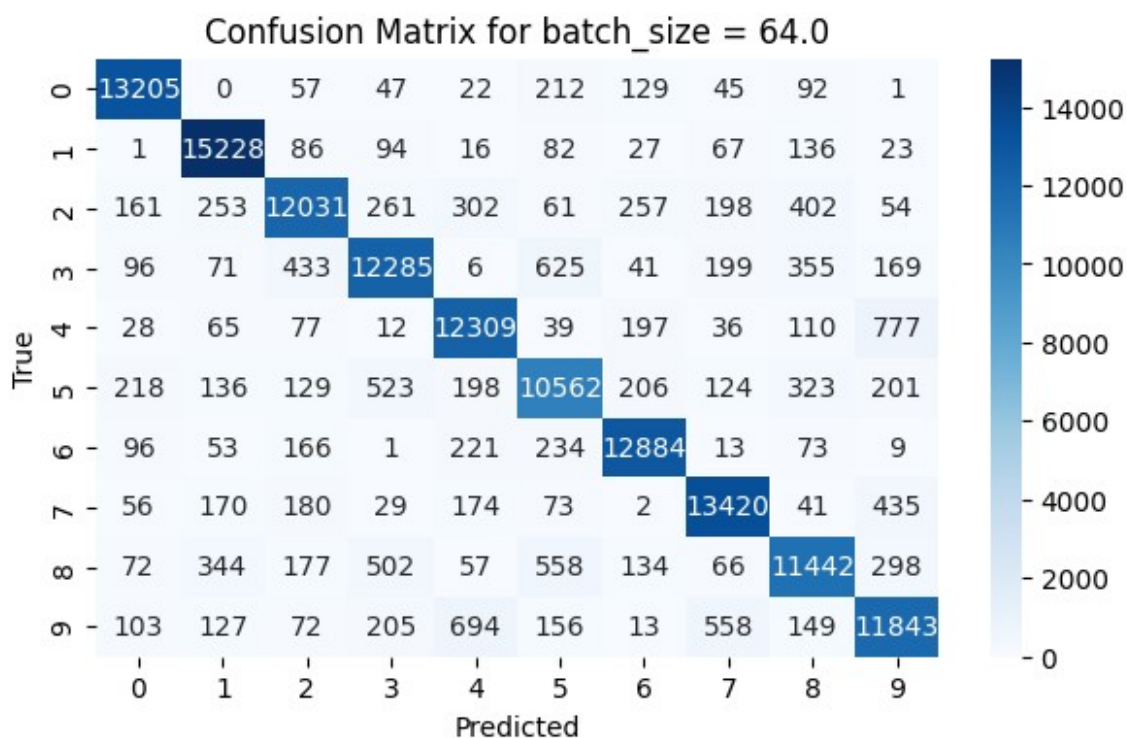
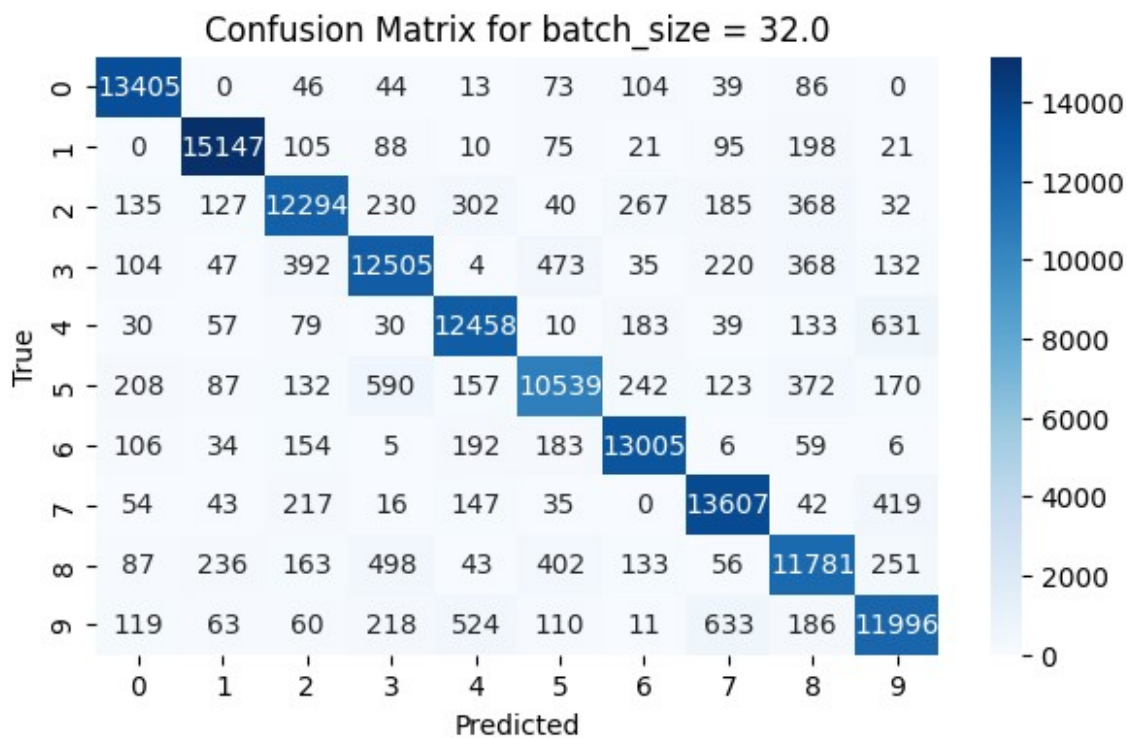


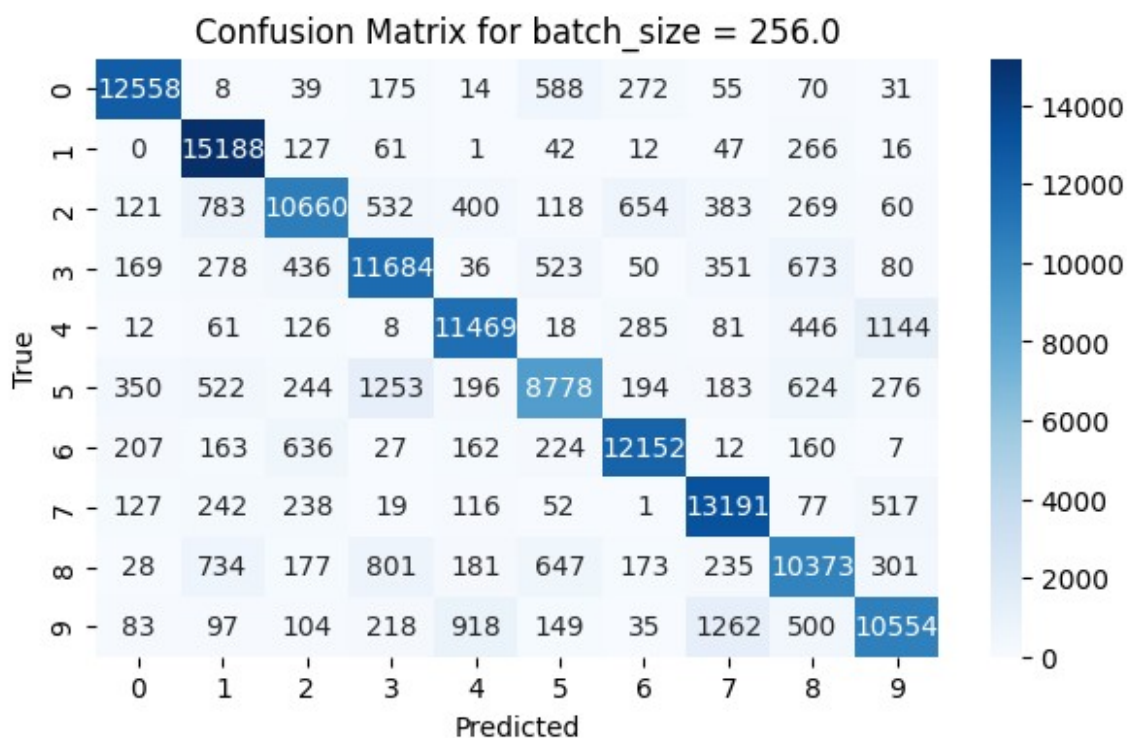
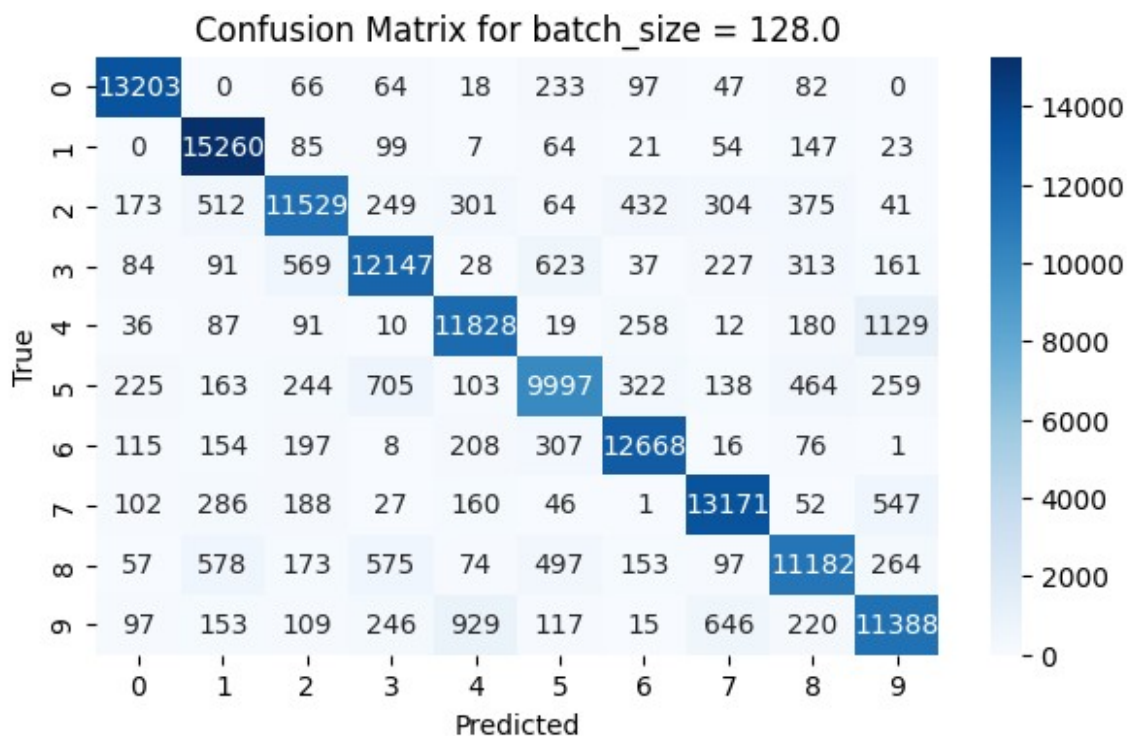
Confusion Matrix for hidden_size = 20.0

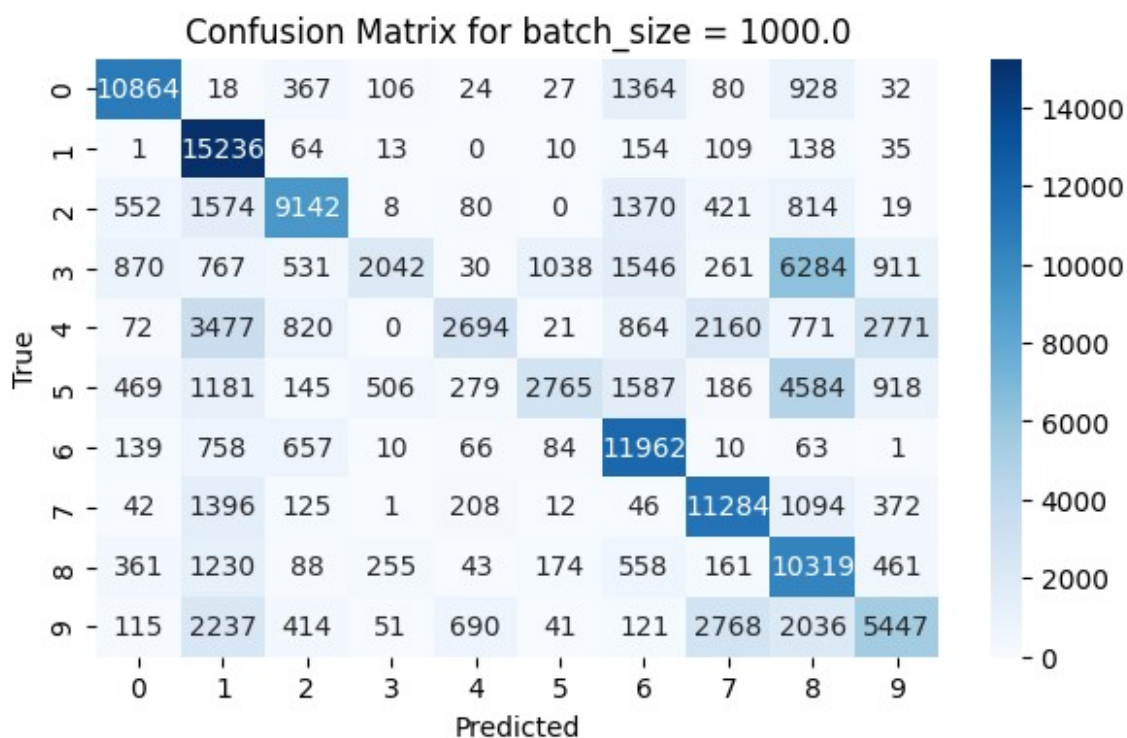
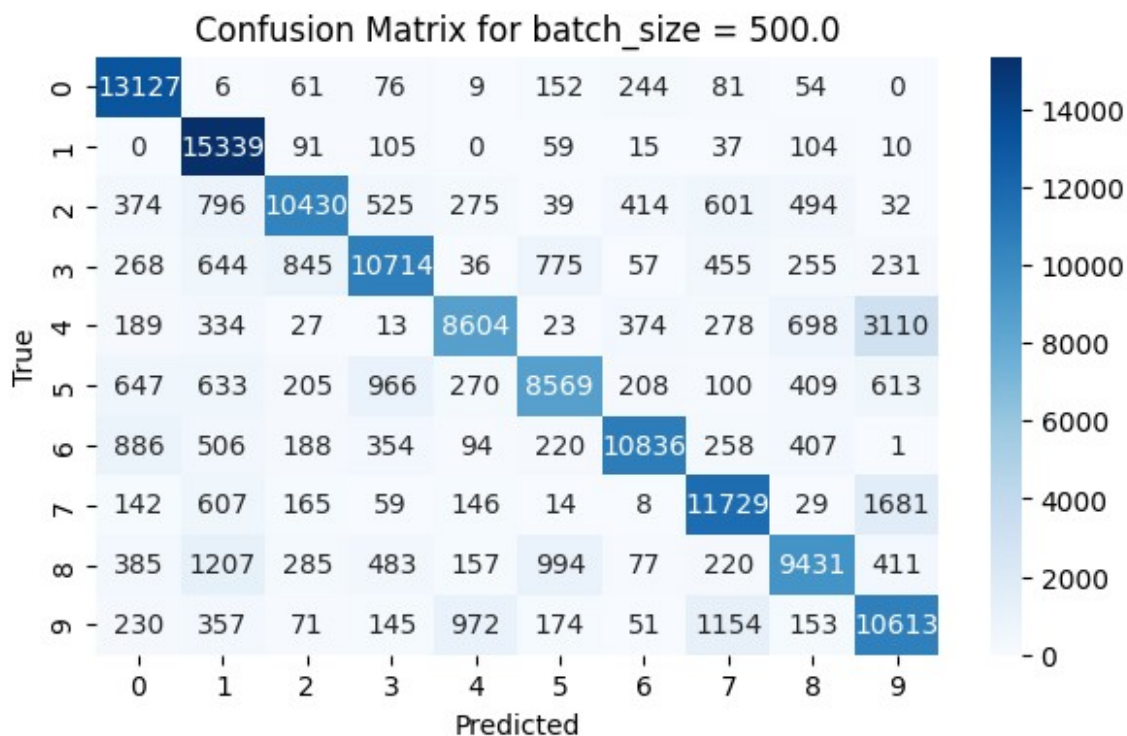


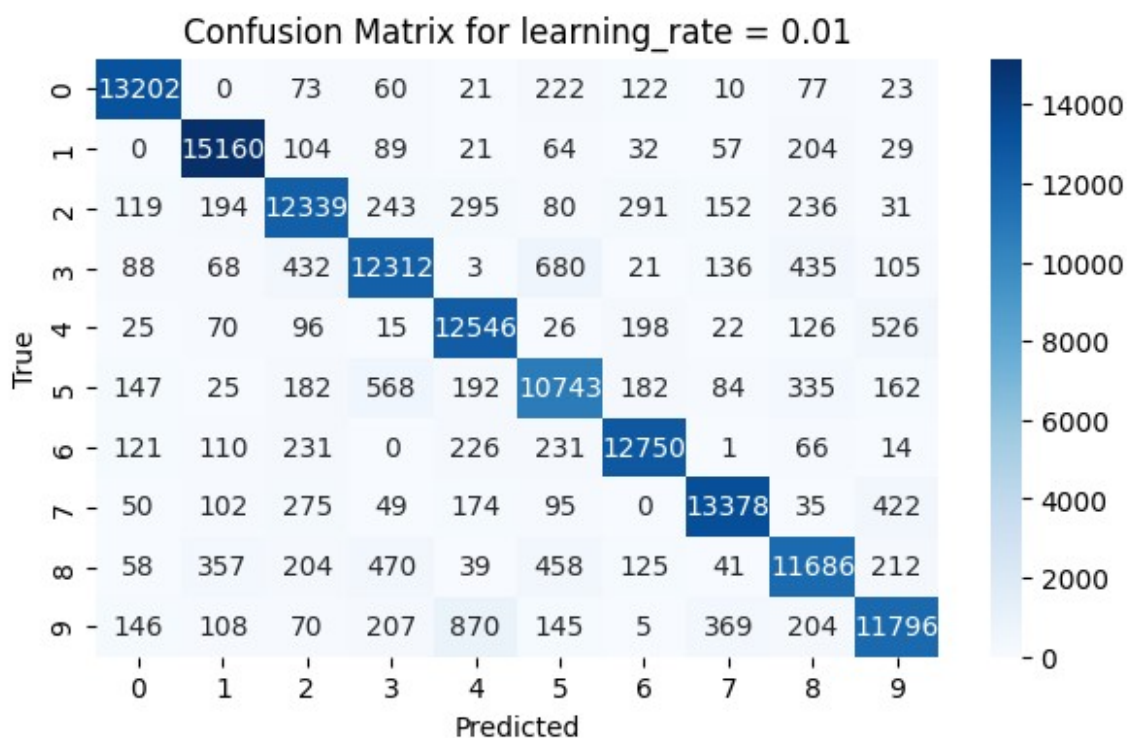
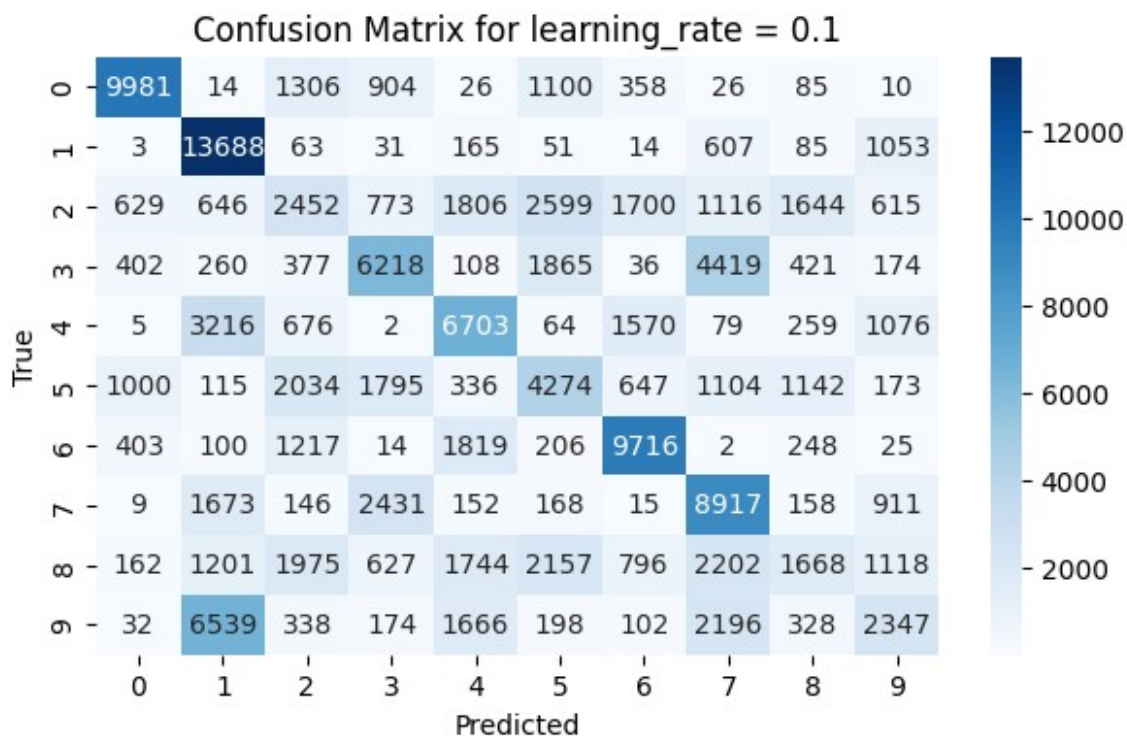


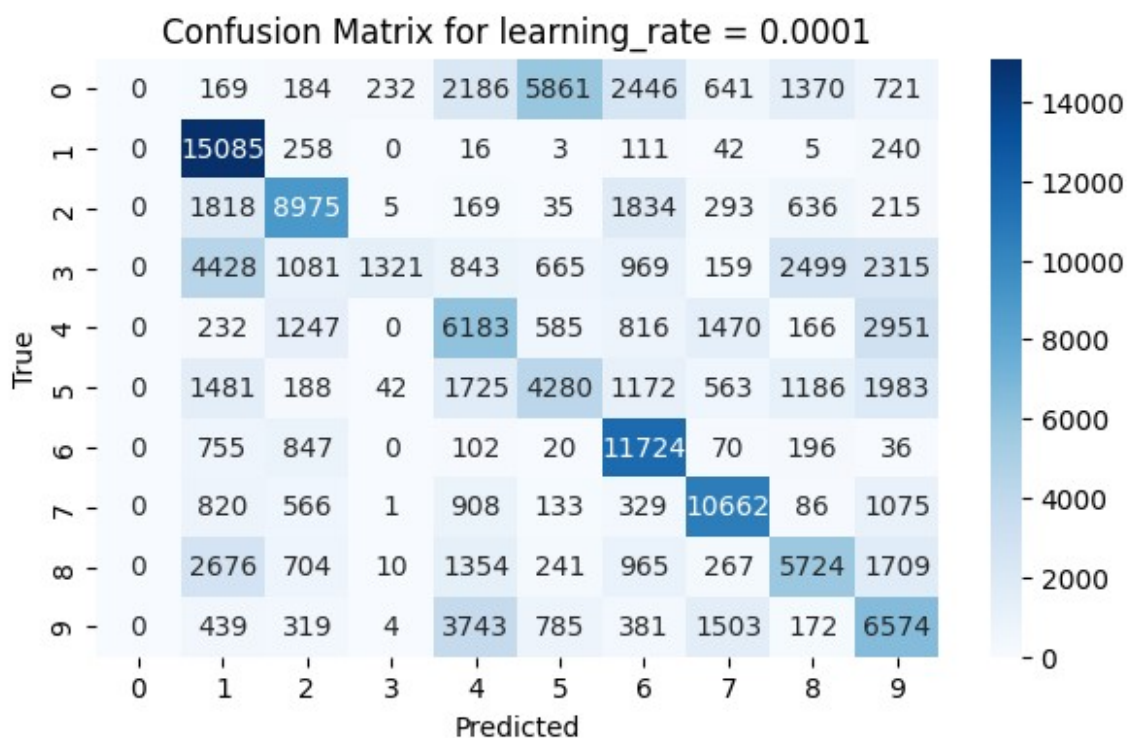
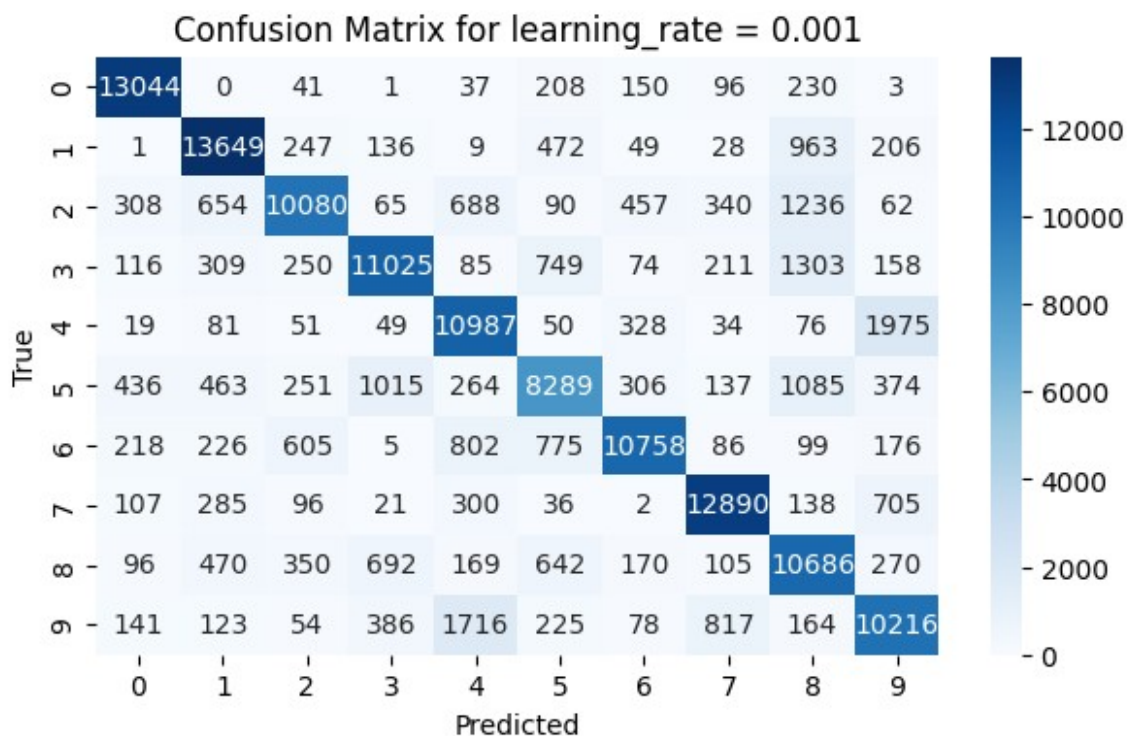


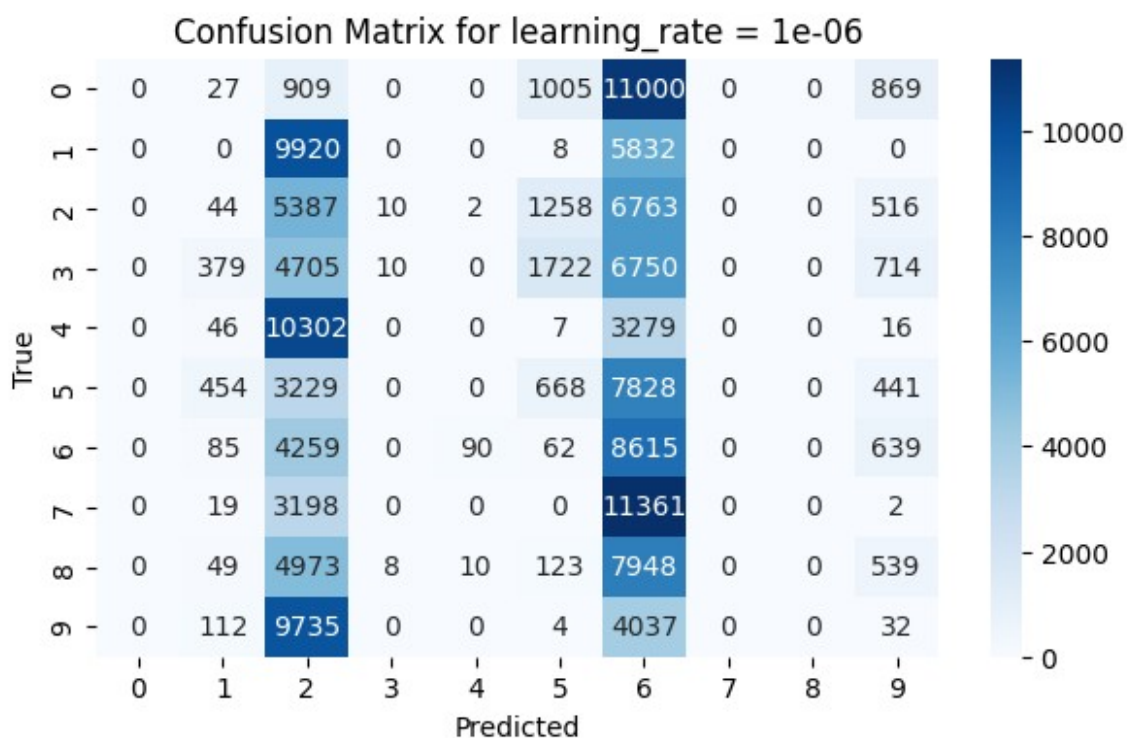
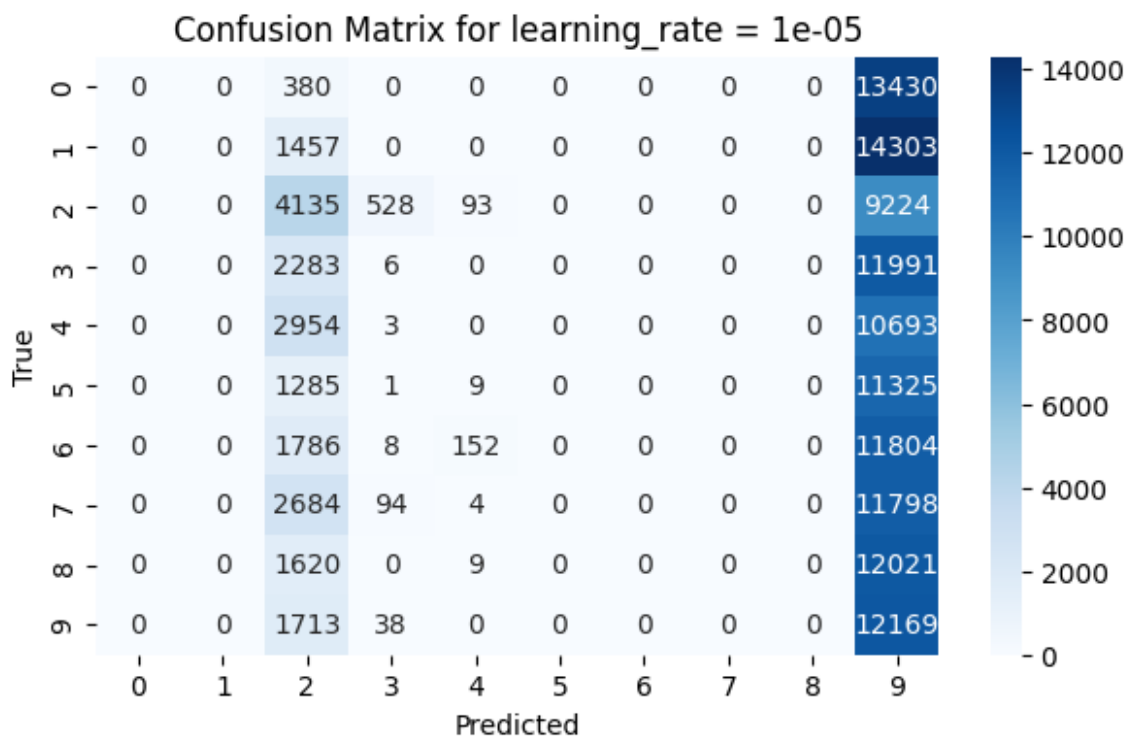












now we inspect the pool for the combination of parameters with the best accuracy, retrain the model using these parameters and finally verify on the test set.

```

# 1. Select the best parameters based on validation accuracy
def select_best_params(results):
    best_result = max(results, key=lambda x: x["val_accuracy"]) #
    Find the best validation accuracy
    best_params = best_result["param"], best_result["value"] #
    Extract the parameter name and value
    print(f"Best Parameter: {best_params[0]} = {best_params[1]}")
    return best_params, best_result

best_params, best_result = select_best_params(results)
print(best_params)

# 2. Train the final model using the best parameters on combined train
+ validation data
combined_train_data = torch.utils.data.ConcatDataset([train_data,
val_data])
combined_train_loader = DataLoader(combined_train_data,
batch_size=default_params["batch_size"], shuffle=True)

# Reinitialize the model with the best hyperparameters
if best_params[0] == "hidden_layers":
    default_params["hidden_layers"] = best_params[1]
elif best_params[0] == "hidden_size":
    default_params["hidden_size"] = best_params[1] # Use the value,
not the name
elif best_params[0] == "batch_size":
    default_params["batch_size"] = best_params[1] # Correct this to
use the value
elif best_params[0] == "learning_rate":
    default_params["learning_rate"] = best_params[1] # Correct this
to use the value

# Create and train the model
final_model = Neural_Network_1_hidden_layer(
    input_size=28*28,
    hidden_size=default_params["hidden_size"],
    num_classes=10
).to(device)

final_optimizer = optim.SGD(final_model.parameters(),
lr=default_params["learning_rate"])
final_criterion = nn.CrossEntropyLoss()

# Train the model on combined data
_, _, train_accs, val_accs, _, _ = train_model(
    final_model, combined_train_loader, val_loader, final_criterion,
    final_optimizer, num_epochs=10
)

```

```

Best Parameter: hidden_size = 50
('hidden_size', 50)
Epoch [1/10], Train Loss: 0.6035, Train Accuracy: 84.06%, Validation
Loss: 0.3581, Validation Accuracy: 90.04%
Epoch [2/10], Train Loss: 0.3235, Train Accuracy: 90.75%, Validation
Loss: 0.2958, Validation Accuracy: 91.68%
Epoch [3/10], Train Loss: 0.2814, Train Accuracy: 91.88%, Validation
Loss: 0.2654, Validation Accuracy: 92.42%
Epoch [4/10], Train Loss: 0.2513, Train Accuracy: 92.76%, Validation
Loss: 0.2376, Validation Accuracy: 93.04%
Epoch [5/10], Train Loss: 0.2249, Train Accuracy: 93.56%, Validation
Loss: 0.2168, Validation Accuracy: 93.59%
Epoch [6/10], Train Loss: 0.2036, Train Accuracy: 94.16%, Validation
Loss: 0.1931, Validation Accuracy: 94.51%
Epoch [7/10], Train Loss: 0.1862, Train Accuracy: 94.62%, Validation
Loss: 0.1788, Validation Accuracy: 95.00%
Epoch [8/10], Train Loss: 0.1713, Train Accuracy: 95.07%, Validation
Loss: 0.1622, Validation Accuracy: 95.44%
Epoch [9/10], Train Loss: 0.1590, Train Accuracy: 95.46%, Validation
Loss: 0.1598, Validation Accuracy: 95.51%
Epoch [10/10], Train Loss: 0.1488, Train Accuracy: 95.79%, Validation
Loss: 0.1437, Validation Accuracy: 95.99%

```

```

def evaluate_on_test_set(model, test_loader):
    model.eval() # Set model to evaluation mode
    correct_test = 0
    total_test = 0
    y_true = []
    y_pred = []

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

            outputs = model(inputs)
            _, predicted = torch.max(outputs.data, 1)
            total_test += labels.size(0)
            correct_test += (predicted == labels).sum().item()

            y_true.extend(labels.cpu().numpy())
            y_pred.extend(predicted.cpu().numpy())

    test_acc = 100 * correct_test / total_test
    print(f'Test Accuracy: {test_acc:.2f}%')

    return y_true, y_pred, test_acc

# Evaluate on the test set
y_true, y_pred, test_acc = evaluate_on_test_set(final_model,
test_loader)

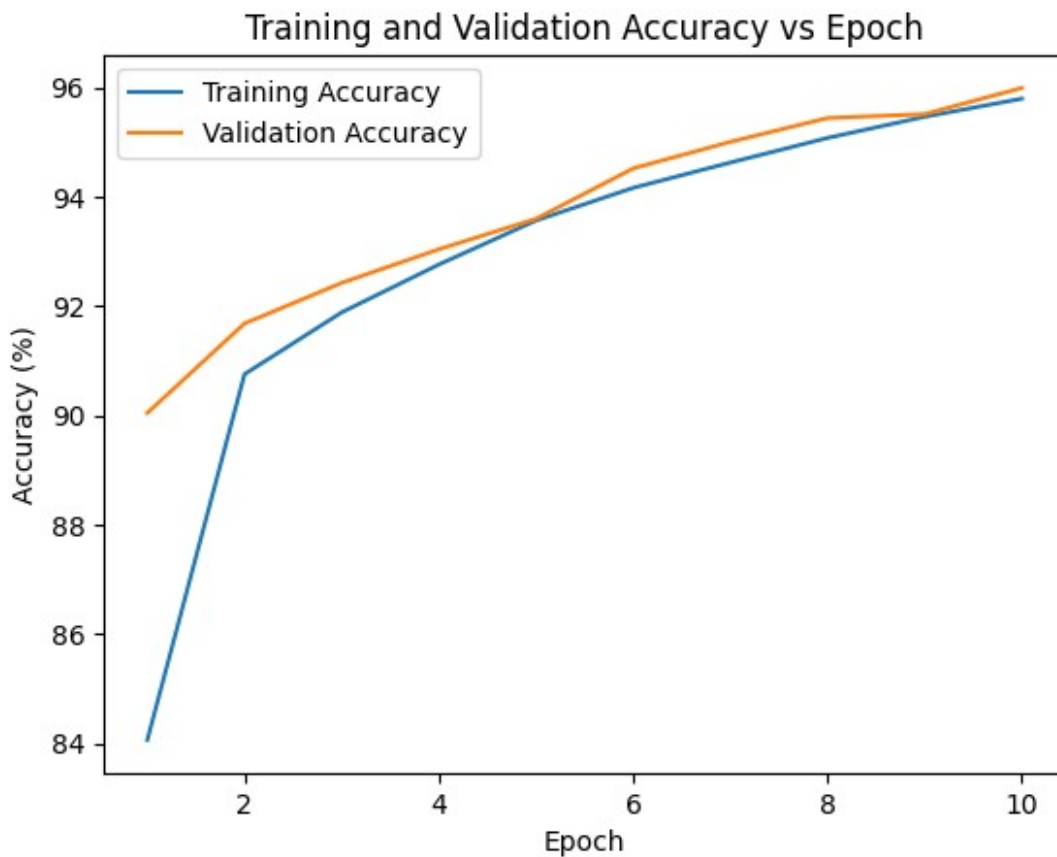
```

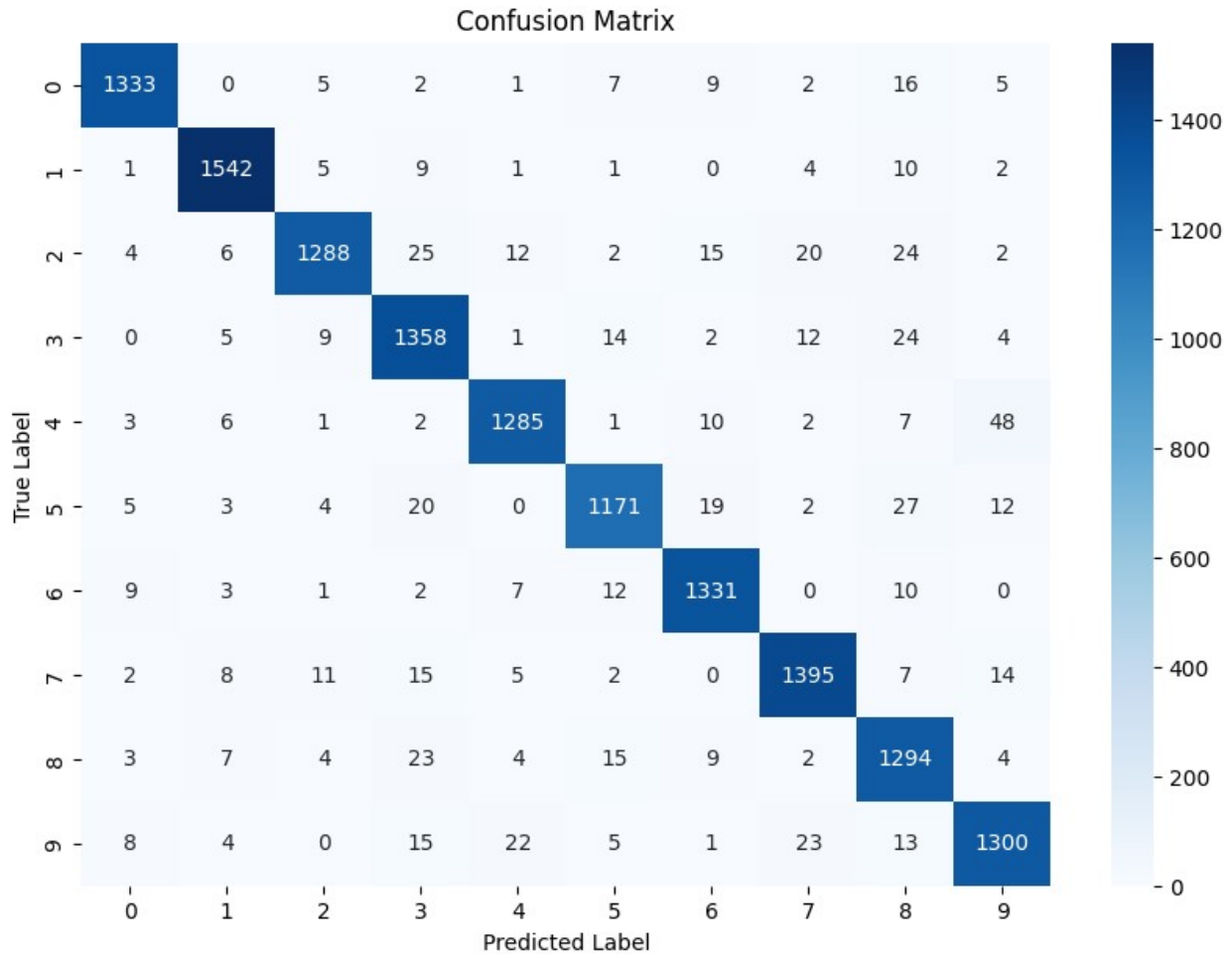

Test Accuracy: 94.98%

```
# Plot the accuracies for training and validation
epochs = list(range(1, 11))
plt.plot(epochs, train_accs, label="Training Accuracy")
plt.plot(epochs, val_accs, label="Validation Accuracy")
plt.xlabel("Epoch")
plt.ylabel("Accuracy (%)")
plt.title("Training and Validation Accuracy vs Epoch")
plt.legend()
plt.show()

# Plot confusion matrix
plot_confusion_matrix(y_true, y_pred)

# Optionally, print the test accuracy
print(f"Test Accuracy: {test_acc:.2f}%")
```





Test Accuracy: 94.98%

Bonus (CNN)

we will adjust the previous code and repeat the process for convolutional Neural Networks and study their features closely.

- notice that we do not need to transform the images when using CNN

```
# Load the MNIST dataset
train_dataset = datasets.MNIST(root='./data', train=True) #this
structure contains data and labels
test_dataset = datasets.MNIST(root='./data', train=False)

#combine the datasets
combined_dataset=ConcatDataset([train_dataset,test_dataset])

#extract labels
train_labels=train_dataset.targets
```

```

test_labels=test_dataset.targets

# Combine labels from both train and test datasets
all_labels = torch.cat((train_labels, test_labels), dim=0)

#split into 60-40
train_idx, temp_idx = train_test_split(
    range(len(combined_dataset)), test_size=0.4, stratify=all_labels,
    random_state=42) # stratify 3lshan not to get skewed data

#split again 20-20
# Split temp (40%) into validation (20%) and test (20%)
val_idx, test_idx = train_test_split(
    temp_idx, test_size=0.5, stratify=all_labels[temp_idx],
    random_state=42) # returns indices

# Create Subset objects for train, validation, and test sets
train_data = Subset(combined_dataset, train_idx)
val_data = Subset(combined_dataset, val_idx)
test_data = Subset(combined_dataset, test_idx)

##recreate dataset w inheirt combatible structure with data loader
# Create DataLoader objects
batch_size = 32
train_loader = DataLoader(train_data, batch_size=batch_size,
    shuffle=True)
val_loader = DataLoader(val_data, batch_size=batch_size,
    shuffle=False)
test_loader = DataLoader(test_data, batch_size=batch_size,
    shuffle=False)

# Print split sizes
print(f"Training set size: {len(train_data)}")
print(f"Validation set size: {len(val_data)}")
print(f"Test set size: {len(test_data)}")
print("Data preparation complete!")

```

```

Training set size: 42000
Validation set size: 14000
Test set size: 14000
Data preparation complete!

```

```

import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
from torchvision import datasets, transforms

```

```

# Default hyperparameters
default_params_cnn = {
    "hidden_layers": 5, # Number of convolutional layers
    "hidden_size": 10, # Number of filters per layer
    "batch_size": 32, # Batch size
    "learning_rate": 0.01,
    "dropout_prob": 0.5 # Dropout probability
}

# Hyperparameter ranges for tuning
param_ranges_cnn = {
    "hidden_layers": [5, 7, 9],
    "hidden_size": [30, 50, 70],
    "batch_size": [128, 256, 512],
    "learning_rate": [0.01, 0.001, 0.0001],
    "dropout_prob": [0.25, 0.5, 0.75]
}

# Device configuration
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Data preparation
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

train_data = datasets.MNIST(root="data", train=True, download=True,
transform=transform)
val_data = datasets.MNIST(root="data", train=False, download=True,
transform=transform)

class ConvNeuralNetwork(nn.Module):
    def __init__(self, input_channels, hidden_layers, hidden_size,
num_classes, dropout_prob):
        super(ConvNeuralNetwork, self).__init__()

        layers = []

        # First convolutional layer
        layers.append(nn.Conv2d(input_channels, hidden_size,
kernel_size=3, padding=1)) # 3x3 kernel(filter)
        layers.append(nn.ReLU())
        layers.append(nn.LayerNorm([hidden_size, 28, 28]))
        layers.append(nn.Dropout(dropout_prob))

        # Additional convolutional layers
        for i in range(1, hidden_layers):

```

```

        layers.append(nn.Conv2d(hidden_size, hidden_size,
kernel_size=3, padding=1))
        layers.append(nn.ReLU())
        layers.append(nn.LayerNorm([hidden_size, 28, 28]))
        layers.append(nn.Dropout(dropout_prob))

    # Pooling layer
    layers.append(nn.MaxPool2d(kernel_size=2, stride=2)) #
    Reduces dimensions to 14x14

    # Flatten layer for the fully connected layer
    self.flatten = nn.Flatten()

    # Fully connected layer
    fc_input_size = hidden_size * 14 * 14 # After pooling
    self.fc = nn.Linear(fc_input_size, num_classes)

    self.network = nn.Sequential(*layers)

def forward(self, x):
    x = self.network(x)
    x = self.flatten(x)
    x = self.fc(x)
    return x

def train_model(model, train_loader, val_loader, criterion, optimizer,
num_epochs=10):
    train_losses, val_losses = [], []
    train_accuracies, val_accuracies = [], []

    for epoch in range(num_epochs):
        # Training phase
        model.train()
        correct, total, train_loss = 0, 0, 0
        for inputs, labels in train_loader:
            inputs, labels = inputs.to(device), labels.to(device)
            optimizer.zero_grad()

            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            train_loss += loss.item()
            _, predicted = torch.max(outputs, 1)
            correct += (predicted == labels).sum().item()
            total += labels.size(0)

        train_losses.append(train_loss / len(train_loader))

```

```

train_accuracies.append(correct / total)

# Validation phase
model.eval()
correct, total, val_loss = 0, 0, 0
y_true, y_pred = [], []
with torch.no_grad():
    for inputs, labels in val_loader:
        inputs, labels = inputs.to(device), labels.to(device)
        outputs = model(inputs)
        loss = criterion(outputs, labels)
        val_loss += loss.item()
        _, predicted = torch.max(outputs, 1)
        correct += (predicted == labels).sum().item()
        total += labels.size(0)
        y_true.extend(labels.cpu().numpy())
        y_pred.extend(predicted.cpu().numpy())

val_losses.append(val_loss / len(val_loader))
val_accuracies.append(correct / total)

print(f"Epoch {epoch + 1}/{num_epochs} - "
      f"Train Loss: {train_losses[-1]:.4f}, Train Accuracy: "
      f"{train_accuracies[-1]:.4f} - "
      f"Val Loss: {val_losses[-1]:.4f}, Val Accuracy: "
      f"{val_accuracies[-1]:.4f}")

return train_losses, val_losses, train_accuracies, val_accuracies,
y_true, y_pred

def tune_hyperparameters(default_params, param_ranges, num_epochs=10):
    results = []

    # Iterate over each parameter
    for param, values in param_ranges.items():
        for value in values:
            # Update the parameter value
            params = default_params.copy()
            params[param] = value

            # Update DataLoader if batch_size changes
            batch_size = params["batch_size"]
            train_loader = DataLoader(train_data,
batch_size=batch_size, shuffle=True)
            val_loader = DataLoader(val_data, batch_size=batch_size,
shuffle=False)

            # Build the model
            model = ConvNeuralNetwork(

```

```

        input_channels=1, # MNIST has 1 channel
        hidden_layers=params["hidden_layers"],
        hidden_size=params["hidden_size"],
        num_classes=10,
        dropout_prob=params["dropout_prob"]
    ).to(device)

    # Define optimizer with new learning rate
    optimizer = optim.Adam(model.parameters(),
lr=params["learning_rate"])
    criterion = nn.CrossEntropyLoss()

    # Train the model
    train_losses, val_losses, train_accuracies,
val_accuracies, y_true, y_pred = train_model(
        model, train_loader, val_loader, criterion, optimizer,
num_epochs=num_epochs
    )

    # Record results
    results.append({
        "param": param,
        "value": value,
        "train_accuracy": train_accuracies[-1],
        "val_accuracy": val_accuracies[-1],
        "train_loss": train_losses[-1],
        "val_loss": val_losses[-1],
        "y_true": y_true,
        "y_pred": y_pred
    })

    print(f"Completed training for {param} = {value}")

    return results

```

Example usage

```

results = tune_hyperparameters(default_params_cnn, param_ranges_cnn,
num_epochs=5)

```

```

Epoch 1/5 - Train Loss: 0.6286, Train Accuracy: 0.8488 - Val Loss:
0.3645, Val Accuracy: 0.8917

```

```

Epoch 2/5 - Train Loss: 0.2694, Train Accuracy: 0.9290 - Val Loss:
0.2912, Val Accuracy: 0.9140

```

```

Epoch 3/5 - Train Loss: 0.2581, Train Accuracy: 0.9356 - Val Loss:
1.0703, Val Accuracy: 0.7722

```

```

Epoch 4/5 - Train Loss: 0.2719, Train Accuracy: 0.9366 - Val Loss:
0.6632, Val Accuracy: 0.8681

```

```

Epoch 5/5 - Train Loss: 0.2767, Train Accuracy: 0.9394 - Val Loss:
0.6576, Val Accuracy: 0.8632

```

Completed training for hidden_layers = 5
Epoch 1/5 - Train Loss: 0.5572, Train Accuracy: 0.8637 - Val Loss: 1.8260, Val Accuracy: 0.4912
Epoch 2/5 - Train Loss: 0.2922, Train Accuracy: 0.9168 - Val Loss: 1.0553, Val Accuracy: 0.7176
Epoch 3/5 - Train Loss: 0.2916, Train Accuracy: 0.9214 - Val Loss: 0.4345, Val Accuracy: 0.8793
Epoch 4/5 - Train Loss: 0.2892, Train Accuracy: 0.9253 - Val Loss: 0.3959, Val Accuracy: 0.9011
Epoch 5/5 - Train Loss: 0.2826, Train Accuracy: 0.9292 - Val Loss: 0.2874, Val Accuracy: 0.9317
Completed training for hidden_layers = 7
Epoch 1/5 - Train Loss: 0.6660, Train Accuracy: 0.8247 - Val Loss: 0.4822, Val Accuracy: 0.8478
Epoch 2/5 - Train Loss: 0.3209, Train Accuracy: 0.9074 - Val Loss: 0.3325, Val Accuracy: 0.9049
Epoch 3/5 - Train Loss: 0.2915, Train Accuracy: 0.9190 - Val Loss: 0.3287, Val Accuracy: 0.9201
Epoch 4/5 - Train Loss: 0.2958, Train Accuracy: 0.9228 - Val Loss: 0.3433, Val Accuracy: 0.8984
Epoch 5/5 - Train Loss: 0.2824, Train Accuracy: 0.9289 - Val Loss: 0.3132, Val Accuracy: 0.9136
Completed training for hidden_layers = 9
Epoch 1/5 - Train Loss: 0.7969, Train Accuracy: 0.8651 - Val Loss: 4.9081, Val Accuracy: 0.2901
Epoch 2/5 - Train Loss: 0.3784, Train Accuracy: 0.9261 - Val Loss: 3.0263, Val Accuracy: 0.7134
Epoch 3/5 - Train Loss: 0.4684, Train Accuracy: 0.9377 - Val Loss: 0.8222, Val Accuracy: 0.8899
Epoch 4/5 - Train Loss: 0.5289, Train Accuracy: 0.9456 - Val Loss: 0.6941, Val Accuracy: 0.9365
Epoch 5/5 - Train Loss: 0.6020, Train Accuracy: 0.9523 - Val Loss: 2.3588, Val Accuracy: 0.8538
Completed training for hidden_size = 30
Epoch 1/5 - Train Loss: 1.3207, Train Accuracy: 0.8887 - Val Loss: 2.1529, Val Accuracy: 0.7586
Epoch 2/5 - Train Loss: 0.6117, Train Accuracy: 0.9394 - Val Loss: 0.9601, Val Accuracy: 0.9368
Epoch 3/5 - Train Loss: 0.7775, Train Accuracy: 0.9505 - Val Loss: 1.7333, Val Accuracy: 0.8878
Epoch 4/5 - Train Loss: 0.8765, Train Accuracy: 0.9589 - Val Loss: 2.3877, Val Accuracy: 0.9195
Epoch 5/5 - Train Loss: 1.0356, Train Accuracy: 0.9642 - Val Loss: 1.0668, Val Accuracy: 0.9639
Completed training for hidden_size = 50
Epoch 1/5 - Train Loss: 1.5462, Train Accuracy: 0.8262 - Val Loss: 30.3408, Val Accuracy: 0.1994
Epoch 2/5 - Train Loss: 0.8332, Train Accuracy: 0.8967 - Val Loss: 19.1903, Val Accuracy: 0.3361

Epoch 3/5 - Train Loss: 1.0777, Train Accuracy: 0.9205 - Val Loss: 11.8448, Val Accuracy: 0.5724
Epoch 4/5 - Train Loss: 1.3010, Train Accuracy: 0.9346 - Val Loss: 19.3208, Val Accuracy: 0.5599
Epoch 5/5 - Train Loss: 1.4493, Train Accuracy: 0.9435 - Val Loss: 23.3425, Val Accuracy: 0.5950
Completed training for hidden_size = 70
Epoch 1/5 - Train Loss: 0.7810, Train Accuracy: 0.8201 - Val Loss: 1.8387, Val Accuracy: 0.4948
Epoch 2/5 - Train Loss: 0.2548, Train Accuracy: 0.9252 - Val Loss: 0.4694, Val Accuracy: 0.8480
Epoch 3/5 - Train Loss: 0.1823, Train Accuracy: 0.9465 - Val Loss: 0.2784, Val Accuracy: 0.9070
Epoch 4/5 - Train Loss: 0.1542, Train Accuracy: 0.9556 - Val Loss: 0.1537, Val Accuracy: 0.9507
Epoch 5/5 - Train Loss: 0.1430, Train Accuracy: 0.9573 - Val Loss: 0.1159, Val Accuracy: 0.9637
Completed training for batch_size = 128
Epoch 1/5 - Train Loss: 1.4737, Train Accuracy: 0.7449 - Val Loss: 5.6710, Val Accuracy: 0.3106
Epoch 2/5 - Train Loss: 0.4352, Train Accuracy: 0.8661 - Val Loss: 2.4213, Val Accuracy: 0.4797
Epoch 3/5 - Train Loss: 0.3141, Train Accuracy: 0.9019 - Val Loss: 1.8878, Val Accuracy: 0.5518
Epoch 4/5 - Train Loss: 0.2500, Train Accuracy: 0.9230 - Val Loss: 2.1881, Val Accuracy: 0.5091
Epoch 5/5 - Train Loss: 0.2089, Train Accuracy: 0.9357 - Val Loss: 1.2663, Val Accuracy: 0.6468
Completed training for batch_size = 256
Epoch 1/5 - Train Loss: 2.0295, Train Accuracy: 0.6843 - Val Loss: 3.6860, Val Accuracy: 0.4168
Epoch 2/5 - Train Loss: 0.5258, Train Accuracy: 0.8383 - Val Loss: 2.7441, Val Accuracy: 0.4734
Epoch 3/5 - Train Loss: 0.4646, Train Accuracy: 0.8554 - Val Loss: 2.0511, Val Accuracy: 0.5145
Epoch 4/5 - Train Loss: 0.3481, Train Accuracy: 0.8916 - Val Loss: 1.1292, Val Accuracy: 0.6891
Epoch 5/5 - Train Loss: 0.2614, Train Accuracy: 0.9219 - Val Loss: 0.7475, Val Accuracy: 0.7613
Completed training for batch_size = 512
Epoch 1/5 - Train Loss: 0.5938, Train Accuracy: 0.8592 - Val Loss: 0.4149, Val Accuracy: 0.8692
Epoch 2/5 - Train Loss: 0.2716, Train Accuracy: 0.9252 - Val Loss: 0.1999, Val Accuracy: 0.9441
Epoch 3/5 - Train Loss: 0.2781, Train Accuracy: 0.9304 - Val Loss: 0.5721, Val Accuracy: 0.8686
Epoch 4/5 - Train Loss: 0.2720, Train Accuracy: 0.9355 - Val Loss: 0.7362, Val Accuracy: 0.8507
Epoch 5/5 - Train Loss: 0.2852, Train Accuracy: 0.9384 - Val Loss:

0.6331, Val Accuracy: 0.8785
Completed training for learning_rate = 0.01
Epoch 1/5 - Train Loss: 0.4270, Train Accuracy: 0.8684 - Val Loss: 0.1632, Val Accuracy: 0.9499
Epoch 2/5 - Train Loss: 0.1981, Train Accuracy: 0.9429 - Val Loss: 0.1018, Val Accuracy: 0.9703
Epoch 3/5 - Train Loss: 0.1560, Train Accuracy: 0.9572 - Val Loss: 0.0898, Val Accuracy: 0.9734
Epoch 4/5 - Train Loss: 0.1376, Train Accuracy: 0.9621 - Val Loss: 0.0885, Val Accuracy: 0.9753
Epoch 5/5 - Train Loss: 0.1187, Train Accuracy: 0.9668 - Val Loss: 0.0706, Val Accuracy: 0.9781
Completed training for learning_rate = 0.001
Epoch 1/5 - Train Loss: 1.0787, Train Accuracy: 0.6462 - Val Loss: 0.4337, Val Accuracy: 0.8765
Epoch 2/5 - Train Loss: 0.3629, Train Accuracy: 0.8865 - Val Loss: 0.2982, Val Accuracy: 0.9088
Epoch 3/5 - Train Loss: 0.2604, Train Accuracy: 0.9189 - Val Loss: 0.2076, Val Accuracy: 0.9361
Epoch 4/5 - Train Loss: 0.2086, Train Accuracy: 0.9355 - Val Loss: 0.1822, Val Accuracy: 0.9462
Epoch 5/5 - Train Loss: 0.1730, Train Accuracy: 0.9466 - Val Loss: 0.1608, Val Accuracy: 0.9511
Completed training for learning_rate = 0.0001
Epoch 1/5 - Train Loss: 0.4303, Train Accuracy: 0.9040 - Val Loss: 0.1624, Val Accuracy: 0.9519
Epoch 2/5 - Train Loss: 0.1589, Train Accuracy: 0.9575 - Val Loss: 0.1885, Val Accuracy: 0.9544
Epoch 3/5 - Train Loss: 0.1715, Train Accuracy: 0.9598 - Val Loss: 0.2638, Val Accuracy: 0.9492
Epoch 4/5 - Train Loss: 0.1849, Train Accuracy: 0.9624 - Val Loss: 0.1579, Val Accuracy: 0.9669
Epoch 5/5 - Train Loss: 0.1979, Train Accuracy: 0.9644 - Val Loss: 0.3136, Val Accuracy: 0.9548
Completed training for dropout_prob = 0.25
Epoch 1/5 - Train Loss: 0.6011, Train Accuracy: 0.8551 - Val Loss: 0.8950, Val Accuracy: 0.6911
Epoch 2/5 - Train Loss: 0.2787, Train Accuracy: 0.9250 - Val Loss: 0.9171, Val Accuracy: 0.7662
Epoch 3/5 - Train Loss: 0.2750, Train Accuracy: 0.9308 - Val Loss: 0.3244, Val Accuracy: 0.9098
Epoch 4/5 - Train Loss: 0.2721, Train Accuracy: 0.9338 - Val Loss: 0.3477, Val Accuracy: 0.9098
Epoch 5/5 - Train Loss: 0.2834, Train Accuracy: 0.9370 - Val Loss: 0.2573, Val Accuracy: 0.9432
Completed training for dropout_prob = 0.5
Epoch 1/5 - Train Loss: 1.2692, Train Accuracy: 0.7437 - Val Loss: 0.7023, Val Accuracy: 0.7478
Epoch 2/5 - Train Loss: 0.5890, Train Accuracy: 0.8254 - Val Loss:

```

1.0721, Val Accuracy: 0.7369
Epoch 3/5 - Train Loss: 0.5701, Train Accuracy: 0.8323 - Val Loss:
0.8930, Val Accuracy: 0.7472
Epoch 4/5 - Train Loss: 0.5742, Train Accuracy: 0.8328 - Val Loss:
2.2996, Val Accuracy: 0.5820
Epoch 5/5 - Train Loss: 0.5587, Train Accuracy: 0.8400 - Val Loss:
2.1126, Val Accuracy: 0.5805
Completed training for dropout_prob = 0.75

```

```
# Convert the results list to a DataFrame
```

```
df = pd.DataFrame(results)
```

```
# Inspect the columns to ensure they match expected names
```

```
print("Columns in DataFrame:", df.columns)
```

```
# Verify sample rows to confirm data integrity
```

```
print(df.head())
```

```

Columns in DataFrame: Index(['param', 'value', 'train_accuracy',
                             'val_accuracy', 'train_loss',
                             'val_loss', 'y_true', 'y_pred'],
                             dtype='object')

```

	param	value	train_accuracy	val_accuracy	train_loss	val_loss
0	hidden_layers	5.0	0.939433	0.8632	0.276677	0.657580
1	hidden_layers	7.0	0.929167	0.9317	0.282560	0.287354
2	hidden_layers	9.0	0.928883	0.9136	0.282382	0.313214
3	hidden_size	30.0	0.952283	0.8538	0.601990	2.358824
4	hidden_size	50.0	0.964200	0.9639	1.035592	1.066752

```

                                y_true \
0  [7, 2, 1, 0, 4, 1, 4, 9, 5, 9, 0, 6, 9, 0, 1, ...
1  [7, 2, 1, 0, 4, 1, 4, 9, 5, 9, 0, 6, 9, 0, 1, ...
2  [7, 2, 1, 0, 4, 1, 4, 9, 5, 9, 0, 6, 9, 0, 1, ...
3  [7, 2, 1, 0, 4, 1, 4, 9, 5, 9, 0, 6, 9, 0, 1, ...
4  [7, 2, 1, 0, 4, 1, 4, 9, 5, 9, 0, 6, 9, 0, 1, ...

```

```

                                y_pred
0  [7, 2, 1, 0, 4, 1, 4, 9, 6, 9, 0, 6, 9, 0, 1, ...
1  [7, 2, 1, 0, 4, 1, 4, 9, 5, 9, 0, 6, 9, 0, 1, ...
2  [7, 2, 1, 0, 4, 1, 4, 9, 5, 9, 0, 6, 9, 0, 1, ...
3  [7, 1, 1, 0, 4, 1, 1, 9, 5, 9, 0, 6, 9, 0, 1, ...
4  [7, 2, 1, 0, 4, 1, 4, 9, 5, 9, 0, 6, 9, 0, 1, ...

```

```

import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix

# Plot Training & Validation Accuracy and Loss for each parameter
separately
unique_params = df["param"].unique()

for param in unique_params:
    # Filter the DataFrame for the current parameter
    subset = df[df["param"] == param]

    print(f"----- Accuracy and
Loss for {param} ----- ")

    # Plot Training and Validation Accuracy on the same graph
    plt.figure(figsize=(7, 4))
    plt.plot(subset["value"], subset["train_accuracy"], linestyle='--',
label="Training Accuracy")
    plt.plot(subset["value"], subset["val_accuracy"], linestyle='--',
label="Validation Accuracy")
    plt.scatter(subset["value"], subset["train_accuracy"], marker='o',
s=80, label="Training Accuracy (scatter)")
    plt.scatter(subset["value"], subset["val_accuracy"], marker='x',
s=80, label="Validation Accuracy (scatter)")
    plt.title(f"Training and Validation Accuracy vs {param}")
    plt.xlabel(f"{param} Value")
    plt.ylabel("Accuracy (%)")
    plt.grid()
    plt.legend()
    plt.show()

    # Plot Training and Validation Loss on the same graph
    plt.figure(figsize=(7, 4))
    plt.plot(subset["value"], subset["train_loss"], linestyle='--',
label="Training Loss")
    plt.plot(subset["value"], subset["val_loss"], linestyle='--',
label="Validation Loss")
    plt.scatter(subset["value"], subset["train_loss"], marker='o',
s=80, label="Training Loss (scatter)")
    plt.scatter(subset["value"], subset["val_loss"], marker='x', s=80,
label="Validation Loss (scatter)")
    plt.title(f"Training and Validation Loss vs {param}")
    plt.xlabel(f"{param} Value")
    plt.ylabel("Loss")
    plt.grid()
    plt.legend()
    plt.show()

print(f"----- Confusion Matrix
for {param} ----- ")

```

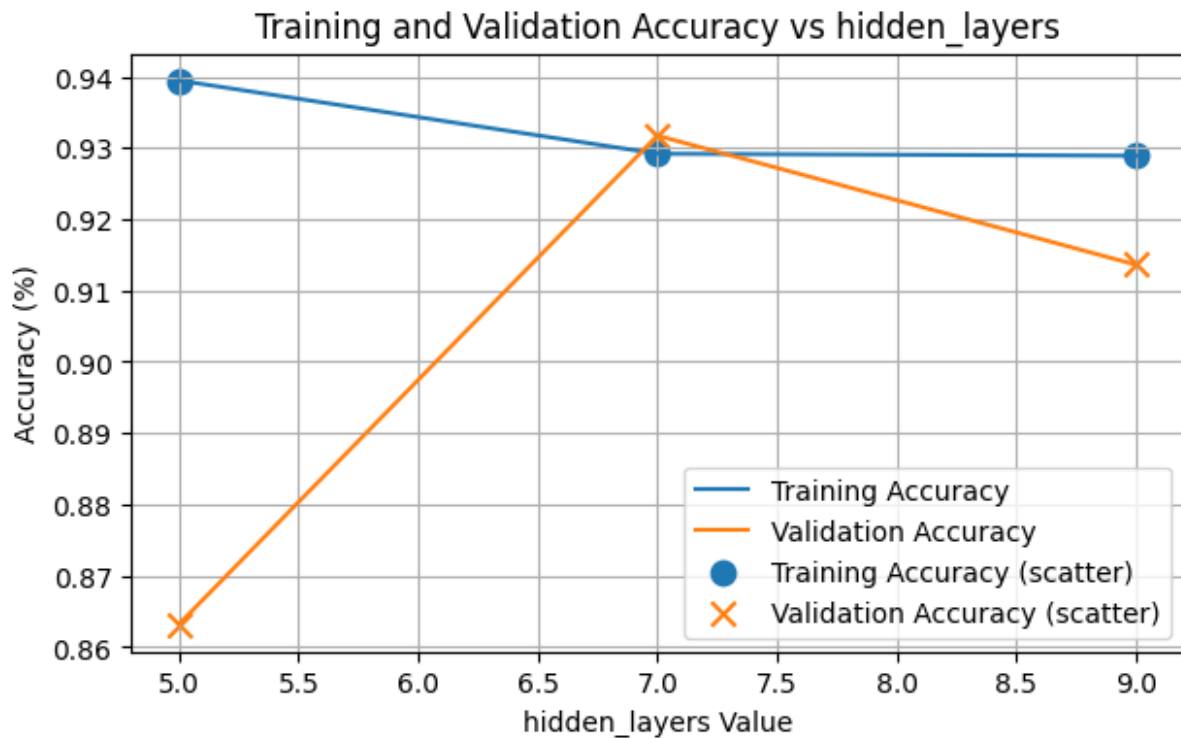
```

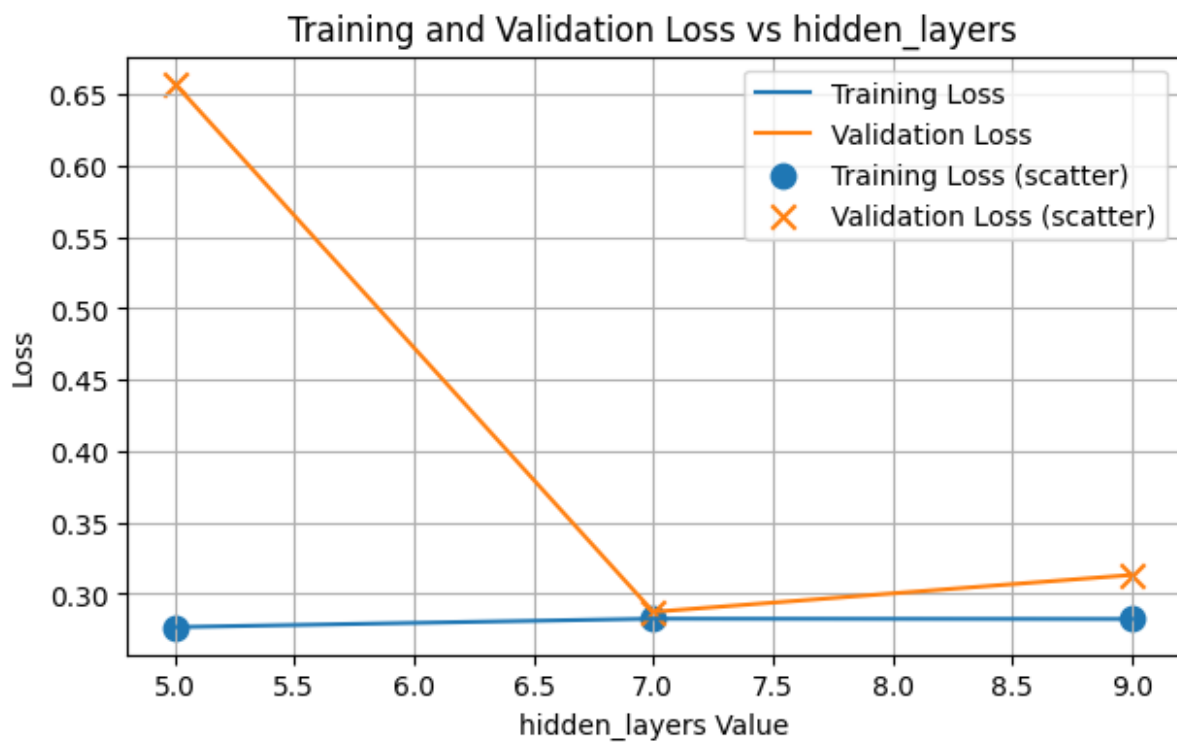
# Plot confusion matrix for each trained model
def plot_confusion_matrix(y_true, y_pred, param, value):
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(7, 4))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
xticklabels=range(10), yticklabels=range(10))
    plt.title(f'Confusion Matrix for {param} = {value}')
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.show()

# Generate confusion matrices for each parameter and value
for idx, row in df.iterrows():
    plot_confusion_matrix(row["y_true"], row["y_pred"], row["param"],
row["value"])

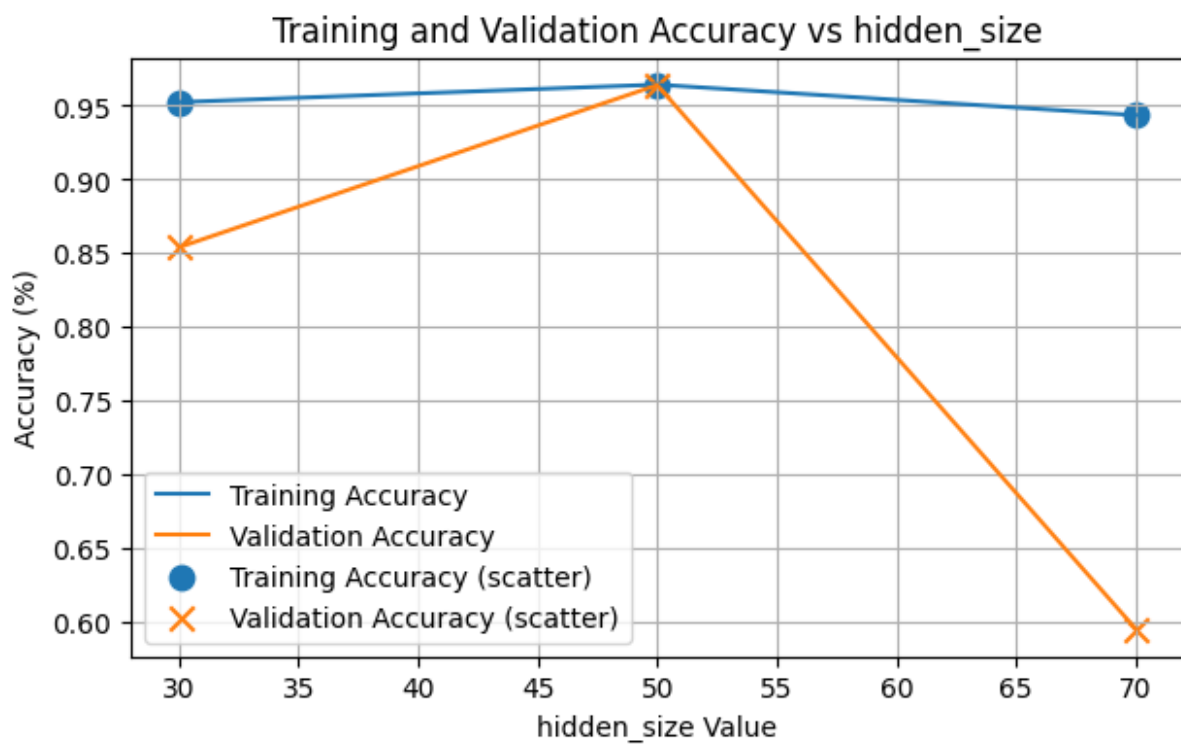
```

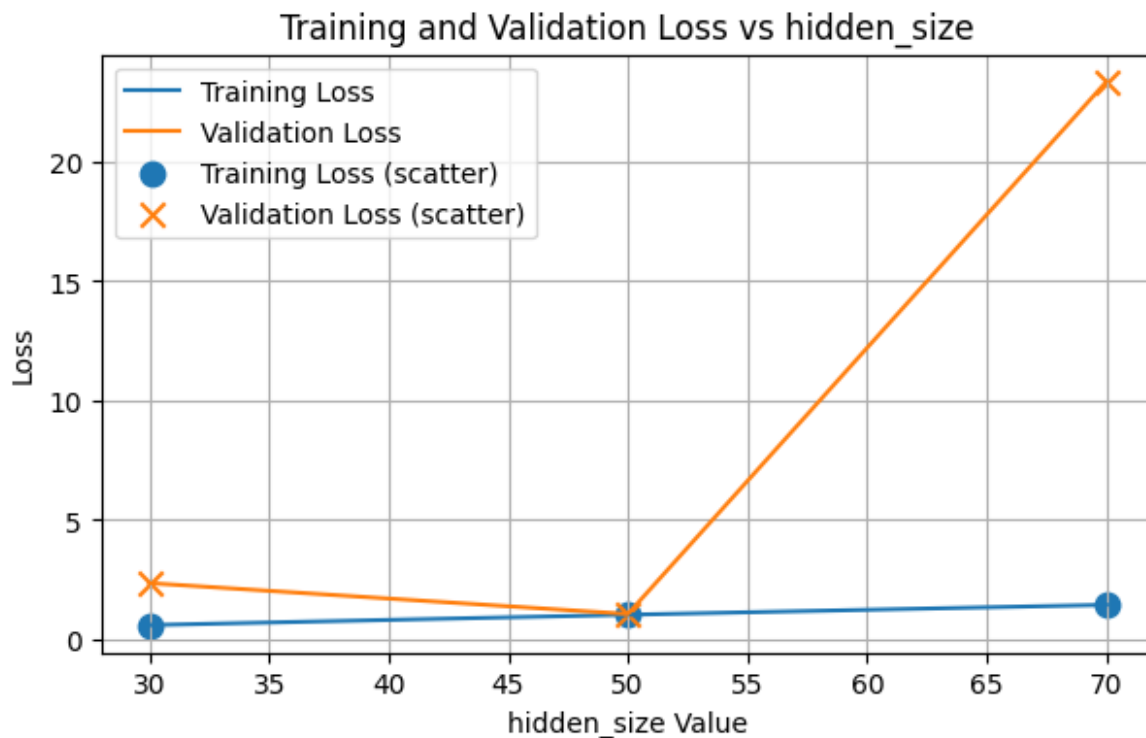
----- Accuracy and Loss for
hidden_layers -----



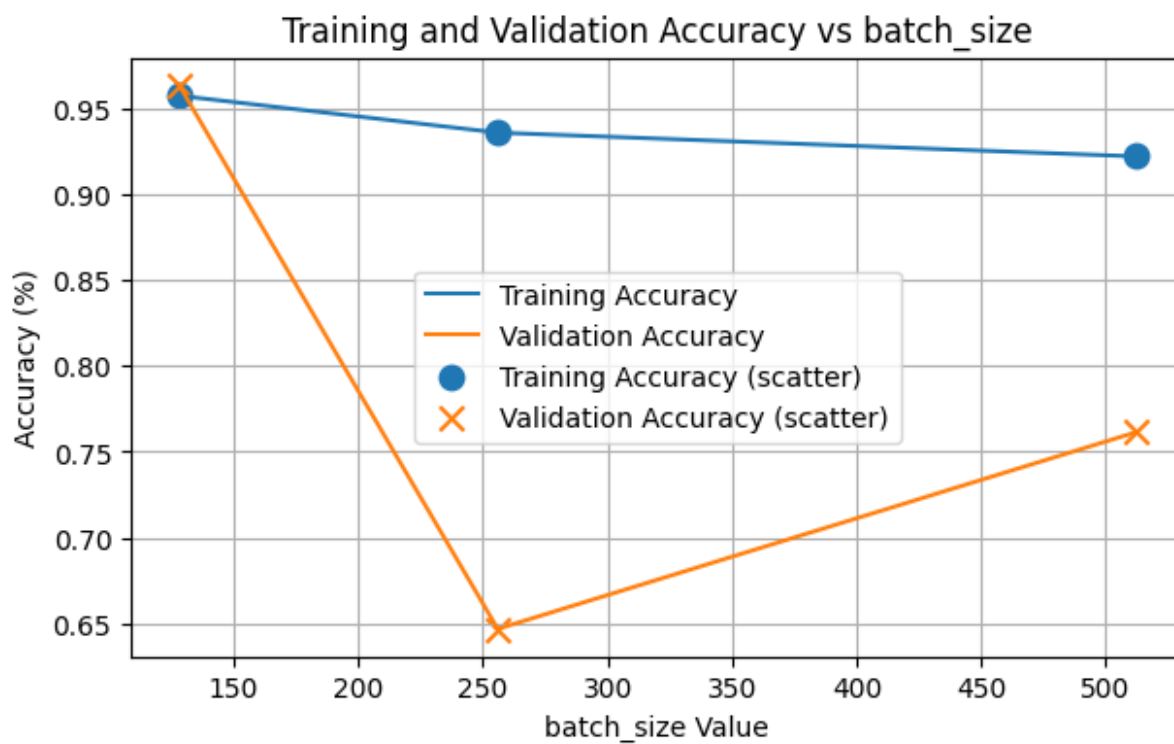


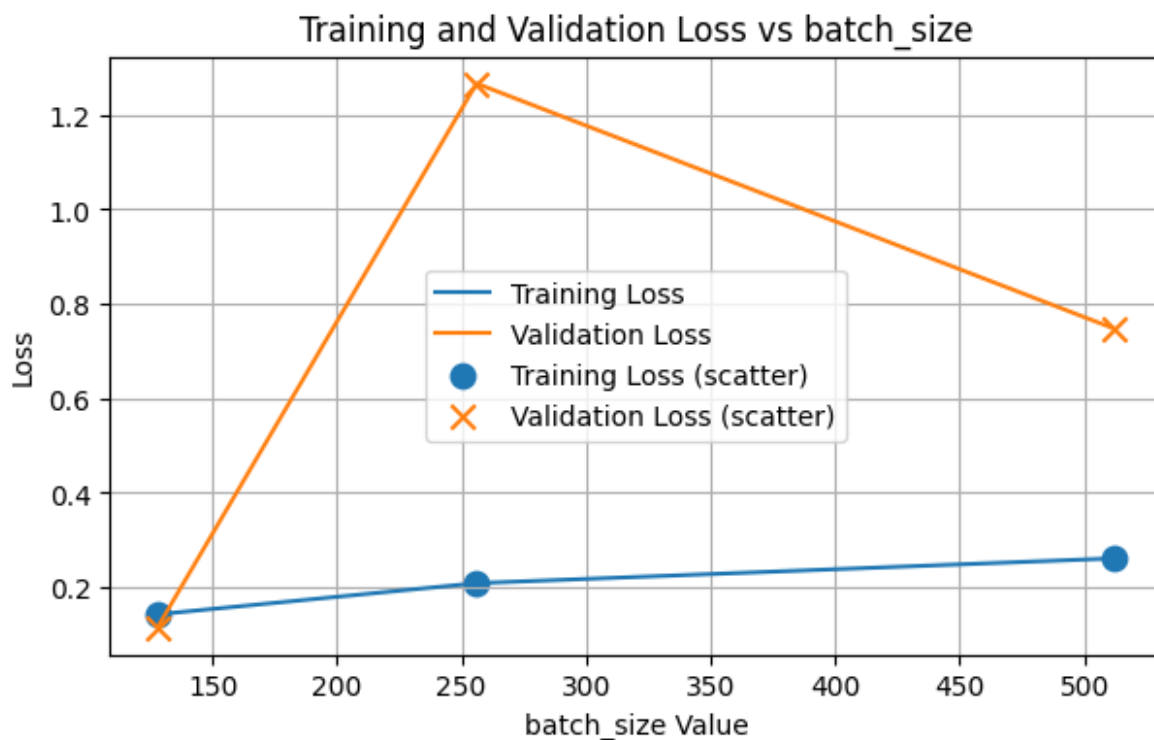
----- Accuracy and Loss for
hidden_size -----



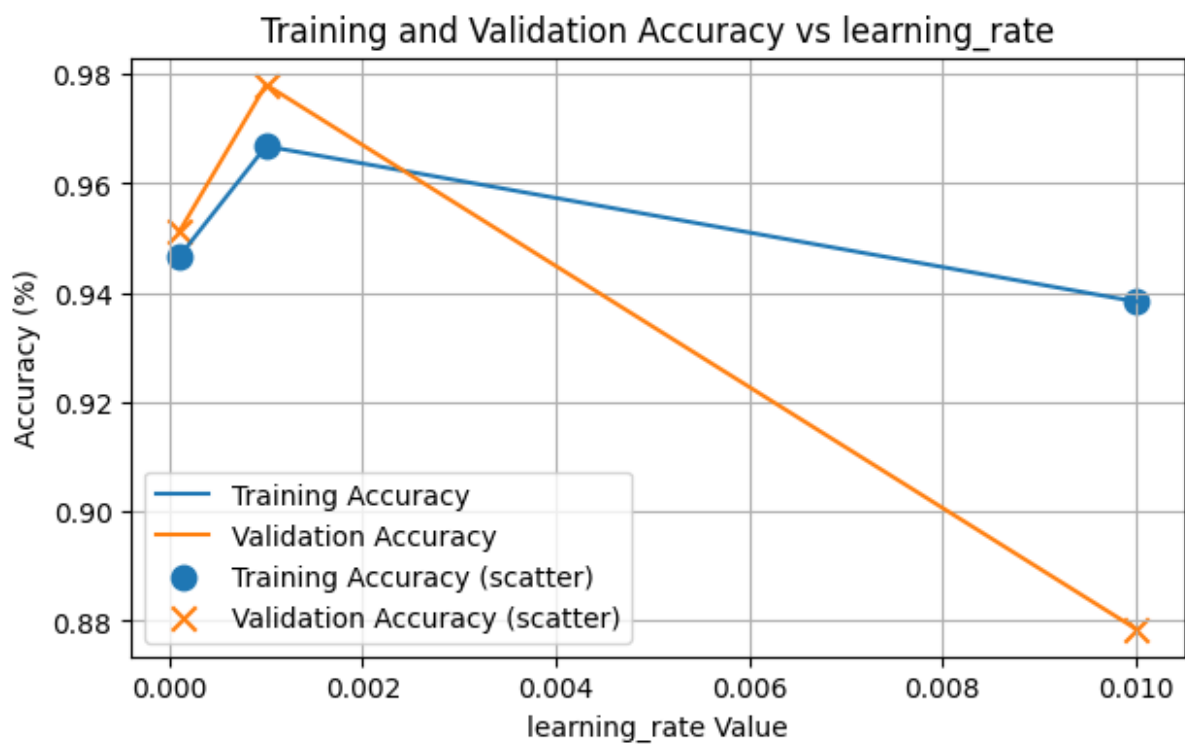


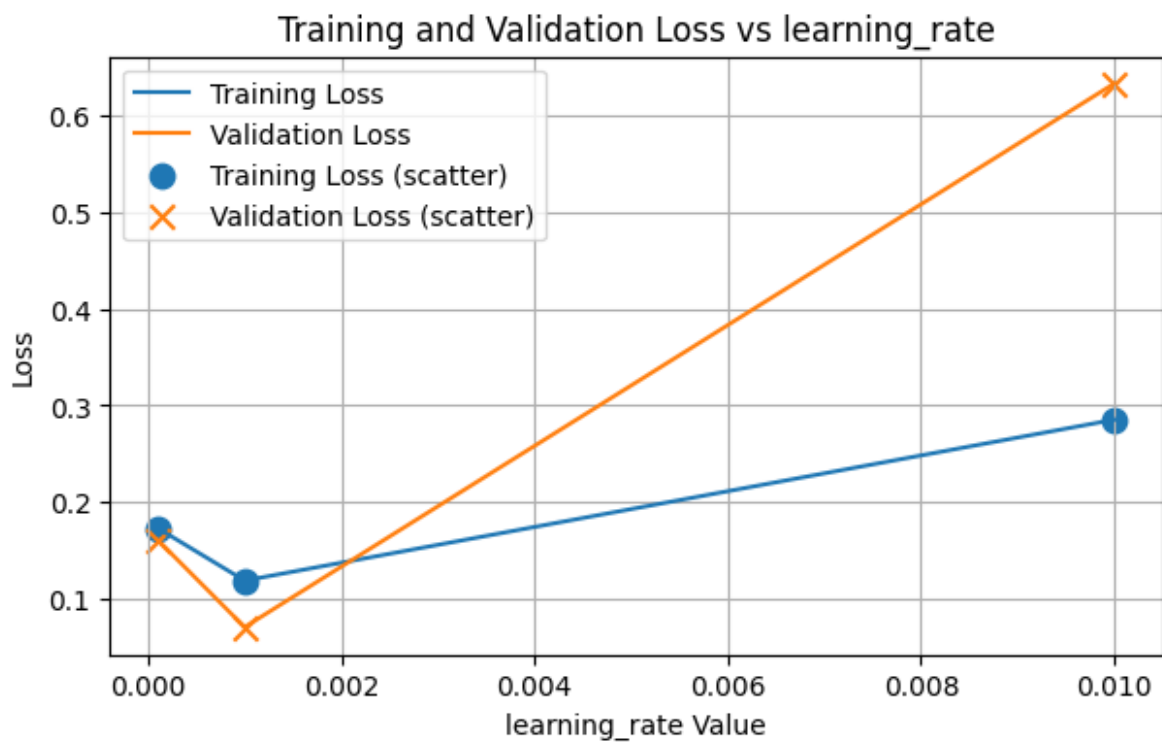
----- Accuracy and Loss for batch_size -----



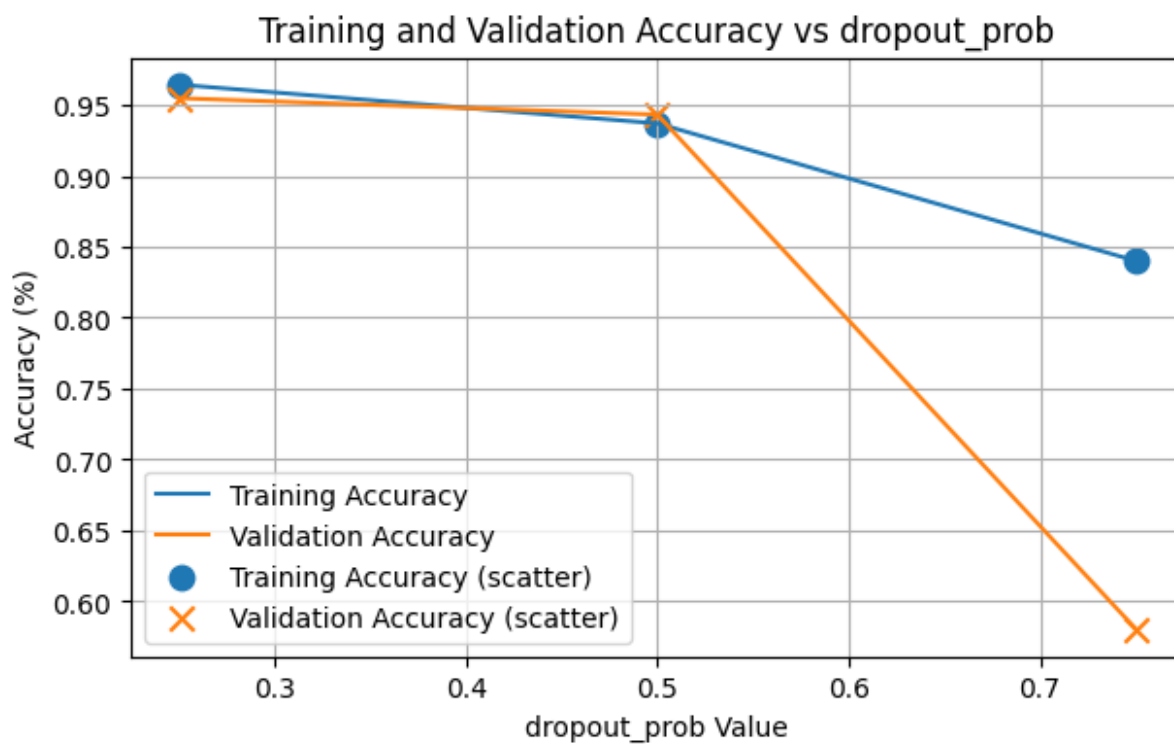


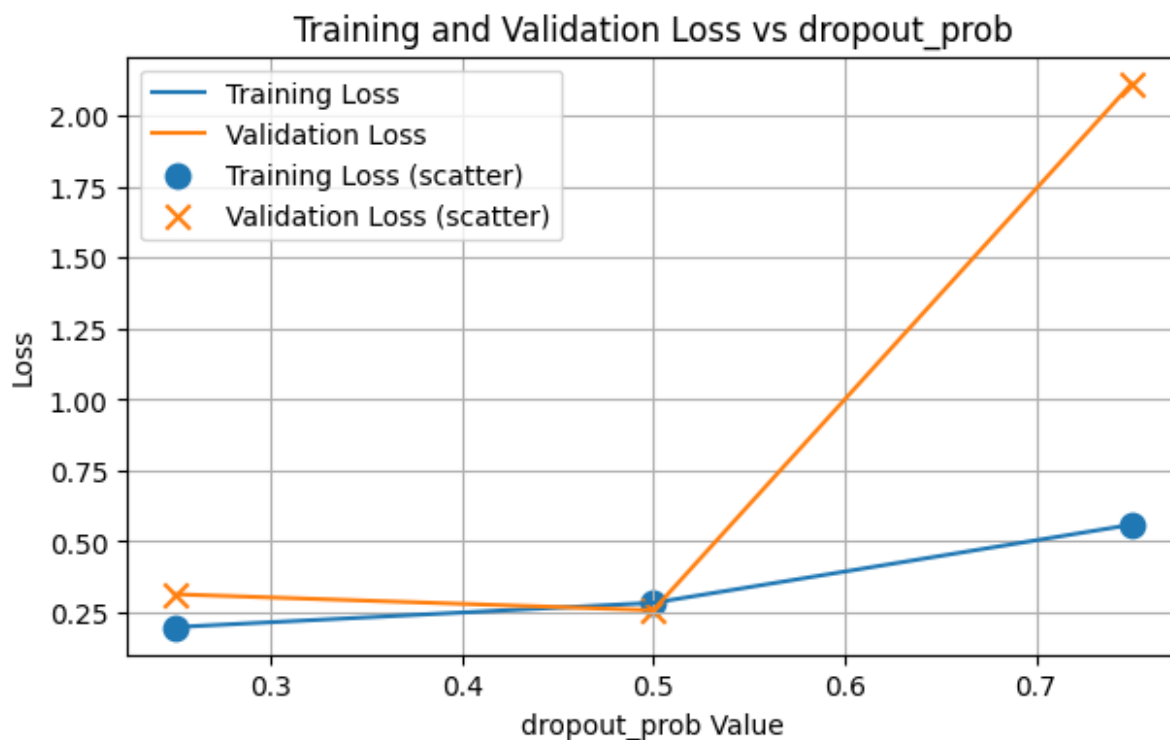
----- Accuracy and Loss for learning_rate -----



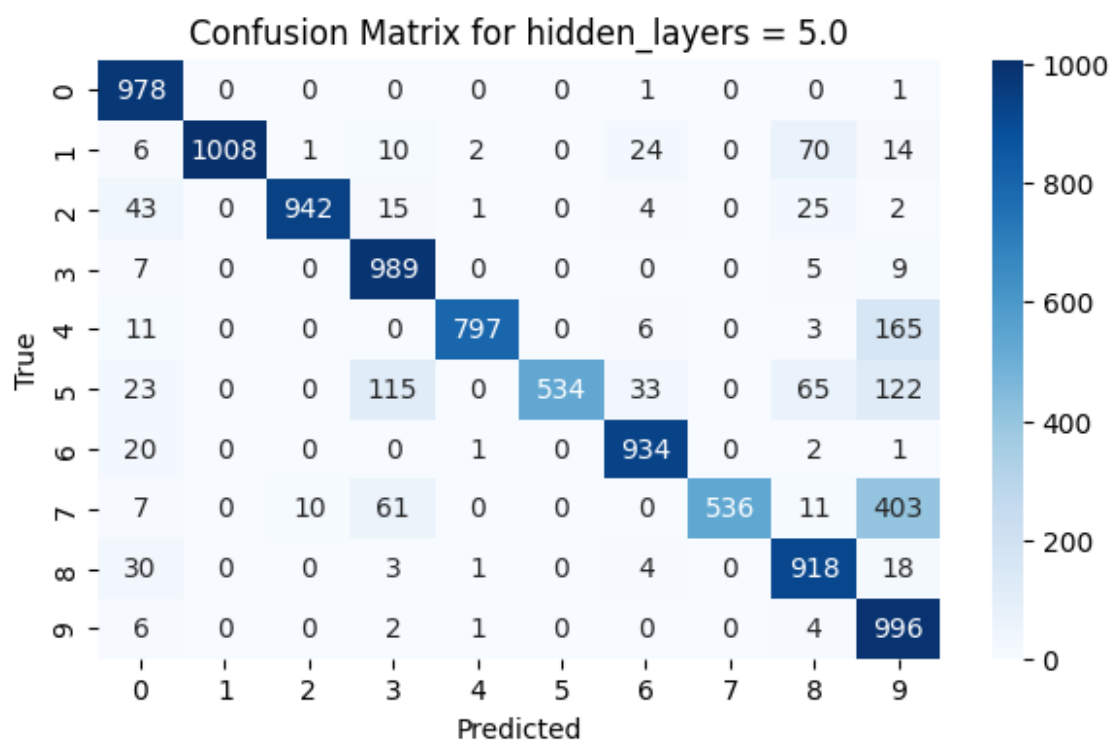


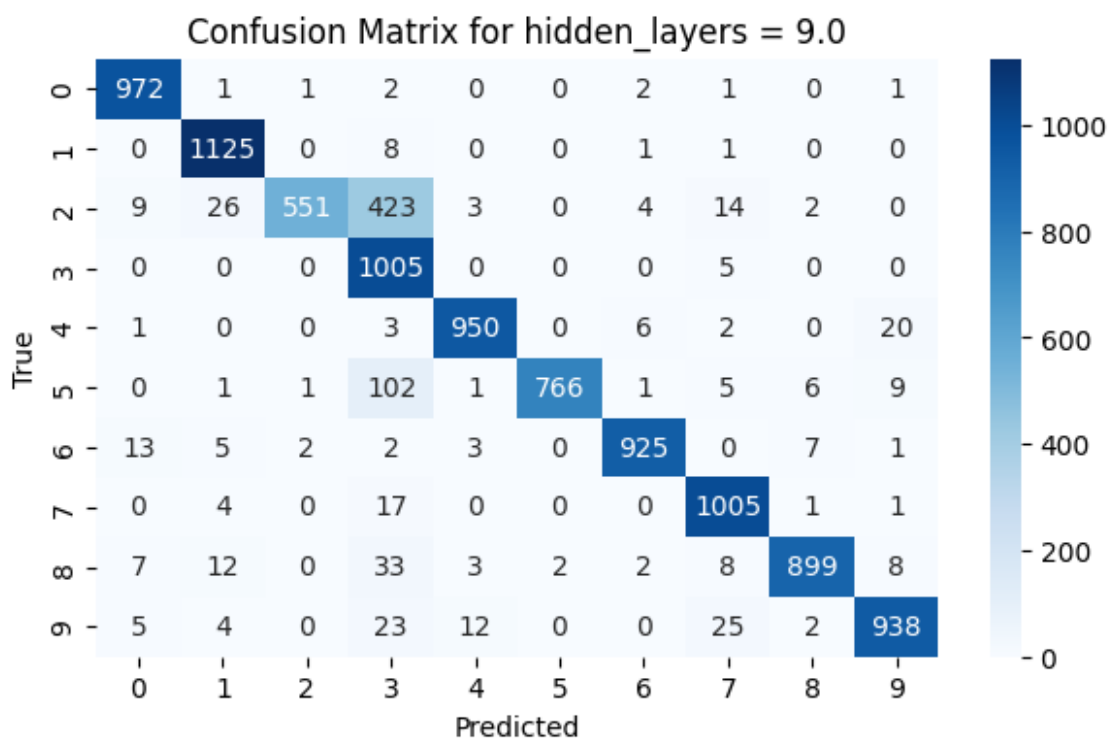
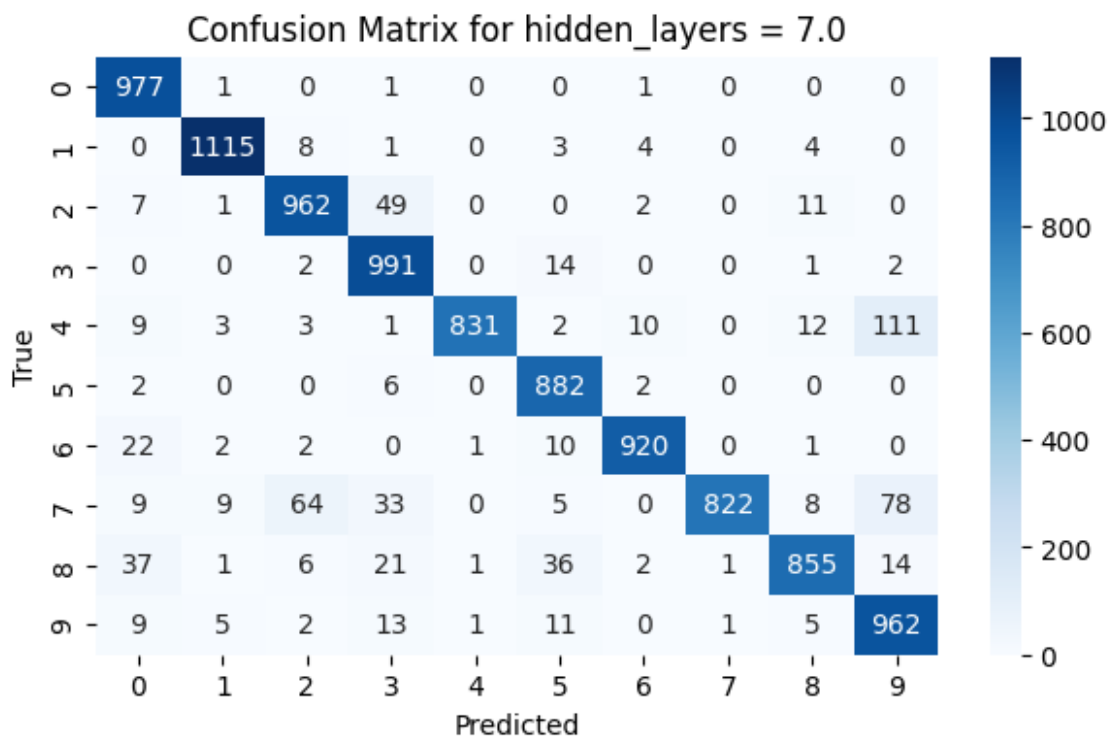
----- Accuracy and Loss for dropout_prob -----

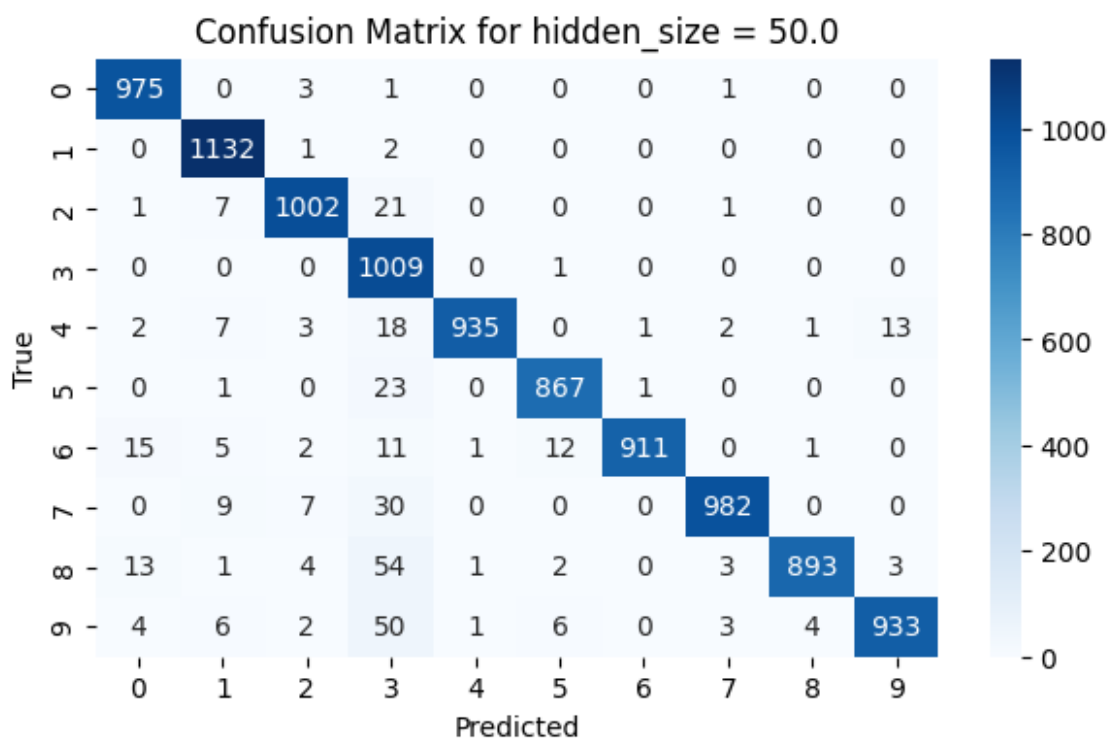
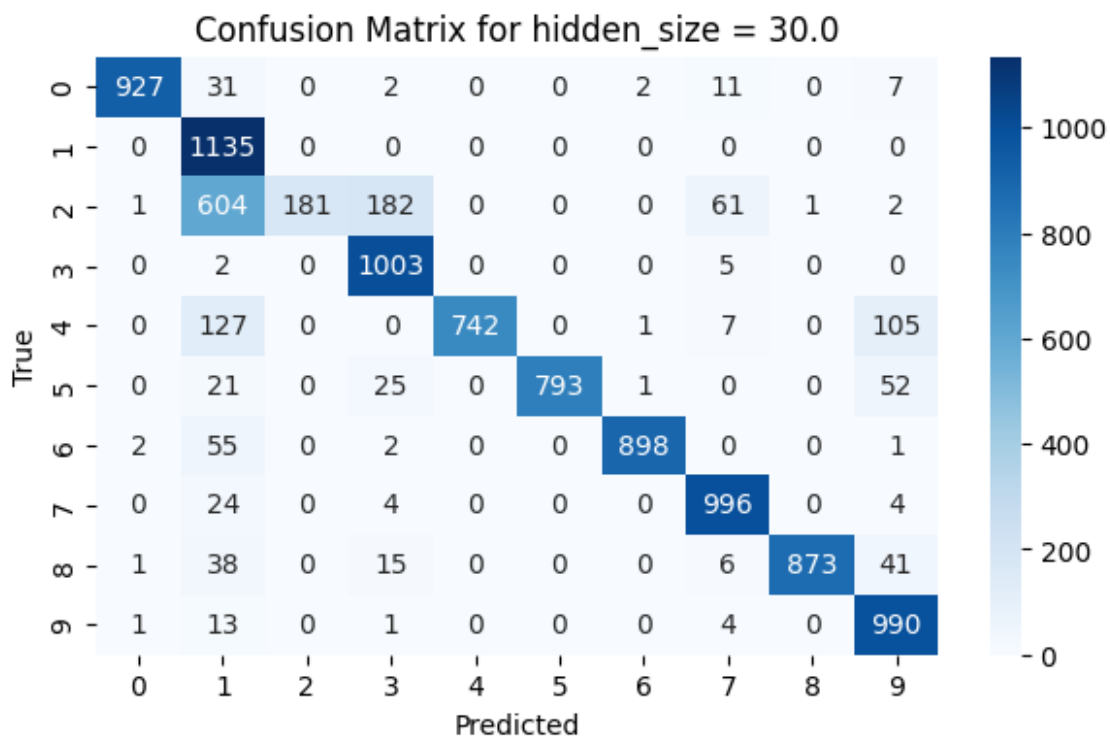


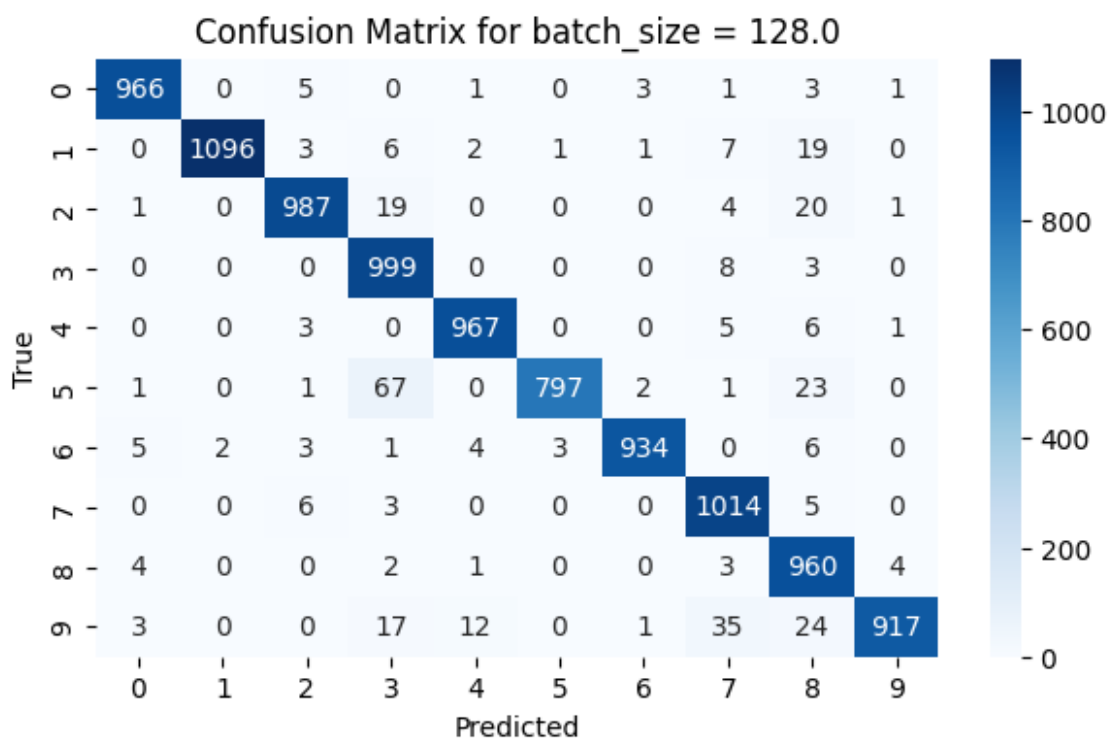
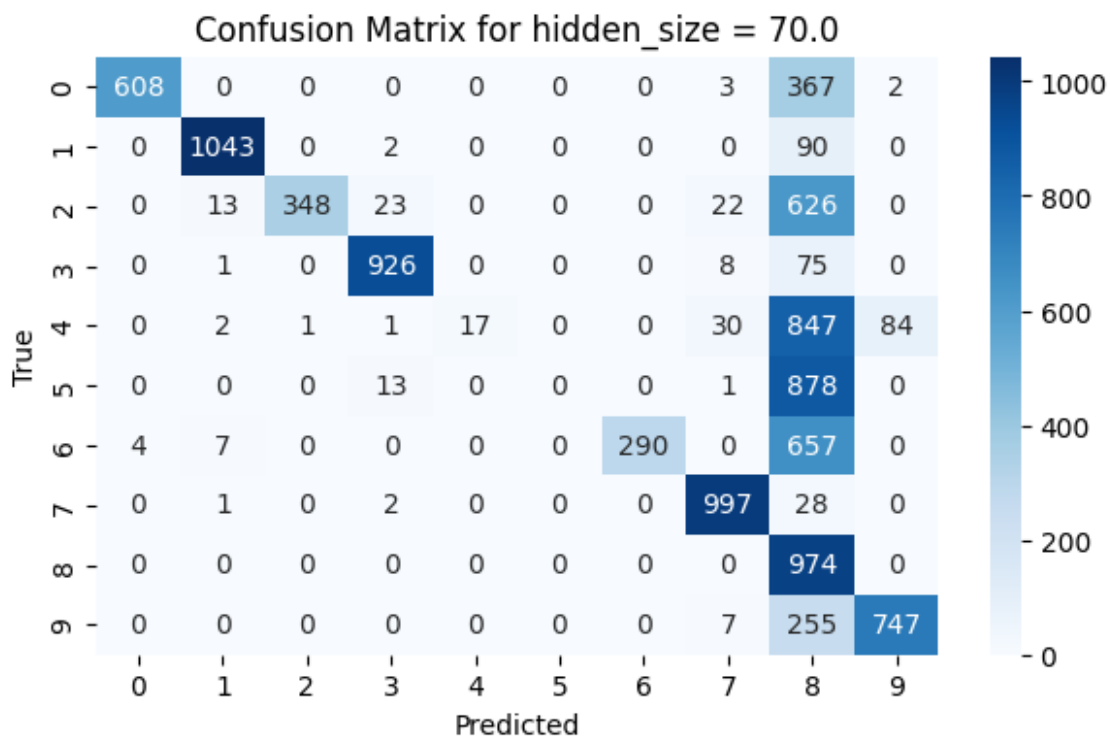


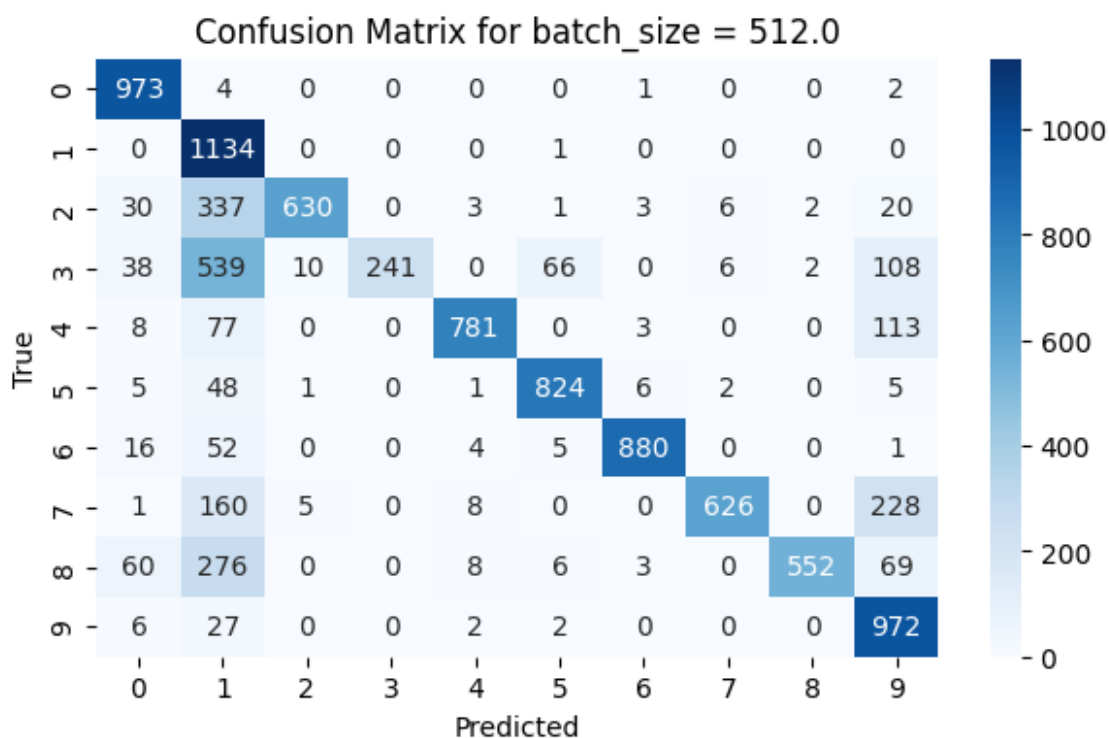
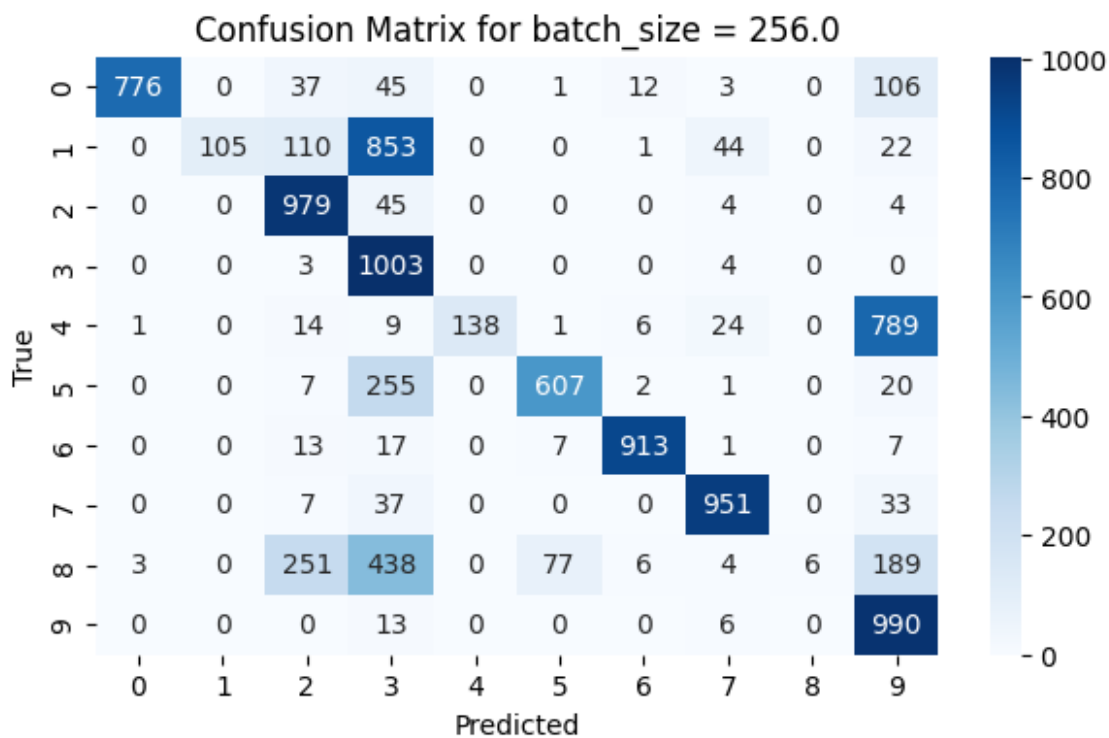
----- Confusion Matrix for dropout_prob -----

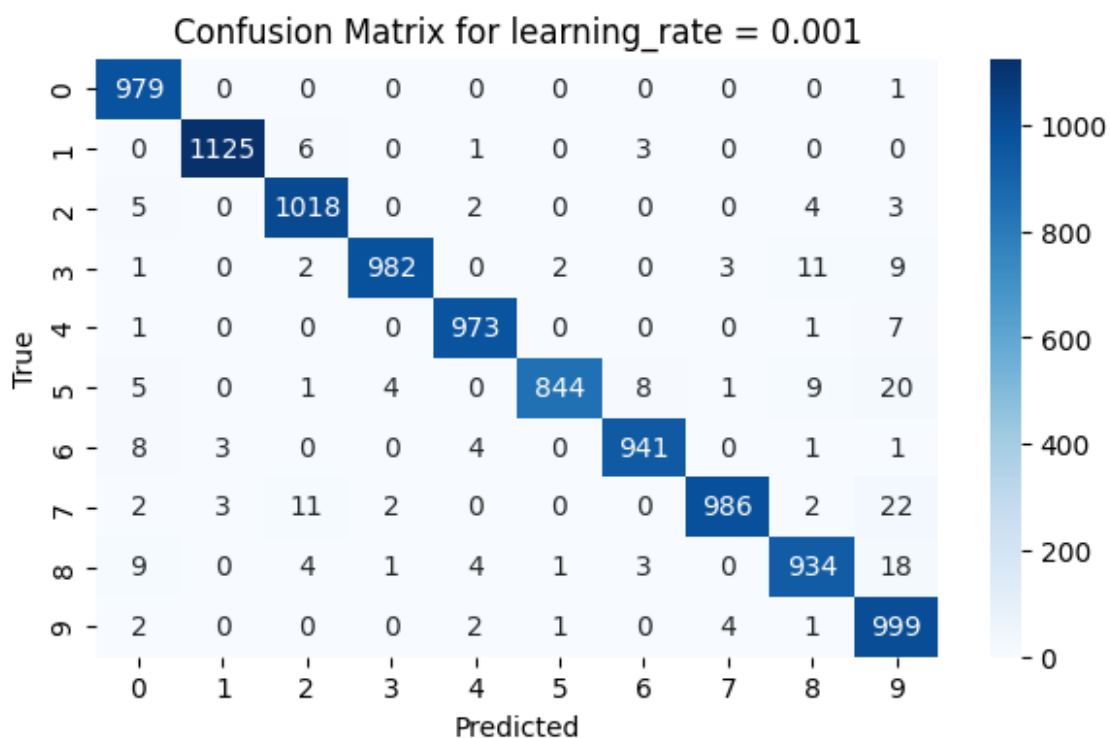
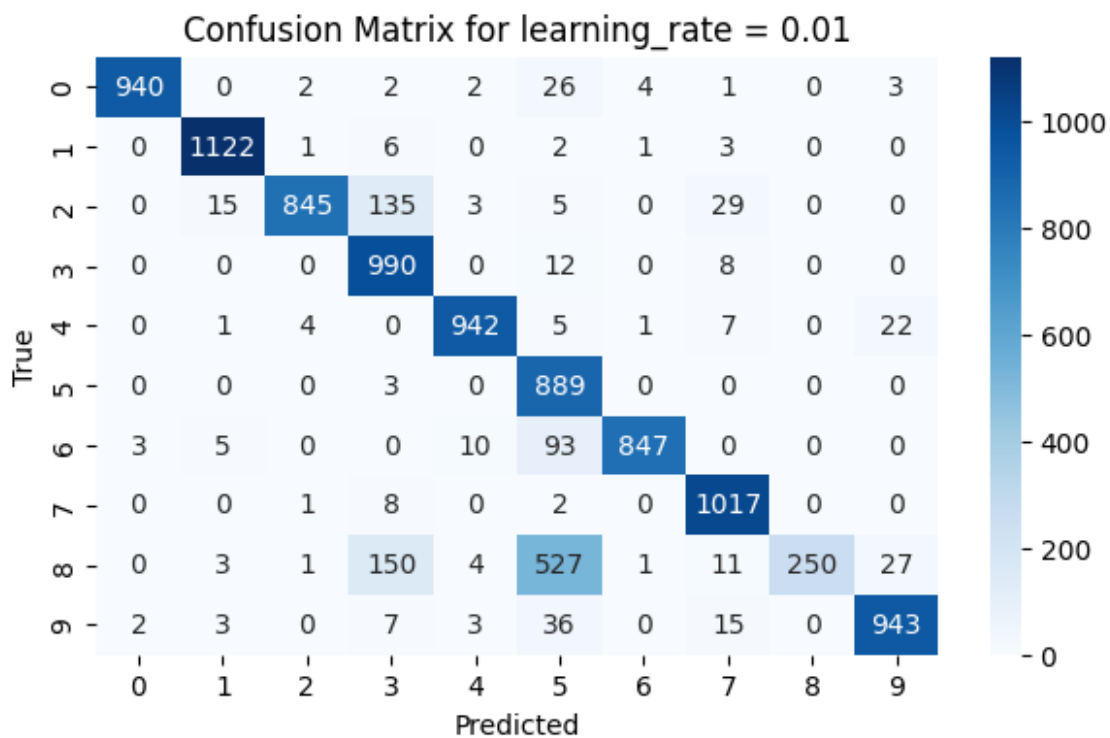




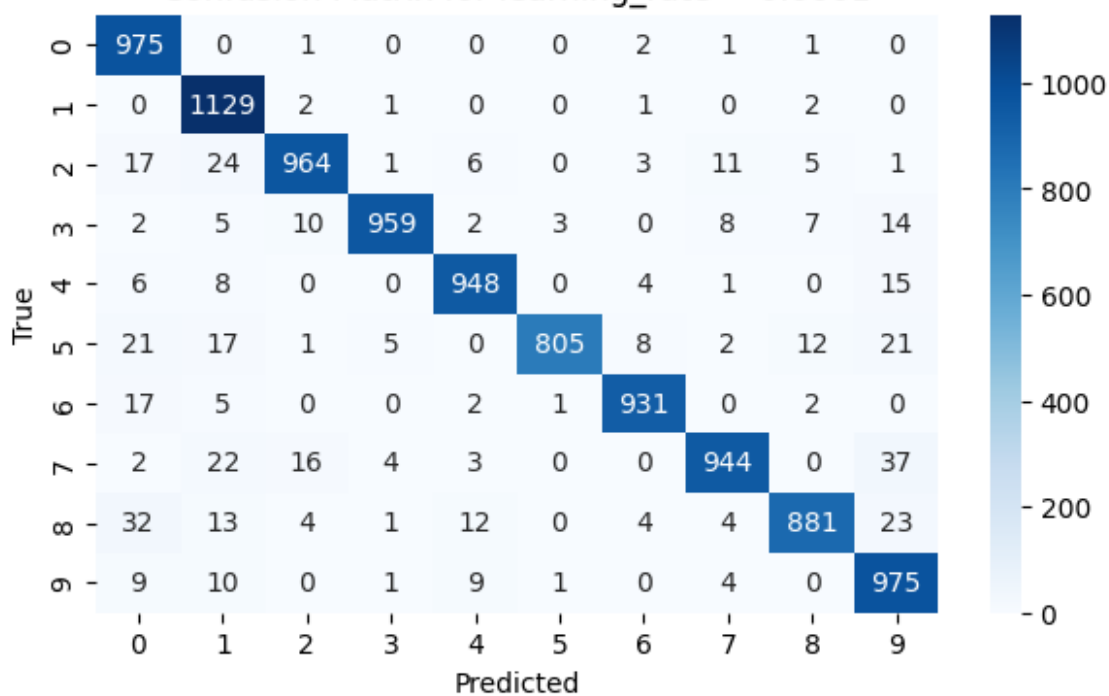








Confusion Matrix for learning_rate = 0.0001



Confusion Matrix for dropout_prob = 0.25

