Importing Libraries, data, and setup

```
import random
import math
import os
import time
import numpy as np
import seaborn as sns
import cv2
import matplotlib.pyplot as plt
import sklearn
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.autograd import Variable
import torch.optim as optim
from torch.utils.data import DataLoader, Subset
import torchvision
import torchvision.transforms as transforms
from torchsummary import summary
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, ConfusionMatrixDisplay
```

```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
torch.manual_seed(42)
np.random.seed(42)
random.seed(42)
if torch.cuda.is_available():
    torch.cuda.manual_seed_all(42)
```

```
transform = transforms.Compose([transforms.ToTensor()])
train_dataset = torchvision.datasets.MNIST(root='./data', train=True, transform=transform, download=True)
test_dataset = torchvision.datasets.MNIST(root='./data', train=False, transform=transform)

train_dataset, val_dataset = torch.utils.data.random_split(train_dataset, [50000, 10000])
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=64, shuffle=True)
val_loader = torch.utils.data.DataLoader(val_dataset, batch_size=64, shuffle=False)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=64, shuffle=False)
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to ./data/MNIST/raw/train-images-idx3-ubyte.gz
100%|██████████| 9912422/9912422 [00:00<00:00, 44069563.79it/s]
Extracting ./data/MNIST/raw/train-images-idx3-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to ./data/MNIST/raw/train-labels-idx1-ubyte.gz
100%|██████████| 28881/28881 [00:00<00:00, 86773419.64it/s]Extracting ./data/MNIST/raw/train-labels-idx1-ubyte.gz to ./data/MNIST/r

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to ./data/MNIST/raw/t10k-images-idx3-ubyte.gz

100%|██████████| 1648877/1648877 [00:00<00:00, 28499513.31it/s]
Extracting ./data/MNIST/raw/t10k-images-idx3-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz
100%|██████████| 4542/4542 [00:00<00:00, 3884691.84it/s]
Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw
```

The RNN Class

```
class RNN(nn.Module):
    def __init__(self, input_size, hidden_size, output_size, layers = 1, rnn_cell_type = 'vanilla', bidirectional = False):
        super(RNN, self).__init__()
        self.hidden_size = hidden_size
        self.num_layers = layers
        self.bidirectional = bidirectional

        if rnn_cell_type == 'vanilla':
            self.rnn = nn.RNN(input_size, hidden_size, num_layers = layers, batch_first = True, bidirectional = bidirectional)
        elif rnn_cell_type == 'lstm':
            self.rnn = nn.LSTM(input_size, hidden_size, num_layers = layers, batch_first = True, bidirectional = bidirectional)
        elif rnn_cell_type == 'gru':
            self.rnn = nn.GRU(input_size, hidden_size, num_layers = layers, batch_first = True, bidirectional = bidirectional)

        linear_input_size = hidden_size * 2 if bidirectional else hidden_size
        self.fc = nn.Linear(linear_input_size, output_size)

    def forward(self, x):
        x = x.view(-1, 28, 28)
        num_dirs = 2 if self.bidirectional else 1
        h0 = torch.zeros(self.num_layers*num_dirs, x.size(0), self.hidden_size).to(device)
        if isinstance(self.rnn, nn.LSTM):
            c0 = torch.zeros(self.num_layers*num_dirs, x.size(0), self.hidden_size).to(device)
            out, _ = self.rnn(x, (h0, c0))
        else:
            out, _ = self.rnn(x, h0)

        if self.bidirectional:
            out = torch.cat((out[:, -1, :self.hidden_size], out[:, 0, self.hidden_size:]), 1)
        else:
            out = out[:, -1, :]

        return self.fc(out)
```

Some useful functions

Function to train and test the model

```
def train_and_evaluate(input_dim, hidden_dim, output_dim, train_loader, val_loader, test_loader, layers, rnn_cell_type, bidirectional):
    net = RNN(input_dim, hidden_dim, output_dim, layers, rnn_cell_type, bidirectional).to(device)
    criterion = nn.CrossEntropyLoss().to(device)
    optimizer = optim.Adam(net.parameters())

    num_epochs = 5
    train_losses, val_losses, accuracies = [], [], []

    start_time = time.time()
    for epoch in range(num_epochs):
        # Training
        net.train()
        train_loss = 0.0
        for inputs, labels in train_loader:
            inputs, labels = inputs.to(device), labels.to(device)
            optimizer.zero_grad()
            outputs = net(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            train_loss += loss.item()

        # Validation
        net.eval()
        val_loss, correct, total = 0.0, 0, 0
        with torch.no_grad():
```

```
            for inputs, labels in val_loader:
                inputs, labels = inputs.to(device), labels.to(device)
                outputs = net(inputs)
                val_loss += criterion(outputs, labels).item()
                _, predicted = outputs.max(1)
                total += labels.size(0)
                correct += predicted.eq(labels).sum().item()

        epoch_train_loss = train_loss / len(train_loader)
        epoch_val_loss = val_loss / len(val_loader)
        epoch_val_accuracy = 100. * correct / total

        print(f'Epoch: {epoch+1}/{num_epochs}, Train Loss: {epoch_train_loss:.4f}, Validation Loss: {epoch_val_loss:.4f}, Validation Ac

        train_losses.append(epoch_train_loss)
        val_losses.append(epoch_val_loss)
        accuracies.append(epoch_val_accuracy)
    end_time = time.time()

    elapsed_time = end_time - start_time
    print(f"Training using {rnn_cell_type.upper()} took {elapsed_time:.2f} seconds.")

    # Plotting
    plt.figure(figsize=(12, 4))

    plt.subplot(1, 3, 1)
    plt.plot(train_losses, label='Train Loss')
    plt.plot(val_losses, label='Validation Loss')
    plt.legend()
    plt.title(f'{rnn_cell_type.upper()} - Train and Validation Losses')

    plt.subplot(1, 3, 2)
    plt.plot(accuracies, label='Validation Accuracy')
    plt.legend()
    plt.title(f'{rnn_cell_type.upper()} - Validation Accuracy')

    plt.tight_layout()
    plt.show()

    test_preds, test_true = [], []
    with torch.no_grad():
        for inputs, labels in test_loader:
            inputs, labels = inputs.to(device), labels.to(device)
            outputs = net(inputs)
            _, predicted = outputs.max(1)
            test_true.extend(labels.cpu().numpy())
            test_preds.extend(predicted.cpu().numpy())

    acc = 100. * sum(np.array(test_true) == np.array(test_preds)) / len(test_true)

    return epoch_val_accuracy, acc, classification_report(test_true, test_preds), confusion_matrix(test_true, test_preds), net
```

Function to plot results

```
def display_results(rnn_cell_type, results):
    print(f"\nResults for {rnn_cell_type.upper()} RNN:")
    print(f"Accuracy: {results[1]:.2f}%")
    print(f"\nClassification Report:\n{results[2]}")

    # Plot confusion matrix as heatmap
    plt.figure(figsize=(8, 6))
    sns.heatmap(results[3], annot=True, fmt="d", cmap="Blues")
    plt.title(f"Confusion Matrix for {rnn_cell_type.upper()} RNN")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()
```

Function to plot predictions

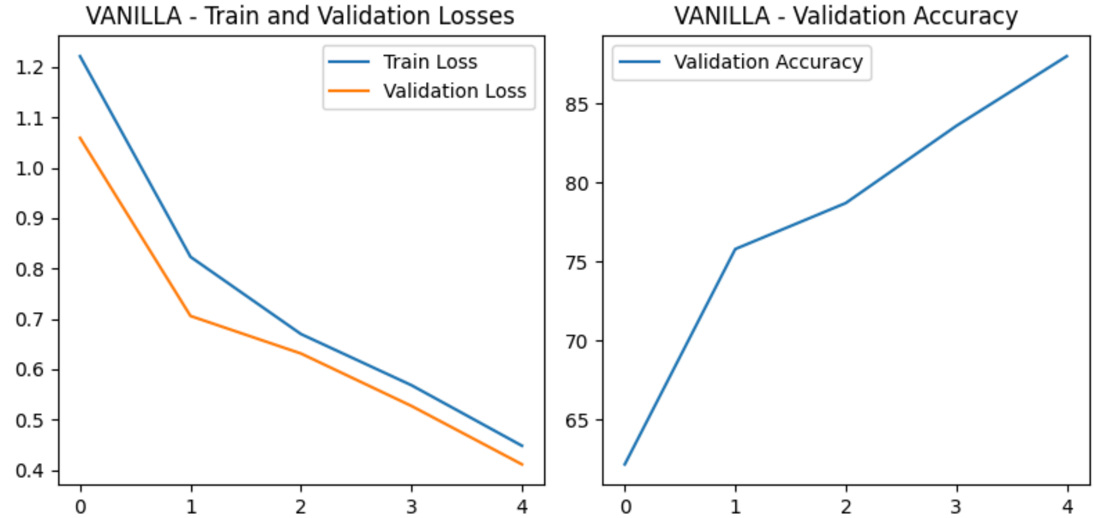
```
def plot_predictions(model, loader, num_samples=12):
    all_images, all_labels = [], []
    for images, labels in loader:
        all_images.append(images)
        all_labels.append(labels)
    all_images = torch.cat(all_images)
    all_labels = torch.cat(all_labels)

    random_indices = random.sample(range(len(all_images)), num_samples)
    images = all_images[random_indices]
    labels = all_labels[random_indices]

    outputs = model(images.to(device))
    _, predictions = outputs.max(1)

    grid_size = int(math.ceil(math.sqrt(num_samples)))

    plt.figure(figsize=(15, 15))
    for i, (img, label, pred) in enumerate(zip(images, labels, predictions)):
        plt.subplot(grid_size, grid_size, i+1)
        plt.imshow(img[0].numpy(), cmap='gray')
        plt.title(f"True: {label.item()}, Pred: {pred.item()}", fontsize=10)
        plt.axis('off')
    plt.tight_layout()
    plt.show()
```

Tuning the hyperparameters with vanilla RNN using a grid-search approach

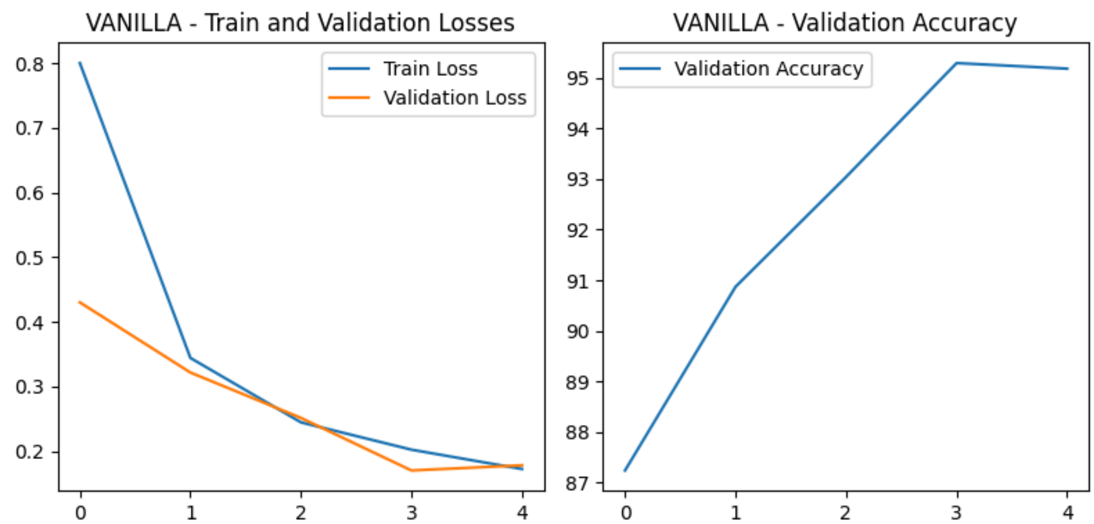
```
hidden_layer_list = [64, 128]
num_layers_list = [1, 2, 3, 4, 5]

best_val_acc = 0.0
best_model = None
best_hidden_size = None
best_num_layers = None
```

```
for hidden_size in hidden_layer_list:
    for num_layers in num_layers_list:
        print(f'Training with hidden size: {hidden_size}, num layers: {num_layers}')
        val_acc, acc, _, _, net = train_and_evaluate(
            input_dim=28,
            hidden_dim=hidden_size,
            output_dim=10,
            train_loader=train_loader,
            val_loader=val_loader,
            test_loader=test_loader,
            layers=num_layers,
            rnn_cell_type='vanilla',
            bidirectional=False
        )

        if val_acc > best_val_acc:  # check the validation accuracy to update the best model
            best_val_acc = val_acc
            best_model = net
            best_hidden_size = hidden_size
            best_num_layers = num_layers
            print(f'New best model found with validation accuracy: {best_val_acc:.2f}%')
```

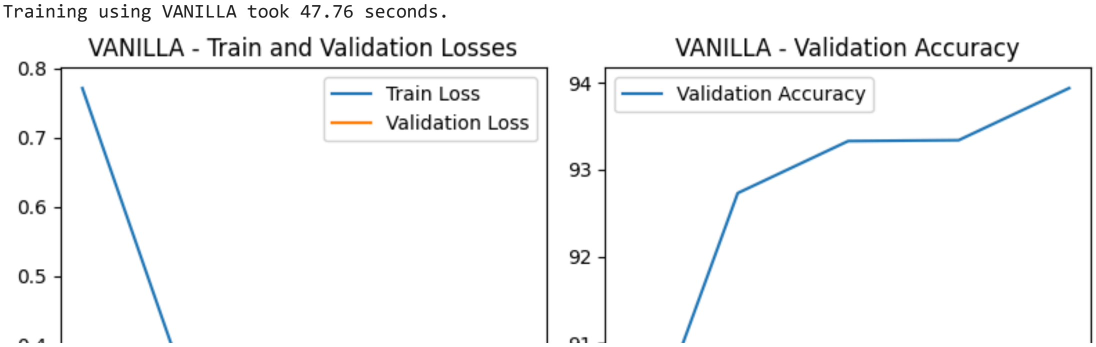
```
Training with hidden size: 64, num layers: 1
Epoch: 1/5, Train Loss: 1.2213, Validation Loss: 1.0592, Validation Accuracy: 62.17%
Epoch: 2/5, Train Loss: 0.8230, Validation Loss: 0.7057, Validation Accuracy: 75.79%
Epoch: 3/5, Train Loss: 0.6698, Validation Loss: 0.6312, Validation Accuracy: 78.70%
Epoch: 4/5, Train Loss: 0.5682, Validation Loss: 0.5271, Validation Accuracy: 83.58%
Epoch: 5/5, Train Loss: 0.4481, Validation Loss: 0.4112, Validation Accuracy: 87.99%
Training using VANILLA took 47.14 seconds.
```

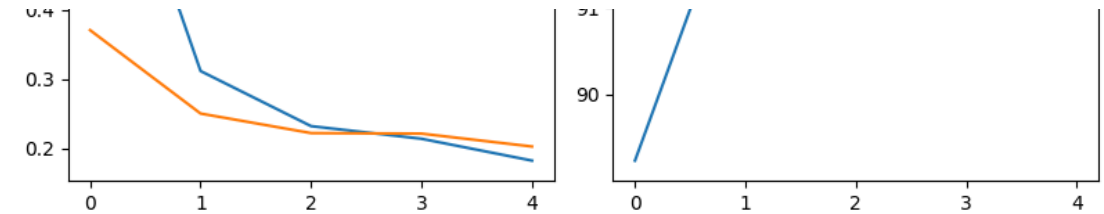



```
New best model found with validation accuracy: 87.99%
Training with hidden size: 64, num layers: 2
Epoch: 1/5, Train Loss: 0.8001, Validation Loss: 0.4300, Validation Accuracy: 87.24%
Epoch: 2/5, Train Loss: 0.3441, Validation Loss: 0.3216, Validation Accuracy: 90.87%
Epoch: 3/5, Train Loss: 0.2445, Validation Loss: 0.2514, Validation Accuracy: 93.04%
Epoch: 4/5, Train Loss: 0.2022, Validation Loss: 0.1701, Validation Accuracy: 95.29%
Epoch: 5/5, Train Loss: 0.1723, Validation Loss: 0.1780, Validation Accuracy: 95.18%
Training using VANILLA took 45.35 seconds.
```

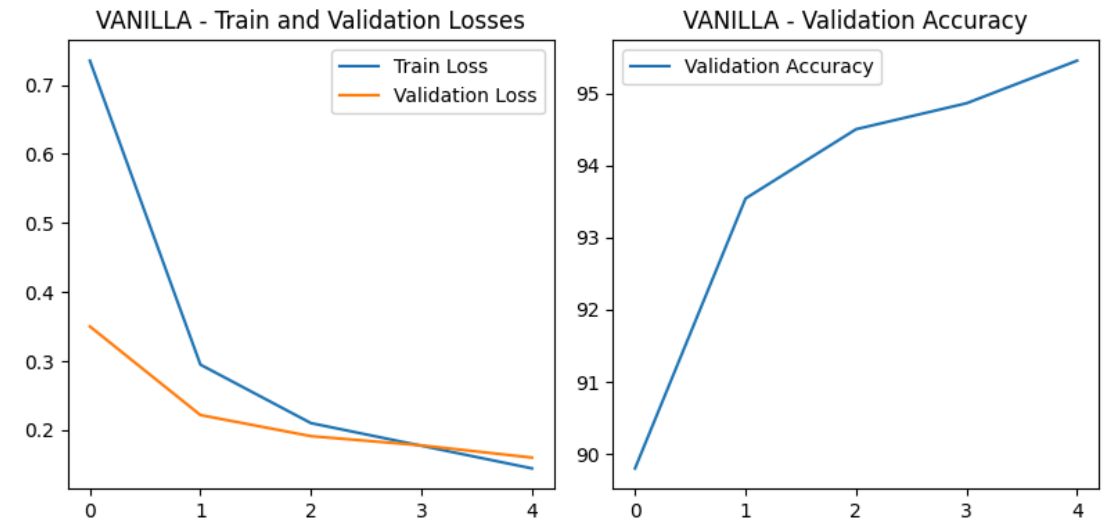



```
New best model found with validation accuracy: 95.18%
Training with hidden size: 64, num layers: 3
Epoch: 1/5, Train Loss: 0.7711, Validation Loss: 0.3705, Validation Accuracy: 89.24%
Epoch: 2/5, Train Loss: 0.3116, Validation Loss: 0.2503, Validation Accuracy: 92.73%
Epoch: 3/5, Train Loss: 0.2321, Validation Loss: 0.2221, Validation Accuracy: 93.33%
Epoch: 4/5, Train Loss: 0.2139, Validation Loss: 0.2213, Validation Accuracy: 93.34%
Epoch: 5/5, Train Loss: 0.1824, Validation Loss: 0.2027, Validation Accuracy: 93.94%
Training using VANILLA took 47.76 seconds.
```

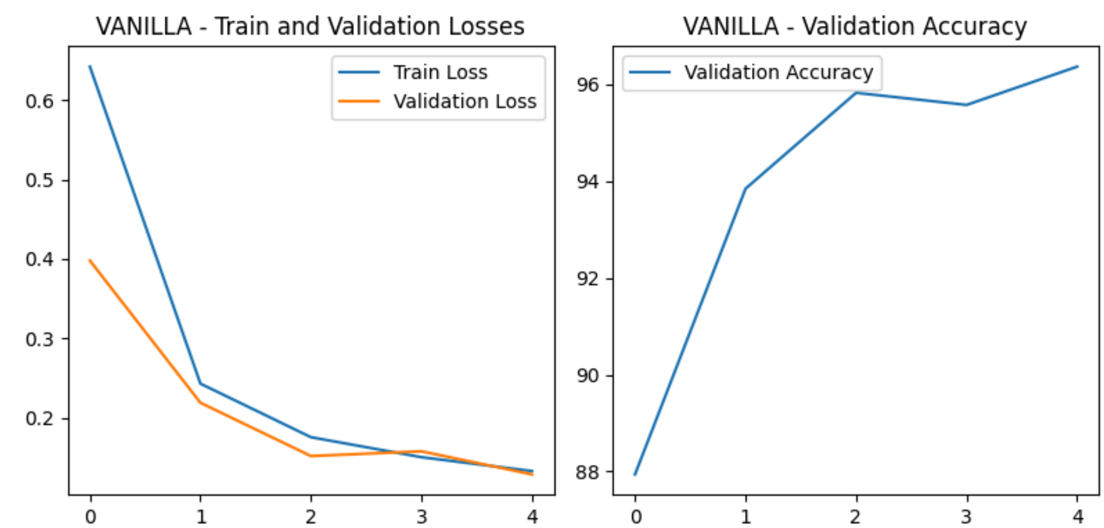




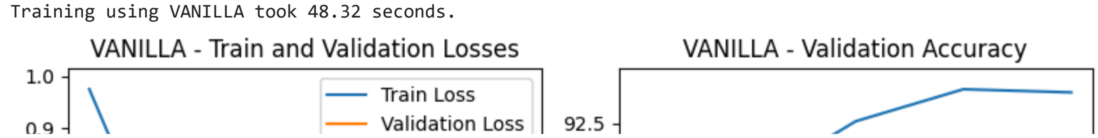
```
Training with hidden size: 64, num layers: 4
Epoch: 1/5, Train Loss: 0.7350, Validation Loss: 0.3502, Validation Accuracy: 89.80%
Epoch: 2/5, Train Loss: 0.2950, Validation Loss: 0.2220, Validation Accuracy: 93.54%
Epoch: 3/5, Train Loss: 0.2103, Validation Loss: 0.1915, Validation Accuracy: 94.50%
Epoch: 4/5, Train Loss: 0.1775, Validation Loss: 0.1781, Validation Accuracy: 94.86%
Epoch: 5/5, Train Loss: 0.1447, Validation Loss: 0.1604, Validation Accuracy: 95.45%
Training using VANILLA took 58.77 seconds.
```

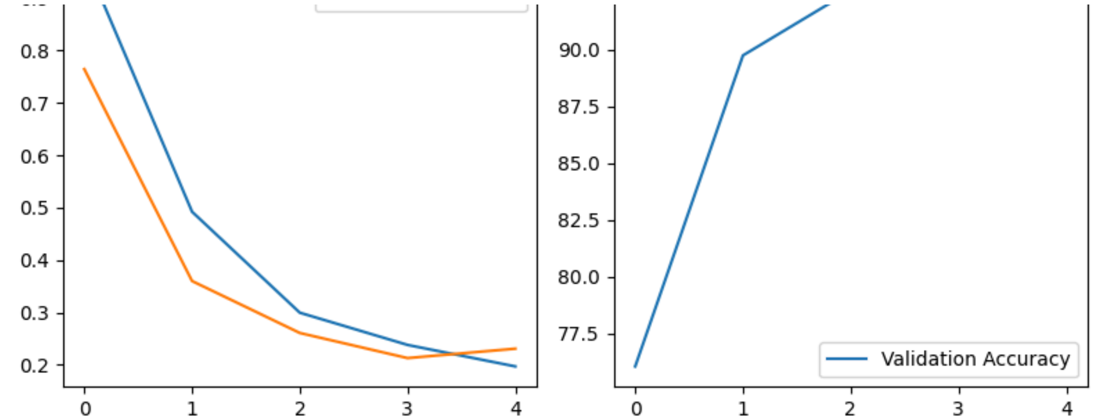



```
New best model found with validation accuracy: 95.45%
Training with hidden size: 64, num layers: 5
Epoch: 1/5, Train Loss: 0.6420, Validation Loss: 0.3978, Validation Accuracy: 87.94%
Epoch: 2/5, Train Loss: 0.2429, Validation Loss: 0.2188, Validation Accuracy: 93.84%
Epoch: 3/5, Train Loss: 0.1755, Validation Loss: 0.1517, Validation Accuracy: 95.82%
Epoch: 4/5, Train Loss: 0.1503, Validation Loss: 0.1577, Validation Accuracy: 95.57%
Epoch: 5/5, Train Loss: 0.1328, Validation Loss: 0.1286, Validation Accuracy: 96.36%
Training using VANILLA took 49.15 seconds.
```

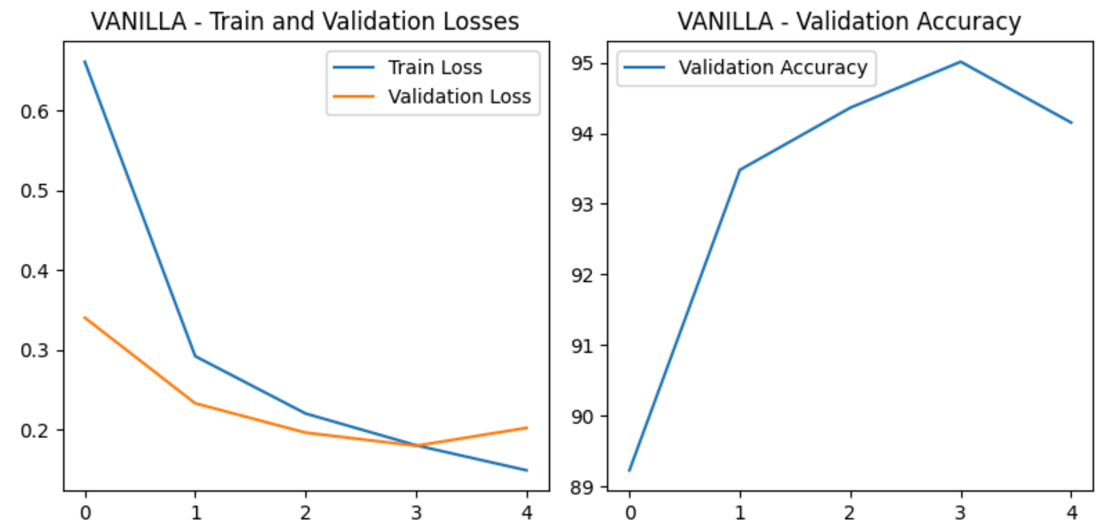



```
New best model found with validation accuracy: 96.36%
Training with hidden size: 128, num layers: 1
Epoch: 1/5, Train Loss: 0.9751, Validation Loss: 0.7643, Validation Accuracy: 76.06%
Epoch: 2/5, Train Loss: 0.4922, Validation Loss: 0.3600, Validation Accuracy: 89.75%
Epoch: 3/5, Train Loss: 0.2995, Validation Loss: 0.2609, Validation Accuracy: 92.60%
Epoch: 4/5, Train Loss: 0.2381, Validation Loss: 0.2129, Validation Accuracy: 94.01%
Epoch: 5/5, Train Loss: 0.1970, Validation Loss: 0.2309, Validation Accuracy: 93.87%
Training using VANILLA took 48.32 seconds.
```

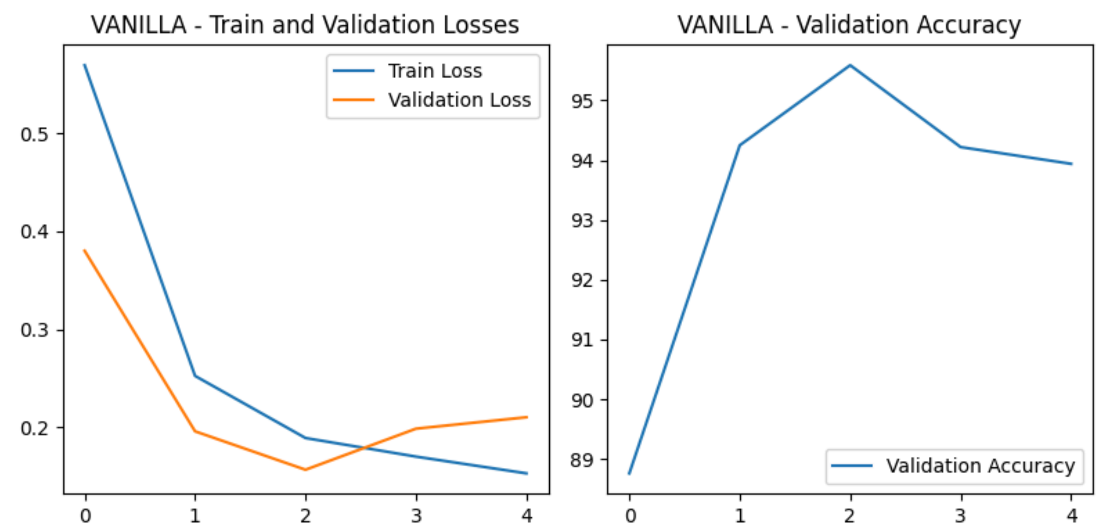





```
Training with hidden size: 128, num layers: 2
Epoch: 1/5, Train Loss: 0.6611, Validation Loss: 0.3406, Validation Accuracy: 89.23%
Epoch: 2/5, Train Loss: 0.2923, Validation Loss: 0.2333, Validation Accuracy: 93.48%
Epoch: 3/5, Train Loss: 0.2205, Validation Loss: 0.1966, Validation Accuracy: 94.36%
Epoch: 4/5, Train Loss: 0.1807, Validation Loss: 0.1801, Validation Accuracy: 95.01%
Epoch: 5/5, Train Loss: 0.1494, Validation Loss: 0.2026, Validation Accuracy: 94.15%
Training using VANILLA took 45.65 seconds.
```

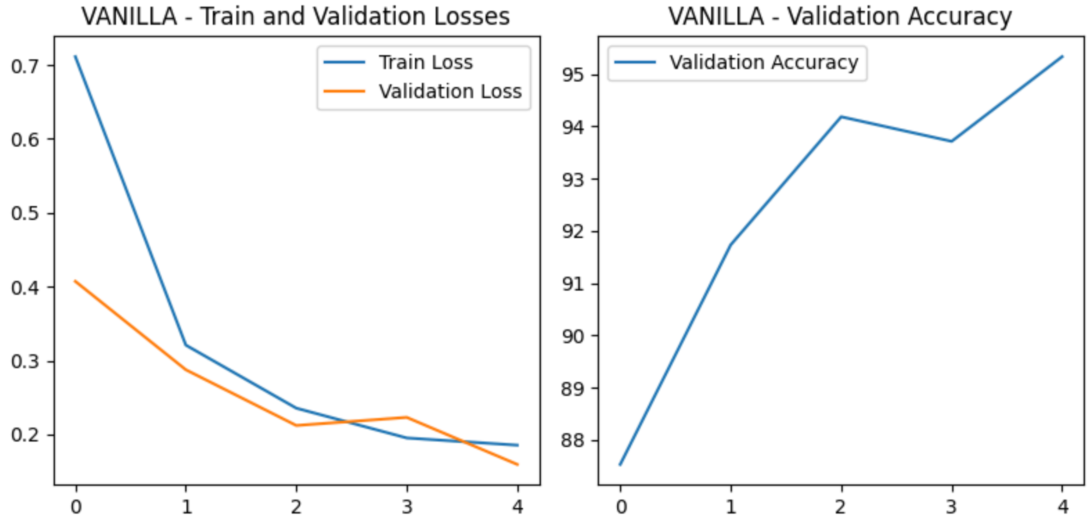



```
Training with hidden size: 128, num layers: 3
Epoch: 1/5, Train Loss: 0.5694, Validation Loss: 0.3802, Validation Accuracy: 88.76%
Epoch: 2/5, Train Loss: 0.2527, Validation Loss: 0.1961, Validation Accuracy: 94.25%
Epoch: 3/5, Train Loss: 0.1893, Validation Loss: 0.1570, Validation Accuracy: 95.59%
Epoch: 4/5, Train Loss: 0.1704, Validation Loss: 0.1988, Validation Accuracy: 94.22%
Epoch: 5/5, Train Loss: 0.1533, Validation Loss: 0.2105, Validation Accuracy: 93.94%
Training using VANILLA took 46.91 seconds.
```

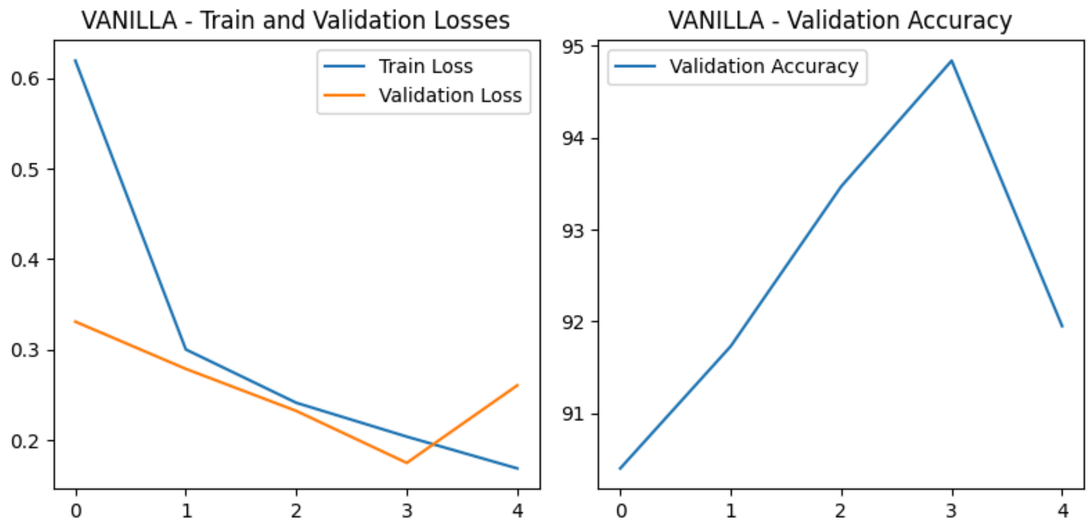



```
Training with hidden size: 128, num layers: 4
Epoch: 1/5, Train Loss: 0.7114, Validation Loss: 0.4073, Validation Accuracy: 87.53%
Epoch: 2/5, Train Loss: 0.3211, Validation Loss: 0.2877, Validation Accuracy: 91.73%
Epoch: 3/5, Train Loss: 0.2357, Validation Loss: 0.2123, Validation Accuracy: 94.18%
Epoch: 4/5, Train Loss: 0.1954, Validation Loss: 0.2232, Validation Accuracy: 93.71%
```

```
Epoch: 5/5, Train Loss: 0.1857, Validation Loss: 0.1596, Validation Accuracy: 95.33%
Training using VANILLA took 47.98 seconds.
```




```
Training with hidden size: 128, num layers: 5
Epoch: 1/5, Train Loss: 0.6193, Validation Loss: 0.3309, Validation Accuracy: 90.40%
Epoch: 2/5, Train Loss: 0.3002, Validation Loss: 0.2787, Validation Accuracy: 91.73%
Epoch: 3/5, Train Loss: 0.2412, Validation Loss: 0.2322, Validation Accuracy: 93.47%
Epoch: 4/5, Train Loss: 0.2038, Validation Loss: 0.1748, Validation Accuracy: 94.84%
Epoch: 5/5, Train Loss: 0.1687, Validation Loss: 0.2604, Validation Accuracy: 91.95%
Training using VANILLA took 50.55 seconds.
```



```
save_path = f'/content/drive/MyDrive/EE5179 DLI/Assignment3/best_model/best_model_hidden_{best_hidden_size}_layers_{best_num_layers}.pt
torch.save(best_model.state_dict(), save_path)
print(f'Best model saved to {save_path} with accuracy: {best_val_acc:.2f}%')
```

```
Best model saved to /content/drive/MyDrive/EE5179 DLI/Assignment3/best_model/best_model_hidden_64_layers_5.pt with accuracy: 96.36%
```

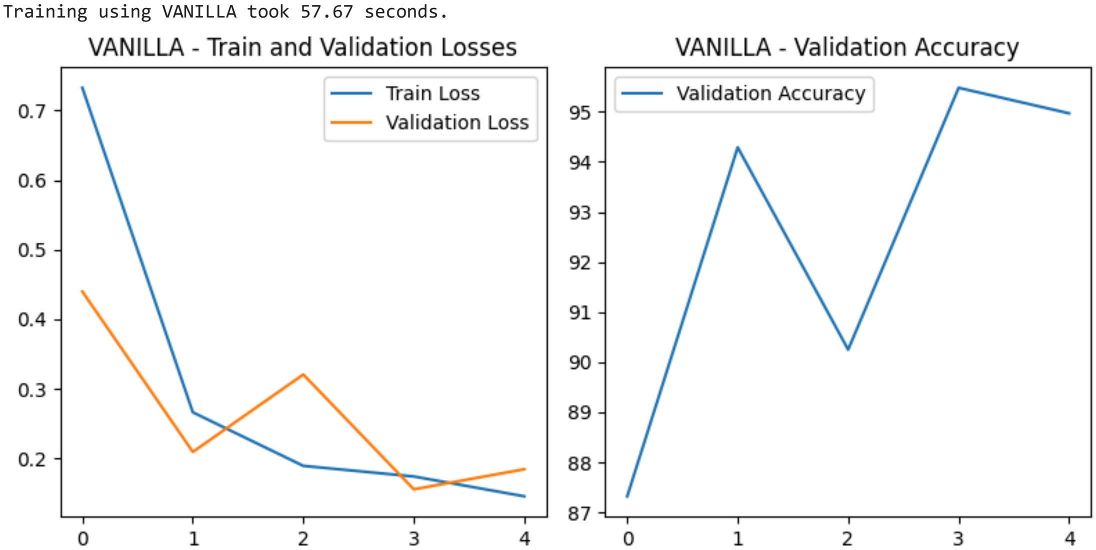
We get the best performance with hidden state size of 64 and 5 layers. We'll stick with this conifiguration for all the further experiments.

Performance with uni-directional models

```
in_dim = 28
hidden_dim = 64
out_dim = 10
num_layers = 5
bidir = False
```

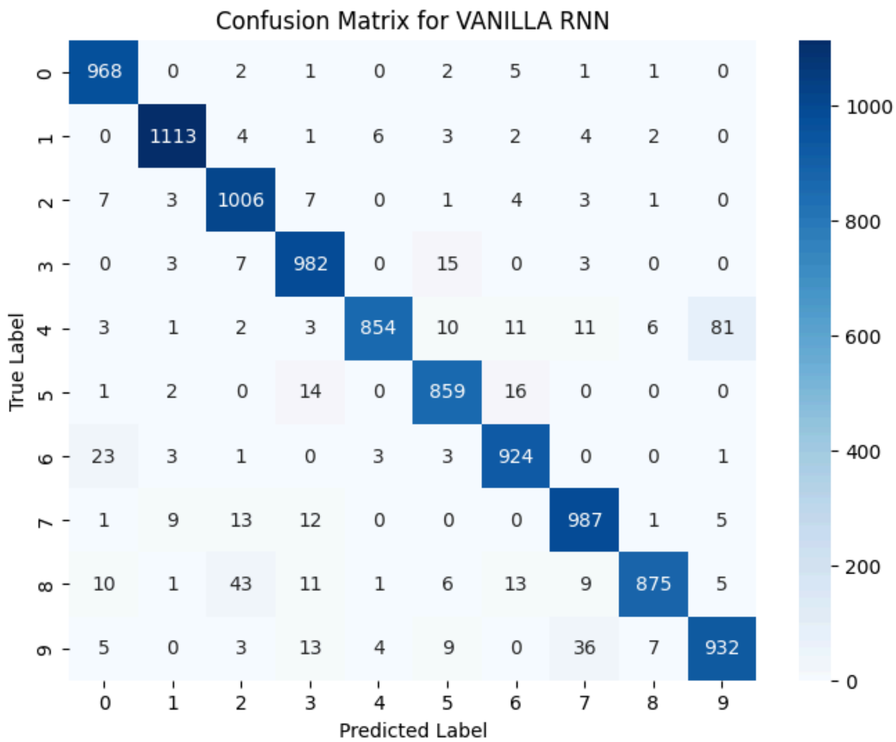
```
rnn_type = 'vanilla'
rnn_res =  train_and_evaluate(in_dim, hidden_dim, out_dim, train_loader, val_loader, test_loader, num_layers, rnn_type, bidir)
```

```
Epoch: 1/5, Train Loss: 0.7325, Validation Loss: 0.4398, Validation Accuracy: 87.32%
Epoch: 2/5, Train Loss: 0.2664, Validation Loss: 0.2095, Validation Accuracy: 94.29%
Epoch: 3/5, Train Loss: 0.1895, Validation Loss: 0.3207, Validation Accuracy: 90.25%
Epoch: 4/5, Train Loss: 0.1742, Validation Loss: 0.1558, Validation Accuracy: 95.48%
Epoch: 5/5, Train Loss: 0.1457, Validation Loss: 0.1846, Validation Accuracy: 94.97%
Training using VANILLA took 57.67 seconds.
```



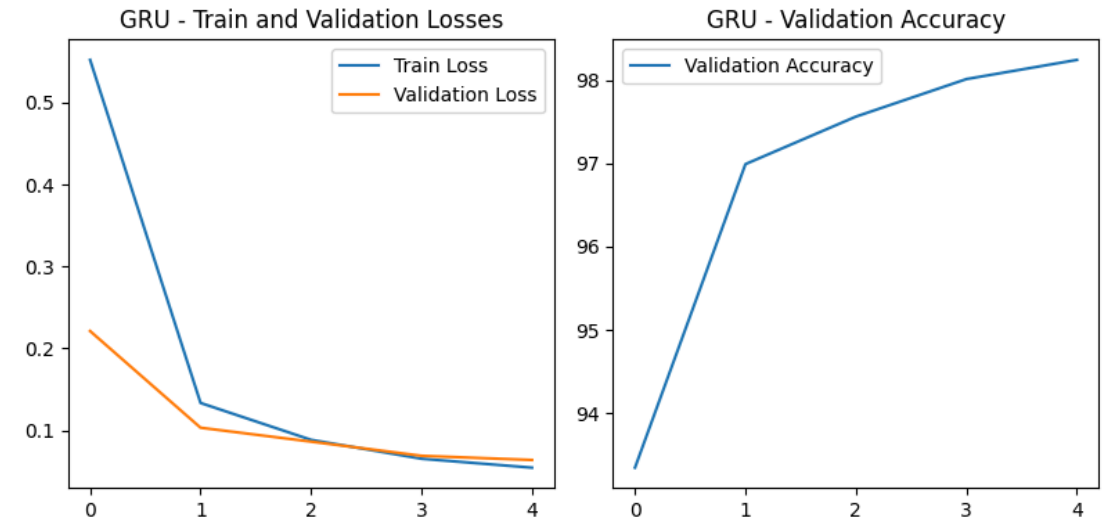

```
display_results(rnn_type, rnn_res)
```

```
Results for VANILLA RNN:
Accuracy: 95.00%

Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.99      0.97       980
           1       0.98      0.98      0.98      1135
           2       0.93      0.97      0.95      1032
           3       0.94      0.97      0.96      1010
           4       0.98      0.87      0.92       982
           5       0.95      0.96      0.95       892
           6       0.95      0.96      0.96       958
           7       0.94      0.96      0.95      1028
           8       0.98      0.90      0.94       974
           9       0.91      0.92      0.92      1009

    accuracy                           0.95     10000
   macro avg       0.95      0.95      0.95     10000
weighted avg       0.95      0.95      0.95     10000
```



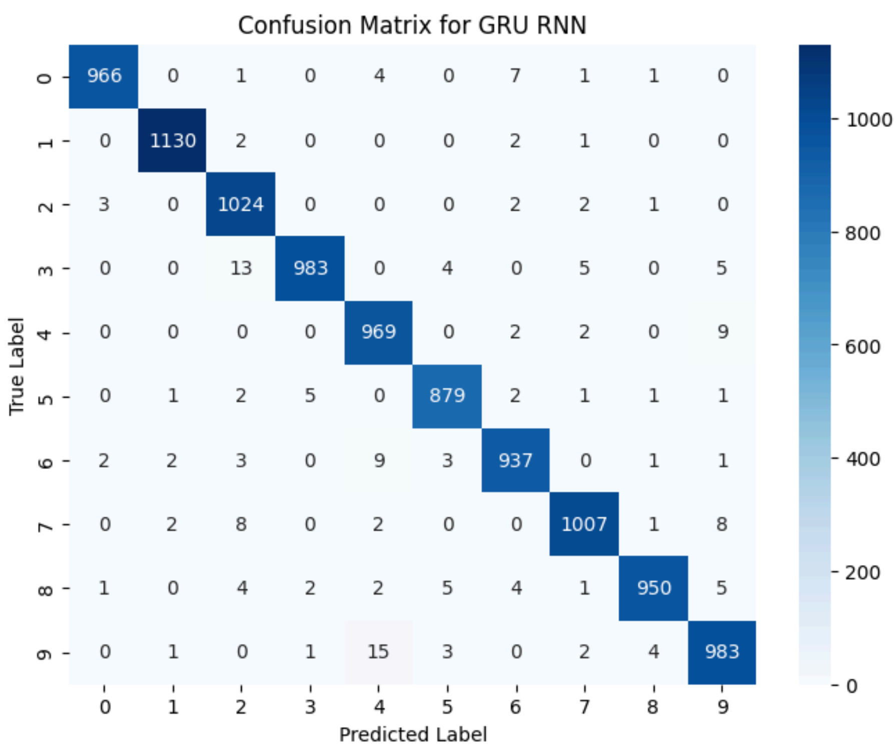

```
rnn_type = 'gru'
gru_res = train_and_evaluate(in_dim, hidden_dim, out_dim, train_loader, val_loader, test_loader, num_layers, rnn_type, bidir)
```

```
Epoch: 1/5, Train Loss: 0.5521, Validation Loss: 0.2212, Validation Accuracy: 93.35%
Epoch: 2/5, Train Loss: 0.1335, Validation Loss: 0.1032, Validation Accuracy: 96.99%
Epoch: 3/5, Train Loss: 0.0884, Validation Loss: 0.0863, Validation Accuracy: 97.56%
Epoch: 4/5, Train Loss: 0.0654, Validation Loss: 0.0689, Validation Accuracy: 98.01%
Epoch: 5/5, Train Loss: 0.0545, Validation Loss: 0.0639, Validation Accuracy: 98.24%
Training using GRU took 49.94 seconds.
```



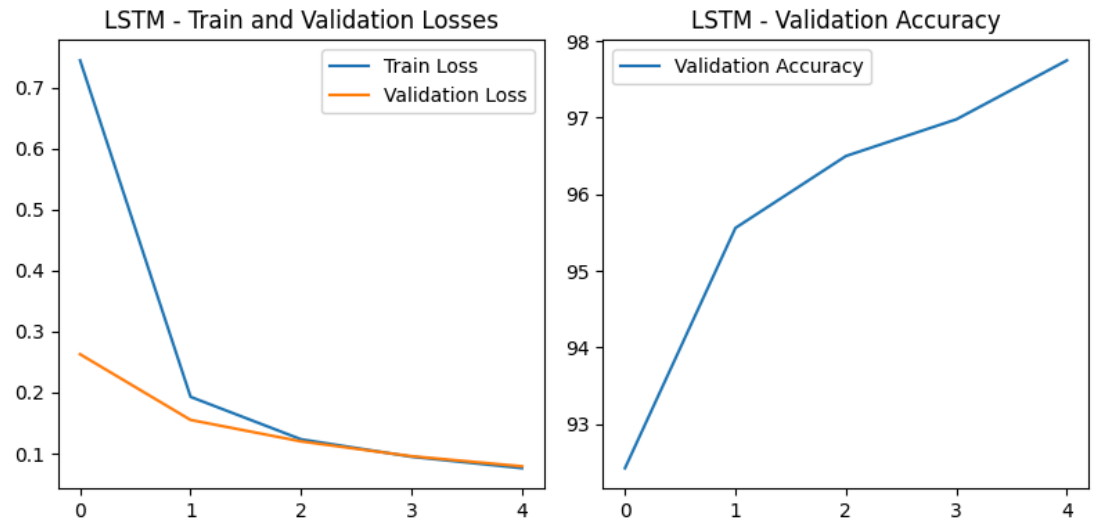

```
display_results(rnn_type, gru_res)
```

```
Results for GRU RNN:
Accuracy: 98.28%

Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       980
           1       0.99      1.00      1.00      1135
           2       0.97      0.99      0.98      1032
           3       0.99      0.97      0.98      1010
           4       0.97      0.99      0.98       982
           5       0.98      0.99      0.98       892
           6       0.98      0.98      0.98       958
           7       0.99      0.98      0.98      1028
           8       0.99      0.98      0.98       974
           9       0.97      0.97      0.97      1009

    accuracy                           0.98     10000
   macro avg       0.98      0.98      0.98     10000
weighted avg       0.98      0.98      0.98     10000
```



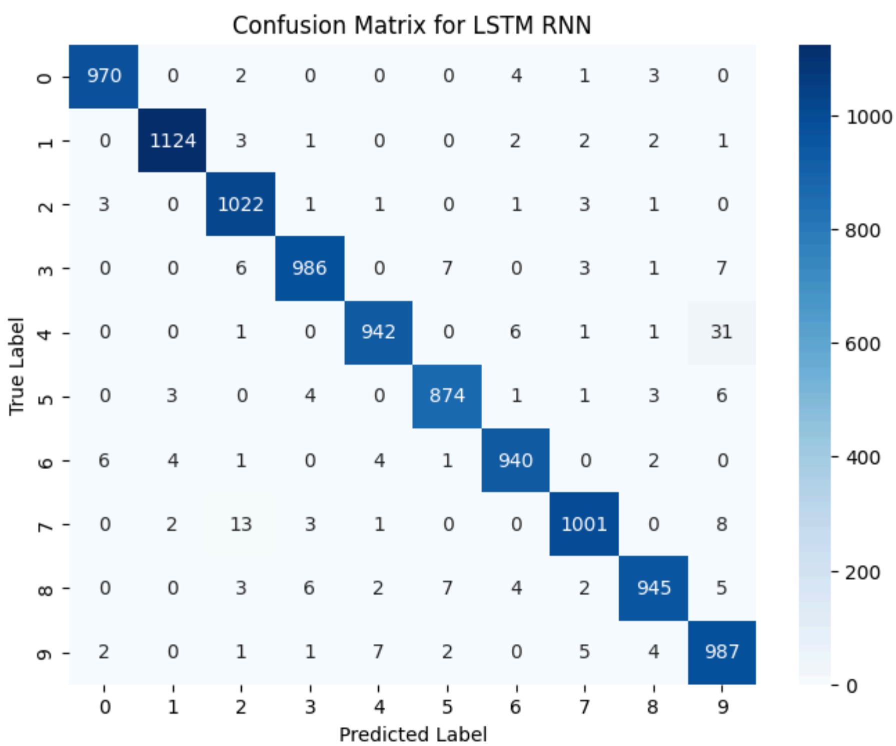

```
rnn_type = 'lstm'
lstm_res = train_and_evaluate(in_dim, hidden_dim, out_dim, train_loader, val_loader, test_loader, num_layers, rnn_type, bidir)
```

```
Epoch: 1/5, Train Loss: 0.7443, Validation Loss: 0.2628, Validation Accuracy: 92.42%
Epoch: 2/5, Train Loss: 0.1930, Validation Loss: 0.1552, Validation Accuracy: 95.56%
Epoch: 3/5, Train Loss: 0.1235, Validation Loss: 0.1200, Validation Accuracy: 96.50%
Epoch: 4/5, Train Loss: 0.0949, Validation Loss: 0.0957, Validation Accuracy: 96.98%
Epoch: 5/5, Train Loss: 0.0762, Validation Loss: 0.0792, Validation Accuracy: 97.75%
Training using LSTM took 51.67 seconds.
```




```
display_results(rnn_type, lstm_res)
```

```
Results for LSTM RNN:
Accuracy: 97.91%

Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       980
           1       0.99      0.99      0.99      1135
           2       0.97      0.99      0.98      1032
           3       0.98      0.98      0.98      1010
           4       0.98      0.96      0.97       982
           5       0.98      0.98      0.98       892
           6       0.98      0.98      0.98       958
           7       0.98      0.97      0.98      1028
           8       0.98      0.97      0.98       974
           9       0.94      0.98      0.96      1009

    accuracy                           0.98     10000
   macro avg       0.98      0.98      0.98     10000
weighted avg       0.98      0.98      0.98     10000
```



The GRU has the best performance and is the least time consuming.

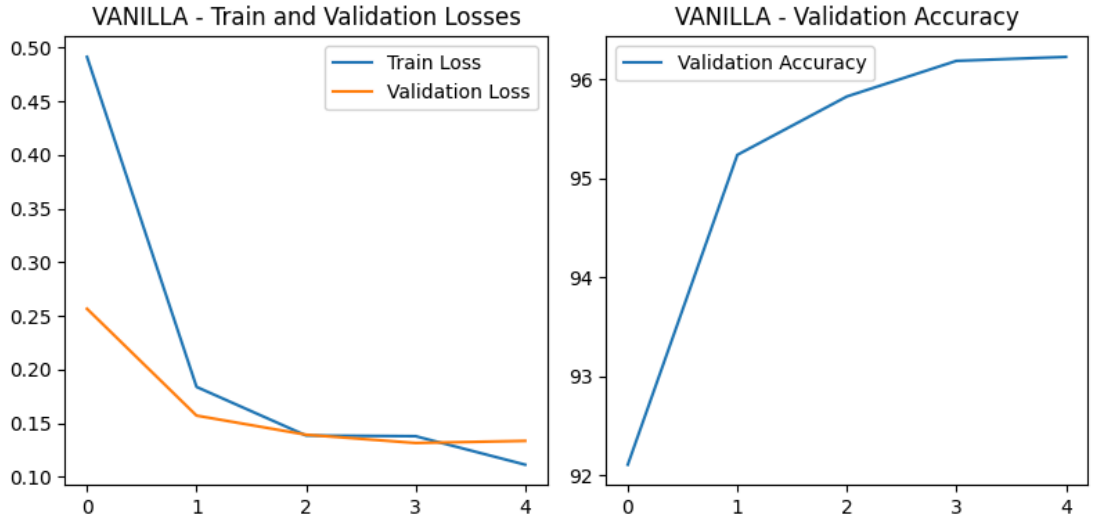
Perfromance with bi-directional models

Ideally one should also tune hyperparameters for a bi-directional setup separately because the number of layers double, but for this simple dataset, we'll just stick with the best hyperparams from the uni-directional tuning experiment.

```
bidir = True
```

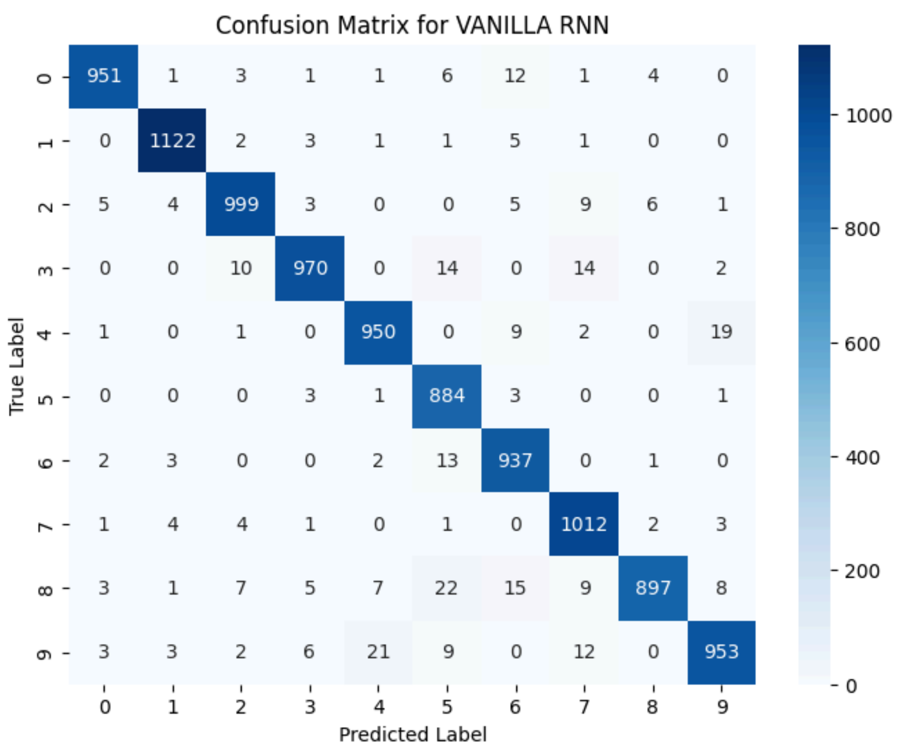
```
rnn_type = 'vanilla'
bi_rnn_res = train_and_evaluate(in_dim, hidden_dim, out_dim, train_loader, val_loader, test_loader, num_layers, rnn_type, bidir)
```

```
Epoch: 1/5, Train Loss: 0.4914, Validation Loss: 0.2568, Validation Accuracy: 92.11%
Epoch: 2/5, Train Loss: 0.1840, Validation Loss: 0.1572, Validation Accuracy: 95.24%
Epoch: 3/5, Train Loss: 0.1387, Validation Loss: 0.1394, Validation Accuracy: 95.83%
Epoch: 4/5, Train Loss: 0.1380, Validation Loss: 0.1317, Validation Accuracy: 96.19%
Epoch: 5/5, Train Loss: 0.1115, Validation Loss: 0.1337, Validation Accuracy: 96.23%
Training using VANILLA took 62.32 seconds.
```



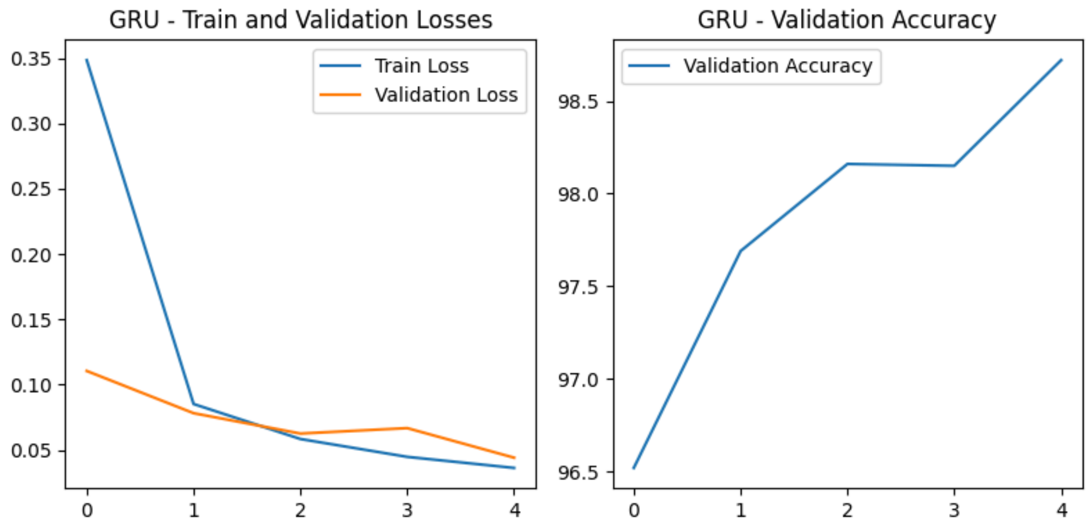

```
display_results(rnn_type, bi_rnn_res)
```

```
Results for VANILLA RNN:
Accuracy: 96.75%

Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.97      0.98       980
           1       0.99      0.99      0.99      1135
           2       0.97      0.97      0.97      1032
           3       0.98      0.96      0.97      1010
           4       0.97      0.97      0.97       982
           5       0.93      0.99      0.96       892
           6       0.95      0.98      0.96       958
           7       0.95      0.98      0.97      1028
           8       0.99      0.92      0.95       974
           9       0.97      0.94      0.95      1009

    accuracy                           0.97     10000
   macro avg       0.97      0.97      0.97     10000
weighted avg       0.97      0.97      0.97     10000
```



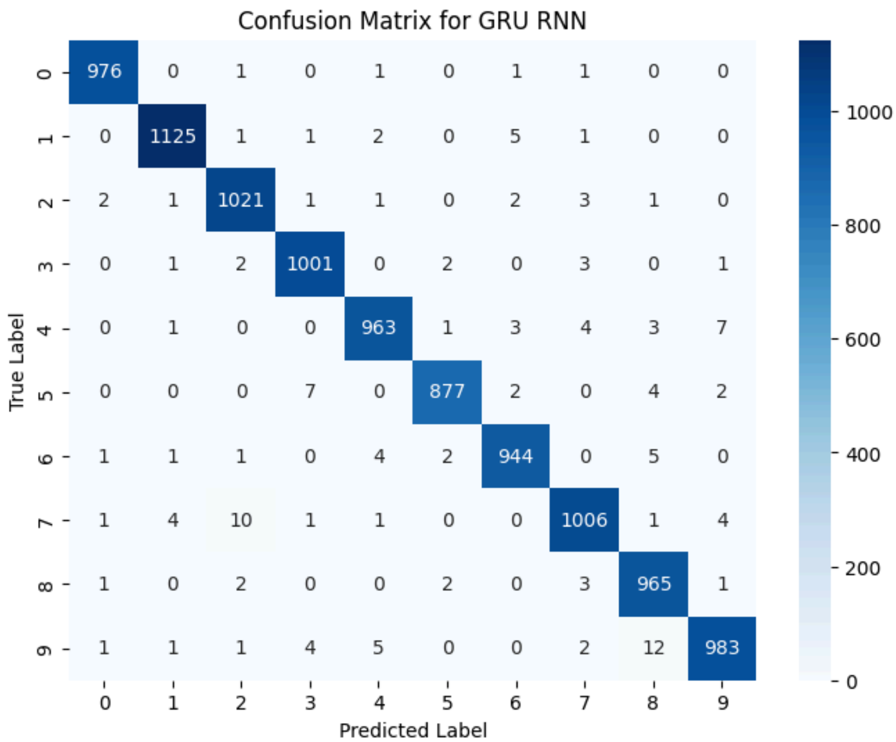

```
rnn_type = 'gru'
bi_gru_res = train_and_evaluate(in_dim, hidden_dim, out_dim, train_loader, val_loader, test_loader, num_layers, rnn_type, bidir)
```

```
Epoch: 1/5, Train Loss: 0.3484, Validation Loss: 0.1105, Validation Accuracy: 96.52%
Epoch: 2/5, Train Loss: 0.0852, Validation Loss: 0.0782, Validation Accuracy: 97.69%
Epoch: 3/5, Train Loss: 0.0584, Validation Loss: 0.0626, Validation Accuracy: 98.16%
Epoch: 4/5, Train Loss: 0.0448, Validation Loss: 0.0667, Validation Accuracy: 98.15%
Epoch: 5/5, Train Loss: 0.0363, Validation Loss: 0.0441, Validation Accuracy: 98.72%
Training using GRU took 62.74 seconds.
```



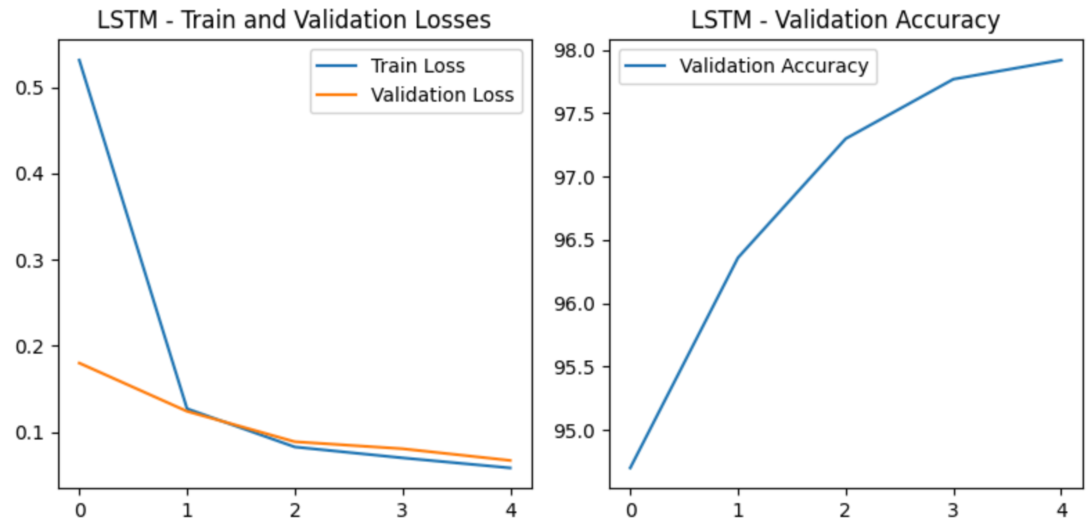

```
display_results(rnn_type, bi_gru_res)
```

```
Results for GRU RNN:
Accuracy: 98.61%

Classification Report:
              precision    recall  f1-score   support

           0       0.99      1.00      0.99       980
           1       0.99      0.99      0.99      1135
           2       0.98      0.99      0.99      1032
           3       0.99      0.99      0.99      1010
           4       0.99      0.98      0.98       982
           5       0.99      0.98      0.99       892
           6       0.99      0.99      0.99       958
           7       0.98      0.98      0.98      1028
           8       0.97      0.99      0.98       974
           9       0.98      0.97      0.98      1009

    accuracy                           0.99     10000
   macro avg       0.99      0.99      0.99     10000
weighted avg       0.99      0.99      0.99     10000
```



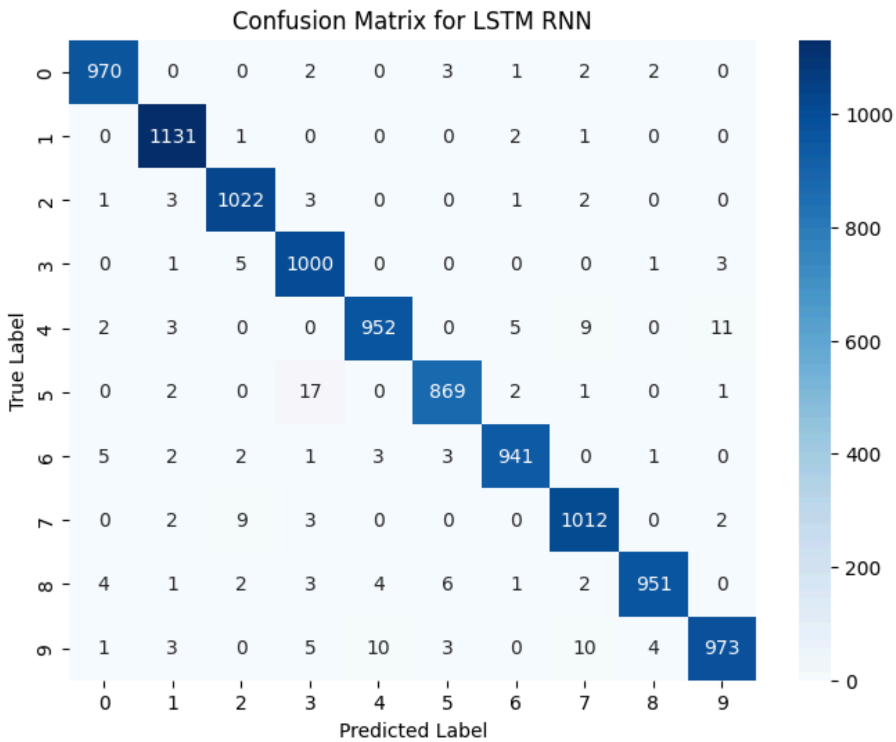

```
rnn_type = 'lstm'
bi_lstm_res = train_and_evaluate(in_dim, hidden_dim, out_dim, train_loader, val_loader, test_loader, num_layers, rnn_type, bidir)
```

```
Epoch: 1/5, Train Loss: 0.5315, Validation Loss: 0.1800, Validation Accuracy: 94.70%
Epoch: 2/5, Train Loss: 0.1271, Validation Loss: 0.1241, Validation Accuracy: 96.36%
Epoch: 3/5, Train Loss: 0.0827, Validation Loss: 0.0888, Validation Accuracy: 97.30%
Epoch: 4/5, Train Loss: 0.0700, Validation Loss: 0.0806, Validation Accuracy: 97.77%
Epoch: 5/5, Train Loss: 0.0584, Validation Loss: 0.0670, Validation Accuracy: 97.92%
Training using LSTM took 61.25 seconds.
```




```
display_results(rnn_type, bi_lstm_res)
```

```
Results for LSTM RNN:
Accuracy: 98.21%

Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       980
           1       0.99      1.00      0.99      1135
           2       0.98      0.99      0.99      1032
           3       0.97      0.99      0.98      1010
           4       0.98      0.97      0.98       982
           5       0.98      0.97      0.98       892
           6       0.99      0.98      0.98       958
           7       0.97      0.98      0.98      1028
           8       0.99      0.98      0.98       974
           9       0.98      0.96      0.97      1009

    accuracy                           0.98     10000
   macro avg       0.98      0.98      0.98     10000
weighted avg       0.98      0.98      0.98     10000
```



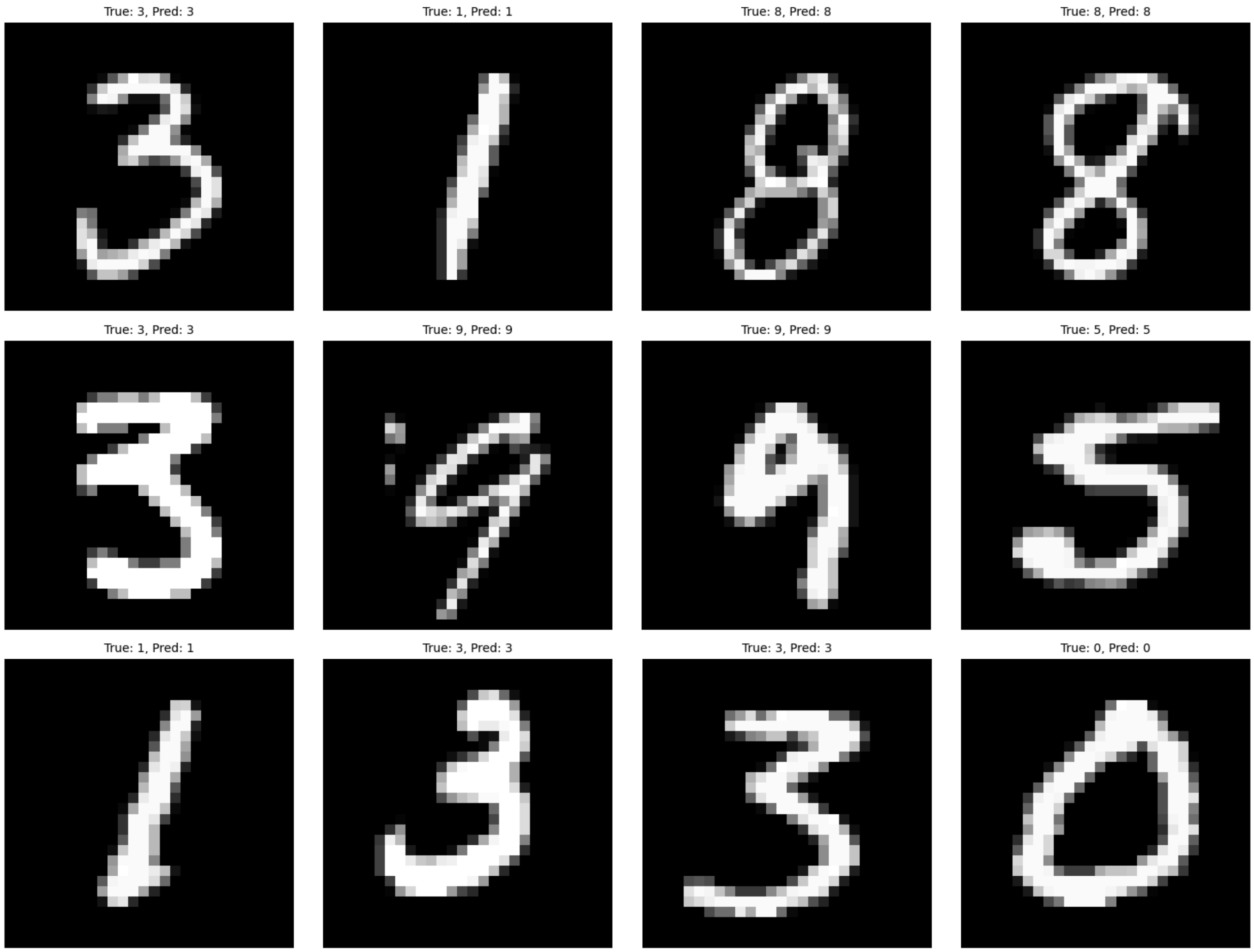
Once again, the GRU performs the best and takes the least amount to be trained.

We see that the performance of a bi-directional setup is definitely better than a uni-directional one. This is expected because of improved context captured and higher complexity.

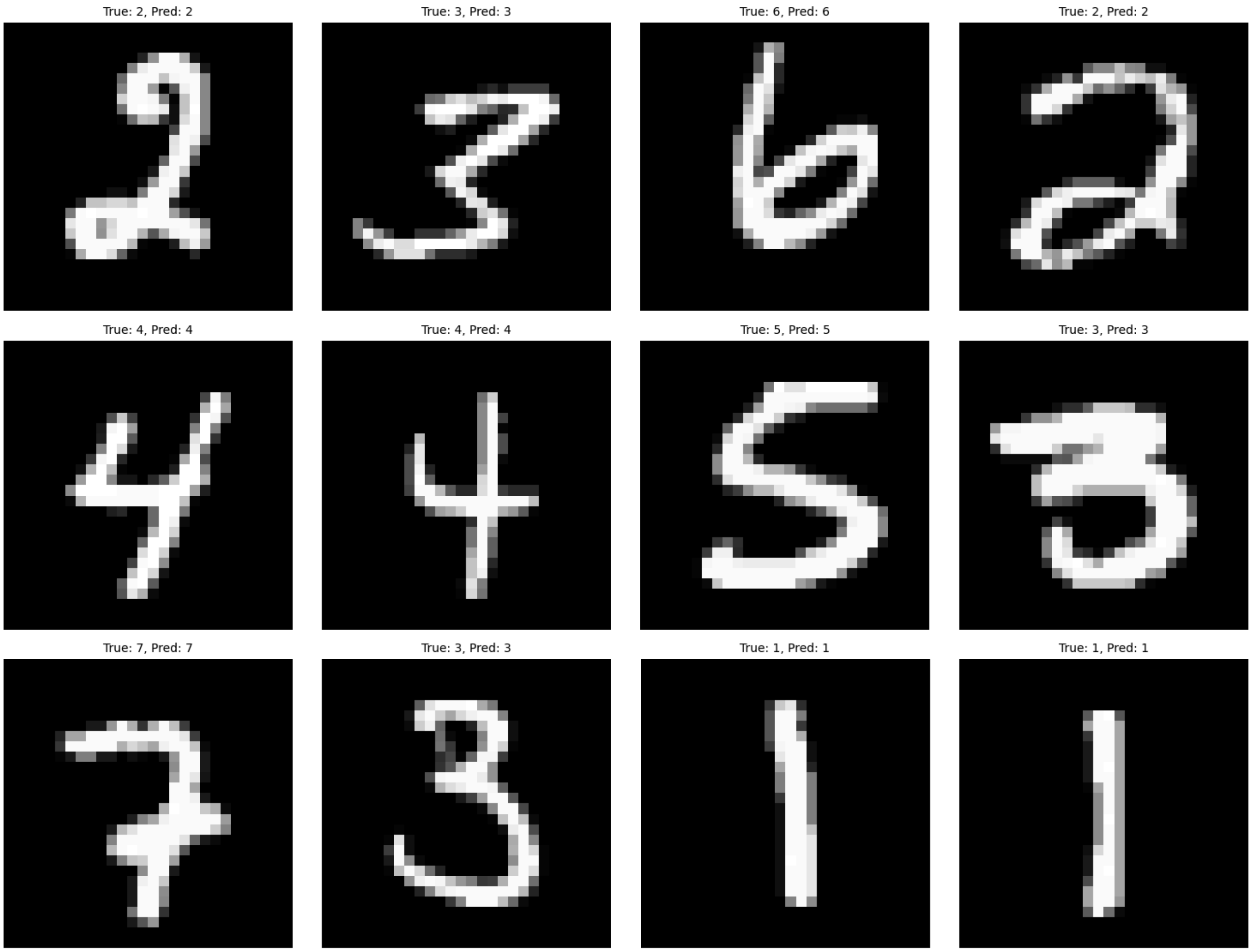
The slightly better performance of GRUs over LSTMs might hint that exposing all the hidden state information without any control is beneficial for the MNIST dataset.

Plotting predcitions

```
top_uni_model = gru_res[-1]
top_uni_model = top_uni_model.to(device)
plot_predictions(top_uni_model, test_loader)
```




```
top_bi_model = bi_gru_res[-1]
top_bi_model = top_bi_model.to(device)
plot_predictions(top_bi_model, test_loader)
```



Predicitons on custom handwritten digits

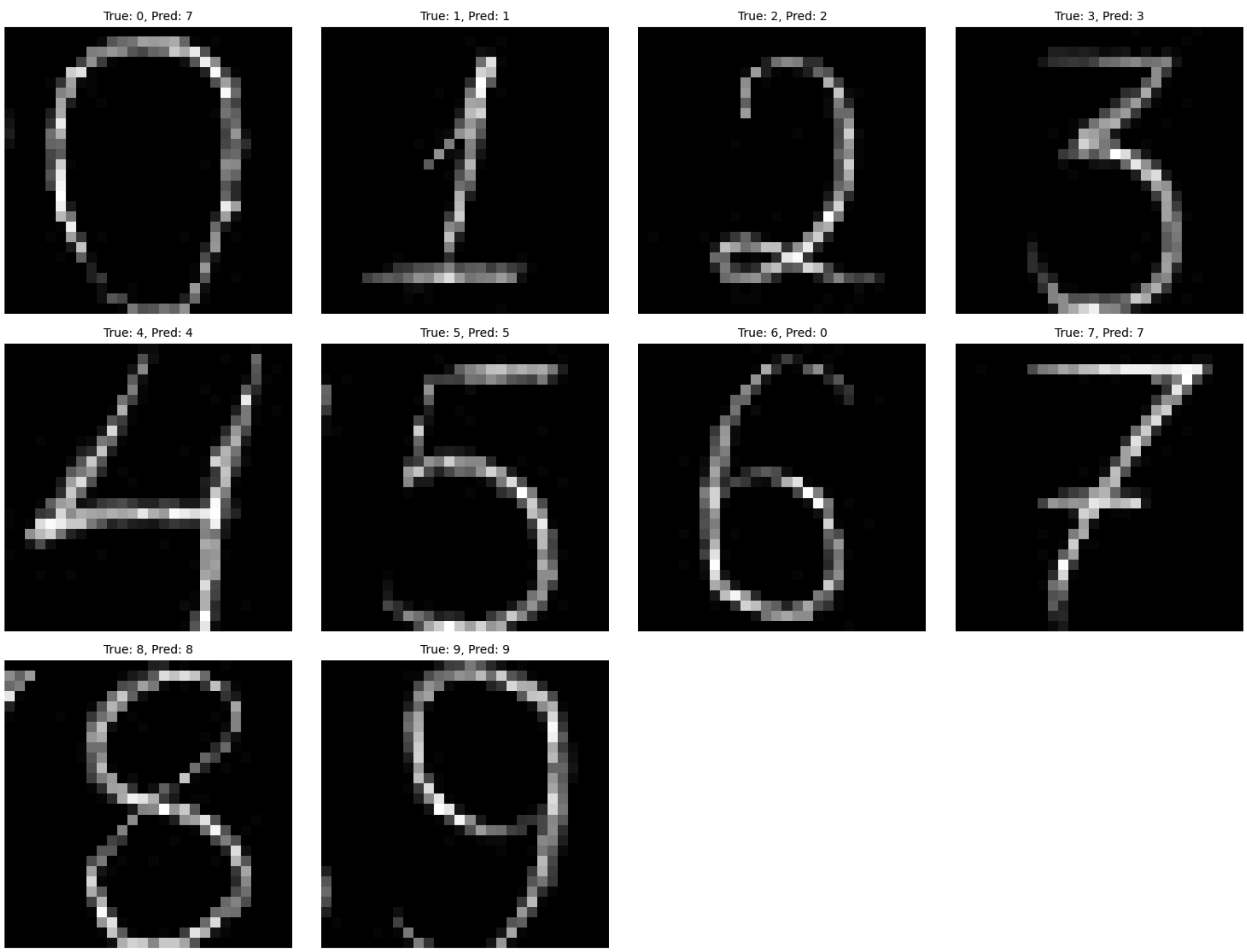
```
def plot_custom_images(model, images, labels, device):
    images_tensor = torch.stack([torch.Tensor(img) for img in X]).unsqueeze(1)
    labels_tensor = torch.Tensor(labels).long()
    #print(labels)

    outputs = model(images_tensor.to(device))
    #print(outputs)
    _, predictions = outputs.max(1)

    num_samples = len(images)
    grid_size = int(math.ceil(math.sqrt(num_samples)))

    plt.figure(figsize=(15, 15))
    for i, (img, label, pred) in enumerate(zip(images_tensor, labels_tensor, predictions)):
        plt.subplot(grid_size, grid_size, i + 1)
        plt.imshow(img[0].cpu().numpy(), cmap='gray')
```

```
        plt.title(f"True: {label.item()}, Pred: {pred.item()}", fontsize=10)
        plt.axis('off')
    plt.tight_layout()
    plt.show()


def preprocess_image(img_path):
    img = cv2.imread(img_path)
    img_gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    img_resized = cv2.resize(img_gray, (28, 28))
    img_normalized = img_resized / 255.0
    # Inverted the colors to match the MNIST format
    img_normalized = 1.0 - img_normalized
    return img_normalized
```

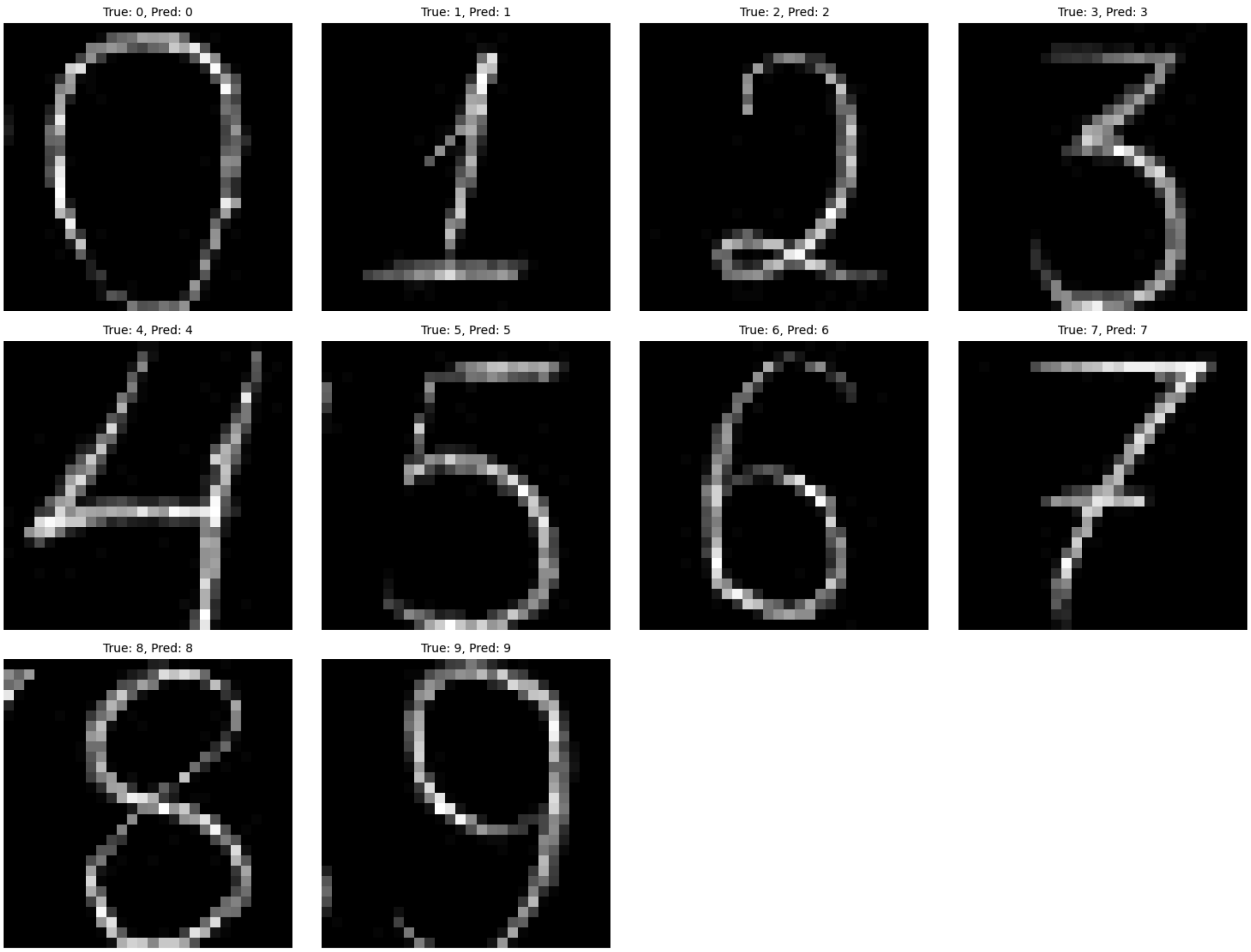
```
# Load and preprocess your images
X = [preprocess_image(f"/content/drive/MyDrive/EE5179 DLI/Assignment3/custom_images/{i}.jpg") for i in range(10)]
y = [i for i in range(10)]
```

Prediciton with GRU

```
plot_custom_images(top_uni_model, X, y, device)
```



```
plot_custom_images(top_bi_model, X, y, device)
```



This experiment shows the robustness of the bi-directional model, as it works well even with the custom images, which clearly have a thinner stroke than the images from the MNIST dataset.

Teaching an RNN to learn binary addition

We'll have 5 layers in our LSTM architecture for this task and train for 5000 epochs with each hidden state size. We'll use a sequence of length 5 for each experiment as specified in the assignment.

Function to generate data

```
def get_batch(K, L):
    max_num = (2 ** L) - 1
    X = np.zeros((K, L + 1, 2))
    y = np.zeros((K, L + 1, 1))

    for i in range(K):
        a, b = random.sample(range(max_num + 1), 2)
        c = a + b

        # Convert to padded binary strings
        a_bin = format(a, f'0{L + 1}b')
        b_bin = format(b, f'0{L + 1}b')
        c_bin = format(c, f'0{L + 1}b')

        for j in range(L + 1):
            X[i, j, 0] = int(a_bin[j])
            X[i, j, 1] = int(b_bin[j])
            y[i, j, 0] = int(c_bin[j])

    return torch.tensor(X).float(), torch.tensor(y).long()
```

The LSTM Architecture

```
class BinaryAdder(nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim, layers = 1):
        super().__init__()
        self.layers = layers
        self.hidden_dim = hidden_dim
        self.rnn = nn.LSTM(input_dim, hidden_dim, num_layers = layers, batch_first = True)
        self.fc = nn.Linear(hidden_dim, output_dim)

    def forward(self, text):
        output, (hidden, cell) = self.rnn(text)
        return self.fc(output)
```

Functions to train, evaluate and plot

```
def evaluate(model, criterion, K, L):
    inputs, labels = get_batch(K, L)
    labels = labels.flatten()
    inputs, labels = inputs.to(device), labels.to(device)
    with torch.no_grad():
        outputs = model(inputs)
        if criterion:
            loss = criterion(outputs.view(-1, 2), labels)
        correct = (torch.argmax(outputs, dim=-1).flatten() == labels).sum().item()
        accuracy = 100 * correct / len(labels)

    if criterion:
        return loss.item(), accuracy
    else:
        return None, accuracy
```

```
def train_model(model, criterion, optimizer, K, L, epochs=1000):
    train_costs = []
    val_costs = []
    train_acc = []
    val_acc = []

    for epoch in range(epochs):
        inputs, labels = get_batch(K, L)
        labels = labels.flatten()
        inputs, labels = inputs.to(device), labels.to(device)
```

```
        optimizer.zero_grad()

        outputs = model(inputs)
        loss = criterion(outputs.view(-1, 2), labels)
        loss.backward()
        optimizer.step()

        train_costs.append(loss.item())

        correct = (torch.argmax(outputs, dim=-1).flatten() == labels).sum().item()
        accuracy = 100 * correct / len(labels)
        train_acc.append(accuracy)

        val_cost, val_accuracy = evaluate(model, criterion, K, L)
        val_costs.append(val_cost)
        val_acc.append(val_accuracy)

        print(f'Epoch: {epoch}. Train Loss: {loss.item()}. Validation Accuracy: {val_accuracy}')
    return train_costs, train_acc, val_costs, val_acc


def plot_curves(train_costs, train_acc, val_costs, val_acc):
    plt.plot(train_costs)
    plt.plot(val_costs)
    plt.ylabel('Cost')
    plt.xlabel('epochs')
    plt.legend(['Train loss', 'Test loss'])
    plt.show()
    print(f'Train loss value after 1000 epochs: {train_costs[-1]}')
    print(f'Vaildation loss value after 1000 epochs: {val_costs[-1]}')

    plt.plot(train_acc)
    plt.plot(val_acc)
    plt.ylabel('Accuracy')
    plt.xlabel('epochs')
    plt.legend(['Train acc', 'Test acc'])
    plt.show()
    print(f'Best Test Accuracy: {max(val_acc)}%')


def plot_accuracy_vs_length(model):
    acc = []
    for L in range(1, 21):
        _, accuracy = evaluate(model, None, 100, L)
        acc.append(accuracy)

    plt.plot(range(1, 21), acc)
    plt.ylabel('Accuracy')
    plt.xlabel('Sequence length - L')
    plt.title('Accuracy vs L plot')
    plt.show()
```

Hyperparameter tuning

```
INPUT_DIM = 2
OUTPUT_DIM = 2
LR = 0.001
K  = 64
num_layers = [1, 3, 5]
hidden_state_sizes = [2, 5, 10]
lengths_of_input = [3, 5, 10]

best_accuracy = 0
best_model = None
best_params = None

for num_layer in num_layers:
    for hidden_state_size in hidden_state_sizes:
        for length_of_input in lengths_of_input:

            model = BinaryAdder(INPUT_DIM, hidden_state_size, OUTPUT_DIM, num_layer).to(device)
            criterion = nn.CrossEntropyLoss()
```

```
        optimizer = optim.Adam(model.parameters(), lr=LR)

        _, _, _, val_acc = train_model(model, criterion, optimizer, K, length_of_input)

        avg_val_acc = sum(val_acc[-10:]) / 10

        if avg_val_acc > best_accuracy:
            best_accuracy = avg_val_acc
            best_model = model
            best_params = (num_layer, hidden_state_size, length_of_input)
```

```
Streaming output truncated to the last 5000 lines.
Epoch: 0. Train Loss: 0.7377268671989441. Validation Accuracy: 49.739583333333336
Epoch: 1. Train Loss: 0.7205824851989746. Validation Accuracy: 49.739583333333336
Epoch: 2. Train Loss: 0.7004799246788025. Validation Accuracy: 48.4375
Epoch: 3. Train Loss: 0.7569630742073059. Validation Accuracy: 47.395833333333336
Epoch: 4. Train Loss: 0.7294548153877258. Validation Accuracy: 50.78125
Epoch: 5. Train Loss: 0.7245316505432129. Validation Accuracy: 53.125
Epoch: 6. Train Loss: 0.7213378548622131. Validation Accuracy: 50.260416666666664
Epoch: 7. Train Loss: 0.7266207337379456. Validation Accuracy: 47.916666666666664
Epoch: 8. Train Loss: 0.7419173717498779. Validation Accuracy: 48.4375
Epoch: 9. Train Loss: 0.7342092990875244. Validation Accuracy: 47.65625
Epoch: 10. Train Loss: 0.7421014308929443. Validation Accuracy: 48.958333333333336
Epoch: 11. Train Loss: 0.7387790679931641. Validation Accuracy: 51.302083333333336
Epoch: 12. Train Loss: 0.738209068775177. Validation Accuracy: 48.697916666666664
Epoch: 13. Train Loss: 0.7320931553840637. Validation Accuracy: 51.302083333333336
Epoch: 14. Train Loss: 0.7301454544067383. Validation Accuracy: 50.78125
Epoch: 15. Train Loss: 0.7432265281677246. Validation Accuracy: 46.354166666666664
Epoch: 16. Train Loss: 0.7290828227996826. Validation Accuracy: 51.822916666666664
Epoch: 17. Train Loss: 0.7138242721557617. Validation Accuracy: 53.385416666666664
Epoch: 18. Train Loss: 0.7253994941711426. Validation Accuracy: 48.4375
Epoch: 19. Train Loss: 0.7157167792320251. Validation Accuracy: 48.697916666666664
Epoch: 20. Train Loss: 0.7453582286834717. Validation Accuracy: 48.697916666666664
Epoch: 21. Train Loss: 0.7201817035675049. Validation Accuracy: 48.958333333333336
Epoch: 22. Train Loss: 0.7260520458221436. Validation Accuracy: 52.083333333333336
Epoch: 23. Train Loss: 0.7178637981414795. Validation Accuracy: 52.864583333333336
Epoch: 24. Train Loss: 0.7327322959899902. Validation Accuracy: 48.4375
Epoch: 25. Train Loss: 0.7308409214019775. Validation Accuracy: 45.3125
Epoch: 26. Train Loss: 0.741461455821991. Validation Accuracy: 50.0
Epoch: 27. Train Loss: 0.7210667133331299. Validation Accuracy: 48.697916666666664
Epoch: 28. Train Loss: 0.7402495741844177. Validation Accuracy: 51.302083333333336
Epoch: 29. Train Loss: 0.7118515372276306. Validation Accuracy: 53.125
Epoch: 30. Train Loss: 0.7242457270622253. Validation Accuracy: 48.958333333333336
Epoch: 31. Train Loss: 0.7059382796287537. Validation Accuracy: 51.302083333333336
Epoch: 32. Train Loss: 0.720845639705658. Validation Accuracy: 48.958333333333336
Epoch: 33. Train Loss: 0.7195854187011719. Validation Accuracy: 51.041666666666664
Epoch: 34. Train Loss: 0.7175690531730652. Validation Accuracy: 49.479166666666664
Epoch: 35. Train Loss: 0.721138060092926. Validation Accuracy: 51.302083333333336
Epoch: 36. Train Loss: 0.7217392921447754. Validation Accuracy: 52.083333333333336
Epoch: 37. Train Loss: 0.7196409702301025. Validation Accuracy: 50.520833333333336
Epoch: 38. Train Loss: 0.7279248833656311. Validation Accuracy: 45.833333333333336
Epoch: 39. Train Loss: 0.7264270186424255. Validation Accuracy: 48.177083333333336
Epoch: 40. Train Loss: 0.7097496390342712. Validation Accuracy: 51.302083333333336
Epoch: 41. Train Loss: 0.7146470546722412. Validation Accuracy: 50.260416666666664
Epoch: 42. Train Loss: 0.7266681790351868. Validation Accuracy: 48.958333333333336
Epoch: 43. Train Loss: 0.7094681262969971. Validation Accuracy: 49.21875
Epoch: 44. Train Loss: 0.7207953929901123. Validation Accuracy: 48.4375
Epoch: 45. Train Loss: 0.7081453204154968. Validation Accuracy: 52.34375
Epoch: 46. Train Loss: 0.708087146282196. Validation Accuracy: 50.0
Epoch: 47. Train Loss: 0.709437906742096. Validation Accuracy: 48.177083333333336
Epoch: 48. Train Loss: 0.710386335849762. Validation Accuracy: 51.041666666666664
Epoch: 49. Train Loss: 0.7193045020103455. Validation Accuracy: 48.958333333333336
Epoch: 50. Train Loss: 0.7107743620872498. Validation Accuracy: 52.34375
Epoch: 51. Train Loss: 0.7100104689598083. Validation Accuracy: 48.697916666666664
Epoch: 52. Train Loss: 0.7102157473564148. Validation Accuracy: 47.135416666666664
Epoch: 53. Train Loss: 0.7113792896270752. Validation Accuracy: 49.739583333333336
Epoch: 54. Train Loss: 0.7036616206169128. Validation Accuracy: 51.302083333333336
Epoch: 55. Train Loss: 0.7060722708702087. Validation Accuracy: 49.479166666666664
Epoch: 56. Train Loss: 0.7114098072052002. Validation Accuracy: 50.0
```

```
print(f"Best Parameters: Num Layers: {best_params[0]}, Hidden State Size: {best_params[1]}, Length of Input: {best_params[2]}")
print(f"Best Validation Accuracy: {best_accuracy}")
```

```
Best Parameters: Num Layers: 3, Hidden State Size: 5, Length of Input: 3
Best Validation Accuracy: 76.328125
```

We'll use 3 layers for our experiments going ahead.

Common Hyperparameters and model setup

```
INPUT_DIM = 2
OUTPUT_DIM = 2
NUM_LAYERS = 3
LR = 0.001
K = 64
```

Length of Input Sequence = 5

```
L = 5
```

Hidden State Size = 2

```
HIDDEN_DIM = 2
```

```
model = BinaryAdder(INPUT_DIM, HIDDEN_DIM, OUTPUT_DIM, NUM_LAYERS).to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=LR)
```

Training

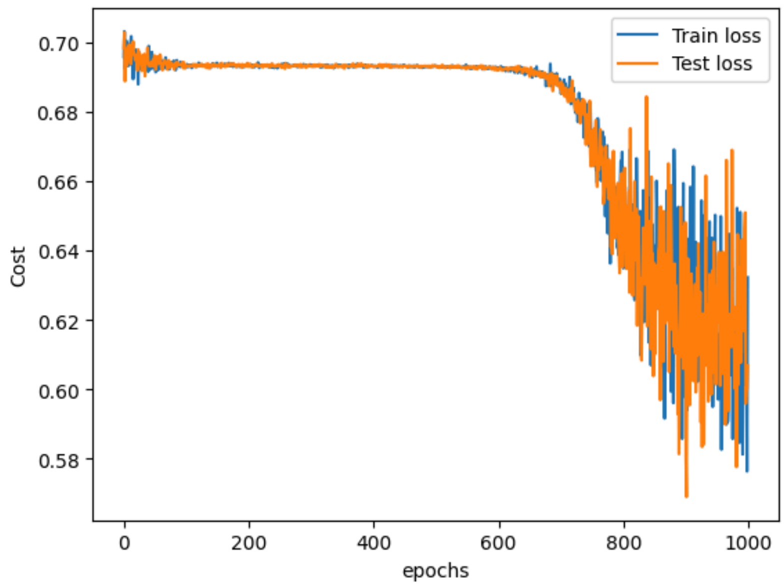
```
train_costs, train_acc, val_costs, val_acc = train_model(model, criterion, optimizer, K, L)
```

```
Epoch: 0. Train Loss: 0.6957761645317078. Validation Accuracy: 50.0
Epoch: 1. Train Loss: 0.703092634677887. Validation Accuracy: 47.65625
Epoch: 2. Train Loss: 0.6923783421516418. Validation Accuracy: 54.6875
Epoch: 3. Train Loss: 0.6939404606819153. Validation Accuracy: 50.0
Epoch: 4. Train Loss: 0.7003850340843201. Validation Accuracy: 52.083333333333336
Epoch: 5. Train Loss: 0.6947600841522217. Validation Accuracy: 52.34375
Epoch: 6. Train Loss: 0.6980153918266296. Validation Accuracy: 49.739583333333336
Epoch: 7. Train Loss: 0.6931083798408508. Validation Accuracy: 49.21875
Epoch: 8. Train Loss: 0.6992072463035583. Validation Accuracy: 51.041666666666664
Epoch: 9. Train Loss: 0.6934331059455872. Validation Accuracy: 48.697916666666664
Epoch: 10. Train Loss: 0.6988725662231445. Validation Accuracy: 50.260416666666664
Epoch: 11. Train Loss: 0.7001850008964539. Validation Accuracy: 51.822916666666664
Epoch: 12. Train Loss: 0.7016766667366028. Validation Accuracy: 48.958333333333336
Epoch: 13. Train Loss: 0.6975440382957458. Validation Accuracy: 48.958333333333336
Epoch: 14. Train Loss: 0.6977971196174622. Validation Accuracy: 48.958333333333336
Epoch: 15. Train Loss: 0.6893685460090637. Validation Accuracy: 47.395833333333336
Epoch: 16. Train Loss: 0.6958773136138916. Validation Accuracy: 49.739583333333336
Epoch: 17. Train Loss: 0.6974307894706726. Validation Accuracy: 49.479166666666664
Epoch: 18. Train Loss: 0.6972792148590088. Validation Accuracy: 50.78125
Epoch: 19. Train Loss: 0.69786137342453. Validation Accuracy: 50.78125
Epoch: 20. Train Loss: 0.6967179775238037. Validation Accuracy: 50.0
Epoch: 21. Train Loss: 0.6972880959510803. Validation Accuracy: 49.739583333333336
Epoch: 22. Train Loss: 0.6946442127227783. Validation Accuracy: 52.864583333333336
Epoch: 23. Train Loss: 0.6878708004951477. Validation Accuracy: 48.177083333333336
Epoch: 24. Train Loss: 0.6961145401000977. Validation Accuracy: 48.958333333333336
Epoch: 25. Train Loss: 0.6969702839851379. Validation Accuracy: 49.21875
Epoch: 26. Train Loss: 0.6926560997962952. Validation Accuracy: 48.958333333333336
Epoch: 27. Train Loss: 0.694315493106842. Validation Accuracy: 51.302083333333336
Epoch: 28. Train Loss: 0.6921423077583313. Validation Accuracy: 51.5625
Epoch: 29. Train Loss: 0.6947746276855469. Validation Accuracy: 52.864583333333336
Epoch: 30. Train Loss: 0.6958961486816406. Validation Accuracy: 48.958333333333336
Epoch: 31. Train Loss: 0.6939713358879089. Validation Accuracy: 50.0
Epoch: 32. Train Loss: 0.6951223015785217. Validation Accuracy: 50.260416666666664
Epoch: 33. Train Loss: 0.6957809925079346. Validation Accuracy: 48.4375
Epoch: 34. Train Loss: 0.6940176486968994. Validation Accuracy: 54.427083333333336
Epoch: 35. Train Loss: 0.6944792866706848. Validation Accuracy: 49.739583333333336
Epoch: 36. Train Loss: 0.6935617923736572. Validation Accuracy: 49.739583333333336
Epoch: 37. Train Loss: 0.6937635540962219. Validation Accuracy: 50.78125
Epoch: 38. Train Loss: 0.6925690770149231. Validation Accuracy: 46.09375
Epoch: 39. Train Loss: 0.6914733052253723. Validation Accuracy: 49.739583333333336
Epoch: 40. Train Loss: 0.6988794803619385. Validation Accuracy: 50.78125
Epoch: 41. Train Loss: 0.6957010626792908. Validation Accuracy: 51.302083333333336
Epoch: 42. Train Loss: 0.6921277642250061. Validation Accuracy: 50.78125
Epoch: 43. Train Loss: 0.6932159066200256. Validation Accuracy: 50.78125
```

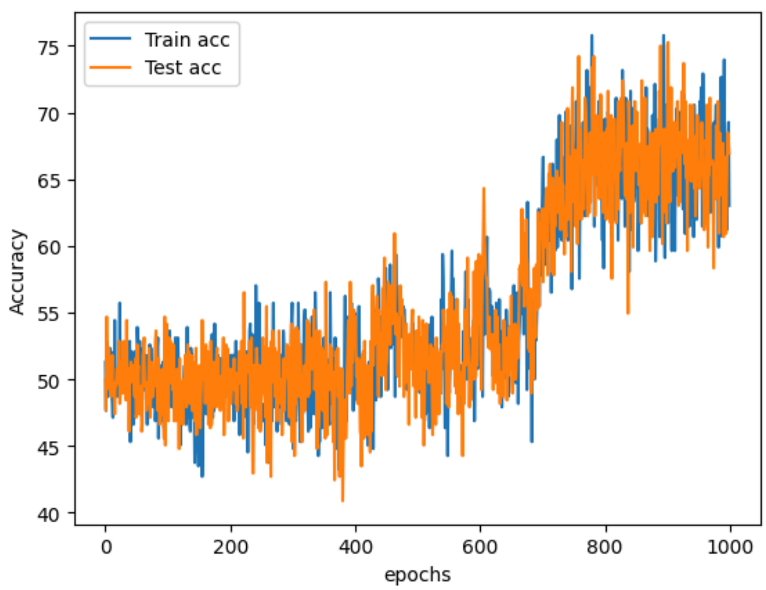
```
Epoch: 44. Train Loss: 0.6934068202972412. Validation Accuracy: 49.739583333333336
Epoch: 45. Train Loss: 0.697160005569458. Validation Accuracy: 51.041666666666664
Epoch: 46. Train Loss: 0.6929470896720886. Validation Accuracy: 49.479166666666664
Epoch: 47. Train Loss: 0.692415714263916. Validation Accuracy: 48.697916666666664
Epoch: 48. Train Loss: 0.6928901672363281. Validation Accuracy: 51.5625
Epoch: 49. Train Loss: 0.6933963298797607. Validation Accuracy: 47.135416666666664
Epoch: 50. Train Loss: 0.6953292489051819. Validation Accuracy: 47.395833333333336
Epoch: 51. Train Loss: 0.6913625597953796. Validation Accuracy: 52.604166666666664
Epoch: 52. Train Loss: 0.6919705867767334. Validation Accuracy: 50.260416666666664
Epoch: 53. Train Loss: 0.6931875348091125. Validation Accuracy: 51.041666666666664
Epoch: 54. Train Loss: 0.6927719712257385. Validation Accuracy: 47.395833333333336
Epoch: 55. Train Loss: 0.6919233202934265. Validation Accuracy: 48.697916666666664
Epoch: 56. Train Loss: 0.6942107081413269. Validation Accuracy: 47.395833333333336
```

Train and test plots

```
plot_curves(train_costs, train_acc, val_costs, val_acc)
```



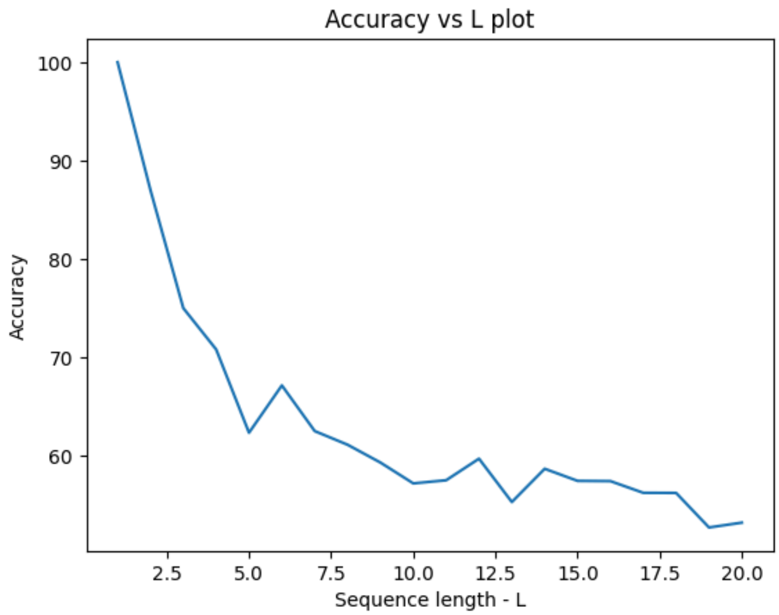

```
Train loss value after 1000 epochs: 0.6322546601295471
Vaildation loss value after 1000 epochs: 0.606839120388031
```




```
Best Test Accuracy: 75.26041666666667%
```

Bitwise Accuracy vs Length

```
plot_accuracy_vs_length(model)
```



Hidden State Size = 5

```
HIDDEN_DIM = 5
```

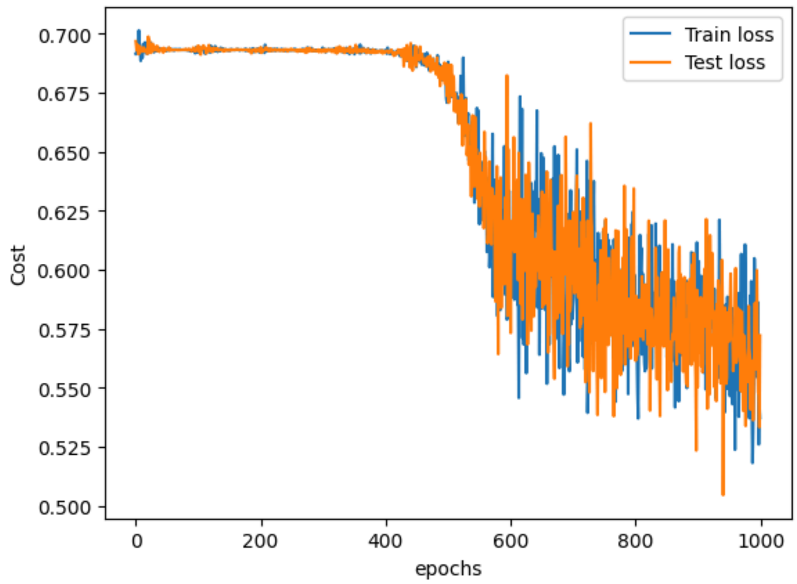
```
model = BinaryAdder(INPUT_DIM, HIDDEN_DIM, OUTPUT_DIM, NUM_LAYERS).to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=LR)
```

Training

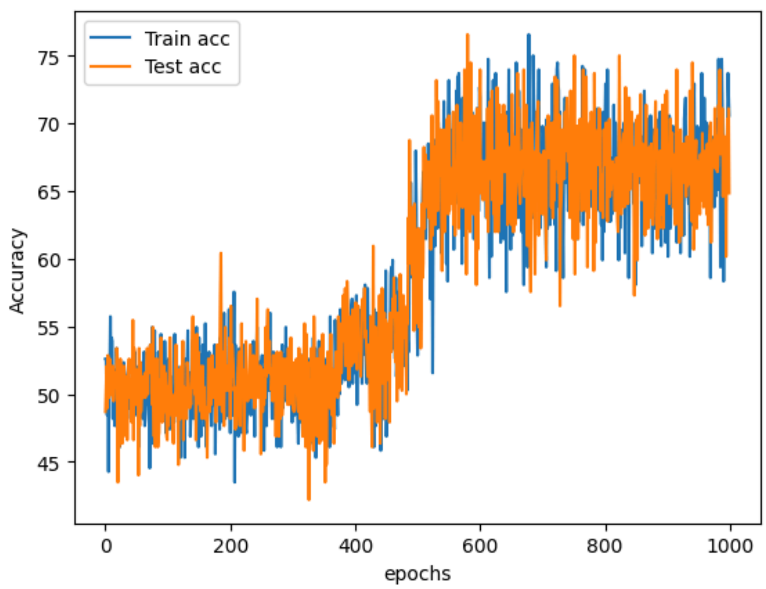
[ ] ↳ *1 cell hidden*

Train and test plots

```
plot_curves(train_costs, train_acc, val_costs, val_acc)
```



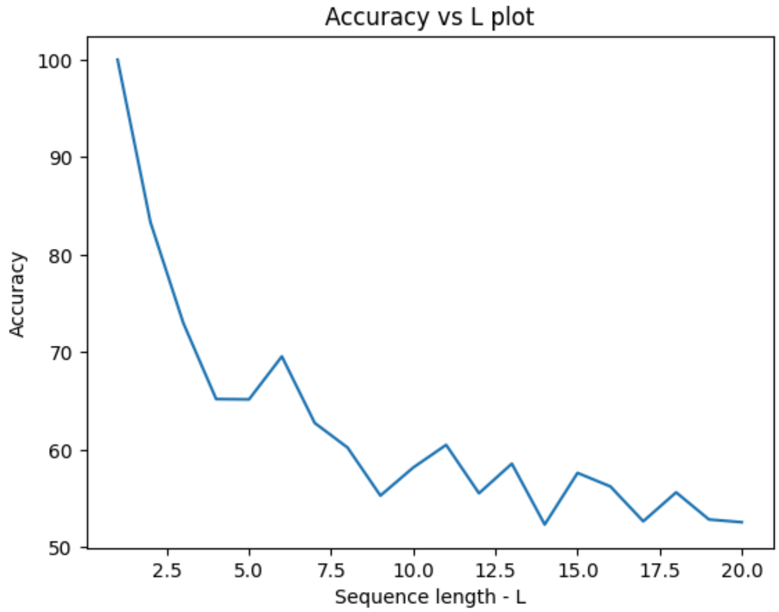

```
Train loss value after 1000 epochs: 0.5373022556304932
Vaildation loss value after 1000 epochs: 0.572155237197876
```




```
Best Test Accuracy: 76.5625%
```

Bitwise Accuracy vs Length

```
plot_accuracy_vs_length(model)
```



Hidden State Size = 10

```
HIDDEN_DIM = 10
```

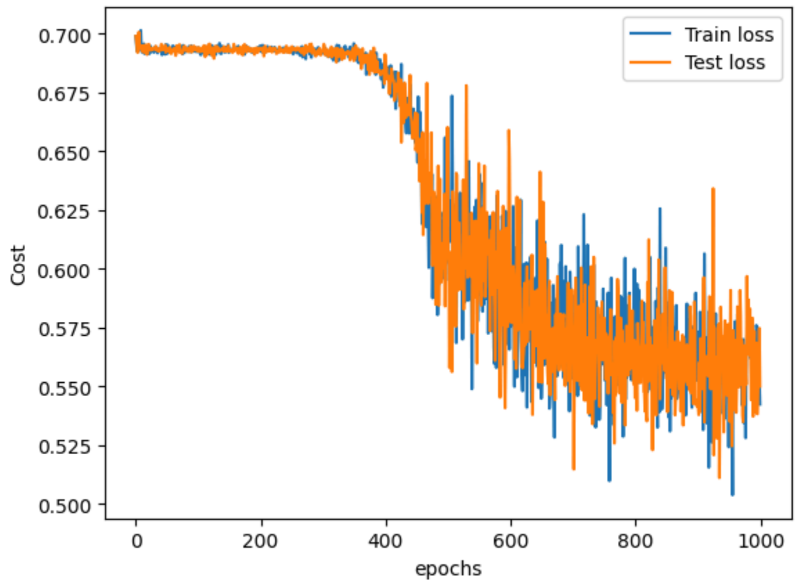
```
model = BinaryAdder(INPUT_DIM, HIDDEN_DIM, OUTPUT_DIM, NUM_LAYERS).to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=LR)
```

Training

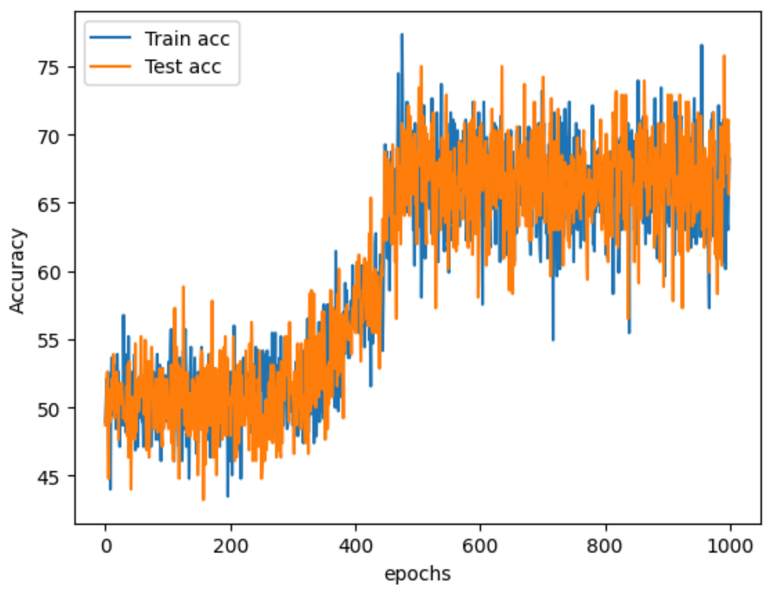
[ ] ↳ *1 cell hidden*

Train and test plots

```
plot_curves(train_costs, train_acc, val_costs, val_acc)
```



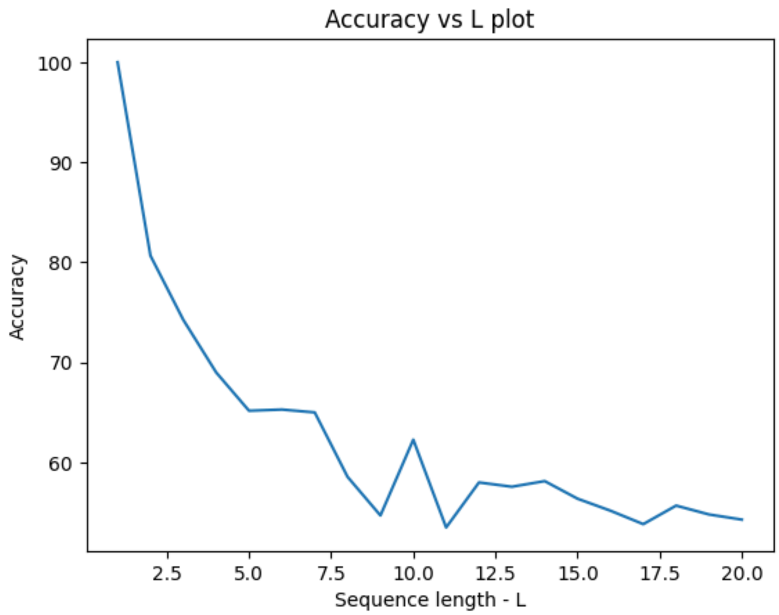

```
Train loss value after 1000 epochs: 0.542336642742157
Vaildation loss value after 1000 epochs: 0.5499600768089294
```




```
Best Test Accuracy: 75.78125%
```

Bitwise Accuracy vs Length

```
plot_accuracy_vs_length(model)
```



Summary of Results

Sequence length = 5

Epochs for training = 1000

State Size	Train loss	Validation Loss	Bitwise Accuracy
2	0.6322	0.6068	75.26%
5	0.5373	0.5721	76.56%
10	0.5423	0.55	75.78%

The performance is comparable but it seems like a hidden state size of 5 or 10 is more ideal. We might discover a trend when we try with other binary string lengths.

Analyzing the relationship between sequence lengths and bitwise accuracy from the plots, there's a noticeable decline in performance with increasing sequence lengths. This performance degradation becomes more pronounced for sequences longer than the ones used during training (in this instance, sequences of length 5). An accuracy nearing 50% isn't commendable for this task. Given that the input consists of binary strings, where the model essentially has to "predict" either 0 or 1, an accuracy of 50% implies that the model is performing no better than random guessing.

Length of Input Sequence = 3

```
L = 3
```

Hidden State Size = 2

```
HIDDEN_DIM = 2
```

```
model = BinaryAdder(INPUT_DIM, HIDDEN_DIM, OUTPUT_DIM, NUM_LAYERS).to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=LR)
```

Training

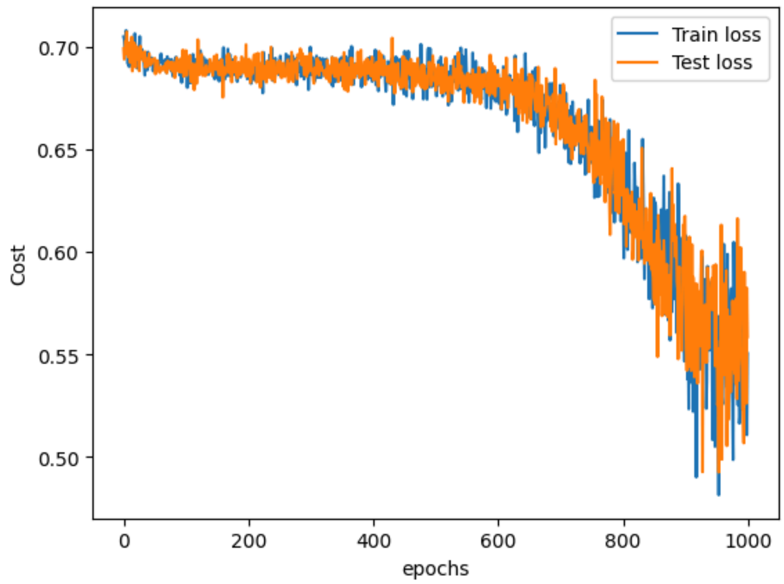
```
train_costs, train_acc, val_costs, val_acc = train_model(model, criterion, optimizer, K, L)
```

```
Epoch: 0. Train Loss: 0.7047699093818665. Validation Accuracy: 51.953125
Epoch: 1. Train Loss: 0.7034203410148621. Validation Accuracy: 51.5625
```

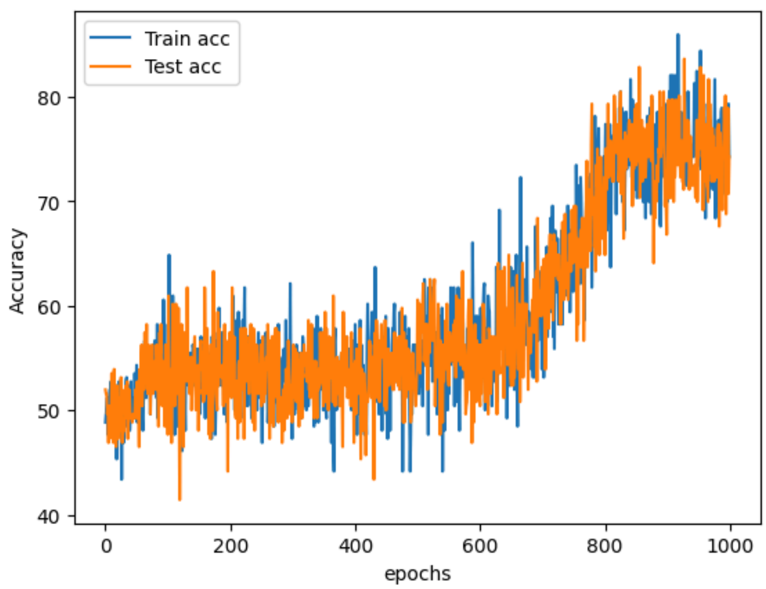
```
Epoch: 2. Train Loss: 0.6994909644126892. Validation Accuracy: 51.5625
Epoch: 3. Train Loss: 0.6980426907539368. Validation Accuracy: 49.609375
Epoch: 4. Train Loss: 0.7078401446342468. Validation Accuracy: 50.390625
Epoch: 5. Train Loss: 0.705805242061615. Validation Accuracy: 46.875
Epoch: 6. Train Loss: 0.6986811757087708. Validation Accuracy: 50.390625
Epoch: 7. Train Loss: 0.6914618015289307. Validation Accuracy: 48.4375
Epoch: 8. Train Loss: 0.6968361139297485. Validation Accuracy: 50.0
Epoch: 9. Train Loss: 0.6901028156280518. Validation Accuracy: 49.21875
Epoch: 10. Train Loss: 0.6977769136428833. Validation Accuracy: 53.515625
Epoch: 11. Train Loss: 0.6968796849250793. Validation Accuracy: 47.265625
Epoch: 12. Train Loss: 0.6984935998916626. Validation Accuracy: 50.78125
Epoch: 13. Train Loss: 0.701556384563446. Validation Accuracy: 46.875
Epoch: 14. Train Loss: 0.7006503939628601. Validation Accuracy: 53.90625
Epoch: 15. Train Loss: 0.6996426582336426. Validation Accuracy: 47.65625
Epoch: 16. Train Loss: 0.6958375573158264. Validation Accuracy: 49.21875
Epoch: 17. Train Loss: 0.6924371123313904. Validation Accuracy: 46.484375
Epoch: 18. Train Loss: 0.7062935829162598. Validation Accuracy: 50.0
Epoch: 19. Train Loss: 0.6995577812194824. Validation Accuracy: 52.34375
Epoch: 20. Train Loss: 0.6971331834793091. Validation Accuracy: 47.265625
Epoch: 21. Train Loss: 0.6966360807418823. Validation Accuracy: 49.609375
Epoch: 22. Train Loss: 0.6893569231033325. Validation Accuracy: 51.171875
Epoch: 23. Train Loss: 0.6962075233459473. Validation Accuracy: 48.046875
Epoch: 24. Train Loss: 0.6990547776222229. Validation Accuracy: 50.0
Epoch: 25. Train Loss: 0.700353741645813. Validation Accuracy: 53.125
Epoch: 26. Train Loss: 0.7048843502998352. Validation Accuracy: 47.65625
Epoch: 27. Train Loss: 0.6952252388000488. Validation Accuracy: 46.875
Epoch: 28. Train Loss: 0.6969618201255798. Validation Accuracy: 47.65625
Epoch: 29. Train Loss: 0.698712944984436. Validation Accuracy: 48.046875
Epoch: 30. Train Loss: 0.6952887177467346. Validation Accuracy: 48.046875
Epoch: 31. Train Loss: 0.6934328079223633. Validation Accuracy: 51.953125
Epoch: 32. Train Loss: 0.695074737071991. Validation Accuracy: 49.609375
Epoch: 33. Train Loss: 0.6899257302284241. Validation Accuracy: 52.34375
Epoch: 34. Train Loss: 0.6859163641929626. Validation Accuracy: 49.21875
Epoch: 35. Train Loss: 0.6960067749023438. Validation Accuracy: 52.734375
Epoch: 36. Train Loss: 0.6964049935340881. Validation Accuracy: 47.265625
Epoch: 37. Train Loss: 0.6915532350540161. Validation Accuracy: 50.390625
Epoch: 38. Train Loss: 0.6884500980377197. Validation Accuracy: 51.953125
Epoch: 39. Train Loss: 0.6973133683204651. Validation Accuracy: 51.171875
Epoch: 40. Train Loss: 0.695439338684082. Validation Accuracy: 49.21875
Epoch: 41. Train Loss: 0.6905331611633301. Validation Accuracy: 49.21875
Epoch: 42. Train Loss: 0.6927372217178345. Validation Accuracy: 49.21875
Epoch: 43. Train Loss: 0.692602276802063. Validation Accuracy: 48.828125
Epoch: 44. Train Loss: 0.6945294737815857. Validation Accuracy: 49.609375
Epoch: 45. Train Loss: 0.6944705247879028. Validation Accuracy: 49.609375
Epoch: 46. Train Loss: 0.6933614611625671. Validation Accuracy: 49.21875
Epoch: 47. Train Loss: 0.6880271434783936. Validation Accuracy: 50.0
Epoch: 48. Train Loss: 0.6904969811439514. Validation Accuracy: 51.953125
Epoch: 49. Train Loss: 0.6916146278381348. Validation Accuracy: 51.171875
Epoch: 50. Train Loss: 0.6906164884567261. Validation Accuracy: 49.21875
Epoch: 51. Train Loss: 0.6918475031852722. Validation Accuracy: 52.734375
Epoch: 52. Train Loss: 0.6897527575492859. Validation Accuracy: 50.390625
Epoch: 53. Train Loss: 0.6909334063529968. Validation Accuracy: 50.0
Epoch: 54. Train Loss: 0.6895126700401306. Validation Accuracy: 46.484375
Epoch: 55. Train Loss: 0.6890684962272644. Validation Accuracy: 53.90625
Epoch: 56. Train Loss: 0.6911104917526245. Validation Accuracy: 50.78125
```

Train and test plots

```
plot_curves(train_costs, train_acc, val_costs, val_acc)
```



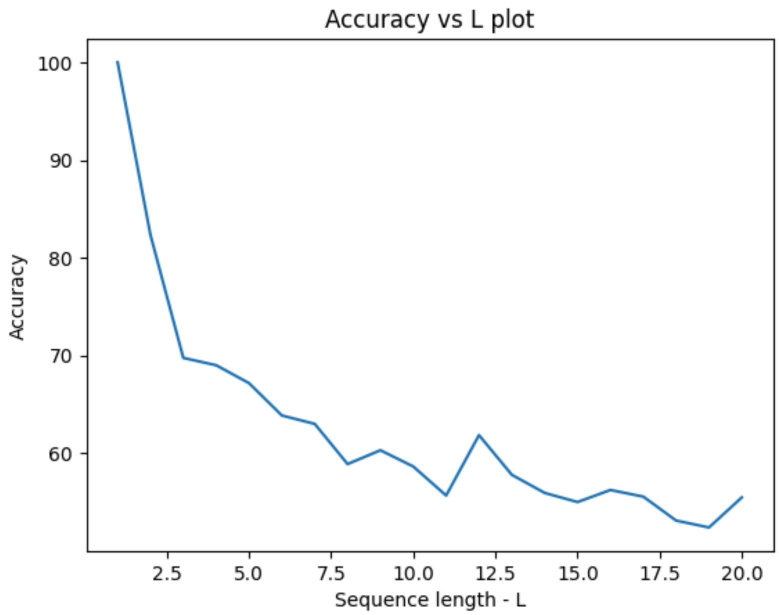

```
Train loss value after 1000 epochs: 0.5504103302955627
Vaildation loss value after 1000 epochs: 0.5584276914596558
```




```
Best Test Accuracy: 83.59375%
```

Bitwise Accuracy vs Length

```
plot_accuracy_vs_length(model)
```



Hidden State Size = 5

```
HIDDEN_DIM = 5
```

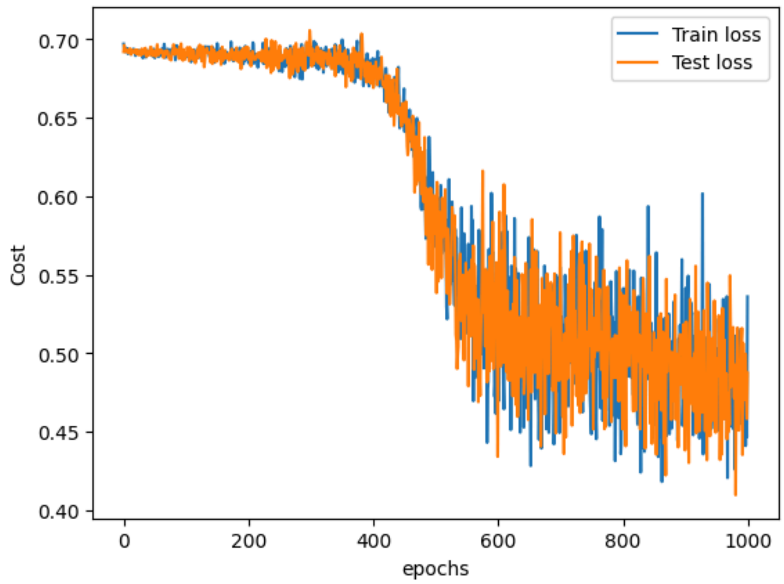
```
model = BinaryAdder(INPUT_DIM, HIDDEN_DIM, OUTPUT_DIM, NUM_LAYERS).to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=LR)
```

Training

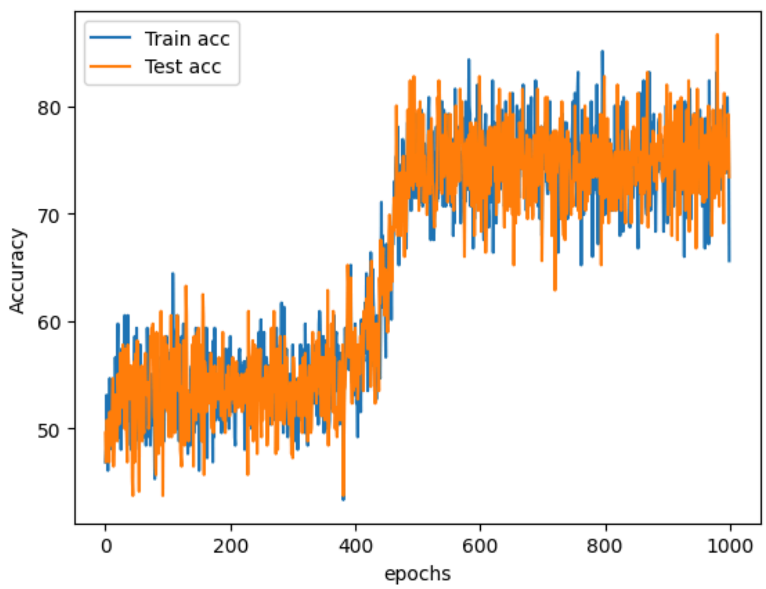
[ ] ↳ *1 cell hidden*

Train and test plots

```
plot_curves(train_costs, train_acc, val_costs, val_acc)
```



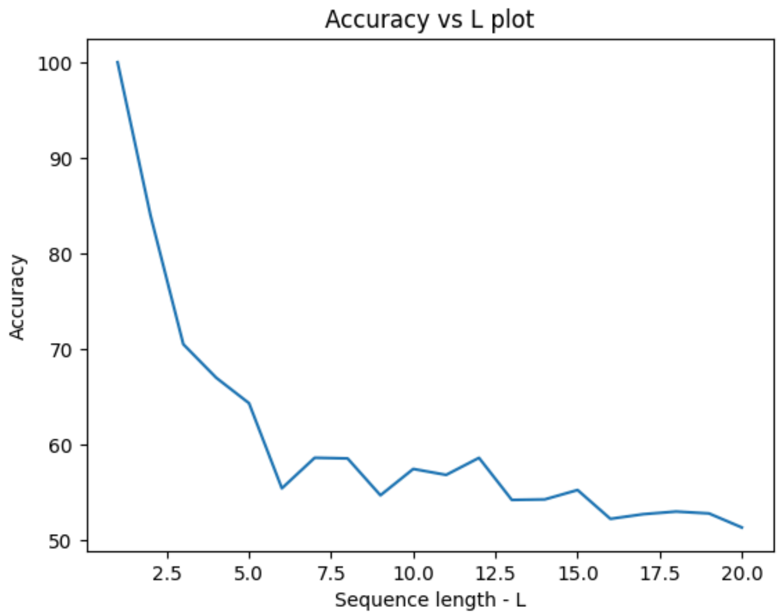

```
Train loss value after 1000 epochs: 0.5359713435173035
Vaildation loss value after 1000 epochs: 0.4874132573604584
```




```
Best Test Accuracy: 86.71875%
```

Bitwise Accuracy vs Length

```
plot_accuracy_vs_length(model)
```



Hidden State Size = 10

```
HIDDEN_DIM = 10
```

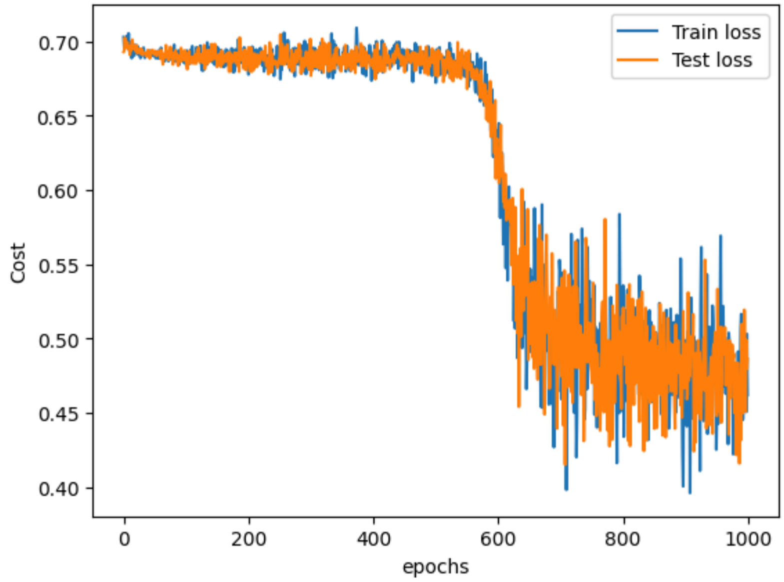
```
model = BinaryAdder(INPUT_DIM, HIDDEN_DIM, OUTPUT_DIM, NUM_LAYERS).to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=LR)
```

Training

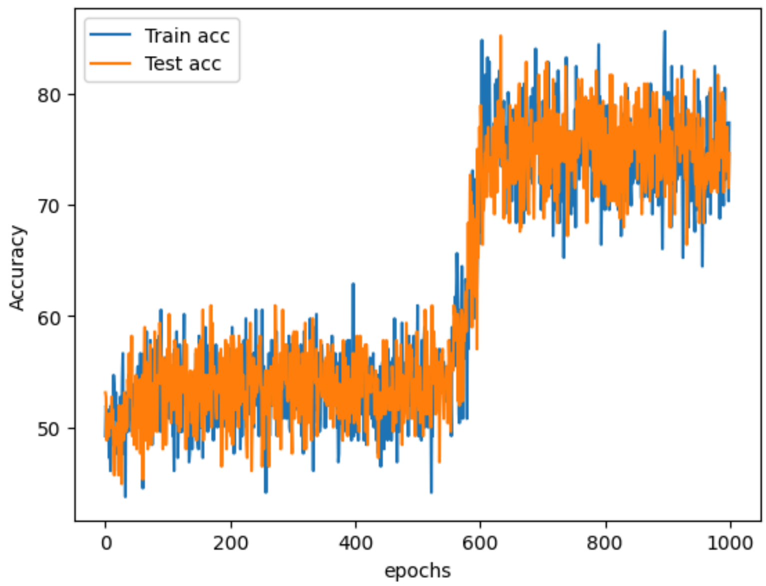
[ ] ↳ *1 cell hidden*

Train and test plots

```
plot_curves(train_costs, train_acc, val_costs, val_acc)
```



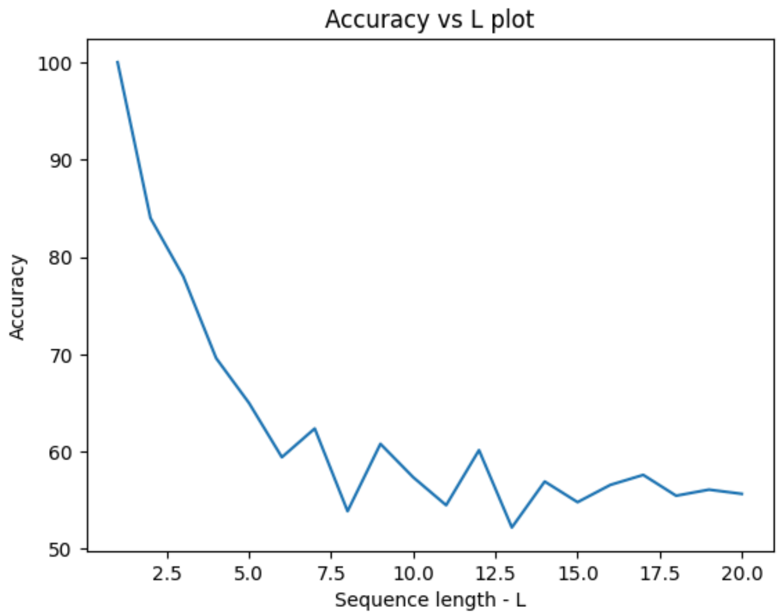

```
Train loss value after 1000 epochs: 0.4619201421737671
Vaildation loss value after 1000 epochs: 0.48619815707206726
```




```
Best Test Accuracy: 85.15625%
```

Bitwise Accuracy vs Length

```
plot_accuracy_vs_length(model)
```



Summary of Results

Sequence length = 3

Epochs for training = 1000

State Size	Train loss	Validation Loss	Bitwise Accuracy
2	0.5504	0.5584	83.59375%
5	0.5359	0.4874	86.71875%
10	0.4619	0.4861	85.15625%

The performance is comparable but it seems like a hidden state size of 5 or 10 is more ideal. We might discover a trend when we try with other binary string lengths.

Analyzing the relationship between sequence lengths and bitwise accuracy from the plots, there's a noticeable decline in performance with increasing sequence lengths.

A noteworthy observation is that our training has been limited to sequences of lengths 3 and 5. In both instances, the bitwise accuracy drops to below 60% around sequence lengths of 5-6. This suggests that models trained on shorter sequences can generalize as effectively as those trained on longer sequences when tasked with processing extended strings, provided the architecture remains consistent and sufficient training epochs are utilized.

Length of Input Sequence = 10

```
L = 10
```

Hidden State Size = 2

```
HIDDEN_DIM = 2
```

```
model = BinaryAdder(INPUT_DIM, HIDDEN_DIM, OUTPUT_DIM, NUM_LAYERS).to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=LR)
```

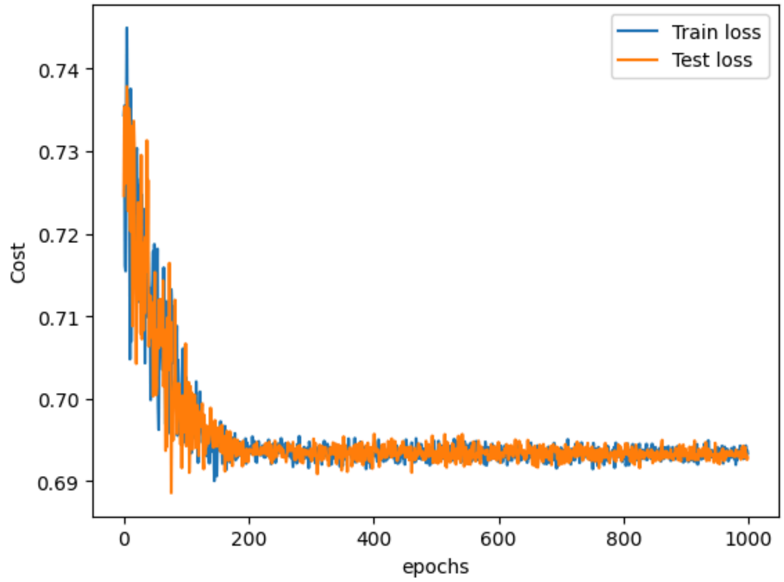
Training

```
train_costs, train_acc, val_costs, val_acc = train_model(model, criterion, optimizer, K, L)
```

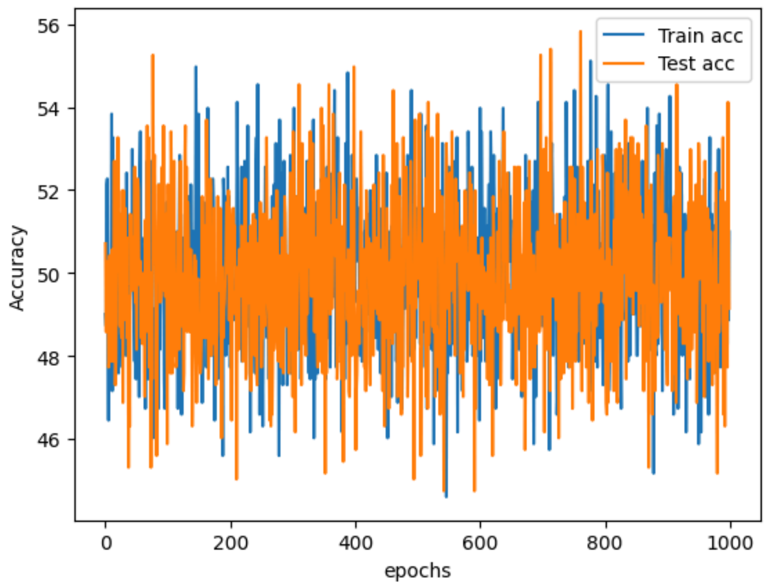
```
Epoch: 0. Train Loss: 0.7343868017196655. Validation Accuracy: 50.71022727272727
Epoch: 1. Train Loss: 0.7355112433433533. Validation Accuracy: 48.57954545454545
Epoch: 2. Train Loss: 0.7161359190940857. Validation Accuracy: 50.28409090909091
Epoch: 3. Train Loss: 0.7154760360717773. Validation Accuracy: 48.86363636363637
Epoch: 4. Train Loss: 0.7339316010475159. Validation Accuracy: 49.43181818181818
Epoch: 5. Train Loss: 0.744961142539978. Validation Accuracy: 47.72727272727273
Epoch: 6. Train Loss: 0.7304225564002991. Validation Accuracy: 47.86931818181818
Epoch: 7. Train Loss: 0.7311573028564453. Validation Accuracy: 50.42613636363637
Epoch: 8. Train Loss: 0.7293918132781982. Validation Accuracy: 47.86931818181818
Epoch: 9. Train Loss: 0.7251937389373779. Validation Accuracy: 48.15340909090909
Epoch: 10. Train Loss: 0.7048021554946899. Validation Accuracy: 50.0
Epoch: 11. Train Loss: 0.7375755310058594. Validation Accuracy: 50.56818181818182
Epoch: 12. Train Loss: 0.7069677114486694. Validation Accuracy: 47.86931818181818
Epoch: 13. Train Loss: 0.7162860631942749. Validation Accuracy: 50.28409090909091
Epoch: 14. Train Loss: 0.7180618643760681. Validation Accuracy: 52.69886363636363
Epoch: 15. Train Loss: 0.7244124412536621. Validation Accuracy: 49.57386363636363
Epoch: 16. Train Loss: 0.7247167229652405. Validation Accuracy: 47.30113636363637
Epoch: 17. Train Loss: 0.7162495851516724. Validation Accuracy: 47.86931818181818
Epoch: 18. Train Loss: 0.7205092906951904. Validation Accuracy: 50.28409090909091
Epoch: 19. Train Loss: 0.7214780449867249. Validation Accuracy: 51.42045454545455
Epoch: 20. Train Loss: 0.7295337915420532. Validation Accuracy: 53.26704545454545
Epoch: 21. Train Loss: 0.7303701639175415. Validation Accuracy: 51.13636363636363
Epoch: 22. Train Loss: 0.7227830290794373. Validation Accuracy: 51.42045454545455
Epoch: 23. Train Loss: 0.7158876657485962. Validation Accuracy: 48.72159090909091
Epoch: 24. Train Loss: 0.711769163608551. Validation Accuracy: 50.42613636363637
Epoch: 25. Train Loss: 0.7258408069610596. Validation Accuracy: 48.57954545454545
Epoch: 26. Train Loss: 0.7223153710365295. Validation Accuracy: 48.4375
Epoch: 27. Train Loss: 0.7267144322395325. Validation Accuracy: 51.98863636363637
Epoch: 28. Train Loss: 0.7103777527809143. Validation Accuracy: 46.875
Epoch: 29. Train Loss: 0.724713146686554. Validation Accuracy: 51.98863636363637
Epoch: 30. Train Loss: 0.7175453901290894. Validation Accuracy: 49.71590909090909
Epoch: 31. Train Loss: 0.7207996845245361. Validation Accuracy: 50.28409090909091
Epoch: 32. Train Loss: 0.7214910387992859. Validation Accuracy: 51.5625
Epoch: 33. Train Loss: 0.7229933142662048. Validation Accuracy: 48.86363636363637
Epoch: 34. Train Loss: 0.7043231725692749. Validation Accuracy: 50.85227272727273
Epoch: 35. Train Loss: 0.7180598974227905. Validation Accuracy: 48.4375
Epoch: 36. Train Loss: 0.7142110466957092. Validation Accuracy: 49.43181818181818
Epoch: 37. Train Loss: 0.7099554538726807. Validation Accuracy: 45.3125
Epoch: 38. Train Loss: 0.718932569026947. Validation Accuracy: 49.28977272727273
Epoch: 39. Train Loss: 0.7142155766487122. Validation Accuracy: 46.30681818181818
Epoch: 40. Train Loss: 0.7122219204902649. Validation Accuracy: 51.42045454545455
Epoch: 41. Train Loss: 0.7089871168136597. Validation Accuracy: 49.71590909090909
Epoch: 42. Train Loss: 0.7134328484535217. Validation Accuracy: 50.0
Epoch: 43. Train Loss: 0.6998595595359802. Validation Accuracy: 49.57386363636363
Epoch: 44. Train Loss: 0.7122673392295837. Validation Accuracy: 50.71022727272727
Epoch: 45. Train Loss: 0.7126872539520264. Validation Accuracy: 50.85227272727273
Epoch: 46. Train Loss: 0.7143450379371643. Validation Accuracy: 50.14204545454545
Epoch: 47. Train Loss: 0.7178571224212646. Validation Accuracy: 52.55681818181818
Epoch: 48. Train Loss: 0.7055233716964722. Validation Accuracy: 49.28977272727273
Epoch: 49. Train Loss: 0.7187389731407166. Validation Accuracy: 49.71590909090909
Epoch: 50. Train Loss: 0.7106661200523376. Validation Accuracy: 48.15340909090909
Epoch: 51. Train Loss: 0.7044285535812378. Validation Accuracy: 50.99431818181818
Epoch: 52. Train Loss: 0.7120078206062317. Validation Accuracy: 52.27272727272727
Epoch: 53. Train Loss: 0.7121255397796631. Validation Accuracy: 51.98863636363637
Epoch: 54. Train Loss: 0.7181755304336548. Validation Accuracy: 49.85795454545455
Epoch: 55. Train Loss: 0.6991395354270935. Validation Accuracy: 49.71590909090909
Epoch: 56. Train Loss: 0.6962584853172302. Validation Accuracy: 50.28409090909091
Epoch: 57. Train Loss: 0.7081544399261475. Validation Accuracy: 48.4375
```

Train and test plots

```
plot_curves(train_costs, train_acc, val_costs, val_acc)
```



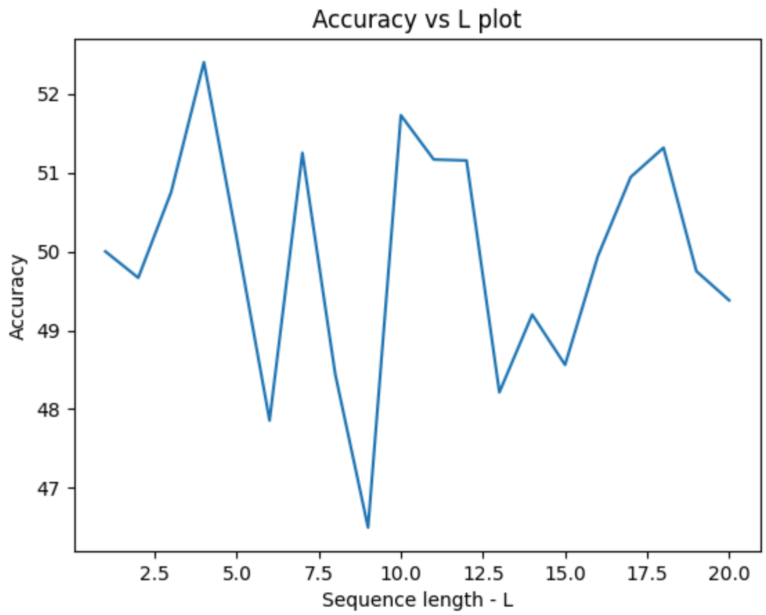

```
Train loss value after 1000 epochs: 0.6933560967445374
Vaildation loss value after 1000 epochs: 0.6928938031196594
```




```
Best Test Accuracy: 55.82386363636363%
```

Bitwise Accuracy vs Length

```
plot_accuracy_vs_length(model)
```



Hidden State Size = 5

```
HIDDEN_DIM = 5
```

```
model = BinaryAdder(INPUT_DIM, HIDDEN_DIM, OUTPUT_DIM, NUM_LAYERS).to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=LR)
```

Training

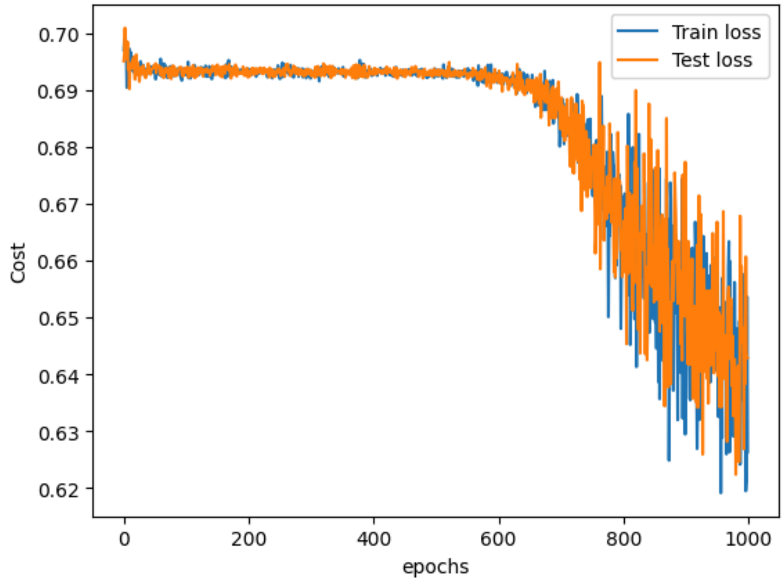
```
train_costs, train_acc, val_costs, val_acc = train_model(model, criterion, optimizer, K, L)
```

```
Epoch: 0. Train Loss: 0.697051465511322. Validation Accuracy: 51.27840909090909
Epoch: 1. Train Loss: 0.6988427639007568. Validation Accuracy: 50.0
Epoch: 2. Train Loss: 0.6985238790512085. Validation Accuracy: 46.875
Epoch: 3. Train Loss: 0.6989428997039795. Validation Accuracy: 50.0
Epoch: 4. Train Loss: 0.6962623000144958. Validation Accuracy: 49.57386363636363
Epoch: 5. Train Loss: 0.6904205083847046. Validation Accuracy: 50.14204545454545
Epoch: 6. Train Loss: 0.6965134143829346. Validation Accuracy: 47.86931818181818
Epoch: 7. Train Loss: 0.6944434642791748. Validation Accuracy: 51.42045454545455
Epoch: 8. Train Loss: 0.6952310800552368. Validation Accuracy: 50.71022727272727
Epoch: 9. Train Loss: 0.697242796421051. Validation Accuracy: 54.26136363636363
Epoch: 10. Train Loss: 0.6957153677940369. Validation Accuracy: 51.27840909090909
Epoch: 11. Train Loss: 0.6966599822044373. Validation Accuracy: 50.28409090909091
Epoch: 12. Train Loss: 0.6960803866386414. Validation Accuracy: 50.14204545454545
Epoch: 13. Train Loss: 0.6937339305877686. Validation Accuracy: 50.42613636363637
Epoch: 14. Train Loss: 0.6933836340904236. Validation Accuracy: 49.43181818181818
Epoch: 15. Train Loss: 0.6939554214477539. Validation Accuracy: 48.01136363636363
Epoch: 16. Train Loss: 0.6936795711517334. Validation Accuracy: 48.57954545454545
Epoch: 17. Train Loss: 0.6930455565452576. Validation Accuracy: 50.14204545454545
Epoch: 18. Train Loss: 0.6956533789634705. Validation Accuracy: 52.69886363636363
Epoch: 19. Train Loss: 0.6939404606819153. Validation Accuracy: 50.71022727272727
Epoch: 20. Train Loss: 0.6932603716850281. Validation Accuracy: 47.15909090909091
Epoch: 21. Train Loss: 0.6938026547431946. Validation Accuracy: 52.55681818181818
Epoch: 22. Train Loss: 0.6934421062469482. Validation Accuracy: 49.57386363636363
Epoch: 23. Train Loss: 0.694248378276825. Validation Accuracy: 49.28977272727273
Epoch: 24. Train Loss: 0.6940188407897949. Validation Accuracy: 49.85795454545455
Epoch: 25. Train Loss: 0.6930805444717407. Validation Accuracy: 51.84659090909091
Epoch: 26. Train Loss: 0.6946388483047485. Validation Accuracy: 50.99431818181818
Epoch: 27. Train Loss: 0.6950274109840393. Validation Accuracy: 51.98863636363637
Epoch: 28. Train Loss: 0.6927909255027771. Validation Accuracy: 50.14204545454545
Epoch: 29. Train Loss: 0.6939578652381897. Validation Accuracy: 50.14204545454545
Epoch: 30. Train Loss: 0.6939519047737122. Validation Accuracy: 50.71022727272727
Epoch: 31. Train Loss: 0.6944156289100647. Validation Accuracy: 48.01136363636363
Epoch: 32. Train Loss: 0.6930623650550842. Validation Accuracy: 48.4375
Epoch: 33. Train Loss: 0.6927012205123901. Validation Accuracy: 52.69886363636363
Epoch: 34. Train Loss: 0.6923609972000122. Validation Accuracy: 51.84659090909091
```

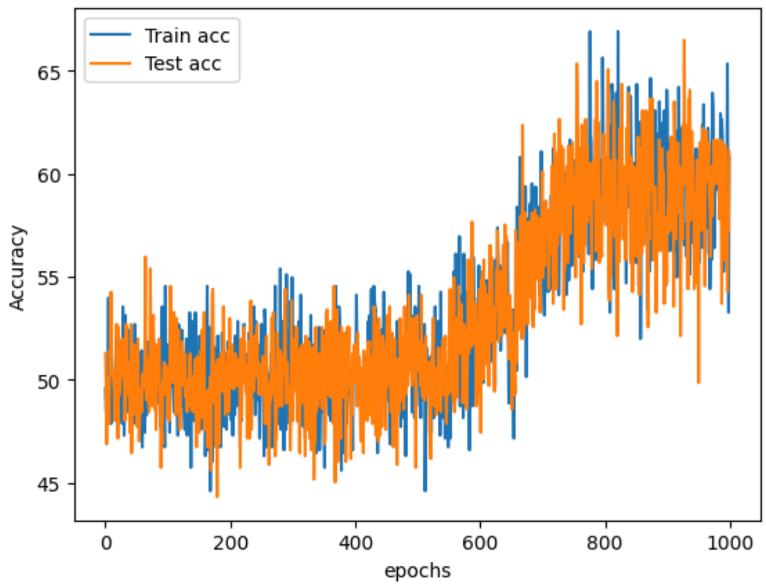
```
Epoch: 35. Train Loss: 0.6936681270599365. Validation Accuracy: 49.28977272727273
Epoch: 36. Train Loss: 0.693416953086853. Validation Accuracy: 50.0
Epoch: 37. Train Loss: 0.6927103400230408. Validation Accuracy: 50.85227272727273
Epoch: 38. Train Loss: 0.6940860748291016. Validation Accuracy: 50.28409090909091
Epoch: 39. Train Loss: 0.6940851211547852. Validation Accuracy: 47.44318181818182
Epoch: 40. Train Loss: 0.6935476660728455. Validation Accuracy: 50.28409090909091
Epoch: 41. Train Loss: 0.693120539188385. Validation Accuracy: 52.69886363636363
Epoch: 42. Train Loss: 0.6938526034355164. Validation Accuracy: 46.44886363636363
Epoch: 43. Train Loss: 0.6934909224510193. Validation Accuracy: 50.71022727272727
Epoch: 44. Train Loss: 0.6939195394515991. Validation Accuracy: 51.70454545454545
Epoch: 45. Train Loss: 0.6937617659568787. Validation Accuracy: 48.4375
Epoch: 46. Train Loss: 0.6941914558410645. Validation Accuracy: 51.70454545454545
Epoch: 47. Train Loss: 0.6930637955665588. Validation Accuracy: 51.27840909090909
Epoch: 48. Train Loss: 0.69342440366745. Validation Accuracy: 48.4375
Epoch: 49. Train Loss: 0.693065881729126. Validation Accuracy: 48.29545454545455
Epoch: 50. Train Loss: 0.6929153800010681. Validation Accuracy: 48.57954545454545
Epoch: 51. Train Loss: 0.6918900012969971. Validation Accuracy: 47.72727272727273
Epoch: 52. Train Loss: 0.693030059337616. Validation Accuracy: 51.98863636363637
Epoch: 53. Train Loss: 0.6938028931617737. Validation Accuracy: 48.86363636363637
Epoch: 54. Train Loss: 0.6929566860198975. Validation Accuracy: 47.01704545454545
Epoch: 55. Train Loss: 0.6938173770904541. Validation Accuracy: 48.15340909090909
Epoch: 56. Train Loss: 0.6937127709388733. Validation Accuracy: 49.57386363636363
Epoch: 57. Train Loss: 0.6926116347312927. Validation Accuracy: 49.00568181818182
```

Train and test plots

```
plot_curves(train_costs, train_acc, val_costs, val_acc)
```



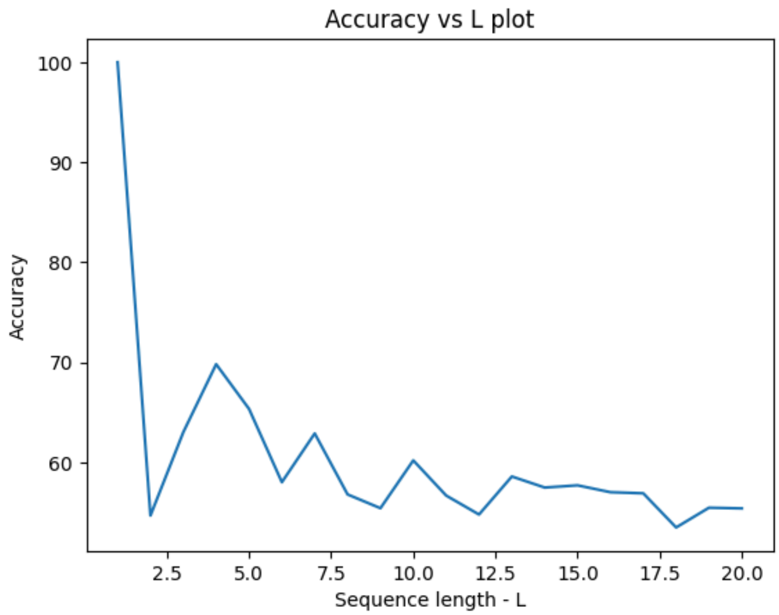

```
Train loss value after 1000 epochs: 0.6263185143470764
Vaildation loss value after 1000 epochs: 0.6428563594818115
```




```
Best Test Accuracy: 66.47727272727273%
```

Bitwise Accuracy vs Length

```
plot_accuracy_vs_length(model)
```



Hidden State Size = 10

```
HIDDEN_DIM = 10
```

```
model = BinaryAdder(INPUT_DIM, HIDDEN_DIM, OUTPUT_DIM, NUM_LAYERS).to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=LR)
```

Training

```
train_costs, train_acc, val_costs, val_acc = train_model(model, criterion, optimizer, K, L)
```

```
Epoch: 0. Train Loss: 0.6963188648223877. Validation Accuracy: 50.71022727272727
Epoch: 1. Train Loss: 0.6934484839439392. Validation Accuracy: 48.72159090909091
Epoch: 2. Train Loss: 0.6949735283851624. Validation Accuracy: 50.42613636363637
Epoch: 3. Train Loss: 0.6926169991493225. Validation Accuracy: 49.71590909090909
Epoch: 4. Train Loss: 0.6951655149459839. Validation Accuracy: 47.72727272727273
Epoch: 5. Train Loss: 0.6935188174247742. Validation Accuracy: 52.69886363636363
Epoch: 6. Train Loss: 0.6924707293510437. Validation Accuracy: 48.72159090909091
Epoch: 7. Train Loss: 0.6929764151573181. Validation Accuracy: 52.41477272727273
Epoch: 8. Train Loss: 0.6924092769622803. Validation Accuracy: 51.42045454545455
Epoch: 9. Train Loss: 0.6931347250938416. Validation Accuracy: 49.71590909090909
Epoch: 10. Train Loss: 0.6938812732696533. Validation Accuracy: 53.55113636363637
Epoch: 11. Train Loss: 0.6930593252182007. Validation Accuracy: 50.56818181818182
Epoch: 12. Train Loss: 0.6930811405181885. Validation Accuracy: 49.57386363636363
Epoch: 13. Train Loss: 0.6935039162635803. Validation Accuracy: 47.58522727272727
Epoch: 14. Train Loss: 0.6924905180931091. Validation Accuracy: 50.0
Epoch: 15. Train Loss: 0.693342387676239. Validation Accuracy: 52.55681818181818
Epoch: 16. Train Loss: 0.6930426359176636. Validation Accuracy: 47.44318181818182
Epoch: 17. Train Loss: 0.6933049559593201. Validation Accuracy: 53.125
Epoch: 18. Train Loss: 0.6931660771369934. Validation Accuracy: 49.57386363636363
Epoch: 19. Train Loss: 0.6931734085083008. Validation Accuracy: 52.13068181818182
Epoch: 20. Train Loss: 0.6932666301727295. Validation Accuracy: 51.42045454545455
Epoch: 21. Train Loss: 0.6932321786880493. Validation Accuracy: 50.42613636363637
Epoch: 22. Train Loss: 0.6931489109992981. Validation Accuracy: 50.28409090909091
Epoch: 23. Train Loss: 0.693105936050415. Validation Accuracy: 48.15340909090909
Epoch: 24. Train Loss: 0.6931804418563843. Validation Accuracy: 49.57386363636363
Epoch: 25. Train Loss: 0.6933560967445374. Validation Accuracy: 49.00568181818182
Epoch: 26. Train Loss: 0.6931856274604797. Validation Accuracy: 49.00568181818182
Epoch: 27. Train Loss: 0.6931050419807434. Validation Accuracy: 51.13636363636363
Epoch: 28. Train Loss: 0.6929448843002319. Validation Accuracy: 49.28977272727273
Epoch: 29. Train Loss: 0.6928566694259644. Validation Accuracy: 48.72159090909091
Epoch: 30. Train Loss: 0.6930693984031677. Validation Accuracy: 52.69886363636363
Epoch: 31. Train Loss: 0.6936048865318298. Validation Accuracy: 51.5625
Epoch: 32. Train Loss: 0.6928601861000061. Validation Accuracy: 49.85795454545455
Epoch: 33. Train Loss: 0.6937487125396729. Validation Accuracy: 47.86931818181818
Epoch: 34. Train Loss: 0.6935480237007141. Validation Accuracy: 47.15909090909091
```

```
Epoch: 35. Train Loss: 0.6933923959732056. Validation Accuracy: 48.4375
Epoch: 36. Train Loss: 0.6934836506843567. Validation Accuracy: 47.44318181818182
Epoch: 37. Train Loss: 0.6924412250518799. Validation Accuracy: 50.85227272727273
Epoch: 38. Train Loss: 0.6939101219177246. Validation Accuracy: 51.5625
```