Installation and Import of libraries

```
!pip install pennylane
```

```
Requirement already satisfied: pennylane in /usr/local/lib/python3.11/dist-packages (0.40.0)
Requirement already satisfied: numpy<2.1 in /usr/local/lib/python3.11/dist-packages (from pennylane) (2.0.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from pennylane) (1.14.1)
Requirement already satisfied: networkx in /usr/local/lib/python3.11/dist-packages (from pennylane) (3.4.2)
Requirement already satisfied: rustworkx>=0.14.0 in /usr/local/lib/python3.11/dist-packages (from pennylane) (0.16.0)
Requirement already satisfied: autograd in /usr/local/lib/python3.11/dist-packages (from pennylane) (1.7.0)
Requirement already satisfied: tomlkit in /usr/local/lib/python3.11/dist-packages (from pennylane) (0.13.2)
Requirement already satisfied: appdirs in /usr/local/lib/python3.11/dist-packages (from pennylane) (1.4.4)
Requirement already satisfied: autoray>=0.6.11 in /usr/local/lib/python3.11/dist-packages (from pennylane) (0.7.1)
Requirement already satisfied: cachetools in /usr/local/lib/python3.11/dist-packages (from pennylane) (5.5.2)
Requirement already satisfied: pennylane-lightning>=0.40 in /usr/local/lib/python3.11/dist-packages (from pennylane) (0.40.0)
Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages (from pennylane) (2.32.3)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.11/dist-packages (from pennylane) (4.12.2)
Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-packages (from pennylane) (24.2)
Requirement already satisfied: diastatic-malt in /usr/local/lib/python3.11/dist-packages (from pennylane) (2.15.2)
Requirement already satisfied: scipy-openblas32>=0.3.26 in /usr/local/lib/python3.11/dist-packages (from pennylane-lightning>=0.40->penn
Requirement already satisfied: astunparse in /usr/local/lib/python3.11/dist-packages (from diastatic-malt->pennylane) (1.6.3)
Requirement already satisfied: gast in /usr/local/lib/python3.11/dist-packages (from diastatic-malt->pennylane) (0.6.0)
Requirement already satisfied: termcolor in /usr/local/lib/python3.11/dist-packages (from diastatic-malt->pennylane) (2.5.0)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests->pennylane) (3.4.1)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests->pennylane) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (from requests->pennylane) (2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (from requests->pennylane) (2025.1.31)
Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.11/dist-packages (from astunparse->diastatic-malt->pennylane
Requirement already satisfied: six<2.0,>=1.6.1 in /usr/local/lib/python3.11/dist-packages (from astunparse->diastatic-malt->pennylane) (
```

```
import torch
from torchvision import datasets, transforms
import numpy as np
import matplotlib.pyplot as plt
import pennylane as qml
import torch.nn as nn
from tqdm import tqdm
from torch.utils.data import Dataset
from torch.utils.data import DataLoader
from torchvision import transforms
from tqdm import tqdm
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import seaborn as sns
from PIL import Image
import random
from sklearn.metrics import precision_recall_fscore_support, roc_curve, auc
```

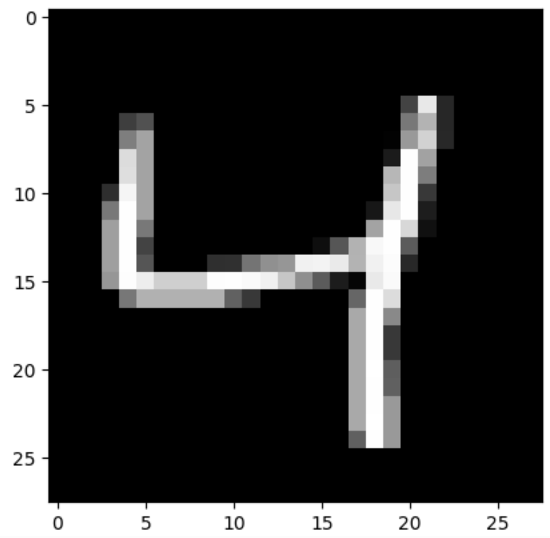
Data Loading and Transformations

```
transform = transforms.Compose([
    transforms.ToTensor(),  # Converts ndarray to a tensor
    transforms.Normalize(mean=[0.5], std=[0.5])
])
```

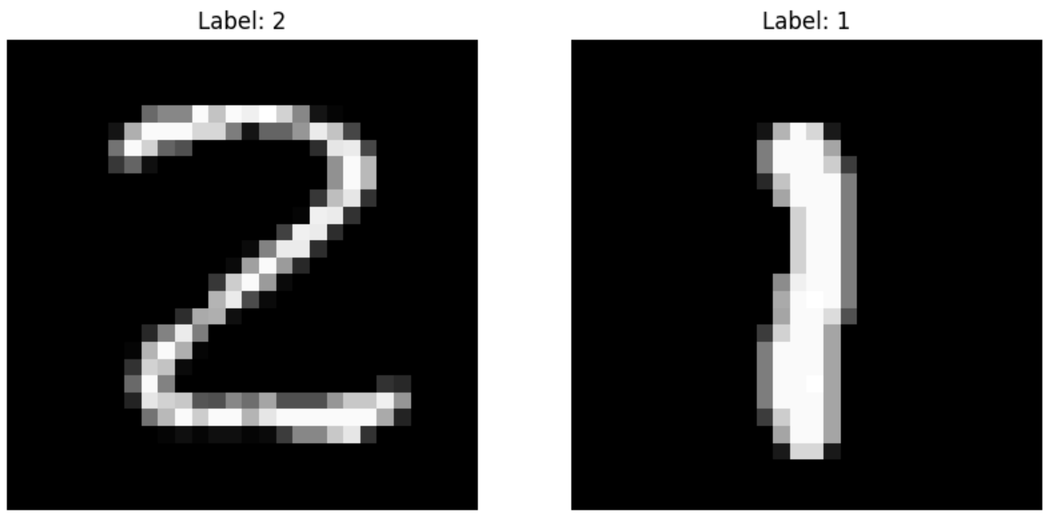
```
MNIST = datasets.MNIST(root='./data', train=True, download=True, transform=transform)
```

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

plt.imshow(train_dataset[2][0].squeeze(), cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7d3f1f3cc5d0>
```

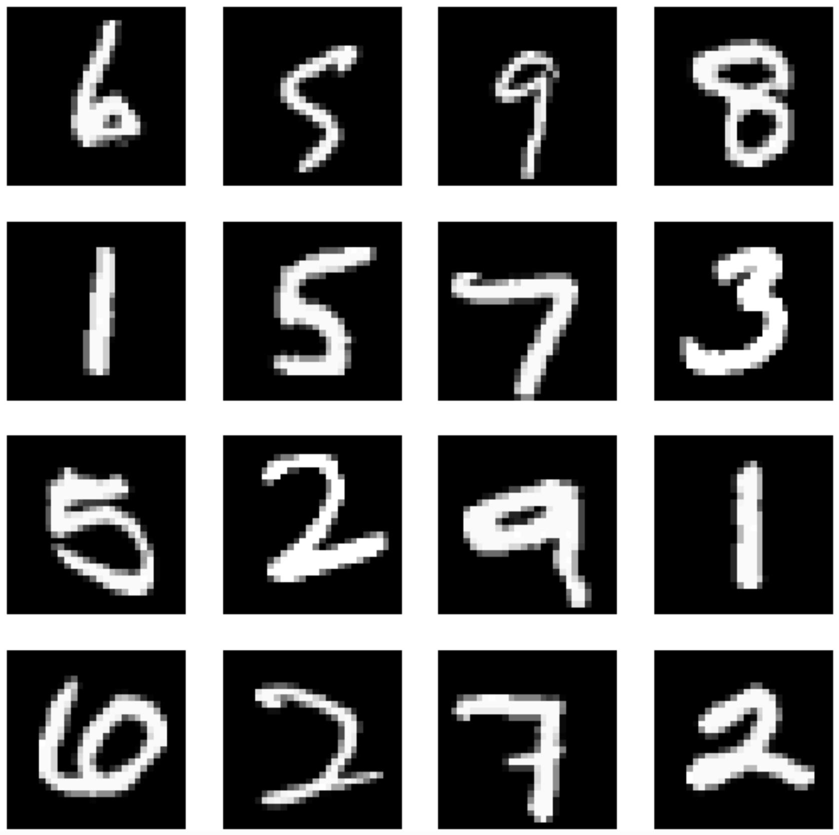


```
# Split into features (X) and labels (y)
# X_train = torch.stack([img for img, label in train_dataset])  # Images as tensors
# y_train = torch.tensor([label for img, label in train_dataset])  # Labels as tensors

# X_test = torch.stack([img for img, label in test_dataset])  # Test images
# y_test = torch.tensor([label for img, label in test_dataset])  # Test labels

# # Print shapes
# print(f"X_train shape: {X_train.shape}")  # (60000, 1, 28, 28)
# print(f"y_train shape: {y_train.shape}")  # (60000,)

# print(f"X_test shape: {X_test.shape}")  # (10000, 1, 28, 28)
# print(f"y_test shape: {y_test.shape}")  # (10000,)


import random

random_indices = random.sample(range(len(train_dataset)), 2)

# Extract the corresponding images and labels
image1, label1 = train_dataset[random_indices[0]]
image2, label2 = train_dataset[random_indices[1]]

# Plot the two selected images
fig, axes = plt.subplots(1, 2, figsize=(10, 5))
axes[0].imshow(image1.squeeze(), cmap='gray')
axes[0].set_title(f'Label: {label1}')
axes[0].axis('off')
axes[1].imshow(image2.squeeze(), cmap='gray')
axes[1].set_title(f'Label: {label2}')
axes[1].axis('off')

plt.show()

print(image1.dim)
```



```
<built-in method dim of Tensor object at 0x7d3f1eb07e30>
```

```
indices = np.random.choice(len(MNIST), 16, replace=False) #Take random images
images = []
for i in indices:
  images.append(MNIST[i][0])

fig, axes = plt.subplots(4, 4, figsize=(8, 8))

for i, ax in enumerate(axes.flat):
    ax.imshow(images[i].squeeze(), cmap='gray')
    ax.axis('off')

plt.show()
```



Preparing a quantum state for a sample image from MNIST

```
# Function which takes two images, prepares two quantum states

dev = qml.device('default.qubit', wires = 10)
@qml.qnode(dev)
def circuit(features=None, params=None):
  qml.AmplitudeEmbedding(features=features, wires=range(10), normalize=True, pad_with=0)

  for i in range(10):
    qml.RX(params[i], wires=i)

  return qml.expval(qml.Z(0)), qml.state()
```

Quantum Circuit

```
num_params = 10
sample_weights = np.random.uniform(0, 2 * np.pi, 10) #1 random rotation around X for each of the 10 qubits
print(sample_weights)

print(qml.draw(circuit)(features=image1.flatten(), params=sample_weights))
```

```
[0.10474685 3.83874417 6.17049405 1.44205668 4.91327561 4.09921739
 2.44931967 5.23739303 5.26212464 3.42456152]
0: ─╭|Ψ⟩──RX(0.10)─┤  <Z>  State
1: ─├|Ψ⟩──RX(3.84)─┤       State
2: ─├|Ψ⟩──RX(6.17)─┤       State
3: ─├|Ψ⟩──RX(1.44)─┤       State
4: ─├|Ψ⟩──RX(4.91)─┤       State
5: ─├|Ψ⟩──RX(4.10)─┤       State
6: ─├|Ψ⟩──RX(2.45)─┤       State
7: ─├|Ψ⟩──RX(5.24)─┤       State
8: ─├|Ψ⟩──RX(5.26)─┤       State
9: ─╰|Ψ⟩──RX(3.42)─┤       State
```

```
res1, state1 = circuit(features=image1.flatten(), params=sample_weights)
res2, state2 = circuit(features=image2.flatten(), params=sample_weights)

print(f"res1 is {res1}, res2 is {res2}")
print("\n")
print(f"state1 is {state1}, state2 is {state2}")
```

```
res1 is 0.31631474449498614, res2 is 0.30455006197400725


state1 is tensor([-0.0163+0.0077j, -0.0213+0.0121j,  0.0116-0.0186j,  ...,
        -0.0257-0.0241j, -0.0257-0.0321j, -0.0298-0.0278j],
       dtype=torch.complex128), state2 is tensor([ 0.0046-0.0181j, -0.0096-0.0054j,  0.0041-0.0225j,  ...,
        -0.0198-0.0147j, -0.0207-0.0141j, -0.0109-0.0173j],
       dtype=torch.complex128)
```

```
# Creating a function with similar functionalities above, and adding the SWAP test with ancillea bits
i1 = state1
i2 = state2

num_qubits = 10
dev = qml.device('default.qubit', wires= 2* num_qubits + 1)

@qml.qnode(dev)
def swap_test(i1, i2):
  inf = np.concatenate([i1,i2]) #Combine both states
  qml.AmplitudeEmbedding(inf, wires=range(1, 2*num_qubits +1), normalize=True, pad_with=0)
  qml.Hadamard(wires=0) # Step 1- Hadamard gate to ancillary bit

  for i in range(num_qubits):
    qml.CSWAP(wires=[0, i+1, i+1+num_qubits]) #Step 2- SWAP operation

  qml.Hadamard(wires=0) #Step 3- Hadamard gate to ancillary bit again

  return qml.expval(qml.PauliZ(0))



print(qml.draw(swap_test)(i2, i2))
```

```
0: ──H───╭●─────╭●─────╭●─────╭●─────╭●─────╭●─────╭●─────╭●─────╭●─────╭●──────H─┤  <Z>
1: ─╭|Ψ⟩─├SWAP─│──────│──────│──────│──────│──────│──────│──────│──────│────────┤
2: ─├|Ψ⟩─│──────├SWAP─│──────│──────│──────│──────│──────│──────│──────│────────┤
```

```
 3: ─├|Ψ⟩─│─────│─────├SWAP─│─────│─────│─────│─────│─────│─────│─────────┤
 4: ─├|Ψ⟩─│─────│─────│─────├SWAP─│─────│─────│─────│─────│─────│─────────┤
 5: ─├|Ψ⟩─│─────│─────│─────│─────├SWAP─│─────│─────│─────│─────│─────────┤
 6: ─├|Ψ⟩─│─────│─────│─────│─────│─────├SWAP─│─────│─────│─────│─────────┤
 7: ─├|Ψ⟩─│─────│─────│─────│─────│─────│─────├SWAP─│─────│─────│─────────┤
 8: ─├|Ψ⟩─│─────│─────│─────│─────│─────│─────│─────├SWAP─│─────│─────────┤
 9: ─├|Ψ⟩─│─────│─────│─────│─────│─────│─────│─────│─────├SWAP─│─────────┤
10: ─├|Ψ⟩─│─────│─────│─────│─────│─────│─────│─────│─────│─────├SWAP─────┤
11: ─├|Ψ⟩─╰SWAP─│─────│─────│─────│─────│─────│─────│─────│─────│─────────┤
12: ─├|Ψ⟩───────╰SWAP─│─────│─────│─────│─────│─────│─────│─────│─────────┤
13: ─├|Ψ⟩─────────────╰SWAP─│─────│─────│─────│─────│─────│─────│─────────┤
14: ─├|Ψ⟩───────────────────╰SWAP─│─────│─────│─────│─────│─────│─────────┤
15: ─├|Ψ⟩─────────────────────────╰SWAP─│─────│─────│─────│─────│─────────┤
16: ─├|Ψ⟩───────────────────────────────╰SWAP─│─────│─────│─────│─────────┤
17: ─├|Ψ⟩─────────────────────────────────────╰SWAP─│─────│─────│─────────┤
18: ─├|Ψ⟩───────────────────────────────────────────╰SWAP─│─────│─────────┤
19: ─├|Ψ⟩─────────────────────────────────────────────────╰SWAP─│─────────┤
20: ─╰|Ψ⟩───────────────────────────────────────────────────────╰SWAP─────┤
```

Quantum Embedding and Fiedlity

```
fidelity = swap_test(i1, i2)
print(fidelity)
```

```
tensor(-9.5568e-05, dtype=torch.float64)
```

```
qml.math.fidelity_statevector(state1, state2)
```

```
tensor(0.5402, dtype=torch.float64)
```

```
s1 = qml.math.dm_from_state_vector(state1)
s2 = qml.math.dm_from_state_vector(state2)
qml.math.fidelity(s1, s2)
```

```
tensor(0.5402, dtype=torch.float64)
```

```
# def calc_fidelity(state1, state2):
#   s1 = qml.math.dm_from_state_vector(state1)
#   s2 = qml.math.dm_from_state_vector(state2)
#   return qml.math.fidelity_statevector(s1, s2)

def calc_fidelity(state1, state2):
  return qml.math.fidelity_statevector(state1, state2)  # Directly calculate fidelity between state vectors
```

```
# def get_quantum_embedding(ft, w):
#   res, state = circuit(features=ft, weights=w)
#   return state

def get_quantum_embedding(ft, w):
    res, state = circuit(features=ft, params=w)  # Changed weights to params
    return state
```

Dataset Preparation, Model, Contrastive Class

Classical Siamese Network on MNIST dataset, we will modify it to create embeddings from our previous quantum functions!

```
# Siamese Network Model

# class SiameseNetwork(nn.Module):
#     def __init__(self):
#         super(SiameseNetwork, self).__init__()

#         # CNN layers
#         self.cnn = nn.Sequential(
#             nn.Conv2d(1, 64, kernel_size=5, stride=1, padding=2), # 1x28x28--> 64x28x28
#             nn.ReLU(),
#             nn.MaxPool2d(kernel_size=2, stride=2),
#             nn.Conv2d(64, 128, kernel_size=5, stride=1, padding=2), # " " " --> 128x28x28
#             nn.ReLU(),
#             nn.MaxPool2d(kernel_size=2, stride=2)
#         )

#         # Fully connected layers
#         self.fc = nn.Sequential(
#             nn.Linear(128 * 7 * 7, 256),  # 128 channels * 7x7 feature map after CNN
#             nn.ReLU(),
#             nn.Linear(256, 128)
#         )

#     def forward(self, x):
#         # Pass through CNN layers
#         x = self.cnn(x)

#         # Flatten the output from CNN layers
#         x = x.view(x.size(0), -1)

#         # Pass through fully connected layers
#         x = self.fc(x)

#         return x
```

Dataset (in pairs)

```
# class SiameseDataset(Dataset):
#     def __init__(self, dataset, transform= None):
#         self.dataset = dataset
#         self.transform = transform

#     def __getitem__(self, index):
#         # Get the image and its label from the dataset
#         img1, label1 = self.dataset[index]

#         # Convert to PIL Image if it's a tensor (for compatibility with torchvision transforms)
#         if isinstance(img1, torch.Tensor):
#             # Convert the tensor to a NumPy array and scale to 0-255
#             img1 = img1.numpy() * 255
#             # Convert to uint8 to make it compatible with Image.fromarray
#             img1 = img1.astype(np.uint8)
#             img1 = Image.fromarray(img1.squeeze()) # Squeeze to remove unnecessary channel dimension

#         # Randomly decide whether to use a positive or negative pair
#         same_class = random.randint(0, 1)  # 0: negative pair, 1: positive pair

#         # Positive pair: Same class
#         if same_class == 1:
#             # Get a random index of the same class
#             same_class_indices = [i for i, (_, label) in enumerate(self.dataset) if label == label1]
#             img2_idx = random.choice(same_class_indices)
#             img2, label2 = self.dataset[img2_idx]

#             # Convert to PIL Image if it's a tensor
#             if isinstance(img2, torch.Tensor):
#                 # Convert the tensor to a NumPy array and scale to 0-255
#                 img2 = img2.numpy() * 255
#                 # Convert to uint8 to make it compatible with Image.fromarray
#                 img2 = img2.astype(np.uint8)
#                 img2 = Image.fromarray(img2.squeeze()) # Squeeze to remove unnecessary channel dimension

#             label = 1  # Same class
#         else:
#             # Negative pair: Different class
#             different_class_indices = [i for i, (_, label) in enumerate(self.dataset) if label != label1]
#             img2_idx = random.choice(different_class_indices)
#             img2, label2 = self.dataset[img2_idx]

#             # Convert to PIL Image if it's a tensor
#             if isinstance(img2, torch.Tensor):
#                 # Convert the tensor to a NumPy array and scale to 0-255
#                 img2 = img2.numpy() * 255
#                 # Convert to uint8 to make it compatible with Image.fromarray
#                 img2 = img2.astype(np.uint8)
#                 img2 = Image.fromarray(img2.squeeze()) # Squeeze to remove unnecessary channel dimension
#             label = 0  # Different class

#         # Apply transformations if provided
#         if self.transform:
#             img1 = self.transform(img1)
#             img2 = self.transform(img2)

#         return img1, img2, label

#     def __len__(self):
#         return len(self.dataset)



class SiameseDataset(Dataset):
    def __init__(self, dataset, transform=None):
        self.dataset = dataset
        self.transform = transform

    def __getitem__(self, index):
        # Get the image and its label from the dataset
        img1, label1 = self.dataset[index]

        # Randomly decide whether to use a positive or negative pair
        same_class = random.randint(0, 1)  # 0: negative pair, 1: positive pair

        # Positive pair: Same class
        if same_class == 1:
            # Get a random index of the same class
            same_class_indices = [i for i, (_, label) in enumerate(self.dataset) if label == label1]
            img2_idx = random.choice(same_class_indices)
            img2, label2 = self.dataset[img2_idx]
            label = 1  # Same class
        else:
            # Negative pair: Different class
            different_class_indices = [i for i, (_, label) in enumerate(self.dataset) if label != label1]
            img2_idx = random.choice(different_class_indices)
            img2, label2 = self.dataset[img2_idx]
            label = 0  # Different class

        # Apply transformations if provided
        if self.transform:
            img1 = self.transform(img1)
            img2 = self.transform(img2)

        return img1, img2, label

    def __len__(self):
        return len(self.dataset)



class SiameseDataset(Dataset):
    def __init__(self, dataset, transform=None):
        self.dataset = dataset
        self.transform = transform

        # Precompute class indices
        self.class_indices = {}
        for i, (_, label) in enumerate(dataset):
            if label not in self.class_indices:
                self.class_indices[label] = []
            self.class_indices[label].append(i)

    def __getitem__(self, index):
        img1, label1 = self.dataset[index]

        # Select same or different class
        same_class = random.randint(0, 1)
        if same_class == 1:  # Positive Pair
            img2_idx = random.choice(self.class_indices[label1])
        else:  # Negative Pair
            label2 = random.choice(list(set(self.class_indices.keys()) - {label1}))
            img2_idx = random.choice(self.class_indices[label2])

        img2, label2 = self.dataset[img2_idx]
        label = 1 if same_class else 0
        # Apply transformations
        if self.transform:
            img1 = self.transform(img1)
            img2 = self.transform(img2)

        return img1, img2, torch.tensor(label, dtype=torch.float32)

    def __len__(self):
        return len(self.dataset)
```

Contrastive Loss

```
# def calc_contrastive_loss(margin, y_true, embedding1, embedding2):
#   D = torch.norm(embedding1 - embedding2, dim=1) # (embedding1 - embedding2) **2
#   min_term = (1-y_true)* D**2
#   max_term = y_true * torch.max(0, margin-D)**2
#   loss = torch.mean(min_term + max_term)
#   return loss

class ContrastiveLoss(nn.Module):
    def __init__(self, margin=1.0):
        super(ContrastiveLoss, self).__init__()
        self.margin = margin

    def forward(self, y_true, embedding1, embedding2):
        D = torch.norm(embedding1 - embedding2, dim=1)  # (embedding1 - embedding2) **2
        min_term = (1 - y_true) * D**2
        max_term = y_true * torch.max(torch.tensor(0.0), self.margin - D)**2  # Use self.margin
        loss = torch.mean(min_term + max_term)
        return loss
```

Siamese Model

```
# # Model Class for Siamese Network with Quantum Embedding
# class SiameseNetwork(nn.Module):
#     def __init__(self):
#         super(SiameseNetwork, self).__init__()

#         # Quantum weights (initialized randomly for simplicity)
#         sample_weights_init = np.random.uniform(0, 2 * np.pi, (10, 2))  # Uniform distribution [0, 2π)
#         self.sample_weights = torch.nn.Parameter(torch.tensor(sample_weights_init, dtype=torch.float32))  # Convert to torch tensor

#     def forward(self, img1, img2):
#     # Flatten images
#      img1_flat = img1.reshape(img1.shape[0], -1)
#      img2_flat = img2.reshape(img2.shape[0], -1)

#     # Generate quantum embeddings for both images
#      embedding1 = get_quantum_embedding(img1_flat, self.sample_weights)
#      embedding2 = get_quantum_embedding(img2_flat, self.sample_weights)

#     # Calculate fidelity (similarity measure)
#      similarity = calc_fidelity(embedding1, embedding2)

#      return similarity

# # Training step for Contrastive Loss
# def train_step(model, x1, x2, labels, criterion, optimizer):
#     # Forward pass through the Siamese network
#     similarity = model(x1, x2)

#     # Calculate contrastive loss
#     loss = criterion(labels, similarity)

#     # Backpropagation
#     optimizer.zero_grad()
#     loss.backward()
#     optimizer.step()

#     return loss.item()
# Training step for Contrastive Loss

def train_step(model, x1, x2, labels, criterion, optimizer):
    # similarity = model(x1, x2)  # This line was the issue
    embedding1, embedding2 = model(x1, x2)  # Update to return embeddings

    # Calculate contrastive loss
    # loss = criterion(labels, similarity)  # Update to use embeddings
    loss = criterion(labels, embedding1, embedding2)

    # Backpropagation
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

    return loss.item()


class SiameseNetwork(nn.Module):
    def __init__(self):
        super(SiameseNetwork, self).__init__()

        sample_weights_init = np.random.uniform(0, 2 * np.pi, (10, 2))  # Uniform distribution [0, 2π)
        self.sample_weights = torch.nn.Parameter(torch.tensor(sample_weights_init, dtype=torch.float32))  # Convert to torch tensor, and par

    def forward(self, img1, img2):
        # Flatten images
        img1_flat = img1.reshape(img1.shape[0], -1)
        img2_flat = img2.reshape(img2.shape[0], -1)

        # Generate quantum embeddings for both images
        embedding1 = get_quantum_embedding(img1_flat, self.sample_weights) #BLUNDER, flatten images
        embedding2 = get_quantum_embedding(img2_flat, self.sample_weights)

        return embedding1, embedding2  # Return both embeddings
```

Parameters

```
#Training parameters

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = SiameseNetwork()
model = model.to(device)

epochs = 5
lr = 0.01
criterion = ContrastiveLoss(margin=1.0)
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)

# siamese_train_dataset = SiameseDataset(train_dataset, transform=transform) #BLUNDER
siamese_train_dataset = SiameseDataset(train_dataset, transform=None)
train_dataloader = DataLoader(siamese_train_dataset, batch_size=128, shuffle=True)


siamese_test_dataset = SiameseDataset(test_dataset, transform=None)
test_dataloader = DataLoader(siamese_test_dataset, batch_size=64, shuffle=False)
```

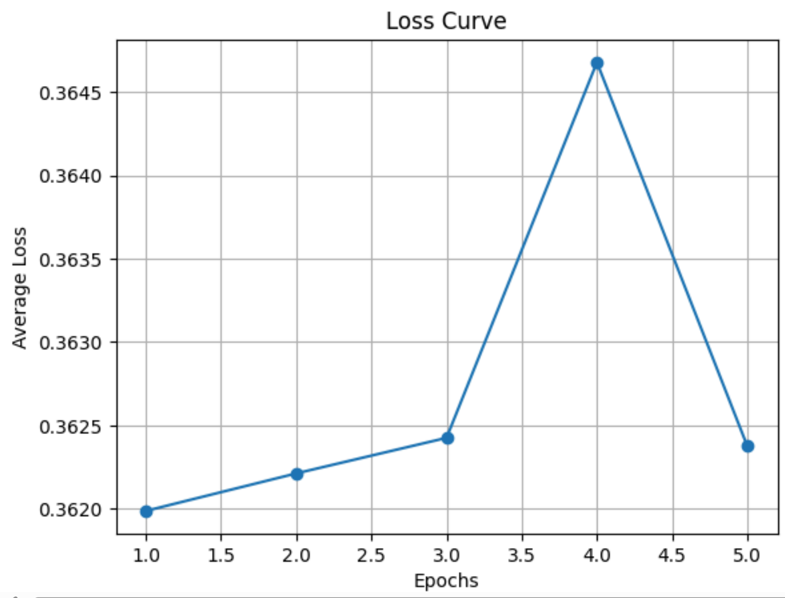
Training

```
threshold= 0.7


# def train_model(model, train_dataloader, criterion, optimizer, epochs=5):
#     model.train()  # Set the model to training mode
#     loss_list = []

#     for epoch in range(epochs):
#         total_loss = 0

#         # Wrap the training dataloader with tqdm for progress tracking
#         for img1, img2, labels in tqdm(train_dataloader, desc=f"Epoch {epoch+1}/{epochs}", unit="batch"):
```

```
#             # Convert the images (ndarrays) to torch tensors
#             img1, img2, labels = img1.float().cuda(), img2.float().cuda(), labels.long().cuda()

#             # Perform training step
#             loss = train_step(model, img1, img2, labels, criterion, optimizer)

#             total_loss += loss

#         # Record loss for the epoch
#         avg_loss = total_loss / len(train_dataloader)
#         loss_list.append(avg_loss)
#         print(f'Epoch {epoch+1}/{epochs} - Average Loss: {avg_loss:.4f}')

#     return loss_list

def train_model(model, train_dataloader, criterion, optimizer, epochs=5):
    model.train()  # Set the model to training mode
    loss_list = []

    for epoch in range(epochs):
        total_loss = 0

        for img1, img2, labels in tqdm(train_dataloader, desc=f"Epoch {epoch+1}/{epochs}", unit="batch"):
            device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
            img1, img2, labels = img1.float().to(device), img2.float().to(device), labels.long().to(device)

            # Process each image in the batch individually
            batch_loss = 0
            # Accumulate loss for the batch
            for i in range(img1.shape[0]):  # Iterate over the batch size
                loss = train_step(model, img1[i].unsqueeze(0), img2[i].unsqueeze(0), labels[i].unsqueeze(0), criterion, optimizer)
                batch_loss += loss

            # Average the loss over the batch
            total_loss += batch_loss / img1.shape[0]

        # Record loss for the epoch
        avg_loss = total_loss / len(train_dataloader)
        loss_list.append(avg_loss)
        print(f'Epoch {epoch+1}/{epochs} - Average Loss: {avg_loss:.4f}')

    return loss_list


# Start the training process

loss_list = train_model(model, train_dataloader, criterion, optimizer, epochs=5)
```

```
Epoch 1/5: 100%|██████████| 469/469 [33:08<00:00,  4.24s/batch]
Epoch 1/5 - Average Loss: 0.3620
Epoch 2/5: 100%|██████████| 469/469 [33:38<00:00,  4.30s/batch]
Epoch 2/5 - Average Loss: 0.3622
Epoch 3/5: 100%|██████████| 469/469 [32:56<00:00,  4.21s/batch]
Epoch 3/5 - Average Loss: 0.3624
Epoch 4/5: 100%|██████████| 469/469 [32:49<00:00,  4.20s/batch]
Epoch 4/5 - Average Loss: 0.3647
Epoch 5/5: 100%|██████████| 469/469 [33:09<00:00,  4.24s/batch]Epoch 5/5 - Average Loss: 0.3624
```

```
def plot_loss_curve(loss_list):
    epochs = range(1, len(loss_list) + 1)
    plt.plot(epochs, loss_list, marker='o')
    plt.title('Loss Curve')
    plt.xlabel('Epochs')
    plt.ylabel('Average Loss')
    plt.grid(True)
    plt.show()

plot_loss_curve(loss_list)
```

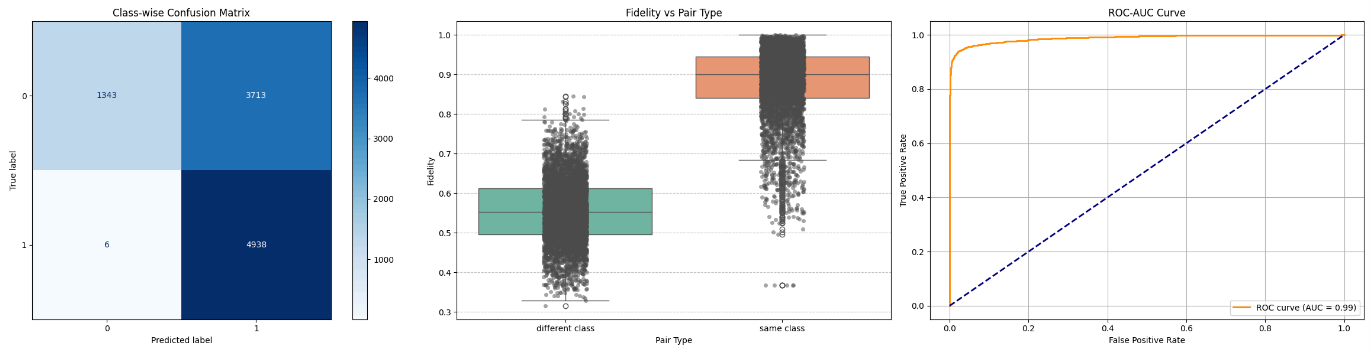


```
class_names = [str(i) for i in range(10)]  # Class names are simply digits

print("Class names:", class_names)
```

```
Class names: ['0', '1', '2', '3', '4', '5', '6', '7', '8', '9']
```

```
def evaluate_and_plot_metrics(model, eval_dataloader, criterion, class_names):
    model.eval()
    total_loss = 0
    fidelities = []
    pair_types = []
    y_true = []
    y_pred = []
    y_scores = []

    with torch.no_grad():
        for img1, img2, labels in tqdm(eval_dataloader, desc="Evaluating", unit="batch"):
            device= torch.device("cuda" if torch.cuda.is_available() else "cpu")
            img1, img2, labels = img1.float().to(device), img2.float().to(device), labels.long().to(device)

            batch_loss = 0
            for i in range(img1.shape[0]):
                # Get embeddings from the model
                embedding1, embedding2 = model(img1[i].unsqueeze(0), img2[i].unsqueeze(0))

                # Calculate the loss using the criterion
                loss = criterion(labels[i].unsqueeze(0), embedding1, embedding2)

                batch_loss += loss

                # Calculate fidelity
                fidelity = torch.exp(-loss).item()  # Example: fidelity derived from loss
                fidelities.append(fidelity)
                y_scores.append(fidelity)

                # Determine pair type based on labels
                pair_types.append('same class' if labels[i].item() == 1 else 'different class')

                # Collect true labels and predicted labels
                y_true.append(labels[i].item())
                y_pred.append(1 if fidelity > 0.5 else 0)  # Modify threshold as needed

            total_loss += batch_loss / img1.shape[0]

    avg_loss = total_loss / len(eval_dataloader)
    print(f'Evaluation - Average Loss: {avg_loss:.4f}')

    # Precision, Recall, and F1-Score
    precision, recall, f1, _ = precision_recall_fscore_support(y_true, y_pred, average='binary')  # Binary classification assumed
    print(f'Precision: {precision:.4f}')
    print(f'Recall: {recall:.4f}')
    print(f'F1-Score: {f1:.4f}')

    fig, axes = plt.subplots(1, 3, figsize=(24, 6))

    # Confusion Matrix
    cm = confusion_matrix(y_true, y_pred)

    unique_labels = sorted(list(set(y_true + y_pred)))
    num_classes = len(unique_labels)

    class_names = [str(label) for label in unique_labels]

    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_names)
    disp.plot(ax=axes[0], cmap=plt.cm.Blues)
    axes[0].set_title("Class-wise Confusion Matrix")

    # Fidelity vs Pair Type
    data = {"Fidelity": fidelities, "Pair Type": pair_types}
    sns.boxplot(x="Pair Type", y="Fidelity", data=data, palette="Set2", ax=axes[1])
    sns.stripplot(x="Pair Type", y="Fidelity", data=data, jitter=True, color=".3", alpha=0.5, ax=axes[1])
    axes[1].set_title("Fidelity vs Pair Type")
    axes[1].set_xlabel("Pair Type")
    axes[1].set_ylabel("Fidelity")
    axes[1].grid(axis='y', linestyle='--', alpha=0.7)

    # ROC-AUC Curve
    fpr, tpr, _ = roc_curve(y_true, y_scores, pos_label=1)  # Assuming positive label is 1
    roc_auc = auc(fpr, tpr)
    axes[2].plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.2f})')
    axes[2].plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')  # Diagonal line
    axes[2].set_title("ROC-AUC Curve")
    axes[2].set_xlabel("False Positive Rate")
    axes[2].set_ylabel("True Positive Rate")
    axes[2].legend(loc="lower right")
    axes[2].grid()

    plt.tight_layout()
    plt.show()

    return avg_loss, fidelities, pair_types


evaluate_and_plot_metrics(model, test_dataloader, criterion, class_names)
```

```
Evaluating: 100%|██████████| 157/157 [04:24<00:00,  1.68s/batch]
<ipython-input-77-7a31207b1401>:70: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `leg

  sns.boxplot(x="Pair Type", y="Fidelity", data=data, palette="Set2", ax=axes[1])
Evaluation - Average Loss: 0.3688
Precision: 0.5708
Recall: 0.9988
F1-Score: 0.7264
```



```
(tensor(0.3688),
 [0.6167662143707275,
  0.46161213517189026,
  0.6213359832763672,
  0.5001491904258728,
  0.7993393540382385,
  0.6718935966491699,
  0.863508939743042,
  0.8638597726821899,
  0.891131579875946,
  0.47870877385139465,
  0.5639660954475403,
  0.5393463373184204,
  0.823914110660553,
  0.823576807975769,
  0.6437981724739075,
  0.5447537899017334,
  0.9318804144859314,
  0.6999076008796692,
  0.9349093437194824,
  0.8344343900680542,
  0.8569682836532593,
  0.8152530193328857,
  0.5765663981437683,
  0.8709997534751892,
  0.8572168350219727,
  0.39167657494544983,
  0.8116233348846436,
  0.6890385150909424,
  0.5609337687492371,
  0.525669515132904,
  0.9245483875274658,
  0.6653746962547302,
  0.6411218047142029,
  0.9360684752464294,
  0.715600311756134,
  0.9486200213432312,
  0.6055905222892761,
  0.7883785367012024,
  0.5640833973884583,
  0.7565417289733887,
  0.7795947790145874,
  0.8709287047386169,
  0.5182890892028809,
  0.9835551977157593,
  0.6493587493896484,
  0.6805007457733154,
  0.6371201872825623,
  0.6953820586204529,
  0.9155187010765076,
  0.5082021951675415,
  0.6189164519309998,
  0.4440605342388153,
  0.9741153717041016,
  0.6153454184532166,
  0.9804734587669373,
  0.6039203405380249,
  0.9528185725212097,
  0.7050374150276184,
```