In [1]:
```python
import os
import random
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader, Subset
from torchvision import datasets, transforms
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

SEED = 40
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)

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

Out[1]:
```
device(type='cuda')
```

In [ ]:
```python
# 配置信息
class Cfg:
    data_root = './data'            # MNIST download/cache dir
    train_fraction = 0.10           # use 10% of the train split
    test_fraction  = 0.10           # use 10% of the test split
    train_num_pairs = 10000         # number of training pairs
    test_num_pairs  = 2000          # number of test pairs
    batch_size = 64
    epochs = 50
    lr = 1e-3
    weight_decay = 1e-4
    num_workers = 2
    save_dir = './output'
    model_name = 'siamese_mnist_same_digit.pth'
    # batch_log = 'batch_log.log'
    epoch_log = 'epoch_log.csv'

os.makedirs(Cfg.save_dir, exist_ok=True)
Cfg.__dict__
```

Out[ ]:
```
mappingproxy({'__module__': '__main__',
              'data_root': './data',
              'train_fraction': 0.1,
              'test_fraction': 0.1,
              'train_num_pairs': 10000,
              'test_num_pairs': 2000,
              'batch_size': 64,
              'epochs': 50,
              'lr': 0.001,
              'weight_decay': 0.0001,
              'num_workers': 2,
              'save_dir': './output',
              'model_name': 'siamese_mnist_same_digit.pth',
              'epoch_log': 'epoch_log.csv',
              '__dict__': <attribute '__dict__' of 'Cfg' objects>,
              '__weakref__': <attribute '__weakref__' of 'Cfg' objects>,
              '__doc__': None})
```

In [3]:
```python
# Transforms预处理
transform = transforms.Compose([
    transforms.ToTensor(), # 归一化[0,1], shape (1,28,28)
```

```python
    transforms.Normalize((0.1307,), (0.3081,)),
])

# 加载MNIST数据集
train_dataset = datasets.MNIST(Cfg.data_root, train=True,  download=True, transform=transform
test_dataset  = datasets.MNIST(Cfg.data_root, train=False, download=True, transform=transform
print(f"原始训练集大小: {len(train_dataset)}")
print(f"原始测试集大小: {len(test_dataset)}")

# 抽取10%的数据
def sample_dataset(dataset, sample_ratio=0.1):
    indices = list(range(len(dataset)))
    sampled_indices = random.sample(indices, int(len(dataset) * sample_ratio))
    return Subset(dataset, sampled_indices)
train_subset = sample_dataset(train_dataset, Cfg.train_fraction)
test_subset = sample_dataset(test_dataset, Cfg.test_fraction)
print(f"采样后训练集大小: {len(train_subset)}")
print(f"采样后测试集大小: {len(test_subset)}")

# 创建配对数据集
class MNISTPairsDataset(Dataset):
    def __init__(self, subset, num_pairs):
        self.subset = subset
        self.num_pairs = num_pairs
        self.labels = [label for _, label in subset]
        self.images = [image for image, _ in subset]
        # 生成相同数字的索引映射
        label_to_indices = {}
        for idx, label in enumerate(self.labels):
            if label not in label_to_indices:
                label_to_indices[label] = []
            label_to_indices[label].append(idx)
        # 创建配对
        self.pairs = []
        self.pair_labels = []
        for _ in range(num_pairs // 2):
            # 正样本对
            label = random.choice(list(label_to_indices.keys()))
            if len(label_to_indices[label]) >= 2:
                idx1, idx2 = random.sample(label_to_indices[label], 2)
                self.pairs.append((idx1, idx2))
                self.pair_labels.append(1)
            # 负样本对
            label1, label2 = random.sample(list(label_to_indices.keys()), 2)
            idx1 = random.choice(label_to_indices[label1])
            idx2 = random.choice(label_to_indices[label2])
            self.pairs.append((idx1, idx2))
            self.pair_labels.append(0)

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

    def __getitem__(self, idx):
        idx1, idx2 = self.pairs[idx]
        x1 = self.images[idx1]
        x2 = self.images[idx2]
        y = self.pair_labels[idx]
        return x1, x2, torch.tensor(y, dtype=torch.float32)

# 创建训练和测试配对数据集
train_pairs_dataset = MNISTPairsDataset(train_subset, num_pairs=Cfg.train_num_pairs)
test_pairs_dataset = MNISTPairsDataset(test_subset, num_pairs=Cfg.test_num_pairs)
print(f"训练配对数据集大小: {len(train_pairs_dataset)}")
print(f"测试配对数据集大小: {len(test_pairs_dataset)}")

# 检查正负样本比例
```

```python
train_labels = [label for _, _, label in train_pairs_dataset]
test_labels = [label for _, _, label in test_pairs_dataset]
print(f"训练集正样本比例: {sum(train_labels) / len(train_labels):.3f}")
print(f"测试集正样本比例: {sum(test_labels) / len(test_labels):.3f}")

# 数据加载器
train_loader = DataLoader(train_pairs_dataset, batch_size=Cfg.batch_size, shuffle=True, num_w
test_loader = DataLoader(test_pairs_dataset, batch_size=Cfg.batch_size, shuffle=False, num_wo
```

```
原始训练集大小: 60000
原始测试集大小: 10000
采样后训练集大小: 6000
采样后测试集大小: 1000
训练配对数据集大小: 10000
测试配对数据集大小: 2000
训练集正样本比例: 0.500
测试集正样本比例: 0.500
```

In [4]:

```python
# 可视化一些配对样本
def show_pairs(ds: MNISTPairsDataset, n=4):
    # 创建三列: 左图、右图和标签
    fig, axes = plt.subplots(nrows=n, ncols=3, figsize=(3, 1*n))
    for i in range(n):
        x1, x2, y = ds[random.randint(0, len(ds)-1)]
        y = int(y.item())
        axes[i,0].imshow(x1.squeeze(0), cmap='gray')
        axes[i,0].axis('off')
        axes[i,1].imshow(x2.squeeze(0), cmap='gray')
        axes[i,1].axis('off')
        axes[i,2].text(0.5, 0.5, f'Label = {y}', fontsize=16, ha='center', va='center')
        axes[i,2].axis('off')
    plt.tight_layout()
    plt.show()

show_pairs(train_pairs_dataset, n=4)
```

In [5]:

```python
class ConvEncoder(nn.Module):
    def __init__(self, emb_dim=64):
        super().__init__()
        self.features = nn.Sequential(
            nn.Conv2d(1, 16, kernel_size=3, padding=1),   # 1x28x28 -> 16x28x28
            nn.ReLU(inplace=True),
```

```python
            nn.MaxPool2d(2),                                # -> 16x14x14
            nn.Conv2d(16, 32, kernel_size=3, padding=1),  # -> 32x14x14
            nn.ReLU(inplace=True),
            nn.MaxPool2d(2),                                # -> 32x7x7
        )
        self.fc = nn.Sequential(
            nn.Flatten(),
            nn.Linear(32*7*7, 128),
            nn.ReLU(inplace=True),
            nn.Dropout(0.2),
            nn.Linear(128, emb_dim),
        )

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

class SiameseSameDigit(nn.Module):
    def __init__(self, emb_dim=64):
        super().__init__()
        self.encoder = ConvEncoder(emb_dim=emb_dim)
        # 使用绝对差和元素级乘积组合特征
        self.head = nn.Sequential(
            nn.Linear(emb_dim*2, 32),
            nn.ReLU(inplace=True),
            nn.Linear(32, 1),  # logit
            nn.Sigmoid()  # 输出概率
        )

    def forward(self, x1, x2):
        z1 = self.encoder(x1)
        z2 = self.encoder(x2)
        feat = torch.cat([torch.abs(z1 - z2), z1 * z2], dim=1)
        logit = self.head(feat)
        return logit.squeeze(1)  # (B,)

    def print_model_parameters(self):
        print(f"{'Layer Name':<40} {'Parameter Shape':<30} {'Param Count':<15}")
        print("=" * 85)
        total_params = 0
        for name, param in self.named_parameters():
            param_count = param.numel()
            total_params += param_count
            print(f"{name:<40} {str(list(param.shape)):<30} {param_count:<15}")
        print("=" * 85)
        print(f"Total Parameters: {total_params}")

model = SiameseSameDigit(emb_dim=64).to(device)
model.print_model_parameters()
```

```
Layer Name                               Parameter Shape                Param Count
=====================================================================================
encoder.features.0.weight                [16, 1, 3, 3]                  144
encoder.features.0.bias                  [16]                           16
encoder.features.3.weight                [32, 16, 3, 3]                 4608
encoder.features.3.bias                  [32]                           32
encoder.fc.1.weight                      [128, 1568]                    200704
encoder.fc.1.bias                        [128]                          128
encoder.fc.4.weight                      [64, 128]                      8192
encoder.fc.4.bias                        [64]                           64
head.0.weight                            [32, 128]                      4096
head.0.bias                              [32]                           32
head.2.weight                            [1, 32]                        32
head.2.bias                              [1]                            1
=====================================================================================
Total Parameters: 218049
```

In [ ]:

```
def evaluate(model, loader, loss_fn):
    model.eval()
    total_loss = 0.0
    total_correct = 0
    total = 0
    with torch.no_grad():
        for x1, x2, y in loader:
            x1, x2, y = x1.to(device), x2.to(device), y.to(device)
            outputs = model(x1, x2)
            loss = loss_fn(outputs, y)
            total_loss += loss.item() * y.size(0)
            preds = (outputs >= 0.5).float()
            total_correct += (preds == y.view_as(preds)).sum().item()
            total += y.size(0)
    return total_loss/total, total_correct/total

def train(model, train_loader, test_loader, epochs, lr, weight_decay):
    # loss_fn = nn.BCEWithLogitsLoss() # 内置sigmoid层
    loss_fn = nn.BCELoss()
    # optimizer = optim.Adam(model.parameters(), lr=lr, weight_decay=weight_decay)
    optimizer = optim.SGD(model.parameters(), lr=lr, momentum=0.9, weight_decay=weight_decay)

    history = {
        'epoch': [],
        'train_loss': [],
        'train_acc': [],
        'test_loss': [],
        'test_acc': []
    }
    # log_file_path = os.path.join(Cfg.save_dir, Cfg.batch_log)

    for epoch in range(1, epochs+1):
        model.train()
        epoch_loss = 0.0
        epoch_correct = 0
        epoch_total = 0

        for b, (x1, x2, y) in enumerate(train_loader):
            x1, x2, y = x1.to(device), x2.to(device), y.to(device)

            optimizer.zero_grad()
            outputs = model(x1, x2)
            loss = loss_fn(outputs, y)
            loss.backward()
            optimizer.step()

            with torch.no_grad():
                preds = (outputs >= 0.5).float()
                correct = (preds == y.view_as(preds)).sum().item()
```

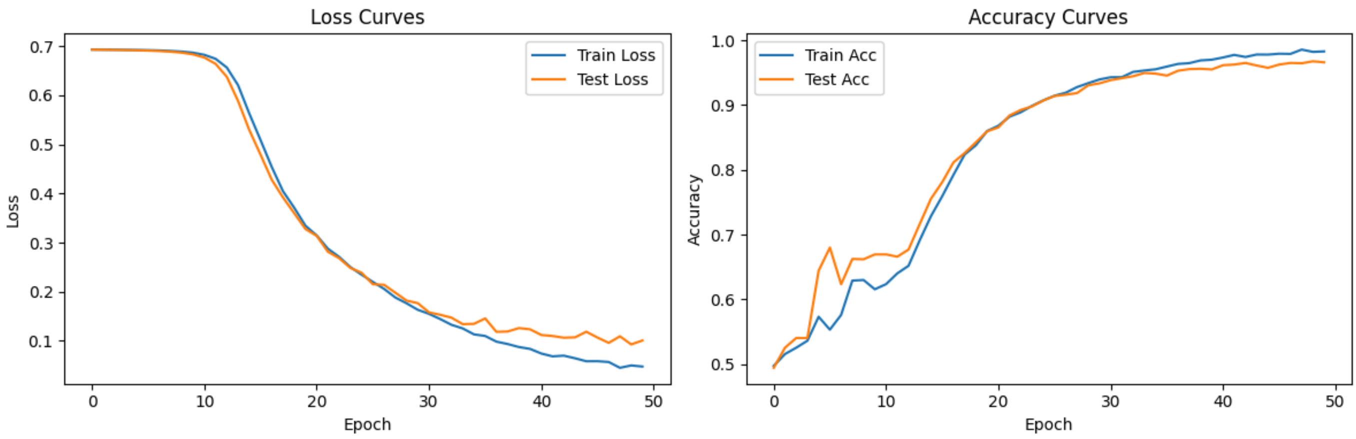
```
            # batch_loss = loss.item()
            # batch_acc = correct / y.size(0)
            epoch_loss += loss.item() * y.size(0)
            epoch_correct += correct
            epoch_total += y.size(0)
            # test_loss_batch, test_acc_batch = evaluate(model, test_loader, loss_fn)
            # with open(log_file_path, 'a') as log_file:
            #     log_file.write(f"[epoch {epoch:2d}] [btach_idx {b:3d}] "+
            #                    f"batch_loss={batch_loss:.4f} batch_acc={batch_acc:.4f} | "+
            #                    f"test_loss={test_loss_batch:.4f} test_acc_batch={test_acc_ba

        train_loss = epoch_loss/epoch_total
        train_acc  = epoch_correct/epoch_total
        test_loss, test_acc = evaluate(model, test_loader, loss_fn)

        history['epoch'].append(epoch)
        history['train_loss'].append(train_loss)
        history['train_acc'].append(train_acc)
        history['test_loss'].append(test_loss)
        history['test_acc'].append(test_acc)

        print(f"[Epoch {epoch:2d}] "+
              f"train_loss={train_loss:.4f} train_acc={train_acc:.4f} | "+
              f"test_loss={test_loss:.4f} test_acc={test_acc:.4f}")

    # print(f"Training log (mini-batch) saved to {log_file_path}")
    hist_df = pd.DataFrame(history)
    csv_path = os.path.join(Cfg.save_dir, Cfg.epoch_log)
    hist_df.to_csv(csv_path, index=False)
    print(f"Training log (epoch) saved to {csv_path}")
    model_path = os.path.join(Cfg.save_dir, Cfg.model_name)
    torch.save(model, model_path)
    print(f"Model saved to {model_path}")

    return history

history = train(model, train_loader, test_loader, Cfg.epochs, Cfg.lr, Cfg.weight_decay)
```

```
[Epoch  1] train_loss=0.6931 train_acc=0.4975 | test_loss=0.6930 test_acc=0.4945
[Epoch  2] train_loss=0.6929 train_acc=0.5157 | test_loss=0.6927 test_acc=0.5255
[Epoch  3] train_loss=0.6928 train_acc=0.5255 | test_loss=0.6924 test_acc=0.5405
[Epoch  4] train_loss=0.6925 train_acc=0.5363 | test_loss=0.6921 test_acc=0.5405
[Epoch  5] train_loss=0.6922 train_acc=0.5733 | test_loss=0.6916 test_acc=0.6445
[Epoch  6] train_loss=0.6919 train_acc=0.5534 | test_loss=0.6910 test_acc=0.6800
[Epoch  7] train_loss=0.6913 train_acc=0.5761 | test_loss=0.6902 test_acc=0.6235
[Epoch  8] train_loss=0.6904 train_acc=0.6291 | test_loss=0.6889 test_acc=0.6625
[Epoch  9] train_loss=0.6890 train_acc=0.6300 | test_loss=0.6868 test_acc=0.6620
[Epoch 10] train_loss=0.6867 train_acc=0.6157 | test_loss=0.6833 test_acc=0.6695
[Epoch 11] train_loss=0.6824 train_acc=0.6236 | test_loss=0.6769 test_acc=0.6695
[Epoch 12] train_loss=0.6743 train_acc=0.6402 | test_loss=0.6641 test_acc=0.6660
[Epoch 13] train_loss=0.6566 train_acc=0.6519 | test_loss=0.6376 test_acc=0.6770
[Epoch 14] train_loss=0.6207 train_acc=0.6914 | test_loss=0.5885 test_acc=0.7165
[Epoch 15] train_loss=0.5630 train_acc=0.7286 | test_loss=0.5293 test_acc=0.7555
[Epoch 16] train_loss=0.5090 train_acc=0.7593 | test_loss=0.4792 test_acc=0.7810
[Epoch 17] train_loss=0.4541 train_acc=0.7922 | test_loss=0.4280 test_acc=0.8115
[Epoch 18] train_loss=0.4047 train_acc=0.8237 | test_loss=0.3920 test_acc=0.8260
[Epoch 19] train_loss=0.3710 train_acc=0.8380 | test_loss=0.3599 test_acc=0.8425
[Epoch 20] train_loss=0.3345 train_acc=0.8599 | test_loss=0.3277 test_acc=0.8595
[Epoch 21] train_loss=0.3146 train_acc=0.8681 | test_loss=0.3138 test_acc=0.8655
[Epoch 22] train_loss=0.2876 train_acc=0.8821 | test_loss=0.2814 test_acc=0.8840
[Epoch 23] train_loss=0.2709 train_acc=0.8889 | test_loss=0.2682 test_acc=0.8925
[Epoch 24] train_loss=0.2502 train_acc=0.8988 | test_loss=0.2485 test_acc=0.8980
[Epoch 25] train_loss=0.2346 train_acc=0.9072 | test_loss=0.2386 test_acc=0.9070
[Epoch 26] train_loss=0.2200 train_acc=0.9144 | test_loss=0.2153 test_acc=0.9140
[Epoch 27] train_loss=0.2058 train_acc=0.9191 | test_loss=0.2141 test_acc=0.9160
[Epoch 28] train_loss=0.1883 train_acc=0.9277 | test_loss=0.1980 test_acc=0.9185
[Epoch 29] train_loss=0.1765 train_acc=0.9338 | test_loss=0.1819 test_acc=0.9305
[Epoch 30] train_loss=0.1632 train_acc=0.9395 | test_loss=0.1767 test_acc=0.9335
[Epoch 31] train_loss=0.1550 train_acc=0.9429 | test_loss=0.1579 test_acc=0.9385
[Epoch 32] train_loss=0.1443 train_acc=0.9431 | test_loss=0.1530 test_acc=0.9415
[Epoch 33] train_loss=0.1326 train_acc=0.9512 | test_loss=0.1472 test_acc=0.9445
[Epoch 34] train_loss=0.1253 train_acc=0.9533 | test_loss=0.1340 test_acc=0.9495
[Epoch 35] train_loss=0.1132 train_acc=0.9552 | test_loss=0.1346 test_acc=0.9485
[Epoch 36] train_loss=0.1099 train_acc=0.9594 | test_loss=0.1456 test_acc=0.9455
[Epoch 37] train_loss=0.0984 train_acc=0.9635 | test_loss=0.1183 test_acc=0.9530
[Epoch 38] train_loss=0.0935 train_acc=0.9647 | test_loss=0.1190 test_acc=0.9555
[Epoch 39] train_loss=0.0874 train_acc=0.9689 | test_loss=0.1259 test_acc=0.9560
[Epoch 40] train_loss=0.0835 train_acc=0.9700 | test_loss=0.1234 test_acc=0.9550
[Epoch 41] train_loss=0.0741 train_acc=0.9734 | test_loss=0.1119 test_acc=0.9615
[Epoch 42] train_loss=0.0684 train_acc=0.9774 | test_loss=0.1098 test_acc=0.9625
[Epoch 43] train_loss=0.0698 train_acc=0.9742 | test_loss=0.1063 test_acc=0.9650
[Epoch 44] train_loss=0.0645 train_acc=0.9780 | test_loss=0.1071 test_acc=0.9610
[Epoch 45] train_loss=0.0584 train_acc=0.9779 | test_loss=0.1185 test_acc=0.9575
[Epoch 46] train_loss=0.0585 train_acc=0.9792 | test_loss=0.1066 test_acc=0.9625
[Epoch 47] train_loss=0.0569 train_acc=0.9789 | test_loss=0.0959 test_acc=0.9650
[Epoch 48] train_loss=0.0450 train_acc=0.9856 | test_loss=0.1092 test_acc=0.9645
[Epoch 49] train_loss=0.0499 train_acc=0.9821 | test_loss=0.0927 test_acc=0.9675
[Epoch 50] train_loss=0.0476 train_acc=0.9828 | test_loss=0.1007 test_acc=0.9660
Training log (epoch) saved to ./output/epoch_log.csv
Model saved to ./output/siamese_mnist_same_digit.pth
```

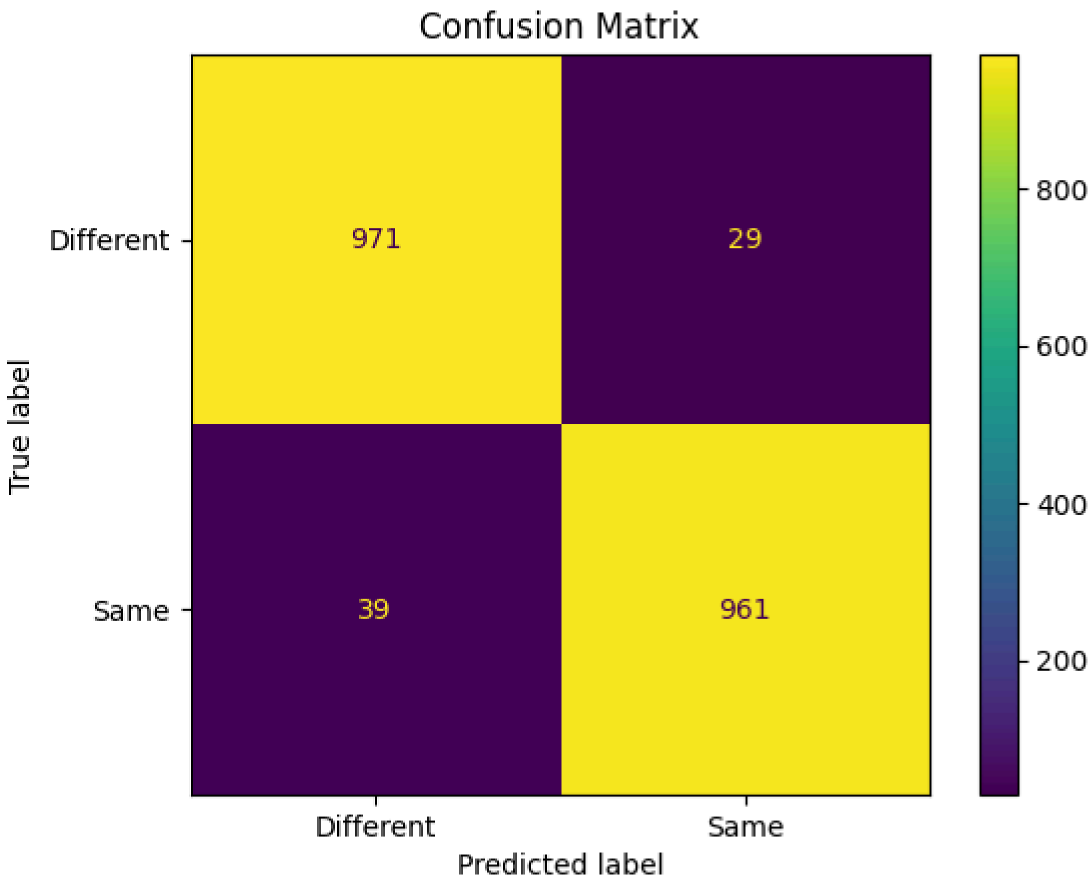
In [7]:

```python
def plot_results(history):
    # 绘制损失和准确率曲线
    fig, axes = plt.subplots(1, 2, figsize=(12, 4))

    # 左图：损失曲线
    axes[0].plot(history['train_loss'], label='Train Loss')
    axes[0].plot(history['test_loss'], label='Test Loss')
    axes[0].set_xlabel('Epoch')
    axes[0].set_ylabel('Loss')
    axes[0].set_title('Loss Curves')
    axes[0].legend()

    # 右图：准确率曲线
```

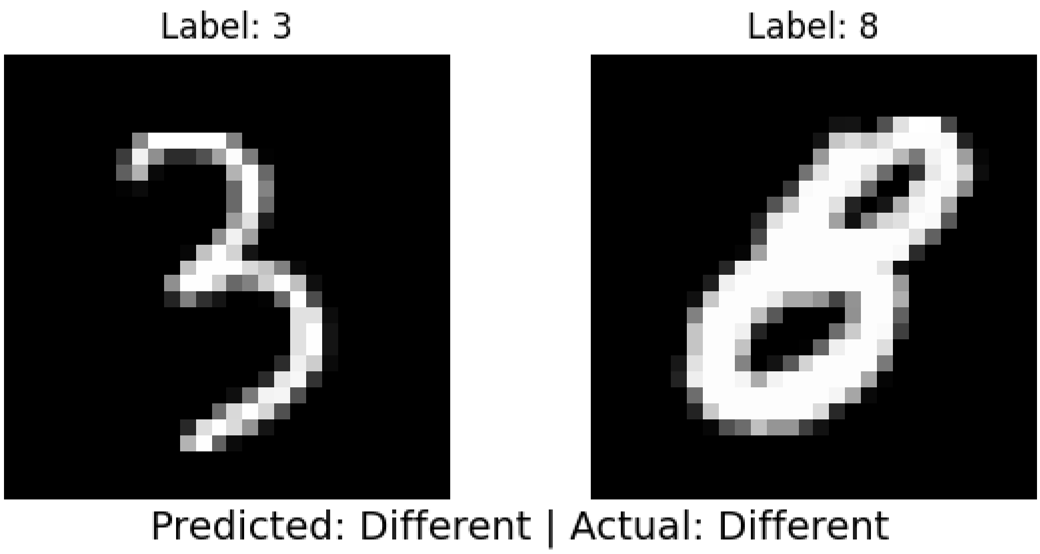
```
    axes[1].plot(history['train_acc'], label='Train Acc')
    axes[1].plot(history['test_acc'], label='Test Acc')
    axes[1].set_xlabel('Epoch')
    axes[1].set_ylabel('Accuracy')
    axes[1].set_title('Accuracy Curves')
    axes[1].legend()

    plt.tight_layout()
    plt.show()

plot_results(history)
```



In [8]:
```
def plot_confusion_matrix(model, loader):
    model.eval()
    y_true = []
    y_pred = []

    with torch.no_grad():
        for x1, x2, y in loader:
            x1, x2, y = x1.to(device), x2.to(device), y.to(device)
            outputs = model(x1, x2)
            preds = (outputs >= 0.5).float()
            y_true.extend(y.cpu().numpy())
            y_pred.extend(preds.cpu().numpy())

    # 计算混淆矩阵
    cm = confusion_matrix(y_true, y_pred)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=["Different", "Same"])
    disp.plot()
    plt.title("Confusion Matrix")
    plt.show()

plot_confusion_matrix(model, test_loader)
```



In [9]:
```
def predict_random_pair(model, test_subset):
    # 随机挑选两张图片
    idx1, idx2 = random.sample(range(len(test_subset)), 2)
    x1, label1 = test_subset[idx1]
    x2, label2 = test_subset[idx2]
    # 将图片转换为批量形式并移动到设备
    x1 = x1.unsqueeze(0).to(device)  # (1, 1, 28, 28)
    x2 = x2.unsqueeze(0).to(device)  # (1, 1, 28, 28)
    # 模型预测
    model.eval()
    with torch.no_grad():
        output = model(x1, x2)  # 输出 logits
        pred = 1 if output >= 0.5 else 0  # 二分类预测
    # 显示图片和预测结果
    fig, axes = plt.subplots(1, 2, figsize=(6, 3))
    axes[0].imshow(x1.cpu().squeeze(0).squeeze(0), cmap='gray')
    axes[0].set_title(f"Label: {label1}")
    axes[0].axis('off')
    axes[1].imshow(x2.cpu().squeeze(0).squeeze(0), cmap='gray')
    axes[1].set_title(f"Label: {label2}")
    axes[1].axis('off')
    result_text = f"Predicted: {'Same' if pred == 1 else 'Different'} | Actual: {'Same' if la
    fig.suptitle(result_text, fontsize=14, y=0.04)
    plt.tight_layout()
    plt.show()

model = torch.load(os.path.join(Cfg.save_dir, Cfg.model_name), map_location=device, weights_o
model = model.to(device)
predict_random_pair(model, test_subset)
```


Label: 3
Label: 8
Predicted: Different | Actual: Different