1: Nhận diện chữ số viết tay (MNIST Dataset)

Khai báo thư viện sử dụng

In [1]:

```
from tensorflow.keras.datasets import mnist
import numpy as np
import cv2
from matplotlib import pyplot as plt
import tensorflow
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, Dropout, Flatten, Input, Reshape
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
```

Load data

In [2]:

```
(X_train, y_train), (X_test, y_test) = mnist.load_data()
print(X_train.shape, X_test.shape)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.n
pz
11490434/11490434 [==============================] - 0s 0us/step
(60000, 28, 28) (10000, 28, 28)
```

Chuẩn hóa dữ liệu input

In [3]:

```
X_train_scaled = np.array(X_train)/255.
X_test_scaled = np.array(X_test)/255.
```

Tách thành tập train và tập validation

In [4]:

```
X_train_scaled, X_val_scaled,y_train, y_val = train_test_split(X_train_scaled, y_train,
test_size=0.2, random_state=42)
```

Chuẩn hóa dữ liệu output

In [5]:

```
# OnehotVector output
encoder = OneHotEncoder()
encoder.fit(y_train.reshape(-1,1))
y_train = encoder.transform(y_train.reshape(-1,1)).toarray()
y_val = encoder.transform(y_val.reshape(-1,1)).toarray()
y_test = encoder.transform(y_test.reshape(-1,1)).toarray()
```

Xây dựng mô hình CNN

In [6]:

```
# CNN model
inp = Input(shape = (28,28,1)) # input shape
cnn = Conv2D(filters = 8, kernel_size = 3, activation='relu')(inp)
pooling = MaxPooling2D(pool_size=(2,2))(cnn)
```

```
drop = Dropout(0.2)(pooling)

cnn = Conv2D(filters = 16, kernel_size = 4, activation='relu')(drop)
pooling = MaxPooling2D(pool_size=(2,2))(cnn)
drop = Dropout(0.2)(pooling)

cnn = Conv2D(filters = 32, kernel_size = 4, activation='relu')(drop)
pooling = MaxPooling2D(pool_size=(2,2))(cnn)

f = Flatten()(pooling)

fc1 = Dense(units = 32, activation = 'relu')(f)
fc2 = Dense(units = 16, activation = 'relu')(fc1)
out = Dense(units = 10, activation = 'softmax')(fc2)

model = Model(inputs = inp, outputs = out)
model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_1 (InputLayer)        [(None, 28, 28, 1)]       0         
                                                                 
 conv2d (Conv2D)             (None, 26, 26, 8)         80        
                                                                 
 max_pooling2d (MaxPooling2  (None, 13, 13, 8)         0         
 D)                                                              
                                                                 
 dropout (Dropout)           (None, 13, 13, 8)         0         
                                                                 
 conv2d_1 (Conv2D)           (None, 10, 10, 16)        2064      
                                                                 
 max_pooling2d_1 (MaxPoolin  (None, 5, 5, 16)          0         
 g2D)                                                            
                                                                 
 dropout_1 (Dropout)         (None, 5, 5, 16)          0         
                                                                 
 conv2d_2 (Conv2D)           (None, 2, 2, 32)          8224      
                                                                 
 max_pooling2d_2 (MaxPoolin  (None, 1, 1, 32)          0         
 g2D)                                                            
                                                                 
 flatten (Flatten)           (None, 32)                0         
                                                                 
 dense (Dense)               (None, 32)                1056      
                                                                 
 dense_1 (Dense)             (None, 16)                528       
                                                                 
 dense_2 (Dense)             (None, 10)                170       
                                                                 
=================================================================
Total params: 12122 (47.35 KB)
Trainable params: 12122 (47.35 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Huấn luyện mô hình ban đầu

In [7]:

```
optimizer1 = tensorflow.keras.optimizers.Adam(learning_rate = 0.001)
model.compile(optimizer = optimizer1, loss='categorical_crossentropy',metrics = ['accura
cy'])

history = model.fit(X_train_scaled,y_train,batch_size=64,
                    epochs = 10, validation_data = (X_val_scaled, y_val))
```

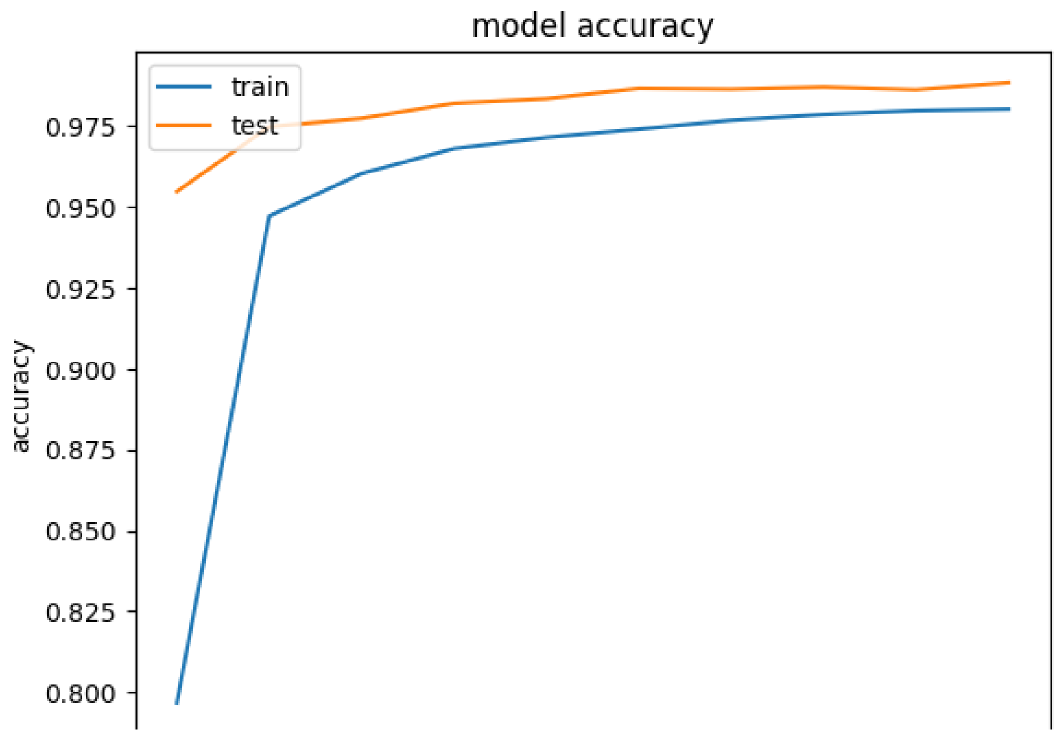
```
Epoch 1/10
750/750 [==============================] - 17s 7ms/step - loss: 0.5971 - accuracy: 0.7968
- val_loss: 0.1514 - val_accuracy: 0.9547
Epoch 2/10
```

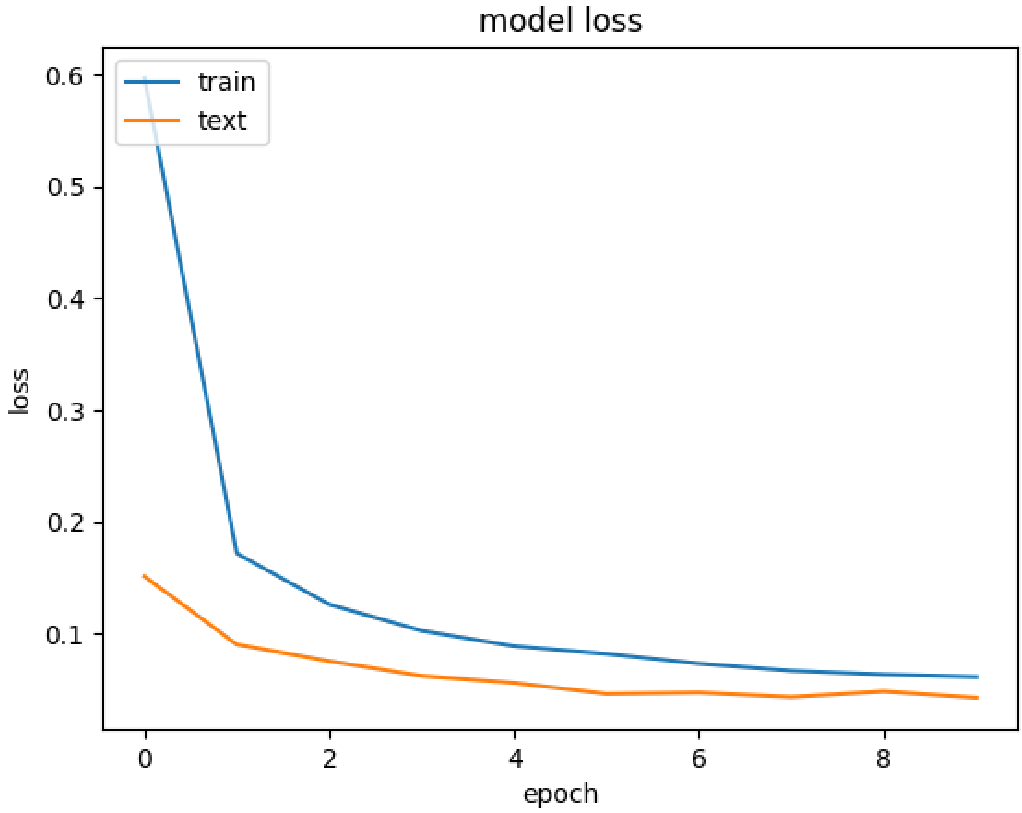
```
Epoch 2/10
750/750 [==============================] - 4s 5ms/step - loss: 0.1719 - accuracy: 0.9471
- val_loss: 0.0904 - val_accuracy: 0.9747
Epoch 3/10
750/750 [==============================] - 4s 5ms/step - loss: 0.1262 - accuracy: 0.9602
- val_loss: 0.0755 - val_accuracy: 0.9772
Epoch 4/10
750/750 [==============================] - 5s 6ms/step - loss: 0.1027 - accuracy: 0.9679
- val_loss: 0.0623 - val_accuracy: 0.9819
Epoch 5/10
750/750 [==============================] - 4s 5ms/step - loss: 0.0889 - accuracy: 0.9714
- val_loss: 0.0560 - val_accuracy: 0.9833
Epoch 6/10
750/750 [==============================] - 4s 5ms/step - loss: 0.0820 - accuracy: 0.9739
- val_loss: 0.0463 - val_accuracy: 0.9865
Epoch 7/10
750/750 [==============================] - 8s 10ms/step - loss: 0.0733 - accuracy: 0.9766
- val_loss: 0.0474 - val_accuracy: 0.9862
Epoch 8/10
750/750 [==============================] - 5s 7ms/step - loss: 0.0669 - accuracy: 0.9785
- val_loss: 0.0436 - val_accuracy: 0.9869
Epoch 9/10
750/750 [==============================] - 4s 5ms/step - loss: 0.0636 - accuracy: 0.9796
- val_loss: 0.0484 - val_accuracy: 0.9861
Epoch 10/10
750/750 [==============================] - 5s 7ms/step - loss: 0.0615 - accuracy: 0.9801
- val_loss: 0.0430 - val_accuracy: 0.9883
```

Trực quan hóa kết quả Accuracy và Loss trên tập Train và Test

In [8]:

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train','test'],loc = 'upper left')
plt.show()
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train','text'],loc='upper left')
plt.show()
```





Lưu mô hình ban đầu, load mô hình đã lưu từ máy

In [9]:

```
model.save('model1.h5')
from tensorflow.keras.models import load_model
model1 = load_model('/content/model1.h5')
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3079: UserWarning: Y
ou are saving your model as an HDF5 file via `model.save()`. This file format is consider
ed legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model
.keras')`.
  saving_api.save_model(
```

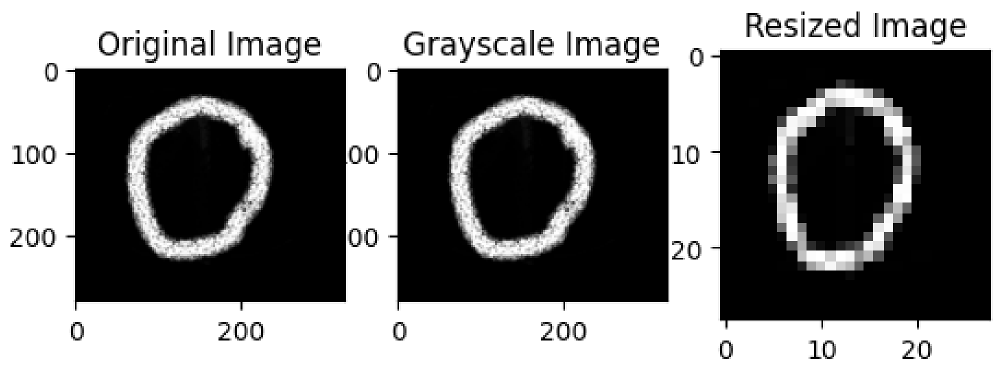
Load ảnh và sử dụng mô hình đã huấn luyện `model1.h5` **để nhận diện 10 ảnh tự vẽ**

In [10]:

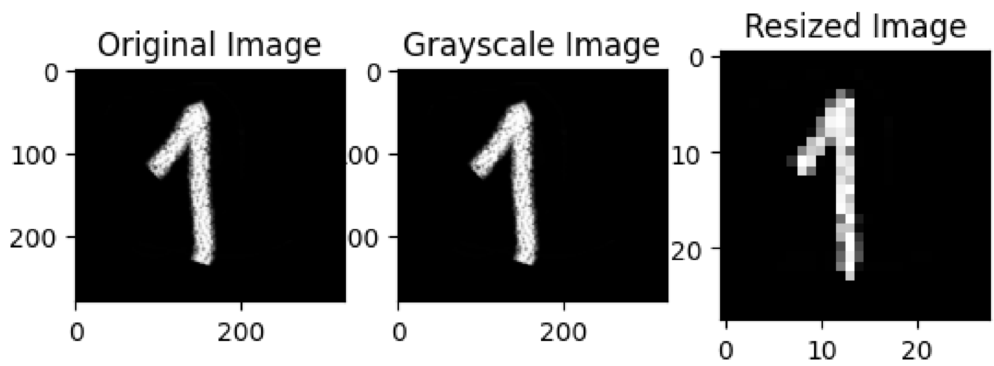
```
import cv2

for i in range(10):
    img_path = f'/content/{i}.png'  # Construct the path for each image
    img = cv2.imread(img_path)

    if img is not None:
        print(f"Processing image {i}.png")

        # Display original image
        plt.subplot(1, 3, 1)
        plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))
        plt.title('Original Image')

        # Convert to grayscale
        gray_img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

        # Display grayscale image
        plt.subplot(1, 3, 2)
        plt.imshow(gray_img, cmap='gray')
```

```python
        plt.title('Grayscale Image')

        # Resize to 28x28
        img_resized = cv2.resize(gray_img, (28, 28))

        # Display resized image
        plt.subplot(1, 3, 3)
        plt.imshow(img_resized, cmap='gray')
        plt.title('Resized Image')

        # Preprocess image for prediction
        img_scaled = np.array([img_resized / 255.])

        # Make prediction using the model
        y_hat = model1.predict(img_scaled)

        # Get the predicted class
        predicted_class = np.argmax(y_hat)
        print(f"Predicted class for {i}.png: {predicted_class}")

        plt.show()   # Show the plotted images for each iteration
    else:
        print(f"Could not find image {i}.png")
```

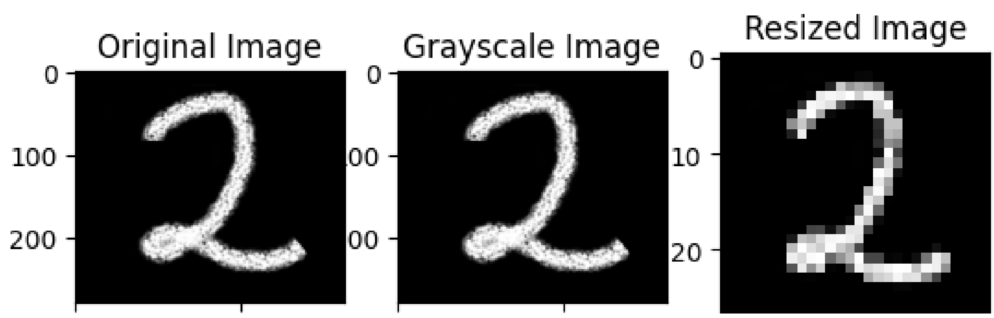
```
Processing image 0.png
1/1 [==============================] - 0s 173ms/step
Predicted class for 0.png: 0
```



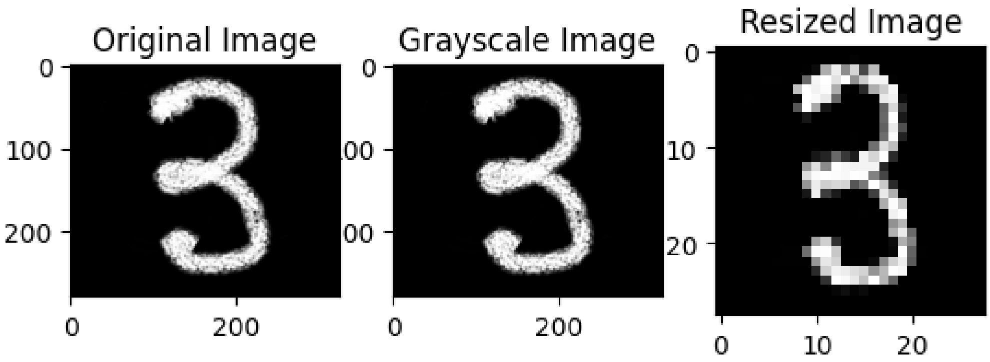

```
Processing image 1.png
1/1 [==============================] - 0s 20ms/step
Predicted class for 1.png: 1
```



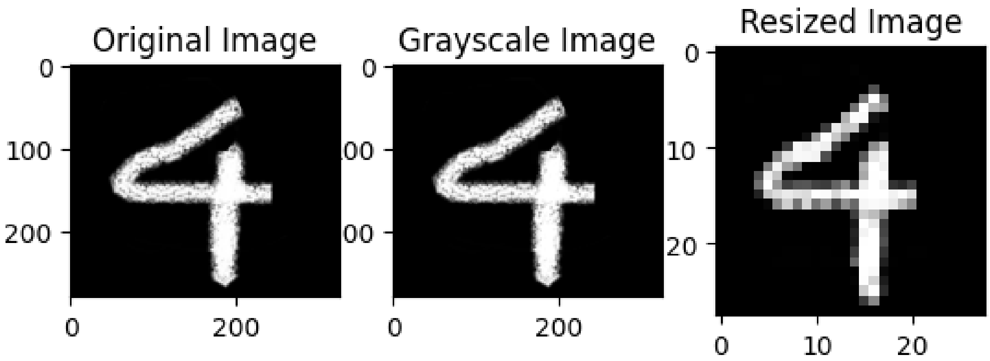

```
Processing image 2.png
1/1 [==============================] - 0s 19ms/step
Predicted class for 2.png: 2
```



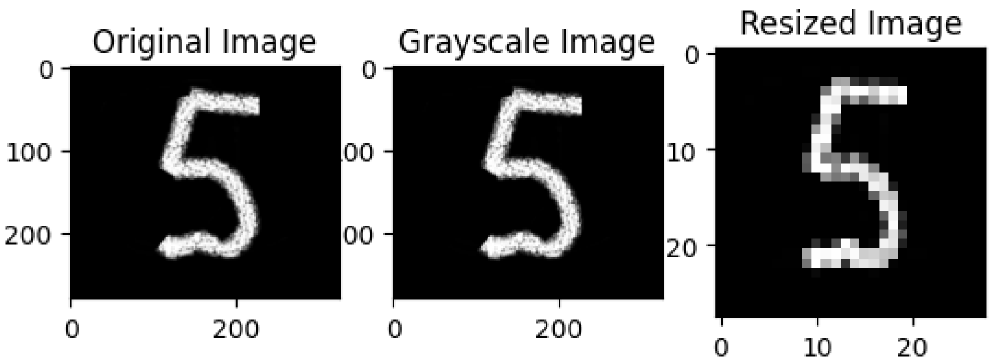
```
Processing image 3.png
1/1 [==============================] - 0s 19ms/step
Predicted class for 3.png: 3
```



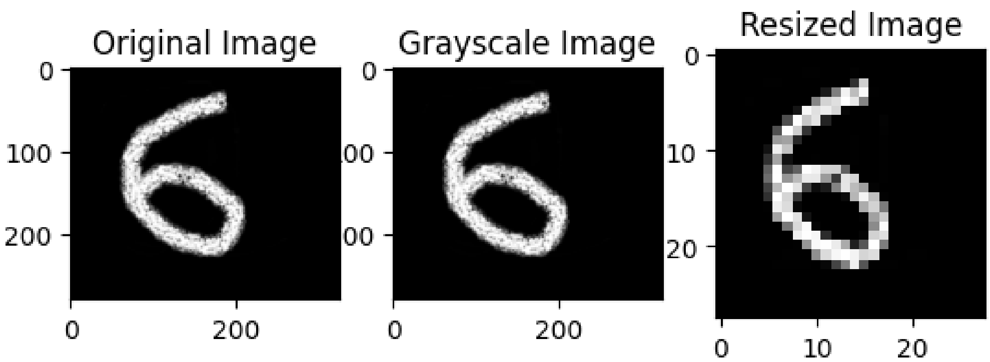

```
Processing image 4.png
1/1 [==============================] - 0s 17ms/step
Predicted class for 4.png: 4
```




```
Processing image 5.png
1/1 [==============================] - 0s 17ms/step
Predicted class for 5.png: 5
```

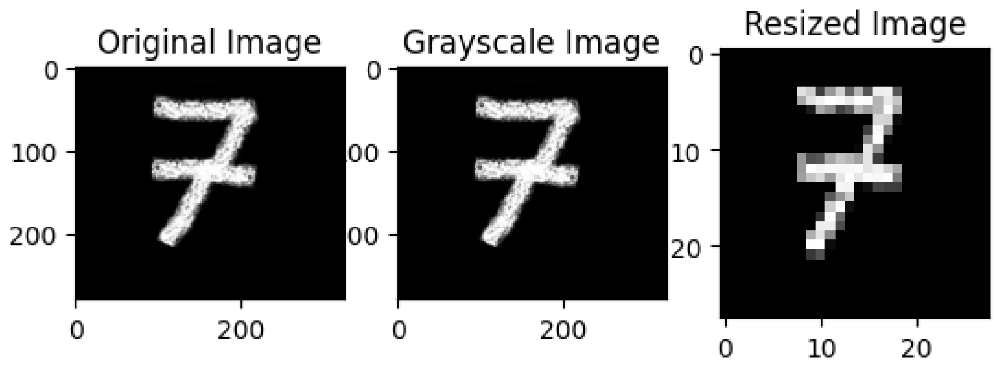



```
Processing image 6.png
1/1 [==============================] - 0s 18ms/step
Predicted class for 6.png: 6
```

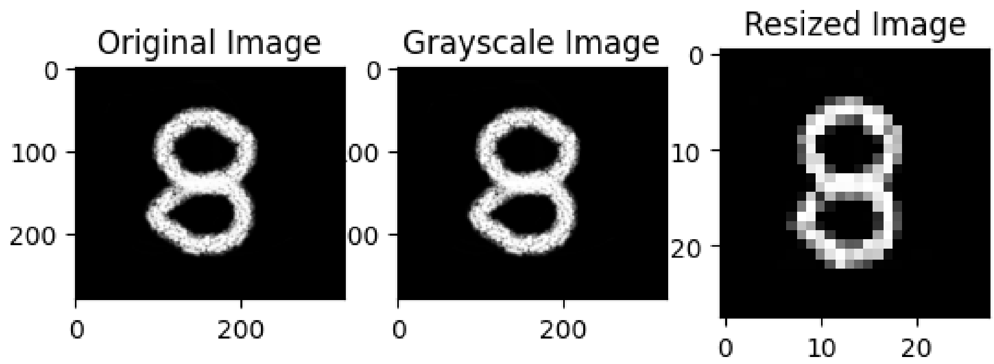



```
Processing image 7.png
```

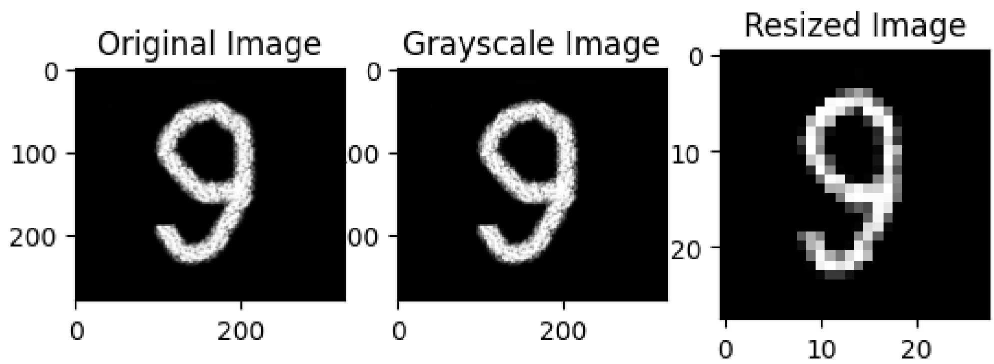
```
1/1 [==============================] - 0s 21ms/step
Predicted class for 7.png: 7
```




```
Processing image 8.png
1/1 [==============================] - 0s 19ms/step
Predicted class for 8.png: 8
```




```
Processing image 9.png
1/1 [==============================] - 0s 20ms/step
Predicted class for 9.png: 9
```



Tính y dự đoán từ mô hình ban đầu đã lưu

In [11]:

```
y_hat = model1.predict(X_test_scaled)
```

```
313/313 [==============================] - 1s 2ms/step
```

In [12]:

```
print(y_hat.shape)
print(y_test.shape)
```

```
(10000, 10)
(10000, 10)
```

Lấy argmax của y dự đoán và y test

In [13]:

```
y_test = np.argmax(y_test, axis=1)
y_hat = np.argmax(y_hat, axis=1)
```

Sử dụng classification_report trong thư viện Sklearn đánh giá kết quả mô hình ban đầu dựa trên kết quả dự đoán tập test

In [14]:

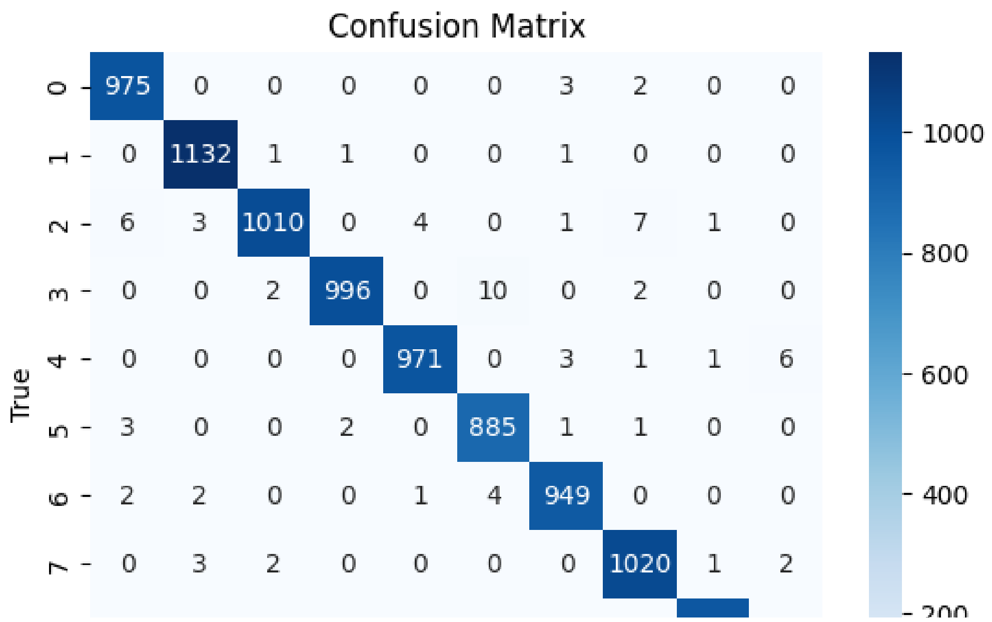
```
from sklearn.metrics import classification_report
target_names = ['0', '1', '2', '3','4','5','6','7','8','9']
print(classification_report(y_test, y_hat,target_names=target_names))
```

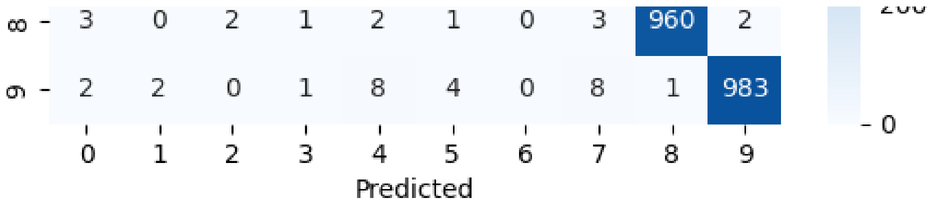
```
              precision    recall  f1-score   support

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

Sử dụng Confusion_matrix trong thư viện Sklearn biểu diễn kết quả dự đoán trên tập test

In [15]:

```
import sklearn.metrics
import seaborn as sn

# Tạo confusion matrix
cm = sklearn.metrics.confusion_matrix(y_test, y_hat)

# Vẽ confusion matrix
plt.figure()
sn.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```





Accuracy

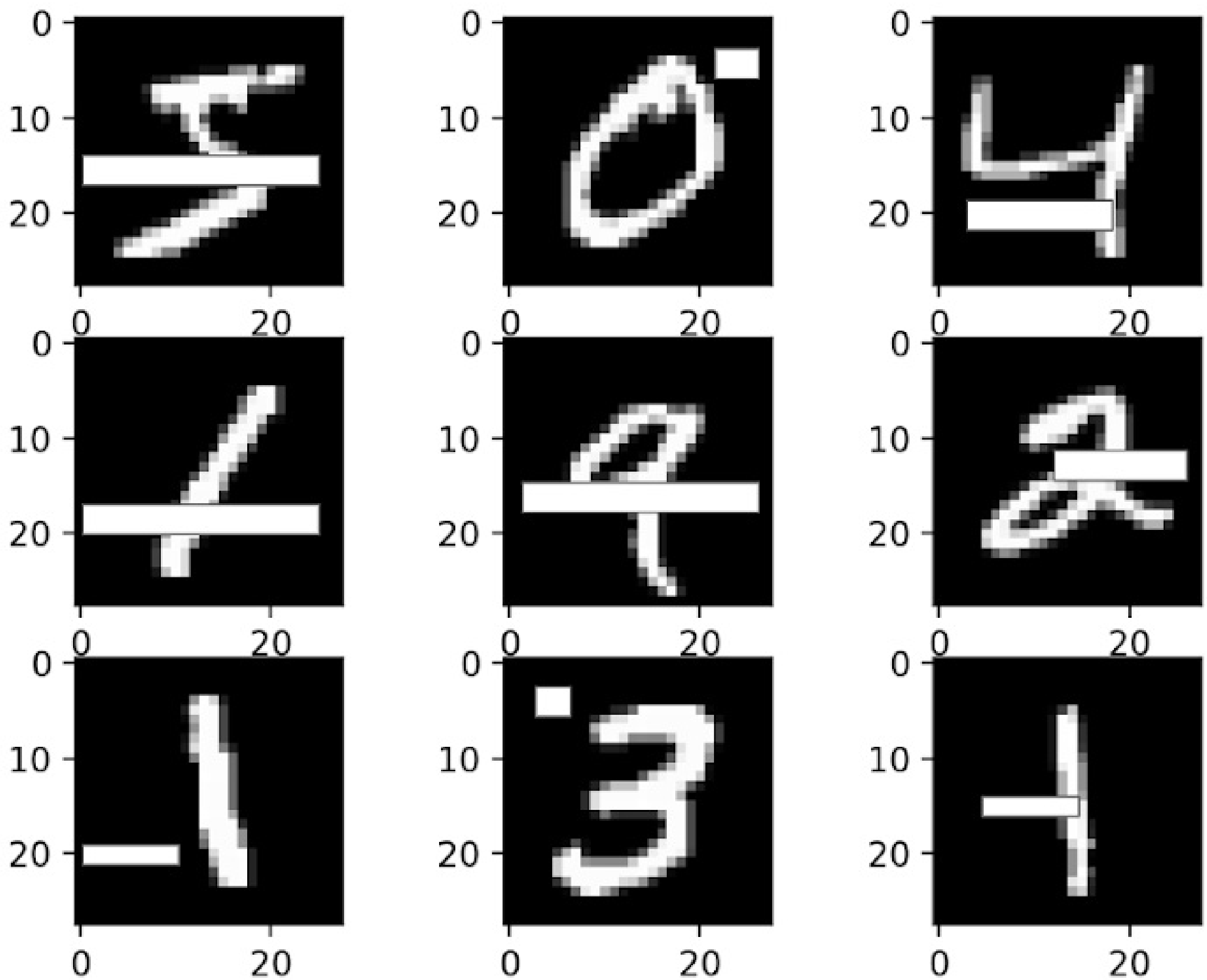
In [16]:

```
from sklearn.metrics import accuracy_score
accuracy1 = accuracy_score(y_test, y_hat)
print('Accuracy:', accuracy1)
```

```
Accuracy: 0.9881
```

Từ đây ta thấy rằng khi ta train dữ liệu không có nhiễu để dự đoán dữ liệu không có nhiễu thì độ chính xác ra kết quả gần 99%

2: Sử dụng tập dữ liệu MNIST, thêm nhiễu vào trong ảnh như hình sau:



In [17]:

```
import random
```

Chuẩn bị data, ví dụ vẽ chèn nhiễu vào dữ liệu

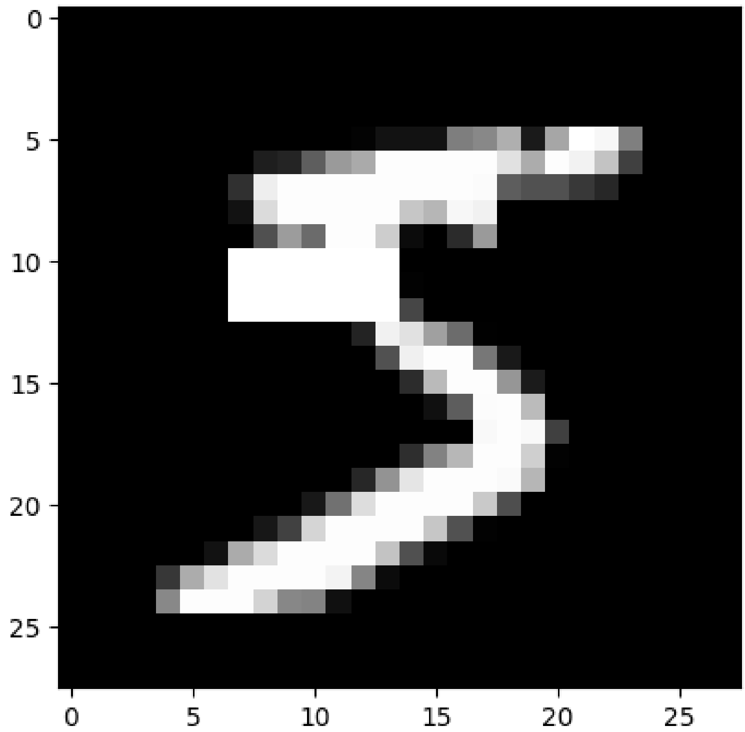
In [110]:

```
(X_train1, y_train1), (X_test1, y_test1) = mnist.load_data()
print(y_train[0])
x_start = random.randint(2,17)
y_start = random.randint(2,25)
x_end = random.randint(13,25)
y_end = random.randint(2,25)
thickness = 1
# cv2.rectangle(X_train1[0],(x_start,y_start),(x_end,y_start),(255,255,255),thickness)
cv2.line(X_train1[0],(x_start,y_start - 1),(x_end,y_start - 1),(255,255,255),thickness)
cv2.line(X_train1[0],(x_start,y_start),(x_end,y_start),(255,255,255),thickness)
cv2.line(X_train1[0],(x_start,y_start + 1),(x_end,y_start + 1),(255,255,255),thickness)
# cv2.line(X_train1[0],(x_start,y_start + 2),(x_end,y_start + 2),(255,255,255),thickness)
plt.imshow(X_train1[0],cmap = 'gray')
```

```
[0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
```

Out[110]:

```
<matplotlib.image.AxesImage at 0x7fbe47ffd930>
```



Vẽ chèn nhiễu vào tất cả ảnh trong tập MNIST ở tập train và tập test

In [111]:

```
for i in range (len(X_train1)):
  x_start = random.randint(2,17)
  y_start = random.randint(2,25)
  x_end = random.randint(13,25)
  y_end = random.randint(2,25)
  thickness = 1
  # cv2.rectangle(X_train1[i],(x_start,y_start),(x_end,y_start),(230,230,230),thickness)
  cv2.line(X_train1[i],(x_start,y_start-1),(x_end,y_start-1),(255,255,255),thickness)
  cv2.line(X_train1[i],(x_start,y_start),(x_end,y_start),(255,255,255),thickness)
  cv2.line(X_train1[i],(x_start,y_start+1),(x_end,y_start+1),(255,255,255),thickness)
  # cv2.line(X_train1[i],(x_start,y_start+2),(x_end,y_start+2),(255,255,255),thickness)
```

In [112]:

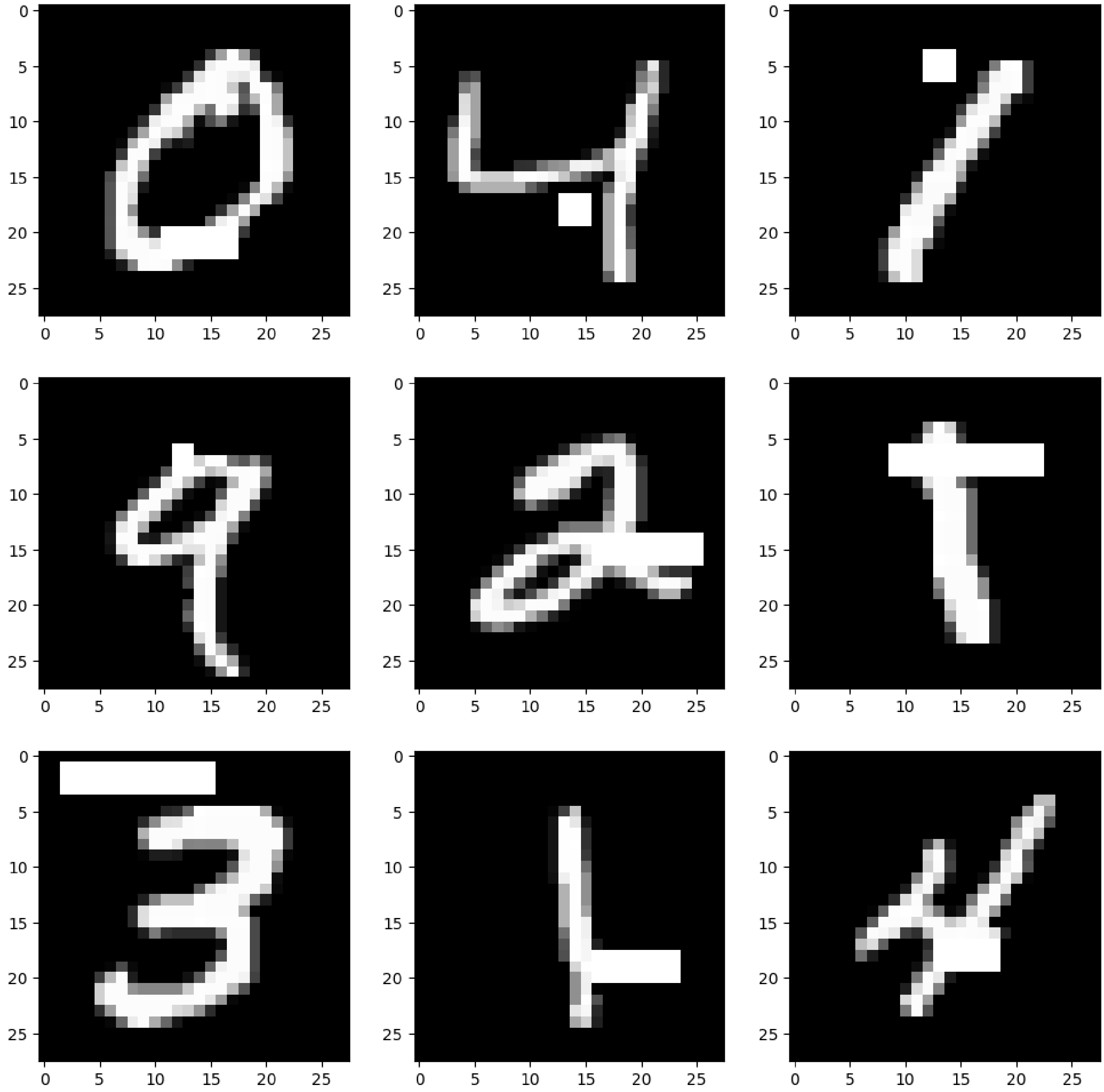
```
for i in range (len(X_test1)):
  x_start = random.randint(2,17)
  y_start = random.randint(2,25)
  x_end = random.randint(13,25)
  y_end = random.randint(2,25)
  thickness = 1
```

```
  # plt.subplot(3,3,i)
  # cv2.rectangle(X_test1[i],(x_start,y_start),(x_end,y_start),(255,255,255),thickness)
  cv2.line(X_test1[i],(x_start,y_start-1),(x_end,y_start-1),(255,255,255),thickness)
  cv2.line(X_test1[i],(x_start,y_start),(x_end,y_start),(255,255,255),thickness)
  cv2.line(X_test1[i],(x_start,y_start+1),(x_end,y_start+1),(255,255,255),thickness)
  # cv2.line(X_test1[i],(x_start,y_start+2),(x_end,y_start+2),(255,255,255),thickness)
  # plt.imshow(X_train[i], cmap = 'gray')
```

Ví dụ 9 ảnh đầu tiên đã được chèn nhiễu

In [113]:

```
plt.figure(figsize=(12,12))
for i in range (1,10):
  plt.subplot(3,3,i)
  # cv2.rectangle(X_train[i],(x_start,y_start),(x_end,y_start),(255,255,255),thickness)
  plt.imshow(X_train1[i], cmap = 'gray')
```



Chuẩn hoá input từ ảnh có nhiễu

In [114]:

```
X_train_scaled1 = np.array(X_train1)/255.
```

```
X_test_scaled1 = np.array(X_test1)/255.
```

In [115]:

```
X_train_scaled1, X_val_scaled1,y_train1, y_val1 = train_test_split(X_train_scaled1, y_tra
in1, test_size=0.2, random_state=42)
```

Chuẩn hoá output

In [116]:

```
# OnehotVector output
from sklearn.preprocessing import OneHotEncoder
encoder = OneHotEncoder()
encoder.fit(y_train1.reshape(-1,1))
y_train1 = encoder.transform(y_train1.reshape(-1,1)).toarray()
y_val1 = encoder.transform(y_val1.reshape(-1,1)).toarray()
y_test1 = encoder.transform(y_test1.reshape(-1,1)).toarray()
```

Xây dựng mô hình CNN

In [117]:

```
# CNN model
inp = Input(shape = (28,28,1)) # input shape
cnn = Conv2D(filters = 8, kernel_size = 3, activation='relu')(inp)
pooling = MaxPooling2D(pool_size=(2,2))(cnn)
drop = Dropout(0.2)(pooling)

cnn = Conv2D(filters = 16, kernel_size = 4, activation='relu')(drop)
pooling = MaxPooling2D(pool_size=(2,2))(cnn)
drop = Dropout(0.2)(pooling)

cnn = Conv2D(filters = 32, kernel_size = 4, activation='relu')(drop)
pooling = MaxPooling2D(pool_size=(2,2))(cnn)

f = Flatten()(pooling)

fc1 = Dense(units = 32, activation = 'relu')(f)
fc2 = Dense(units = 16, activation = 'relu')(fc1)
out = Dense(units = 10, activation = 'softmax')(fc2)

model = Model(inputs = inp, outputs = out)
model.summary()
```

```
Model: "model_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_7 (InputLayer)        [(None, 28, 28, 1)]       0         
                                                                 
 conv2d_18 (Conv2D)          (None, 26, 26, 8)         80        
                                                                 
 max_pooling2d_18 (MaxPooli  (None, 13, 13, 8)         0         
 ng2D)                                                           
                                                                 
 dropout_12 (Dropout)        (None, 13, 13, 8)         0         
                                                                 
 conv2d_19 (Conv2D)          (None, 10, 10, 16)        2064      
                                                                 
 max_pooling2d_19 (MaxPooli  (None, 5, 5, 16)          0         
 ng2D)                                                           
                                                                 
 dropout_13 (Dropout)        (None, 5, 5, 16)          0         
                                                                 
 conv2d_20 (Conv2D)          (None, 2, 2, 32)          8224      
                                                                 
 max_pooling2d_20 (MaxPooli  (None, 1, 1, 32)          0         
 ng2D)                                                           
```

```
 flatten_6 (Flatten)         (None, 32)               0

 dense_18 (Dense)            (None, 32)               1056

 dense_19 (Dense)            (None, 16)               528

 dense_20 (Dense)            (None, 10)               170

=================================================================
Total params: 12122 (47.35 KB)
Trainable params: 12122 (47.35 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Train dữ liệu từ tập train có nhiễu và tập validation không có nhiễu

In [118]:

```
optimizer1 = tensorflow.keras.optimizers.Adam(learning_rate = 0.001)
model.compile(optimizer = optimizer1, loss='categorical_crossentropy',metrics = ['accura
cy'])

history = model.fit(X_train_scaled1,y_train1,batch_size=64,
                    epochs = 10, validation_data = (X_val_scaled1, y_val1))
```

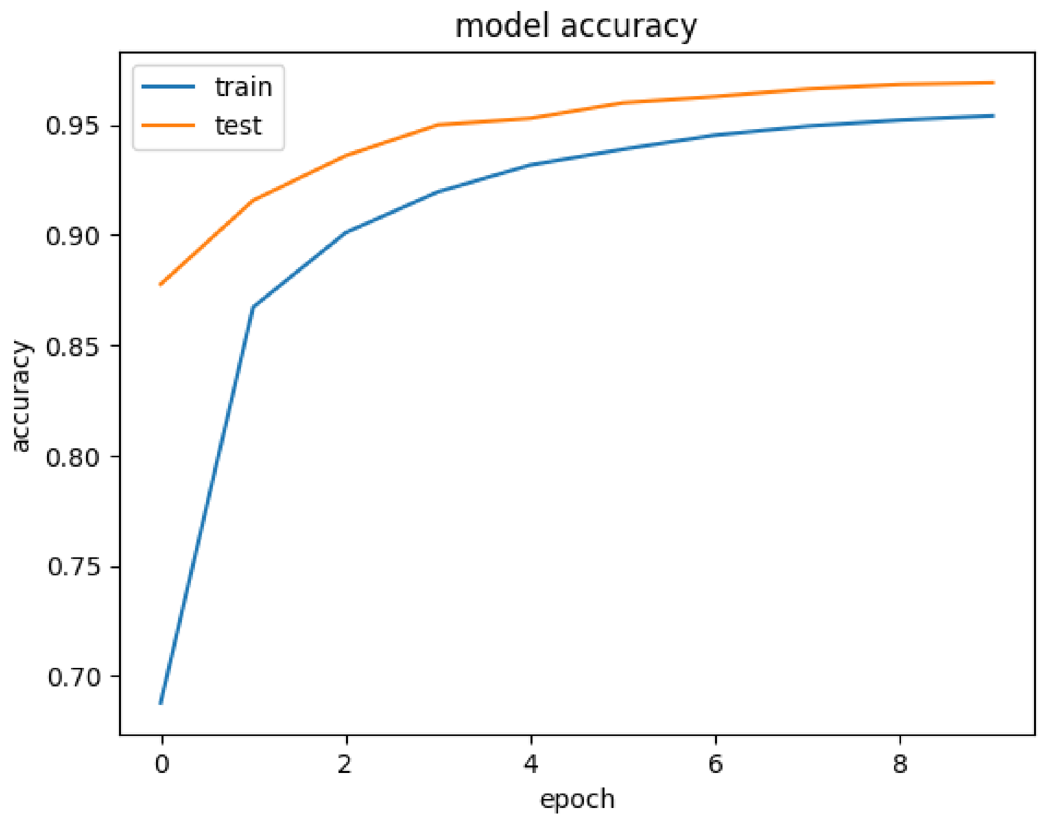
```
Epoch 1/10
750/750 [==============================] - 6s 5ms/step - loss: 0.9185 - accuracy: 0.6878
- val_loss: 0.3707 - val_accuracy: 0.8776
Epoch 2/10
750/750 [==============================] - 4s 5ms/step - loss: 0.4005 - accuracy: 0.8672
- val_loss: 0.2606 - val_accuracy: 0.9156
Epoch 3/10
750/750 [==============================] - 4s 6ms/step - loss: 0.2993 - accuracy: 0.9009
- val_loss: 0.1944 - val_accuracy: 0.9358
Epoch 4/10
750/750 [==============================] - 4s 5ms/step - loss: 0.2462 - accuracy: 0.9195
- val_loss: 0.1636 - val_accuracy: 0.9498
Epoch 5/10
750/750 [==============================] - 4s 5ms/step - loss: 0.2115 - accuracy: 0.9316
- val_loss: 0.1438 - val_accuracy: 0.9528
Epoch 6/10
750/750 [==============================] - 4s 5ms/step - loss: 0.1898 - accuracy: 0.9388
- val_loss: 0.1266 - val_accuracy: 0.9598
Epoch 7/10
750/750 [==============================] - 5s 6ms/step - loss: 0.1689 - accuracy: 0.9452
- val_loss: 0.1185 - val_accuracy: 0.9627
Epoch 8/10
750/750 [==============================] - 4s 5ms/step - loss: 0.1583 - accuracy: 0.9492
- val_loss: 0.1096 - val_accuracy: 0.9661
Epoch 9/10
750/750 [==============================] - 4s 5ms/step - loss: 0.1485 - accuracy: 0.9520
- val_loss: 0.1025 - val_accuracy: 0.9682
Epoch 10/10
750/750 [==============================] - 5s 7ms/step - loss: 0.1410 - accuracy: 0.9539
- val_loss: 0.0962 - val_accuracy: 0.9689
```

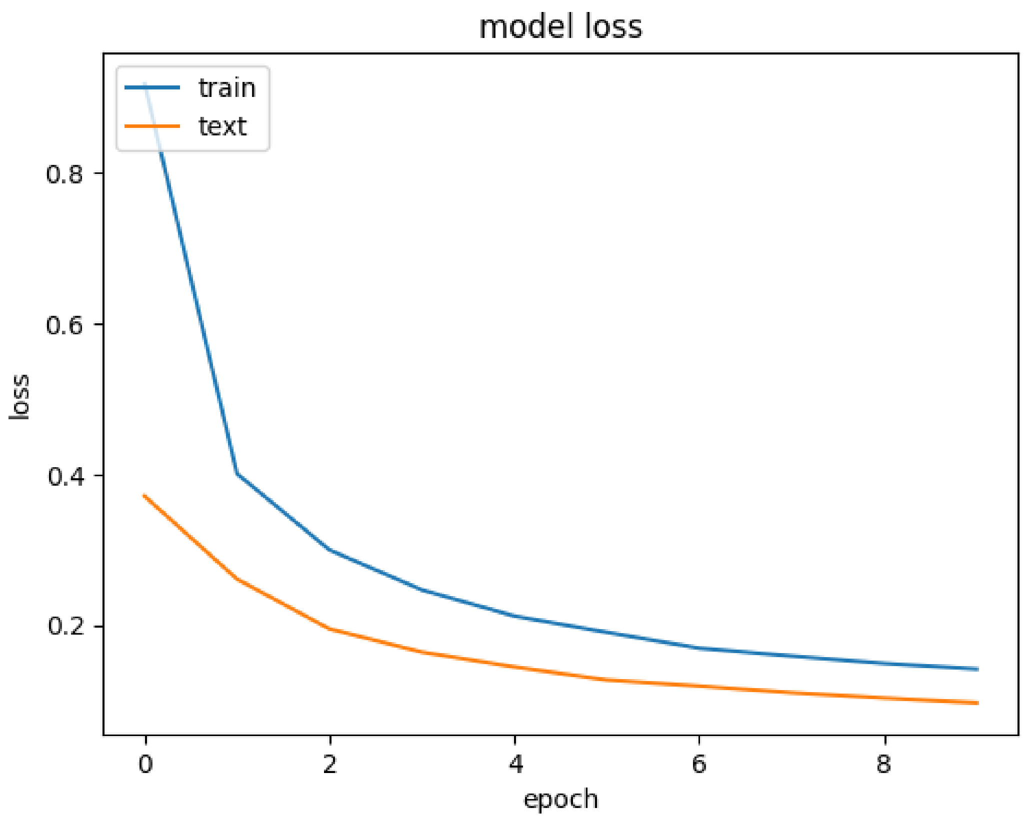
Trực quan hoá kết quả train và validation

In [119]:

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train','test'],loc = 'upper left')
plt.show()
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
```

```
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train','text'],loc='upper left')
plt.show()
```





Lưu và load model 2

In [120]:

```
model.save('model2.h5')
from tensorflow.keras.models import load_model
model2 = load_model('/content/model2.h5')
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3079: UserWarning: Y
ou are saving your model as an HDF5 file via `model.save()`. This file format is consider
```

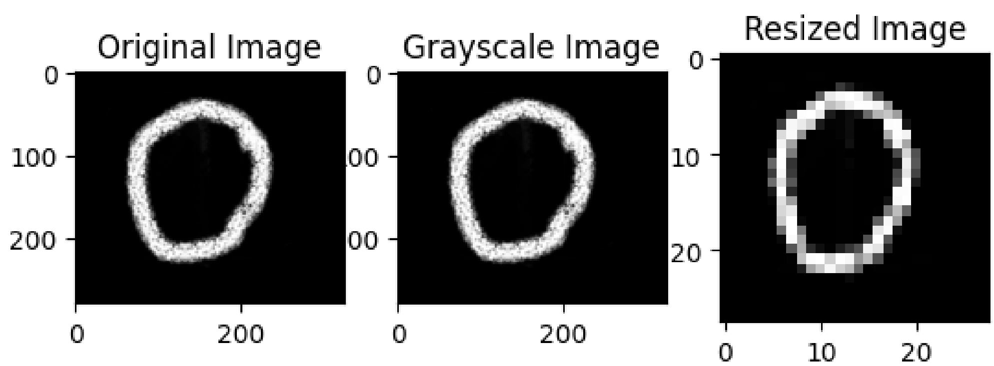
```
ou are saving your model as an HDF5 file via `model.save()`. This file format is consider
ed legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model
.keras')`.
  saving_api.save_model(
```

Dùng `model2.h5` test ví dụ 10 ảnh tự vẽ

In [121]:

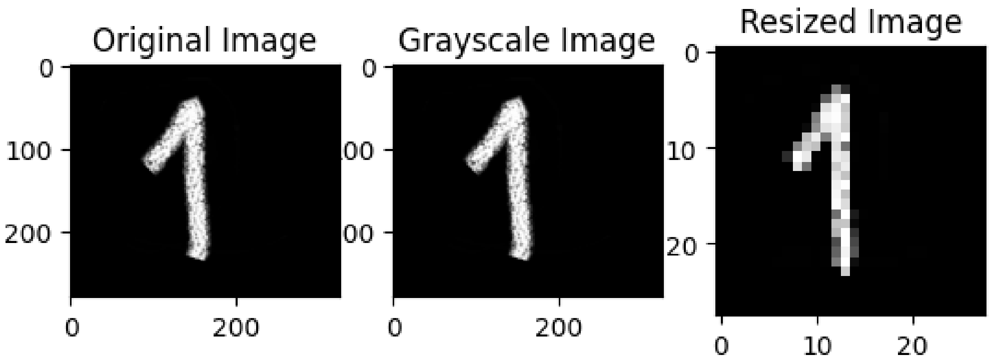
```python
import cv2

for i in range(10):
    img_path = f'/content/{i}.png'  # Construct the path for each image
    img = cv2.imread(img_path)

    if img is not None:
        print(f"Processing image {i}.png")

        # Display original image
        plt.subplot(1, 3, 1)
        plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))
        plt.title('Original Image')

        # Convert to grayscale
        gray_img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

        # Display grayscale image
        plt.subplot(1, 3, 2)
        plt.imshow(gray_img, cmap='gray')
        plt.title('Grayscale Image')

        # Resize to 28x28
        img_resized = cv2.resize(gray_img, (28, 28))

        # Display resized image
        plt.subplot(1, 3, 3)
        plt.imshow(img_resized, cmap='gray')
        plt.title('Resized Image')

        # Preprocess image for prediction
        img_scaled = np.array([img_resized / 255.])

        # Make prediction using the model
        y_hat1 = model2.predict(img_scaled)

        # Get the predicted class
        predicted_class = np.argmax(y_hat1)
        print(f"Predicted class for {i}.png: {predicted_class}")

        plt.show()  # Show the plotted images for each iteration
    else:
        print(f"Could not find image {i}.png")
```

```
Processing image 0.png
1/1 [==============================] - 0s 77ms/step
Predicted class for 0.png: 0
```

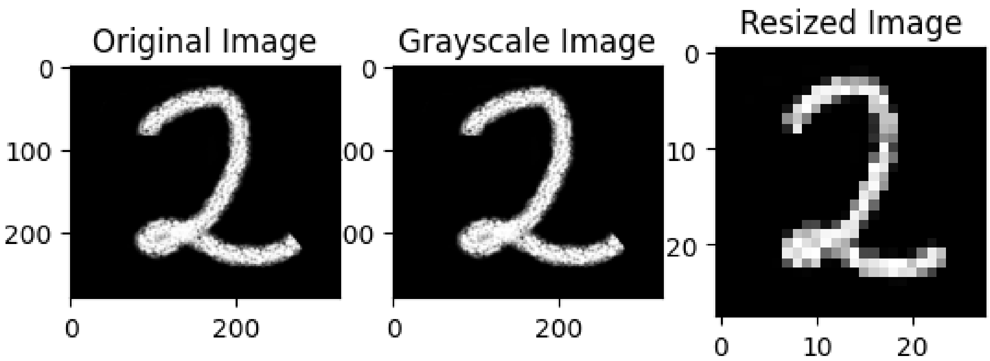



```
Processing image 1.png
1/1 [==============================] - 0s 17ms/step
```

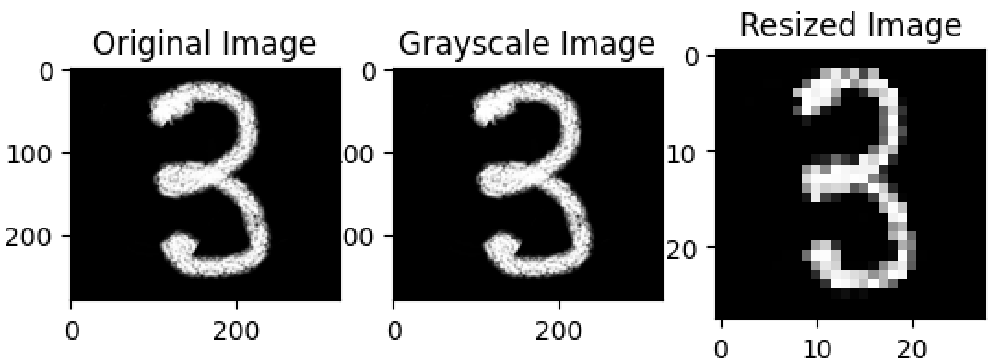
1/1 [==============================] - 0s 17ms/step
Predicted class for 1.png: 1



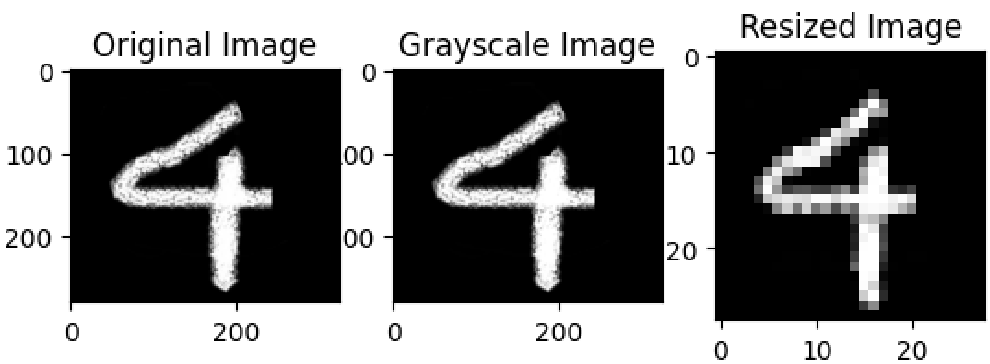
Processing image 2.png
1/1 [==============================] - 0s 18ms/step
Predicted class for 2.png: 2



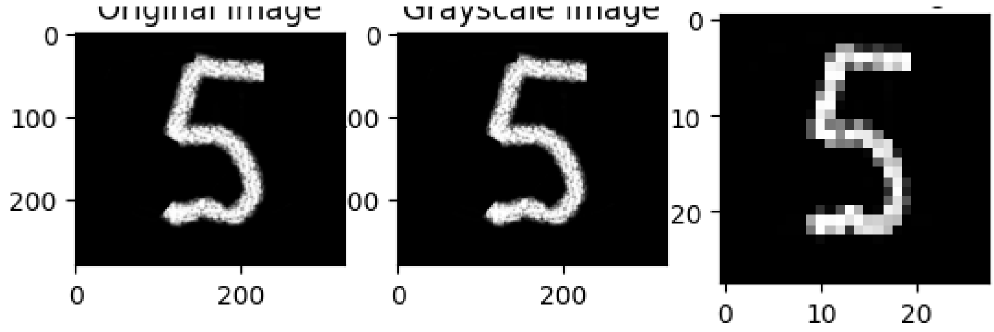
Processing image 3.png
1/1 [==============================] - 0s 17ms/step
Predicted class for 3.png: 3



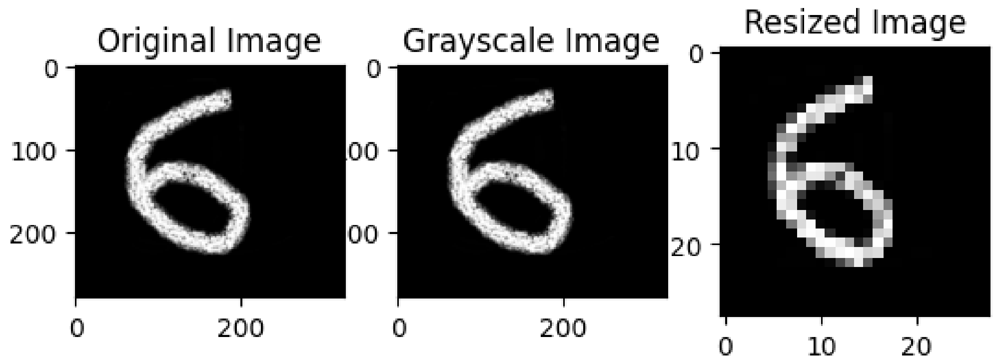
Processing image 4.png
1/1 [==============================] - 0s 19ms/step
Predicted class for 4.png: 9



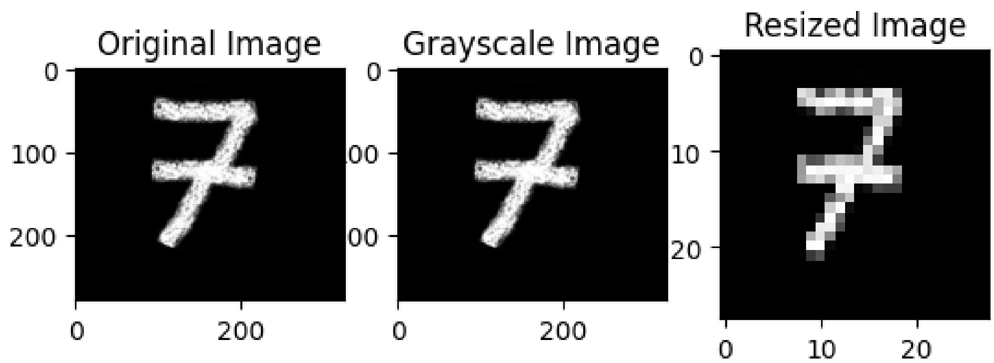
Processing image 5.png
1/1 [==============================] - 0s 19ms/step
Predicted class for 5.png: 5



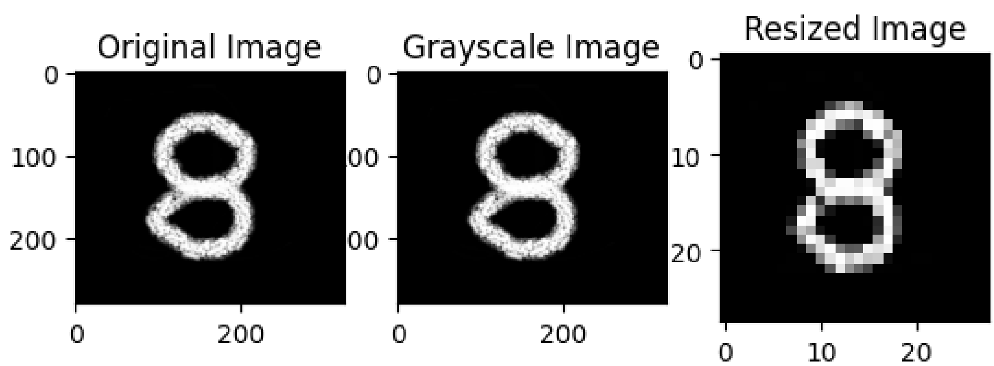
```
Processing image 6.png
1/1 [==============================] - 0s 17ms/step
Predicted class for 6.png: 6
```



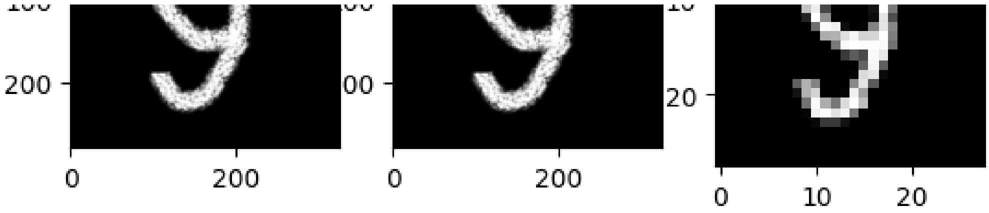

```
Processing image 7.png
1/1 [==============================] - 0s 25ms/step
Predicted class for 7.png: 1
```




```
Processing image 8.png
1/1 [==============================] - 0s 20ms/step
Predicted class for 8.png: 8
```




```
Processing image 9.png
1/1 [==============================] - 0s 18ms/step
Predicted class for 9.png: 9
```



Tính y dự đoán tập test không có nhiễu dùng `model2.h5`

In [122]:

```
y_hat1 = model2.predict(X_test_scaled)
```

```
313/313 [==============================] - 1s 3ms/step
```

Chuẩn hoá y dự đoán và y thật

In [123]:

```
y_test1 = np.argmax(y_test1, axis=1)
y_hat1 = np.argmax(y_hat1, axis=1)
```

Đánh giá khả năng dự đoán của tập MNIST không chèn nhiễu

In [124]:

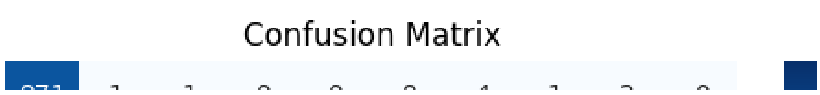
```
target_names = ['0', '1', '2', '3','4','5','6','7','8','9']
print(classification_report(y_test1, y_hat1,target_names=target_names))
```

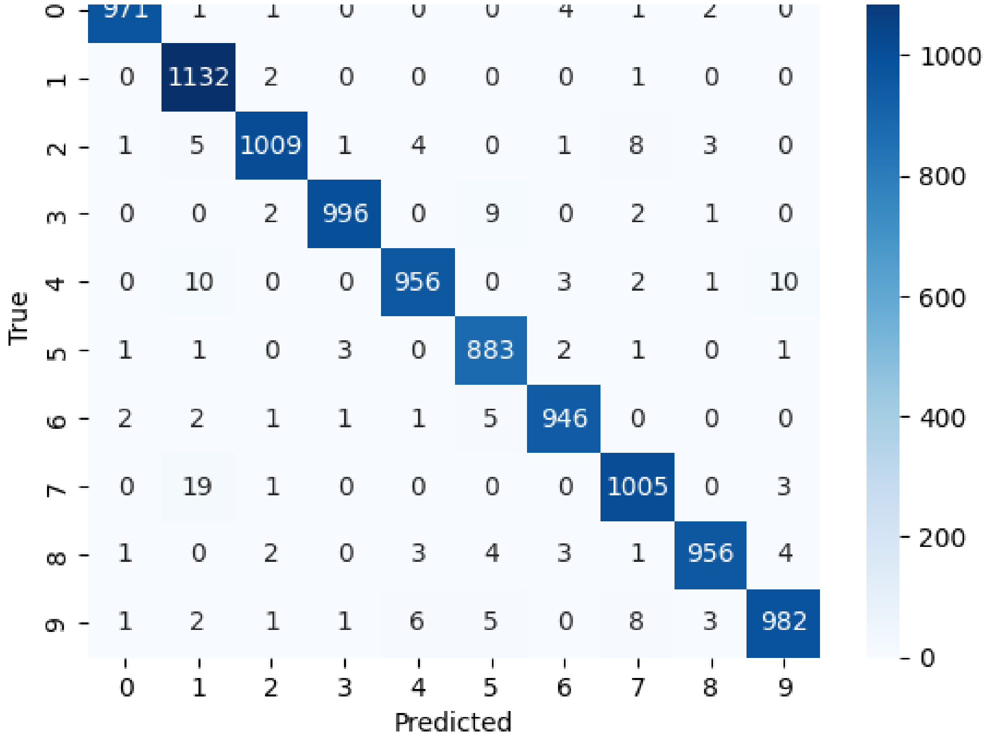
```
              precision    recall  f1-score   support

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

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

Confusion matrix

In [125]:

```
import sklearn.metrics
import seaborn as sn

# Tạo confusion matrix
cm = sklearn.metrics.confusion_matrix(y_test1, y_hat1)

# Vẽ confusion matrix
plt.figure()
sn.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```





Accuracy

In [126]:

```
from sklearn.metrics import accuracy_score
accuracy1 = accuracy_score(y_test1, y_hat1)
print('Accuracy:', accuracy1)
```

```
Accuracy: 0.9836
```

Từ đây ta thấy rằng khi ta train dữ liệu có 1 đường thẳng nhiễu để dự đoán dữ liệu không có nhiễu thì độ chính xác ra kết quả gần 98%

Tính y dự đoán tập test có 1 đường thẳng nhiễu dùng `model1.h5` **và chuẩn hoá**

In [127]:

```
y_hat2 = model1.predict(X_test_scaled1)
```

```
313/313 [==============================] - 1s 3ms/step
```

In [128]:

```
y_hat2 = np.argmax(y_hat2, axis=1)
```

Đánh giá khả năng dự đoán của tập MNIST chèn 1 đường thẳng nhiễu

In [129]:

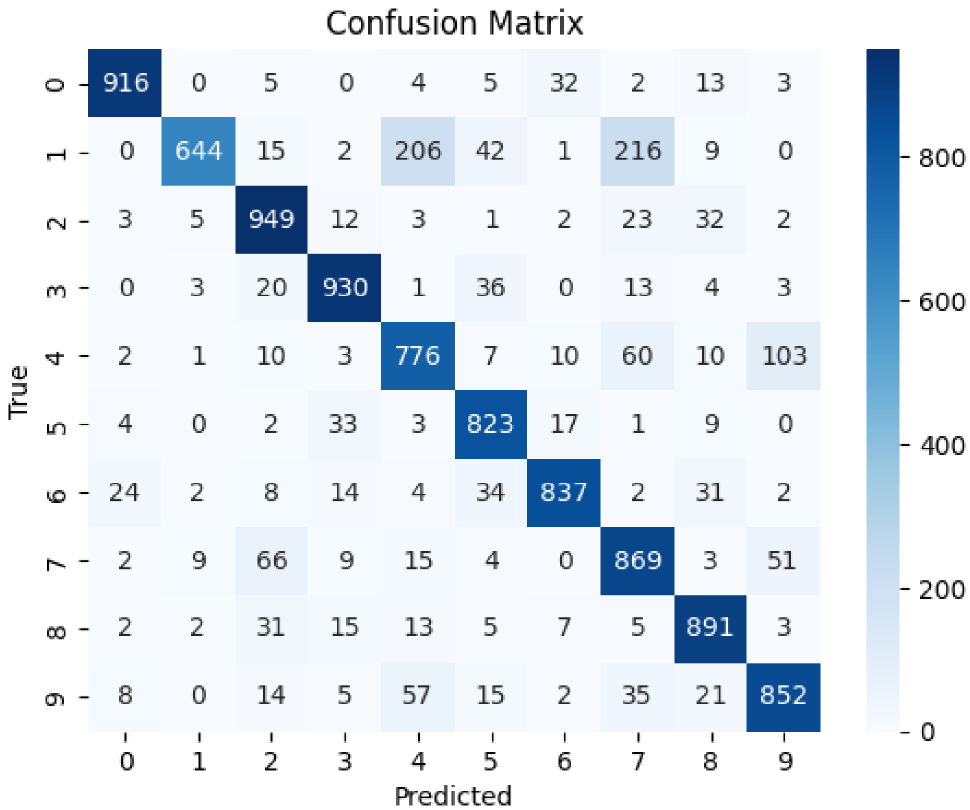
```
target_names = ['0', '1', '2', '3','4','5','6','7','8','9']
print(classification_report(y_test1, y_hat2,target_names=target_names))
```

```
              precision    recall  f1-score   support

           0       0.95      0.93      0.94       980
           1       0.97      0.57      0.72      1135
           2       0.85      0.92      0.88      1032
           3       0.91      0.92      0.91      1010
           4       0.72      0.79      0.75       982
           5       0.85      0.92      0.88       892
           6       0.92      0.87      0.90       958
           7       0.71      0.85      0.77      1028
           8       0.87      0.91      0.89       974
           9       0.84      0.84      0.84      1009
```

```
           9       0.84      0.84      0.84      1009

    accuracy                           0.85     10000
   macro avg       0.86      0.85      0.85     10000
weighted avg       0.86      0.85      0.85     10000
```

In [130]:

```python
import sklearn.metrics
import seaborn as sn

# Tạo confusion matrix
cm = sklearn.metrics.confusion_matrix(y_test1, y_hat2)

# Vẽ confusion matrix
plt.figure()
sn.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```



Đánh giá khả năng dự đoán của tập MNIST đã chèn nhiễu

In [131]:

```python
from sklearn.metrics import accuracy_score
accuracy2 = accuracy_score(y_test1, y_hat2)
print('Accuracy:', accuracy2)
```

```
Accuracy: 0.8487
```

Từ đây ta thấy rằng khi ta train dữ liệu không có nhiễu để dự đoán dữ liệu có 1 đường thẳng nhiễu thì độ chính xác ra kết quả 85%

3. Thêm 2 đường thẳng nhiễu vào tập ảnh MNIST

Trích xuất dữ liệu, thêm 2 đường thẳng nhiễu vào ảnh làm ví dụ

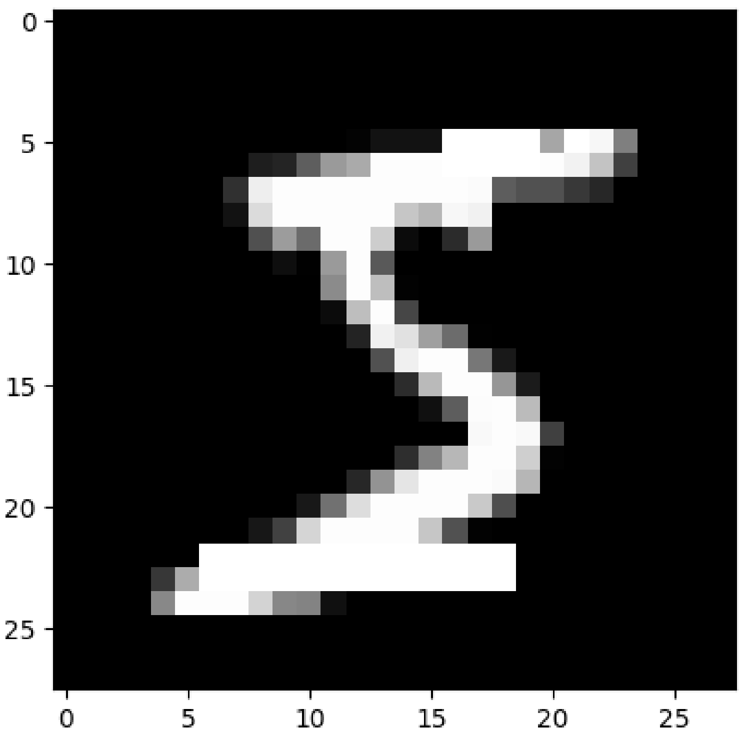
In [152]:

```
(X_train2, y_train2), (X_test2, y_test2) = mnist.load_data()
print(y_train2[0])
x_start = random.randint(2,17)
y_start = random.randint(2,13)
x_end = random.randint(13,25)
y_end = random.randint(2,13)
x_start1 = random.randint(2,17)
y_start1 = random.randint(17,25)
x_end1 = random.randint(13,25)
y_end1 = random.randint(17,25)
thickness = 1
# cv2.rectangle(X_train1[0],(x_start,y_start),(x_end,y_start),(255,255,255),thickness)
# cv2.line(X_train2[0],(x_start,y_start - 1),(x_end,y_start - 1),(255,255,255),thickness)
cv2.line(X_train2[0],(x_start,y_start),(x_end,y_start),(255,255,255),thickness)
cv2.line(X_train2[0],(x_start,y_start + 1),(x_end,y_start + 1),(255,255,255),thickness)
# cv2.line(X_train2[0],(x_start1,y_start1 - 1),(x_end1,y_start1 - 1),(255,255,255),thickn
ess)
cv2.line(X_train2[0],(x_start1,y_start1),(x_end1,y_start1),(255,255,255),thickness)
cv2.line(X_train2[0],(x_start1,y_start1 + 1),(x_end1,y_start1 + 1),(255,255,255),thicknes
s)
plt.imshow(X_train2[0],cmap = 'gray')
```

5

Out[152]:

<matplotlib.image.AxesImage at 0x7fbdb5fccf40>



Thêm nhiễu vào tập train và tập test

In [153]:

```
for i in range (len(X_train2)):
  x_start = random.randint(2,17)
  y_start = random.randint(2,13)
  x_end = random.randint(13,25)
  y_end = random.randint(2,13)
  x_start1 = random.randint(2,17)
  y_start1 = random.randint(17,25)
  x_end1 = random.randint(13,25)
  y_end1 = random.randint(17,25)
  thickness = 1
  # cv2.line(X_train2[i],(x_start,y_start - 1),(x_end,y_start - 1),(255,255,255),thicknes
s)
```

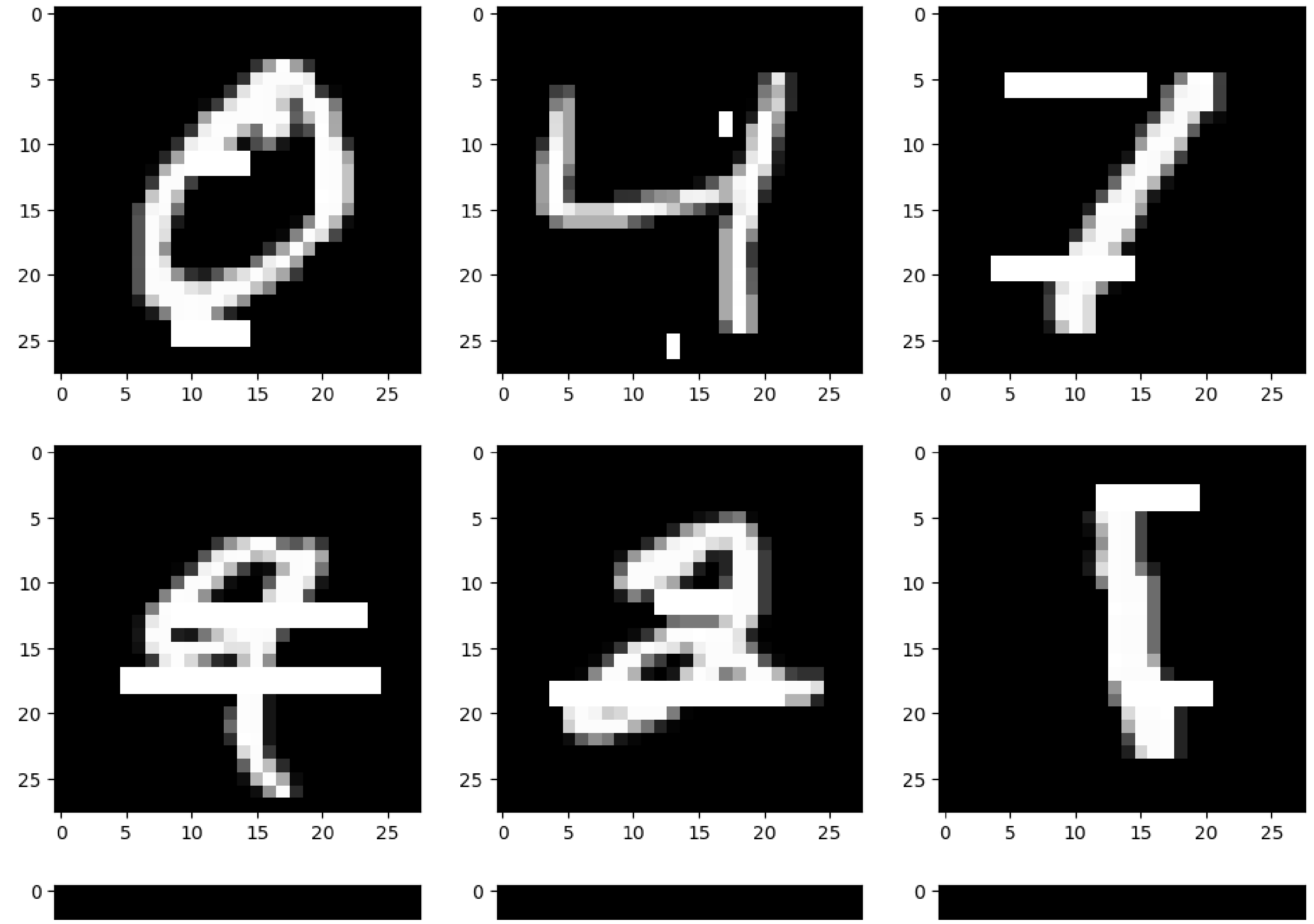
```
    cv2.line(X_train2[i],(x_start,y_start),(x_end,y_start),(255,255,255),thickness)
    cv2.line(X_train2[i],(x_start,y_start + 1),(x_end,y_start + 1),(255,255,255),thickness)
    # cv2.line(X_train2[i],(x_start1,y_start1 - 1),(x_end1,y_start1 - 1),(255,255,255),thickness)
    cv2.line(X_train2[i],(x_start1,y_start1),(x_end1,y_start1),(255,255,255),thickness)
    cv2.line(X_train2[i],(x_start1,y_start1 + 1),(x_end1,y_start1 + 1),(255,255,255),thickness)
```

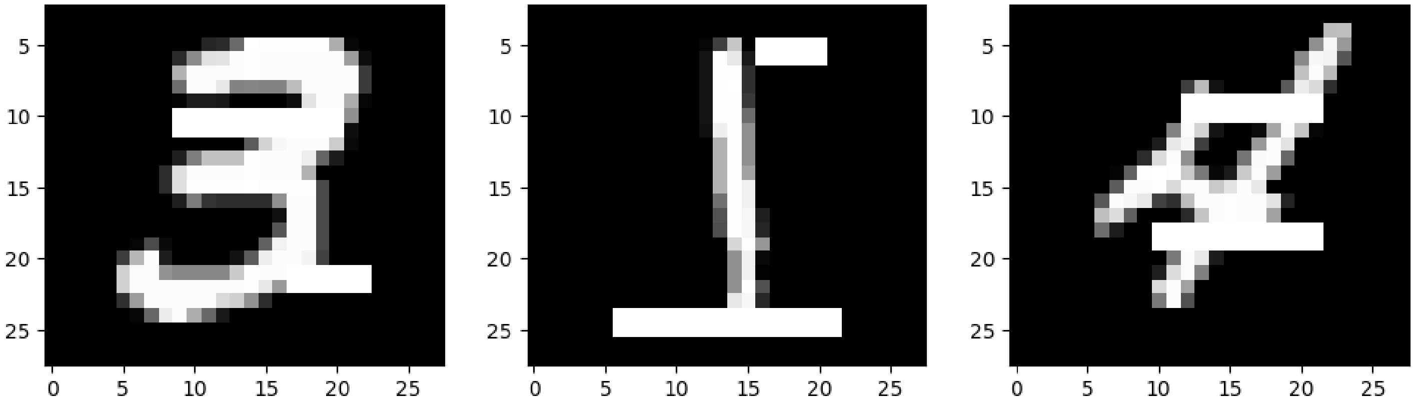
In [154]:

```
for i in range (len(X_test2)):
    x_start = random.randint(2,17)
    y_start = random.randint(2,13)
    x_end = random.randint(13,25)
    y_end = random.randint(2,13)
    x_start1 = random.randint(2,17)
    y_start1 = random.randint(17,25)
    x_end1 = random.randint(13,25)
    y_end1 = random.randint(17,25)
    thickness = 1
    # cv2.line(X_test2[i],(x_start,y_start - 1),(x_end,y_start - 1),(255,255,255),thickness)
    cv2.line(X_test2[i],(x_start,y_start),(x_end,y_start),(255,255,255),thickness)
    cv2.line(X_test2[i],(x_start,y_start + 1),(x_end,y_start + 1),(255,255,255),thickness)
    # cv2.line(X_test2[i],(x_start1,y_start1 - 1),(x_end1,y_start1 - 1),(255,255,255),thickness)
    cv2.line(X_test2[i],(x_start1,y_start1),(x_end1,y_start1),(255,255,255),thickness)
    cv2.line(X_test2[i],(x_start1,y_start1 + 1),(x_end1,y_start1 + 1),(255,255,255),thickness)
```

In [155]:

```
plt.figure(figsize=(12,12))
for i in range (1,10):
    plt.subplot(3,3,i)
    # cv2.rectangle(X_train[i],(x_start,y_start),(x_end,y_start),(255,255,255),thickness)
    plt.imshow(X_train2[i], cmap = 'gray')
```





Chuẩn hoá input, output

In [156]:

```
X_train_scaled2 = np.array(X_train2)/255.
X_test_scaled2 = np.array(X_test2)/255.
X_train_scaled2, X_val_scaled2,y_train2, y_val2 = train_test_split(X_train_scaled2, y_tra
in2, test_size=0.2, random_state=42)
# OnehotVector output
from sklearn.preprocessing import OneHotEncoder
encoder = OneHotEncoder()
encoder.fit(y_train2.reshape(-1,1))
y_train2 = encoder.transform(y_train2.reshape(-1,1)).toarray()
y_val2 = encoder.transform(y_val2.reshape(-1,1)).toarray()
y_test2 = encoder.transform(y_test2.reshape(-1,1)).toarray()
```

Mạng CNN

In [157]:

```
# CNN model
inp = Input(shape = (28,28,1)) # input shape
cnn = Conv2D(filters = 8, kernel_size = 3, activation='relu')(inp)
pooling = MaxPooling2D(pool_size=(2,2))(cnn)
drop = Dropout(0.2)(pooling)

cnn = Conv2D(filters = 16, kernel_size = 4, activation='relu')(drop)
pooling = MaxPooling2D(pool_size=(2,2))(cnn)
drop = Dropout(0.2)(pooling)

cnn = Conv2D(filters = 32, kernel_size = 4, activation='relu')(drop)
pooling = MaxPooling2D(pool_size=(2,2))(cnn)

f = Flatten()(pooling)

fc1 = Dense(units = 32, activation = 'relu')(f)
fc2 = Dense(units = 16, activation = 'relu')(fc1)
out = Dense(units = 10, activation = 'softmax')(fc2)

model = Model(inputs = inp, outputs = out)
model.summary()
```

```
Model: "model_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_9 (InputLayer)        [(None, 28, 28, 1)]       0

 conv2d_24 (Conv2D)          (None, 26, 26, 8)         80

 max_pooling2d_24 (MaxPooli  (None, 13, 13, 8)         0
 ng2D)

 dropout_16 (Dropout)        (None, 13, 13, 8)         0

 conv2d_25 (Conv2D)          (None, 10, 10, 16)        2064
```

```
 max_pooling2d_25 (MaxPooli  (None, 5, 5, 16)          0
 ng2D)

 dropout_17 (Dropout)        (None, 5, 5, 16)          0

 conv2d_26 (Conv2D)          (None, 2, 2, 32)          8224

 max_pooling2d_26 (MaxPooli  (None, 1, 1, 32)          0
 ng2D)

 flatten_8 (Flatten)         (None, 32)                0

 dense_24 (Dense)            (None, 32)                1056

 dense_25 (Dense)            (None, 16)                528

 dense_26 (Dense)            (None, 10)                170

=================================================================
Total params: 12122 (47.35 KB)
Trainable params: 12122 (47.35 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Train dữ liệu

In [158]:

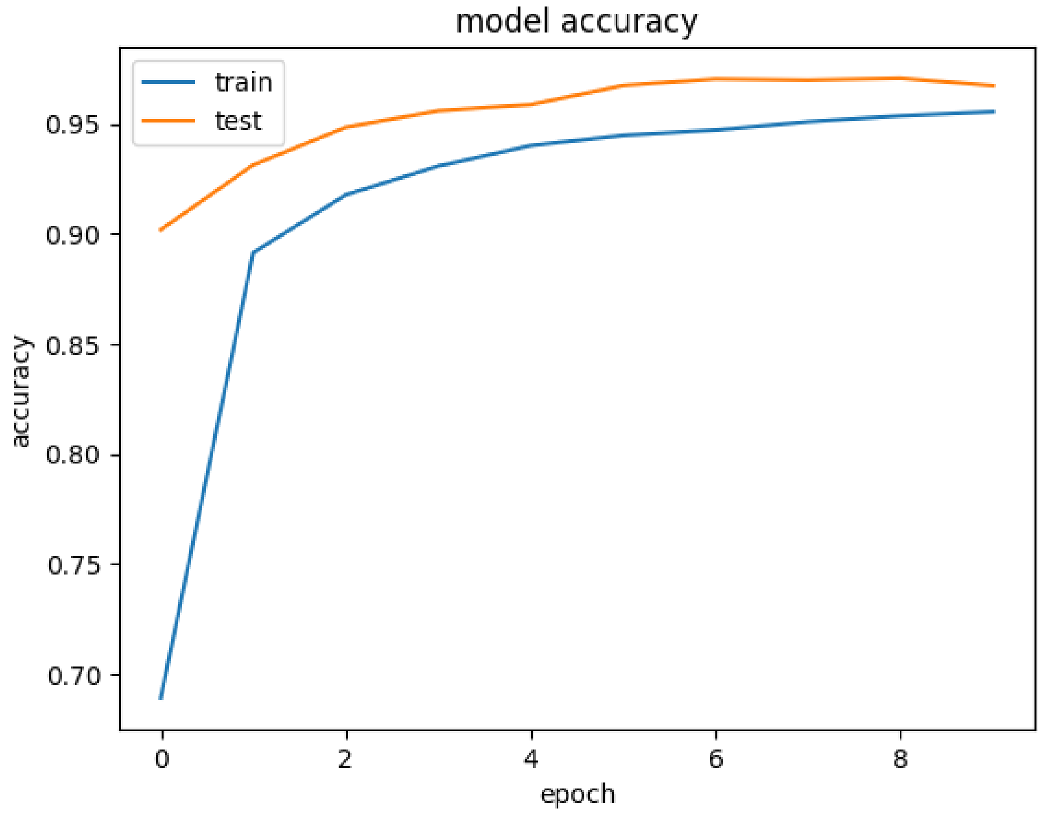
```
optimizer1 = tensorflow.keras.optimizers.Adam(learning_rate = 0.001)
model.compile(optimizer = optimizer1, loss='categorical_crossentropy',metrics = ['accura
cy'])

history = model.fit(X_train_scaled2,y_train2,batch_size=64,
                    epochs = 10, validation_data = (X_val_scaled2, y_val2))
```

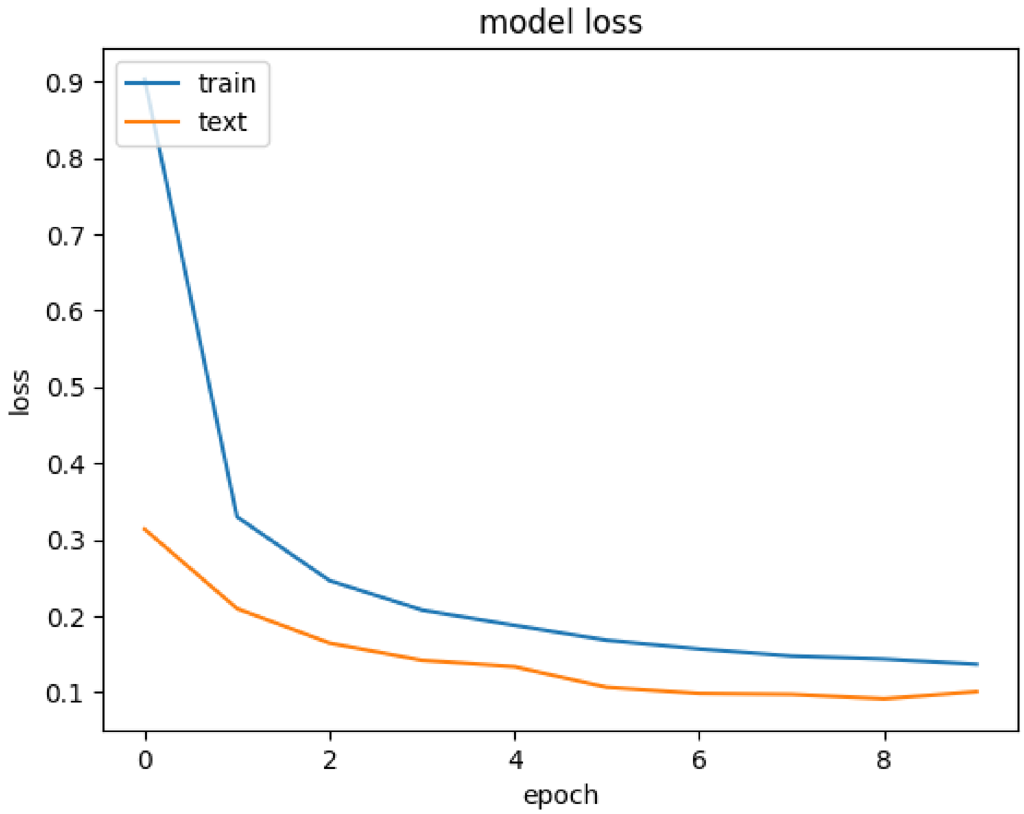
```
Epoch 1/10
750/750 [==============================] - 6s 6ms/step - loss: 0.9029 - accuracy: 0.6891
- val_loss: 0.3136 - val_accuracy: 0.9019
Epoch 2/10
750/750 [==============================] - 5s 6ms/step - loss: 0.3298 - accuracy: 0.8915
- val_loss: 0.2097 - val_accuracy: 0.9314
Epoch 3/10
750/750 [==============================] - 4s 5ms/step - loss: 0.2464 - accuracy: 0.9178
- val_loss: 0.1645 - val_accuracy: 0.9485
Epoch 4/10
750/750 [==============================] - 4s 5ms/step - loss: 0.2078 - accuracy: 0.9309
- val_loss: 0.1419 - val_accuracy: 0.9560
Epoch 5/10
750/750 [==============================] - 4s 6ms/step - loss: 0.1877 - accuracy: 0.9402
- val_loss: 0.1336 - val_accuracy: 0.9588
Epoch 6/10
750/750 [==============================] - 5s 6ms/step - loss: 0.1682 - accuracy: 0.9448
- val_loss: 0.1066 - val_accuracy: 0.9675
Epoch 7/10
750/750 [==============================] - 4s 5ms/step - loss: 0.1568 - accuracy: 0.9473
- val_loss: 0.0984 - val_accuracy: 0.9705
Epoch 8/10
750/750 [==============================] - 4s 5ms/step - loss: 0.1475 - accuracy: 0.9510
- val_loss: 0.0973 - val_accuracy: 0.9700
Epoch 9/10
750/750 [==============================] - 5s 6ms/step - loss: 0.1435 - accuracy: 0.9537
- val_loss: 0.0915 - val_accuracy: 0.9708
Epoch 10/10
750/750 [==============================] - 4s 5ms/step - loss: 0.1366 - accuracy: 0.9556
- val_loss: 0.1007 - val_accuracy: 0.9674
```

Trực quan hoá kết quả vừa train

In [159]:

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train','test'],loc = 'upper left')
plt.show()
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train','text'],loc='upper left')
plt.show()
```





Lưu và load dữ liệu vào file `model3.h5`

In [160]:

```
model.save('model3.h5')
from tensorflow.keras.models import load_model
model3 = load_model('/content/model3.h5')
```

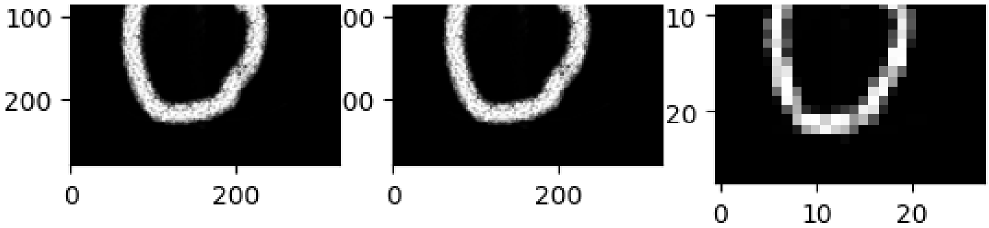
```
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3079: UserWarning: Y
ou are saving your model as an HDF5 file via `model.save()`. This file format is consider
ed legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model
.keras')`.
  saving_api.save_model(
```

Dùng `model3.h5` **test ví dụ 10 ảnh tự vẽ**

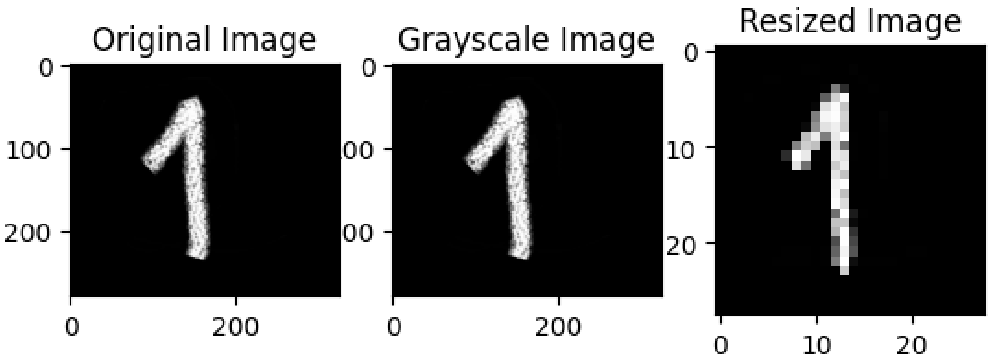
In [161]:

```
import cv2

for i in range(10):
    img_path = f'/content/{i}.png'  # Construct the path for each image
    img = cv2.imread(img_path)

    if img is not None:
        print(f"Processing image {i}.png")

        # Display original image
        plt.subplot(1, 3, 1)
        plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))
        plt.title('Original Image')

        # Convert to grayscale
        gray_img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

        # Display grayscale image
        plt.subplot(1, 3, 2)
        plt.imshow(gray_img, cmap='gray')
        plt.title('Grayscale Image')

        # Resize to 28x28
        img_resized = cv2.resize(gray_img, (28, 28))

        # Display resized image
        plt.subplot(1, 3, 3)
        plt.imshow(img_resized, cmap='gray')
        plt.title('Resized Image')

        # Preprocess image for prediction
        img_scaled = np.array([img_resized / 255.])

        # Make prediction using the model
        y_hat3 = model3.predict(img_scaled)

        # Get the predicted class
        predicted_class = np.argmax(y_hat3)
        print(f"Predicted class for {i}.png: {predicted_class}")

        plt.show()  # Show the plotted images for each iteration
    else:
        print(f"Could not find image {i}.png")
```

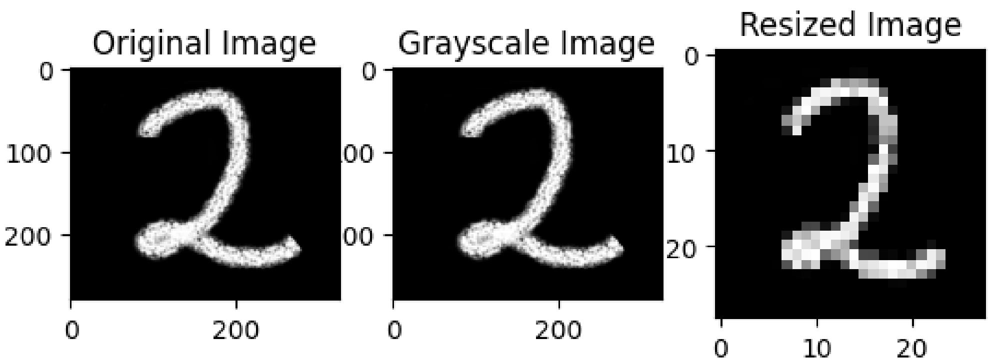
```
Processing image 0.png
1/1 [==============================] - 0s 81ms/step
Predicted class for 0.png: 0
```



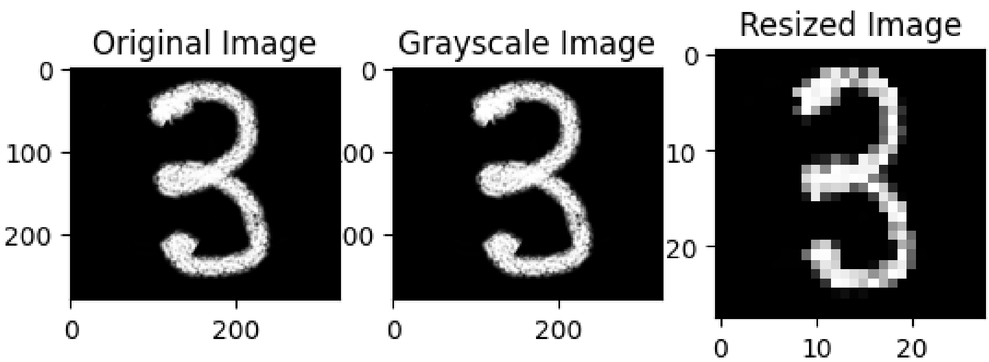
```
Processing image 1.png
1/1 [==============================] - 0s 19ms/step
Predicted class for 1.png: 1
```



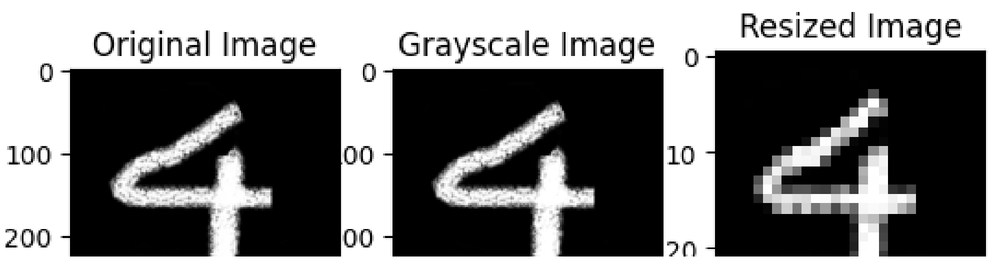

```
Processing image 2.png
1/1 [==============================] - 0s 17ms/step
Predicted class for 2.png: 2
```



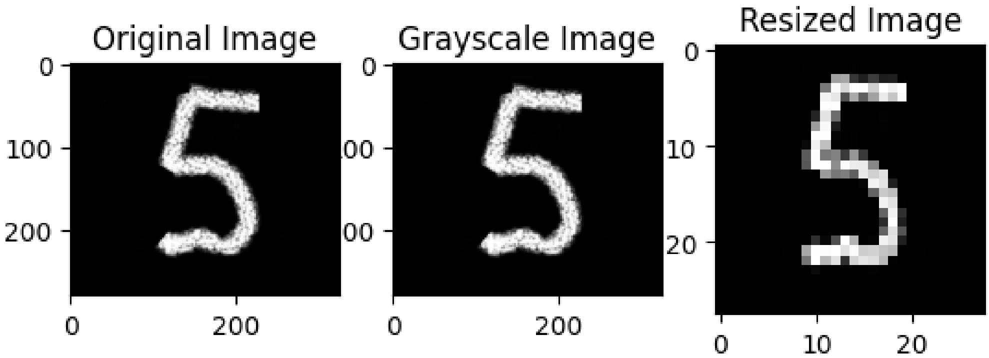

```
Processing image 3.png
1/1 [==============================] - 0s 18ms/step
Predicted class for 3.png: 3
```



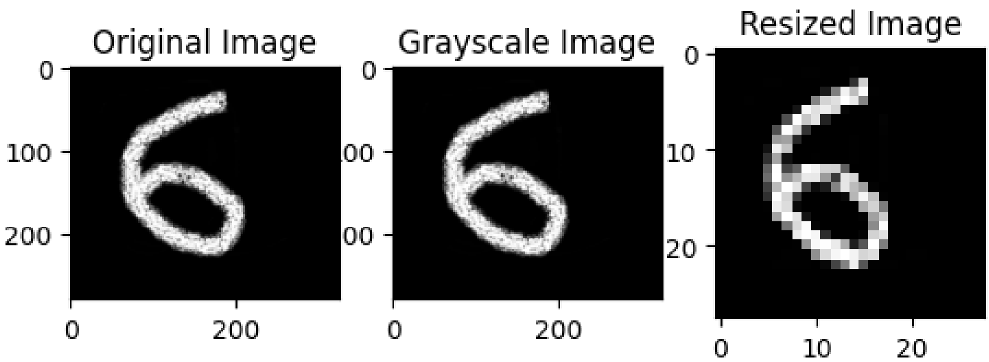

```
Processing image 4.png
1/1 [==============================] - 0s 19ms/step
Predicted class for 4.png: 9
```



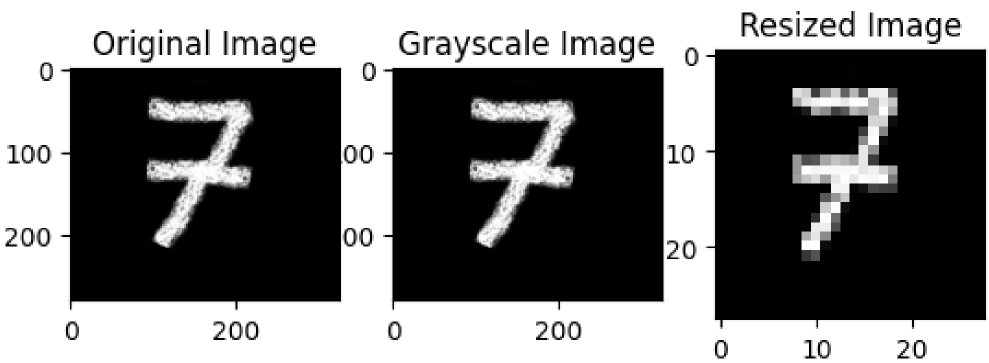
```
Processing image 5.png
1/1 [==============================] - 0s 16ms/step
Predicted class for 5.png: 5
```



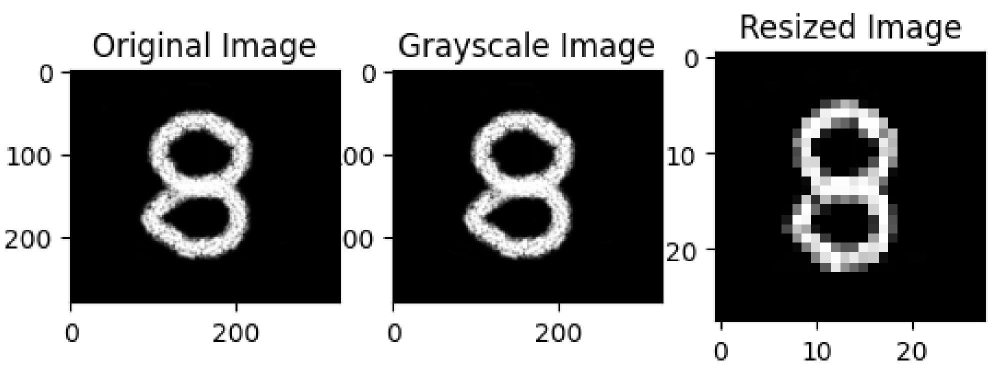

```
Processing image 6.png
1/1 [==============================] - 0s 17ms/step
Predicted class for 6.png: 6
```



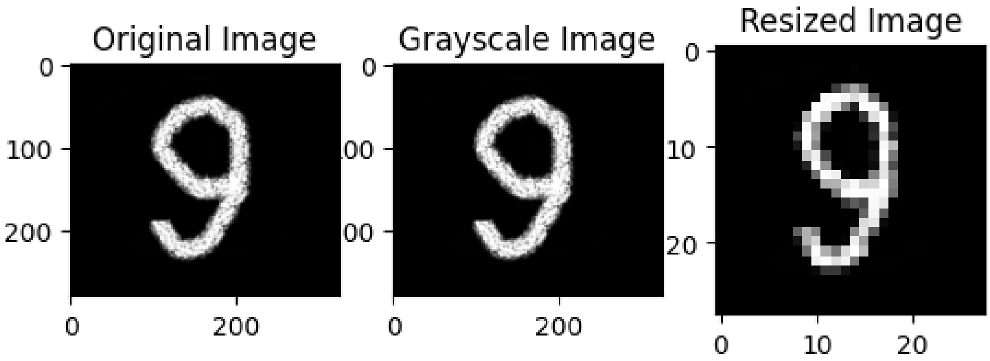

```
Processing image 7.png
1/1 [==============================] - 0s 19ms/step
Predicted class for 7.png: 1
```




```
Processing image 8.png
1/1 [==============================] - 0s 22ms/step
Predicted class for 8.png: 8
```



```
Processing image 9.png
1/1 [==============================] - 0s 31ms/step
Predicted class for 9.png: 9
```



Tính y dự đoán tập test không có nhiễu dùng `model3.h5`

In [162]:

```
y_hat3 = model3.predict(X_test_scaled)
```

```
313/313 [==============================] - 1s 3ms/step
```

Chuẩn hoá y dự đoán và y thật

In [163]:

```
y_test2 = np.argmax(y_test2, axis=1)
y_hat3 = np.argmax(y_hat3, axis=1)
```

Đánh giá khả năng dự đoán của tập MNIST không chèn nhiễu

In [164]:

```
target_names = ['0', '1', '2', '3','4','5','6','7','8','9']
print(classification_report(y_test2, y_hat3,target_names=target_names))
```

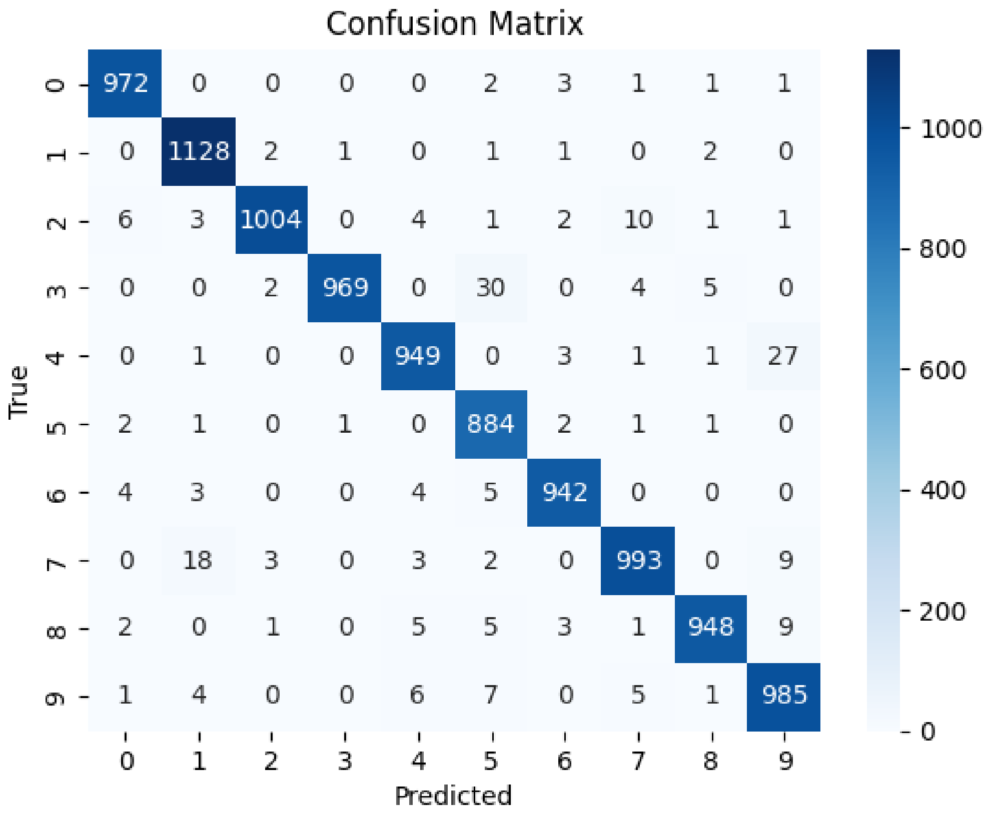
```
              precision    recall  f1-score   support

           0       0.98      0.99      0.99       980
           1       0.97      0.99      0.98      1135
           2       0.99      0.97      0.98      1032
           3       1.00      0.96      0.98      1010
           4       0.98      0.97      0.97       982
           5       0.94      0.99      0.97       892
           6       0.99      0.98      0.98       958
           7       0.98      0.97      0.97      1028
           8       0.99      0.97      0.98       974
           9       0.95      0.98      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
```

Confusion matrix

In [165]:

```
import sklearn.metrics
import seaborn as sn

# Tạo confusion matrix
cm = sklearn.metrics.confusion_matrix(y_test2, y_hat3)
```

```
# Vẽ confusion matrix
plt.figure()
sn.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```



Accuracy

In [166]:

```
from sklearn.metrics import accuracy_score
accuracy3 = accuracy_score(y_test2, y_hat3)
print('Accuracy:', accuracy3)
```

```
Accuracy: 0.9774
```

Từ đây ta thấy rằng khi ta train dữ liệu có 2 đường thẳng nhiễu để dự đoán dữ liệu không có nhiễu thì độ chính xác ra kết quả gần 98%

Tính y dự đoán tập test có 2 đường thẳng nhiễu dùng `model1.h5` và chuẩn hoá

In [167]:

```
y_hat4 = model1.predict(X_test_scaled2)
```

```
313/313 [==============================] - 1s 3ms/step
```

In [168]:

```
y_hat4 = np.argmax(y_hat4, axis=1)
```

Đánh giá khả năng dự đoán của tập MNIST chèn 2 đường thẳng nhiễu

In [169]:

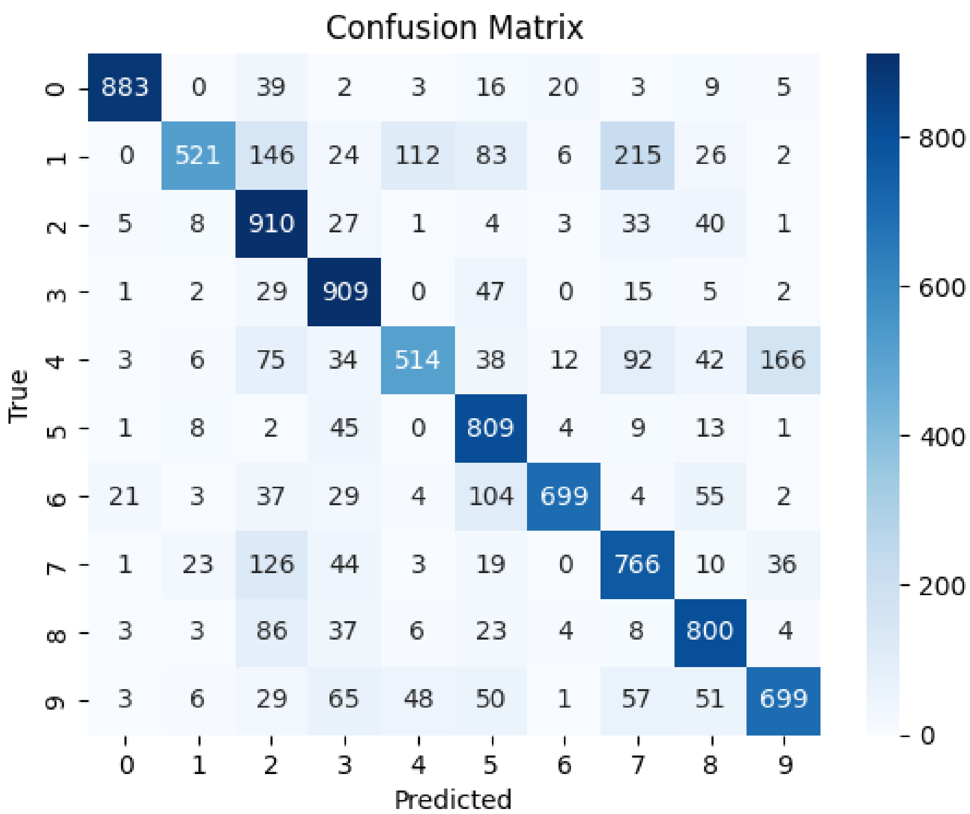
```
target_names = ['0', '1', '2', '3','4','5','6','7','8','9']
print(classification_report(y_test2, y_hat4,target_names=target_names))
```

```
              precision    recall  f1-score   support
```

0	0.96	0.90	0.93	980
1	0.90	0.46	0.61	1135
2	0.62	0.88	0.72	1032
3	0.75	0.90	0.82	1010
4	0.74	0.52	0.61	982
5	0.68	0.91	0.78	892
6	0.93	0.73	0.82	958
7	0.64	0.75	0.69	1028
8	0.76	0.82	0.79	974
9	0.76	0.69	0.73	1009
accuracy			0.75	10000
macro avg	0.77	0.76	0.75	10000
weighted avg	0.77	0.75	0.75	10000

In [170]:

```
import sklearn.metrics
import seaborn as sn

# Tạo confusion matrix
cm = sklearn.metrics.confusion_matrix(y_test2, y_hat4)

# Vẽ confusion matrix
plt.figure()
sn.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```



Accuracy

In [171]:

```
from sklearn.metrics import accuracy_score
accuracy4 = accuracy_score(y_test2, y_hat4)
print('Accuracy:', accuracy4)
```

Accuracy: 0.751

Từ đây ta thấy rằng khi ta train dữ liệu không có nhiễu để dự đoán dữ liệu có 2 đường thẳng nhiễu thì độ chính xác ra kết quả 75%

Từ bài lab ta thấy rằng khi ta train dữ liệu có nhiễu để dự đoán dữ liệu không có nhiễu thì độ chính xác ra kết quả tiệm cận 100% (không khả thi), trong khi đó khi ta train dữ liệu không có nhiễu để dự đoán dữ liệu có 1 hoặc 2 đường thẳng nhiễu thì độ chính xác ra kết quả thấp hơn (trong khoảng 80% ± 5% khả thi)