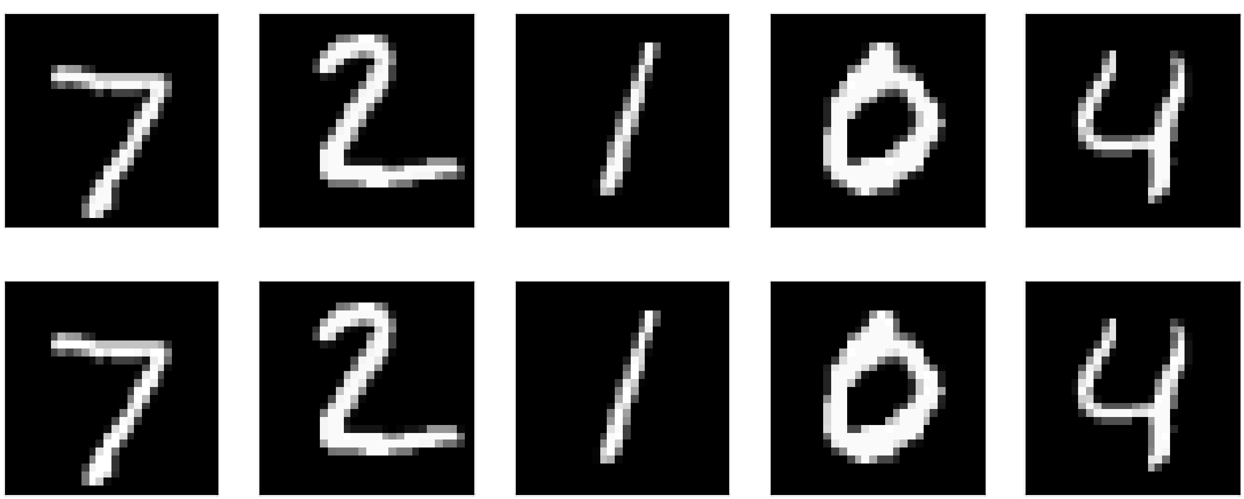
In [1]:
```
import keras
from keras.datasets import mnist
from tensorflow.keras.models import Sequential
from keras.optimizers import RMSprop
from tensorflow.keras.layers import Dense, Dropout, Flatten
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from keras import backend
```

```
Using TensorFlow backend.
```

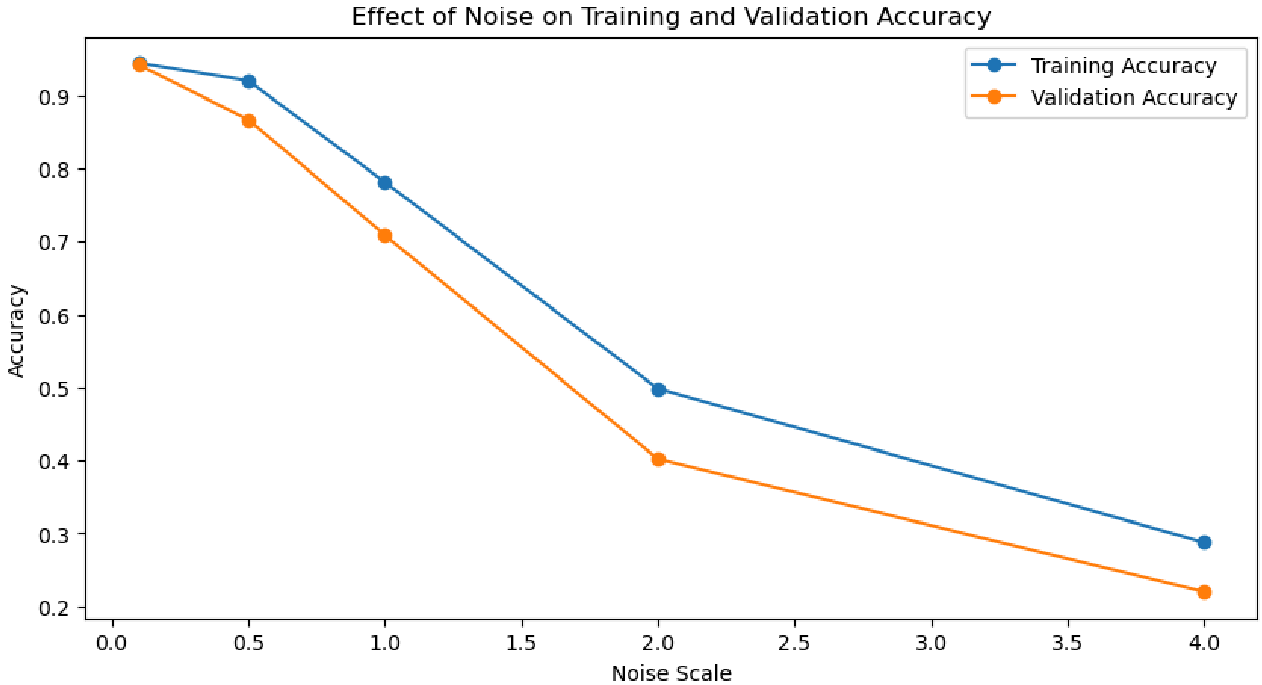
In [2]:
```
# Part 1
import numpy as np
from keras.datasets import mnist
import matplotlib.pyplot as plt

# Load the MNIST dataset
(x_train, _), (x_test, _) = mnist.load_data()

# Add random noise to the training images
noisy_x_train = x_train + np.random.normal(loc=0.5, scale=0.3, size=x_train.shape)
noisy_x_train = np.clip(noisy_x_train, 0, 255)  # Clip the values to ensure they are within the valid ran

# Add random noise to the testing images
noisy_x_test = x_test + np.random.normal(loc=0.5, scale=0.3, size=x_test.shape)
noisy_x_test = np.clip(noisy_x_test, 0, 255)  # Clip the values to ensure they are within the valid range

# Print out several original and noisy images for inspection
n = 5  # Number of images to display
plt.figure(figsize=(10, 4))
for i in range(n):
    # Display original images
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test[i])
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

    # Display noisy images
    ax = plt.subplot(2, n, i + 1 + n)
    plt.imshow(noisy_x_test[i])
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
plt.show()
```



In [4]:
```
# Part 2
import numpy as np
from keras.datasets import mnist
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense, Flatten
from keras.utils import to_categorical
from tensorflow.keras.optimizers import Adam

# Load the MNIST dataset
(x_train, y_train), (x_test, y_test) = mnist.load_data()

# Preprocess the data
x_train = x_train.reshape(-1, 28, 28, 1) / 255.0
x_test = x_test.reshape(-1, 28, 28, 1) / 255.0
y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)

# Define the MLNN model
model = Sequential([
    Flatten(input_shape=(28, 28, 1)),
    Dense(128, activation='relu'),
    Dense(10, activation='softmax')
])

# Compile the model
model.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model on original data
model.fit(x_train, y_train, epochs=10, validation_data=(x_test, y_test))

# Evaluate the model on original test data
original_data_accuracy = model.evaluate(x_test, y_test, verbose=0)[1]

# Add random noise to the training and testing data
noisy_x_train = x_train + np.random.normal(loc=0.5, scale=0.3, size=x_train.shape)
noisy_x_train = np.clip(noisy_x_train, 0, 1)  # Clip the values to ensure they are within the valid range
noisy_x_test = x_test + np.random.normal(loc=0.5, scale=0.3, size=x_test.shape)
noisy_x_test = np.clip(noisy_x_test, 0, 1)  # Clip the values to ensure they are within the valid range

# Train the model on noisy data
model.fit(noisy_x_train, y_train, epochs=10, validation_data=(noisy_x_test, y_test))

# Evaluate the model on noisy test data
noisy_data_accuracy = model.evaluate(noisy_x_test, y_test, verbose=0)[1]

# Compare the accuracies
print("Accuracy on original data:", original_data_accuracy)
print("Accuracy on noisy data:", noisy_data_accuracy)
```

```
Epoch 1/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.2527 - accuracy: 0.9277 - val_loss:
0.1253 - val_accuracy: 0.9629
Epoch 2/10
1875/1875 [==============================] - 3s 1ms/step - loss: 0.1100 - accuracy: 0.9675 - val_loss:
0.1049 - val_accuracy: 0.9676
Epoch 3/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0755 - accuracy: 0.9773 - val_loss:
0.0846 - val_accuracy: 0.9733
Epoch 4/10
1875/1875 [==============================] - 3s 1ms/step - loss: 0.0571 - accuracy: 0.9827 - val_loss:
0.0774 - val_accuracy: 0.9755
Epoch 5/10
1875/1875 [==============================] - 3s 1ms/step - loss: 0.0425 - accuracy: 0.9869 - val_loss:
0.0751 - val_accuracy: 0.9765
Epoch 6/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0358 - accuracy: 0.9891 - val_loss:
0.0801 - val_accuracy: 0.9759
Epoch 7/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0280 - accuracy: 0.9913 - val_loss:
0.0711 - val_accuracy: 0.9778
Epoch 8/10
1875/1875 [==============================] - 3s 1ms/step - loss: 0.0216 - accuracy: 0.9935 - val_loss:
0.0789 - val_accuracy: 0.9764
Epoch 9/10
1875/1875 [==============================] - 3s 1ms/step - loss: 0.0181 - accuracy: 0.9944 - val_loss:
0.0840 - val_accuracy: 0.9766
Epoch 10/10
1875/1875 [==============================] - 3s 1ms/step - loss: 0.0150 - accuracy: 0.9953 - val_loss:
0.0821 - val_accuracy: 0.9772
Epoch 1/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.6377 - accuracy: 0.8065 - val_loss:
0.4155 - val_accuracy: 0.8709
Epoch 2/10
1875/1875 [==============================] - 3s 1ms/step - loss: 0.3585 - accuracy: 0.8849 - val_loss:
0.3667 - val_accuracy: 0.8836
Epoch 3/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.2973 - accuracy: 0.9037 - val_loss:
0.3203 - val_accuracy: 0.8964
Epoch 4/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.2559 - accuracy: 0.9170 - val_loss:
0.2993 - val_accuracy: 0.9043
Epoch 5/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.2279 - accuracy: 0.9267 - val_loss:
0.3182 - val_accuracy: 0.8995
Epoch 6/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.2071 - accuracy: 0.9324 - val_loss:
0.2656 - val_accuracy: 0.9149
Epoch 7/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.1905 - accuracy: 0.9373 - val_loss:
0.2919 - val_accuracy: 0.9114
Epoch 8/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.1757 - accuracy: 0.9426 - val_loss:
0.2844 - val_accuracy: 0.9104
Epoch 9/10
1875/1875 [==============================] - 3s 1ms/step - loss: 0.1617 - accuracy: 0.9468 - val_loss:
0.2799 - val_accuracy: 0.9133
Epoch 10/10
1875/1875 [==============================] - 3s 1ms/step - loss: 0.1509 - accuracy: 0.9498 - val_loss:
0.2654 - val_accuracy: 0.9183
Accuracy on original data: 0.9771999716758728
Accuracy on noisy data: 0.9182999730110168
```

In [6]:
```
# Part 3
import numpy as np
from keras.datasets import mnist
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense, Flatten
from keras.utils import to_categorical
from tensorflow.keras.optimizers import Adam
import matplotlib.pyplot as plt

# Load the MNIST dataset
(x_train, y_train), (x_test, y_test) = mnist.load_data()

# Preprocess the data
x_train = x_train.reshape(-1, 28, 28, 1) / 255.0
x_test = x_test.reshape(-1, 28, 28, 1) / 255.0
y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)

# Define the MLNN model
model = Sequential([
    Flatten(input_shape=(28, 28, 1)),
    Dense(128, activation='relu'),
    Dense(10, activation='softmax')
])

# Compile the model
model.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy'])

# Vary the amount of noise and track the accuracies
scales = [0.1, 0.5, 1.0, 2.0, 4.0]
train_accuracies = []
val_accuracies = []

for scale in scales:
    # Add random noise to the training and testing data
    noisy_x_train = x_train + np.random.normal(loc=0.5, scale=scale, size=x_train.shape)
    noisy_x_train = np.clip(noisy_x_train, 0, 1)  # Clip the values to ensure they are within the valid r
    noisy_x_test = x_test + np.random.normal(loc=0.5, scale=scale, size=x_test.shape)
    noisy_x_test = np.clip(noisy_x_test, 0, 1)  # Clip the values to ensure they are within the valid ran

    # Train the model on noisy data
    history = model.fit(noisy_x_train, y_train, epochs=10, validation_data=(noisy_x_test, y_test), verbos

    # Evaluate the model on noisy training and validation data
    train_accuracy = history.history['accuracy'][-1]
    val_accuracy = history.history['val_accuracy'][-1]

    train_accuracies.append(train_accuracy)
    val_accuracies.append(val_accuracy)

# Plot the results
plt.figure(figsize=(10, 5))
plt.plot(scales, train_accuracies, marker='o', label='Training Accuracy')
plt.plot(scales, val_accuracies, marker='o', label='Validation Accuracy')
plt.xlabel('Noise Scale')
plt.ylabel('Accuracy')
plt.title('Effect of Noise on Training and Validation Accuracy')
plt.legend()
plt.show()
```



In [ ]:

```
# Part 4
# Compared to last week, the accuracy between the training and validation data is much closer graphically
```